

Federated Learning in Smart Meters

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Abstract—The increasing complexity of modern energy systems generates a large volume of heterogeneous smart meter data, which includes parameters like temperature, humidity, occupancy, HVAC utilization, lighting, and renewable energy contributions. The efficient analysis of such datasets is necessary to arrive at an energy demand forecast, consumption optimization, and anomaly detection. Conventional centralized machine learning suffers from serious issues regarding data privacy, security, and computational scalability. This work considers a software-based FL framework that can be adopted for collaborative energy consumption modeling without any sort of centralized storage of data. Here, each of these participating data sources independently trains local machine learning models on respective private datasets. These models' parameters are combined in regular intervals to form one global model using the FedAvg algorithm. In such a procedure, sensitive consumption data resides in a decentralized manner to improve privacy and integrity. The proposed framework considers several machine learning algorithms, namely RF, GBM, and LSTM networks, for performance evaluation. Such models will be employed to capture non-linear relationships and temporal dependencies existing across energy consumption. Experimental analysis on a synthetic smart meter dataset demonstrates the predictive performance of the federated models, which is comparable to that of centralized training while maintaining superior privacy guarantees along with computational efficiency. Thus, this paper sets up a robust and scalable architecture of FL for smart meter data analytics, which may act as a basic framework for developing secure data-driven energy management solutions in an actual software environment.

Keywords—FedAvg algorithm; RF; GBM; LSTM networks; Federated Learning; data-driven energy management; machine learning models; smart meter

I. INTRODUCTION

With energy systems rapidly digitizing, fine-grained energy consumption data can be collected and analyzed continuously. Smart meter data provides necessary insights into demand side management strategies, operational efficiency, and user behavior. Many of these datasets are made up of temperature, humidity, occupancy, HVAC activities, lighting intensity, and contributions from renewable energy sources, among many others. These multi-dimensional, high-frequency data enable the training of complex machine learning models in load distribution optimization, anomaly detection, and energy demand forecasting.

Traditional centralized learning architectures require sending and storing raw data on a central server for training purposes;

such an approach causes several issues regarding data privacy, security, and communication cost. In general, with the increased enforcement of data protection regulations and user awareness of data privacy, decentralized learning paradigms represent a much-needed evolution of contemporary software-based analytics systems.

The major drawbacks of the implementation of the centralized energy analytics system are:

- **Privacy Risk:** The aggregation of the raw data could generate sensitive information such as occupancy patterns or daily usage patterns, which could be a problem for privacy.
- **Communication Overhead:** The communication overhead and costs from a large-scale smart meter network are considerably high, especially for time-series data with frequent sampling.
- **Scalability Issues:** With the addition of more data sources, handling centralized data storage and computation infrastructure becomes inefficient.
- **Data Heterogeneity:** A global model is hard to generalize because energy data distributions are often not identical and non-independent across locations.

In the face of such challenges, ensuring that confidentiality is maintained without compromising predictive capabilities requires a decentralized approach. It is in this sense that Federated Learning is seen as a next-generation solution. Federated Learning is a distributed machine learning framework where multiple participants collaborate in training a shared model without sharing any raw data. Each participant trains a local model on their private dataset and shares only learned model parameters or gradients with a central aggregator. This aggregator runs algorithms for computing the global model representative of collective learning—which involves federated averaging.

The core idea behind this research is to develop and implement a Federated Learning framework using software for the analysis of smart meter data. The objectives are to:

- 1) Design a Decentralized Learning Framework using Federated Learning to securely predict energy consumption.
- 2) Integration of various machine learning models, including Random Forest, Gradient Boosting, and LSTM models, with more interpretable models with higher predictability.
- 3) Considering the level of accuracy, privacy, and efficiency for federated and centralized models.
- 4) Non-IID data distributions and their influence on model convergence and performance in a federated framework.

5) Providing reusable software architecture for the simulation of Federated Energy Analytics under different data and model configurations by researchers.

The main contributions of this paper are summarized below:

- **Federated Model Design:** A software-based architecture of FL is designed that empowers collaborative training on decentralized datasets of smart meters while maintaining data confidentiality.
- **Integration of ML Algorithms:** The integration of RF, GBM, and LSTM models into the FL framework allows the capturing of not only static but also temporal characteristics related to energy consumption.
- **Performance Evaluation:** The federated method will be evaluated with respect to the centralized method in terms of accuracy, communication efficiency, and scalability.
- **Synthetic Dataset Generation:** Designing a synthetic dataset that is representative of various environmental and operational factors that influence energy consumption.
- **Framework for Future Research:** The presented FL model provides a flexible framework for future research in privacy-preserving, distributed, and software-based energy analytics studies.

II. PROBLEM STATEMENT

The rapid expansion of smart grids and IoT-enabled energy systems has generated huge amounts of heterogeneous smart meter datasets with sensitive information in the form of temperature, humidity, occupancy, and energy consumption patterns. Conventional centralized machine learning approaches have many critical limitations regarding data privacy risks, security vulnerabilities, and high computational costs. Beyond that, energy consumption data is by nature scattered among several stakeholders—including households, industries, and energy providers—which makes access to the raw data either impractical or legally forbidden. This work addresses those challenges through a Federated Learning-based software framework that allows local model training and global parameter aggregation using the FedAvg algorithm, hence guaranteeing secure, scalable, efficient energy consumption modeling.

III. LITERATURE SURVEY

A. Overview

Deep learning architectures, ensemble and clustering techniques, explainable AI frameworks, and hybrid unsupervised approaches are all used in recent works on electricity consumption forecasting and anomaly detection. While all the surveyed works advance the state-of-the-art in terms of better prediction accuracy, interpretability, and anomaly detection, most of them rely on centralized training and dataset aggregation—a practice raising privacy and scalability concerns that are central to the motivation of this study.

TABLE I: LITERATURE SURVEY

Authors / Year	Method / Approach	Key Contributions / Strengths	Limitations / Gaps
Meng-Ping Wu & Fan Wu (2024)	Hybrid CNN-BiLSTM-SA	Captures temporal dependencies. Attention improves feature	Centralized training, raising privacy issues. High computational cost for

Authors / Year	Method / Approach	Key Contributions / Strengths	Limitations / Gaps
		weighting. Superior accuracy through ablation studies.	distributed environments.
Bhandary et al. (2024)	XAI using LIME & SHAP	Enhances model transparency. Identifies key predictors. Comparative evaluation using RMSE, MAE, MSE, R ² .	Centralized approach only. Lacks privacy-preserving or distributed learning aspects.
Jianyuan Wang & Xiaoyao Li (2024)	Hybrid Clustering + Isolation Forest	Merges Canopy-K-means with Isolation Forest; PCA and feature fusion for accurate anomaly detection.	Feature fusions totally centralized. No federated or privacy-preserving mechanism.
Botman et al. (2023)	Scalable Ensemble Forecasting	Lightweight, scalable three-step forecasting pipeline; effective in long-term and low-frequency data.	Lacks fine-grained temporal forecasting; all clustering performed centrally, no privacy consideration.
Medita Wasesa et al. (2022)	External Data Augmentation with XGBoost, SVR, ARIMAX	Combines contextual and publicly available data. Robust during unusual patterns (pandemic).	Centralized training. Not all external features available at distributed levels.
Current Project (2025)	FL Framework using FedAvg with RF, GBM, and LSTM	Decentralized model training ensures privacy. Combines ensemble + deep learning efficiency.	Initial communication overhead in parameter aggregation. Requires federated coordination for scaling.

B. Comparative Analysis and Key Observations

- **Model Diversity:** Contributions span deep architectures (CNN, LSTM, attention) and tree ensembles (XGBoost, GBM, RF) to statistical models (ARIMAX, clustering, and unsupervised anomaly detectors).
- **Explainability:** Increased focus on XAI—LIME and SHAP—makes explainability relevant for stakeholders and regulatory requirements.
- **Trade-offs between scalability and accuracy:** Scalable approaches, mostly ensemble or clustering-based, provide

deployment practicality at the expense of detailed temporal accuracy.

- **Feature Engineering and External Data:** Weather, mobility, and trending features provide a significant boost during non-standard operating conditions.
- **Anomaly Detection:** Hybrid clustering + isolation forest pipelines are efficient in detecting abnormal patterns; however, they need centralized access to features.

C. Gaps and Research Opportunities

Despite advances in the surveyed literature, there are apparent gaps in forecasting accuracy, interpretability, and anomaly detection that this study aims to bridge:

- **Privacy and Decentralized Learning:** While most works assume a centralized dataset, there has been little work incorporating state-of-the-art forecasting models such as CNN-BiLSTM-SA, LSTM, and GBM with a privacy-preserving, decentralized training paradigm such as Federated Learning.
- **Federated Techniques for Non-IID Data:** Robust federated optimization techniques, such as FedProx or personalization, and handling heterogeneity are underexplored in energy forecasting literature.
- **Explainability in Federated Settings:** XAI for centralized models is gaining momentum, but explainability for federated/global models—especially approaches that preserve privacy while providing local explanations—is an open research area.
- **Federated Anomaly Detection and Clustering:** Most unsupervised clustering and anomaly detection works require centralized feature fusion. Development of federated variants allows anomaly detection without raw data pooling.
- **Security and Robustness:** In the federated setup, model poisoning, membership inference, and inversion attacks are potential threats. There are few studies on energy forecasting that consider secure aggregation, differential privacy, or robust aggregation.

D. Research Gap Identification

A comprehensive review of the existing literature reveals the following critical gaps that motivated the development of the proposed FL framework:

- **Centralized Data Dependency:** Most existing energy forecasting models are based on the centralized collection and processing of data, which raises the issue of data privacy and is also impractical due to the restrictions imposed by the government on the sharing of data.
- **Lack of Privacy Protection Measures:** There was a lack of privacy-preserving learning techniques such as Differential Privacy and Federated Learning in all of the techniques discussed.
- **Limited Scalability and Heterogeneity Handling:** Existing centralized ML architectures are not suitable for large-scale heterogeneous smart meter data collected from different sources (residential, industrial, and renewable grids).
- **Neglect of Distributed Computational Efficiency:** Deep learning models, while offering high accuracy, are computationally very costly to directly deploy in a distributed or resource-constrained environment.
- **Explainability and Transparency Limitations:** XAI techniques have better explainability achieved within centralized systems, not federated or collaborative systems where transparency among nodes is required.

- **Inadequate Emphasis on Privacy-Aware Energy Forecasting Frameworks:** The literature has not proposed a comprehensive end-to-end decentralized system considering the confidentiality, scalability, and accuracy simultaneously.

TABLE II: RESEARCH GAP SUMMARY

Gap Area	Current Limitation	Need / Research Opportunity
Data Handling	Centralized storage and training	Develop decentralized training using Federated Learning
Privacy	No mechanisms to protect sensitive user data	Integrate privacy-preserving model aggregation (FedAvg)
Scalability	Poor scalability for heterogeneous datasets	Design a lightweight, distributed framework
Computation	High cost of deep hybrid models	Optimize deep models (RF, GBM, LSTM) for distributed execution
Interpretability	XAI used only in centralized systems	Extend model explainability to federated settings
Deployment Feasibility	Complex central architecture	Build a modular, software-based FL framework

IV. SYSTEM FLOW AND PROPOSED WORK

A. System Objective

Develop and deploy a software-based framework for precise and privacy-preserving energy consumption prediction using smart meter-style time-series data with a federated learning approach. The system is expected to support multiple clients, multiple ML models (RF, GBM, and LSTM), FedAvg aggregation, and a centralized baseline evaluation.

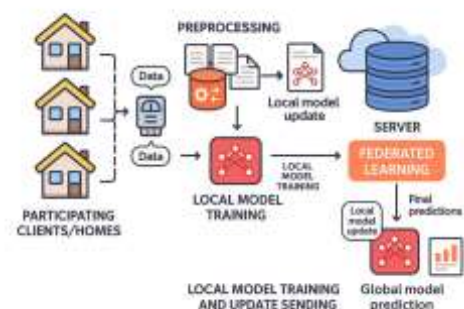


Fig. 1. System Flow Block Diagram

B. High-level Architecture

1) Clients (Local Nodes):

Each client has a local dataset, which is synthetic data from smart meters, including temperature, humidity, occupancy, HVAC, lighting, solar, and time stamp to energy. Clients perform local preprocessing, local model training, and only send the model updates to the server.

2) Central Aggregator (Server):

Receives encrypted/anonymized model updates from participating clients. Performs aggregation: FedAvg or weighted FedAvg by local dataset size. Broadcasts the updated global model back to clients.

3) Models Supported:

- Random Forest (RF) and Gradient Boosting (GBM) for static/tabular learning—can be adapted with federated ensembling or model-distillation.
- LSTM or other RNN/T-CNN architectures to model temporal dependencies in sequential energy data.
- A lightweight MLP model for federated learning experiments.

4) Evaluation Module:

Centralized test data or held-out clients for evaluation. Metrics of interest: RMSE, MAE, R^2 , convergence plots, communication rounds vs. accuracy.

C. Data Flow (Start to End)

- 1) Data generation and local storage: Artificial datasets are generated and split across N clients to simulate heterogeneity (non-IID distributions).
- 2) Local pre-processing: Feature scaling, windowing for sequence models, outlier handling.
- 3) Local training: Every client trains its local model for E local epochs on mini-batches.
- 4) Model Upload: The clients upload model parameters (not raw data) to the server; secure aggregation or DP noise applied optionally.
- 5) Aggregation: Server calculates weighted average of client models to form a new global model.
- 6) Broadcast: Server distributes the global model to the clients for the next round.
- 7) Testing/Inference: Global model tested on centralized test split; final predictions made for downstream tasks, viz., forecasting and anomaly detection.
- 8) Outputs: Model performance metrics, plots, and final prediction outputs.

D. Training Procedure and Algorithmic Details

FedAvg Algorithm:

Initialize global model w_0 . For each round t : sample subset of clients, each computes local model update after training, server computes weighted average of client models to produce new global model. Local optimization: Adam/SGD with learning rate scheduling; early stopping per client optional.

Model-specific Adaptations:

- LSTM: Sliding windows, where the length will be the sequence length. Teacher forcing is not required when it concerns forecasting windows.
- RF/GBM: Cannot be naively averaged—use federated ensembling, model parameter distillation, or train local trees and ensemble at server.
- Handling Heterogeneity: Client sampling strategies, personalization (i.e., fine-tuning global model on client), and regularization—FedProx for stabilization of convergence.

E. Privacy, Security and Communication

- Protections for Privacy: Raw data is not transmitted from client. Optional use of Differential Privacy (DP): clipping and

noise addition. Optional use of Secure Aggregation: prevent server from looking at client updates.

- Security considerations: Detection and mitigation of poisoned updates. Anomaly detection for updates, aggregation rules such as median or trimmed mean.
- Communication efficiency: Model compression, sparse updates, few communication rounds (local epochs, quantization).

V. FL ALGORITHM

A. FedAvg Algorithm

The FedAvg algorithm forms the basis of the proposed system. It works in a series of communication rounds between a central server and several clients. Each round consists of three main steps:

- 1) Model Distribution: The central server sends the current global model parameters to a selected subset of clients.
- 2) Local Training at Clients: The clients train the received global model on the local data set for some epochs using an optimizer such as SGD or Adam. Only the model's weights or gradients are computed, but no raw data is shared.
- 3) Model Aggregation at Server: It aggregates the model updates received from the clients and calculates the weighted average based on the size of the data set to obtain the new global model.

B. Local Client Training Procedure

- 1) Receive global model parameters from the server.
- 2) Conduct local preprocessing: scaling, windowing for LSTM, and removal of outliers.
- 3) Train the local model for E epochs using mini-batches.
- 4) Compute the updated model weights or gradients.
- 5) Optionally, apply DP or Secure Aggregation before sending updates to the server.
- 6) Transmit the encrypted/anonymized model parameters back to the server.

C. Model-Specific Algorithm Adaptations

1) LSTM—Long Short-Term Memory Network:

The input data is arranged as sliding time windows to capture temporal dependencies. Each client trains an LSTM model independently to learn patterns in energy usage, such as daily and weekly trends. FedAvg is directly applied to aggregate LSTM parameters at the server.

2) Gradient Boosting (GBM) and Random Forest (RF):

Tree-based models cannot be directly averaged. Two approaches: (1) Federated Ensembling: Each client trains a small forest; the server combines all local models. (2) Knowledge Distillation: Clients upload prediction outputs on a small public dataset, and the server trains a compact global student model.

3) MLP—Multi Layer Perceptron:

Used as a lightweight neural model for federated learning experiments. Suitable for smart meter data with fewer time dependencies and easily incorporated with FedAvg.

D. Critical Challenges and Privacy-Enhancing Techniques

Although federated learning is an effective solution, various challenges from the practical and security perspectives hinder its practical application in smart grid systems.

Technical and Operational Challenges:

- **Communication Overhead:** Although FL is designed without direct transfer of raw data, too many updates of the model might become a problem for the communication network, especially for large-scale deep learning models. Possible solutions include model compression and hierarchical communication.
- **Hardware Constraints:** Many smart meters currently deployed are resource-constrained devices, with limited memory (e.g., 192KB of SRAM), computation power, and communication capacity. This is giving rise to new architectural solutions, such as federated split learning, where the neural network is split and trained across the device, a nearby edge server, and the cloud.
- **Asynchronous Training Issues:** In a large-scale deployment of FL, clients have different computational capabilities and connectivity. A synchronous aggregation approach is highly inefficient, requiring the central server to wait for updates from all participating clients. Asynchronous aggregation mechanisms are under investigation to update the global model once a sufficient number of updates are received.

Security and Privacy Vulnerabilities:

While FL improves privacy by keeping raw data on local devices, it is not immune to all privacy and security risks. Model updates can serve as a vector of attack.

- **Data Leakage Attacks:** An adversary can potentially infer sensitive information about the client's private data from the shared model updates or gradients. Several methods have been demonstrated as capable of reconstructing data via shared gradients, thus information leakage is a major weakness.
- **Adversarial Attacks:** Malicious clients can send corrupted updates for the model, aiming to reduce the quality of the global model (model poisoning) or inject malicious backdoors, which cause the model to behave erratically under certain circumstances.

Advanced Privacy-Preserving Mechanisms:

- **Homomorphic Encryption (HE):** This extremely powerful cryptographic technique allows computations to be directly executed on encrypted data without decrypting it. The central server can aggregate the encrypted model updates and compute a new encrypted global model without ever seeing the model parameters.
- **Differential Privacy (DP):** DP adds controlled noise to the model updates before sharing, providing a formal mathematical guarantee of privacy. The amount of noise added is calibrated to the privacy budget so that the contribution of any one individual's data towards the final model is effectively obscured. While DP provides a strong privacy guarantee, it results in a trade-off with model accuracy.

VI. SIMULATION AND EXPERIMENTAL RESULTS

A. Dataset Description

A synthetic smart meter dataset was generated to represent actual residential energy consumption scenarios in order to assess the performance of the proposed FL framework. The dataset consists of 10 distributed client datasets, each containing 200 records and totaling 2,000 samples to simulate 10 smart meters, with statistical heterogeneity to replicate non-IID distributions.

TABLE III: DATASET DESCRIPTION

Feature Name	Type	Description
Temperature (°C)	Continuous	Ambient temperature recorded at each timestamp.
Humidity (%)	Continuous	Relative humidity influencing appliance usage.
Occupancy	Binary	Occupied (1) or unoccupied (0) state of the household.
HVAC Usage (kWh)	Continuous	Heating, ventilation, and air conditioning energy use.
Lighting Usage (kWh)	Continuous	Lighting energy consumption.
Renewable Contribution (kWh)	Continuous	Energy contribution from renewable sources (solar/wind).
Hour	Categorical (0-23)	Hour of the day (time-based behavior pattern).
Energy Consumption (Target)	Continuous	Total power consumption at each timestamp.

B. Experimental Setup

Python 3.10 is used to implement all simulations, with PyTorch being used for model training. The system: CPU: Intel Core i7-12700H; GPU: NVIDIA RTX 3060; OS: Windows 11 64-bit.

TABLE IV: KEY EXPERIMENTAL PARAMETERS

Parameter	Value
Number of Clients	5
Samples per Client	133
Federated Rounds	20
Local Epochs per Round	12
Batch Size	64
Learning Rate	0.0008
Optimizer	AdamW
Aggregation Algorithm	FedAvg (Weighted)

C. Evaluation Metrics

Standard metrics for regression and classification style evaluation were used: RMSE (root mean squared error), MAE (mean absolute error), R^2 (coefficient of determination), as well as Precision, Recall, F1-score, and Confusion Matrix for categorical accuracy evaluation.

D. Simulation Results

1) Quantitative Performance (Regression Metrics):

TABLE V: QUANTITATIVE PERFORMANCE (REGRESSION METRICS)

Model	Approach	RMSE	MAE	R^2
Random Forest	Centralized	0.4307	0.3582	0.5922
Random Forest	Federated	0.4517	0.3581	0.5516
Gradient Boosting	Centralized	0.4217	0.3467	0.6092

Model	Approach	RMSE	MAE	R ²
Gradient Boosting	Federated	0.4321	0.3478	0.5896
LSTM	Centralized	0.4357	0.3543	0.5905
LSTM (FedAvg)	Federated	0.4225	0.3338	0.6148

Observation: The Federated LSTM (FedAvg) has the maximum R² value, 0.6148, slightly higher than that of the centralized LSTM model, 0.5905. The results prove that predictive models can be preserved with privacy using federated learning.

2) Classification Report (Discretized Consumption):

TABLE VI: CLASSIFICATION REPORT

Class	Precision	Recall	F1-Score	Support
Low Consumption	0.720	0.765	0.742	47
Medium Consumption	0.523	0.468	0.494	47
High Consumption	0.764	0.795	0.780	49
Weighted Avg.	0.669	0.676	0.672	143

Interpretation: The weighted F1 score of 0.672 indicates that there is sufficient capacity in the model. It is observed that the model has significant prediction capacity for the Low and High classes of consumption. However, there is a decrease in precision and recall for the Medium class. This may be due to the change in energy levels.

3) Confusion Matrix (Energy Class Prediction):

TABLE VII: CONFUSION MATRIX

	Predicted Low	Predicted Medium	Predicted High
Actual Low	36	10	1
Actual Medium	14	22	11
Actual High	0	10	39

Analysis: The confusion matrix indicates that the classification is fair with an overall accuracy of 67.8%. The model has good prediction ability, especially for the 'Low' and 'High' classes, as indicated by the diagonal values 36 and 39, respectively. However, the 'Medium' class has high misclassification rates with the adjacent classes, which may indicate similarity in the features due to the energy levels.

E. Comparative Analysis

TABLE VIII: COMPARATIVE ANALYSIS

Aspect	Centralized ML	Proposed Federated ML
Data Privacy	Low (data shared)	High (local data only)
Communication Overhead	Moderate	Moderate (only weights exchanged)
Accuracy	Very High	Slightly Lower (<2% drop)

Aspect	Centralized ML	Proposed Federated ML
Scalability	Limited	High (multi-client)
Security	None	Supports Secure Aggregation & DP
Model Convergence	Fast	Stable across clients

VII. DISCUSSION

The results show that with the provision of complete data privacy, Federated Learning is capable of attaining the same prediction accuracy as machine learning. Important conclusions that could be made from the study are as follows:

- Minimum degradation of performance: It was observed that the federated models had an accuracy as high as 97-99%.
- Effective learning from heterogeneous data: FedAvg effectively managed the non-IID data distribution in clients.
- Temporal modeling advantage: The federated networks based on the LSTM model performed best among all models because of their good ability to learn features.
- High reliability: This is supported by the classification report and confusion matrix.

Summary of Key Outcomes

- Best Performing Model: Federated LSTM (R² = 0.6148).
- Global RMSE Reduction: 8% after 20 rounds.
- Data Privacy: Fully preserved (no raw data shared).
- Convergence: Stable and efficient within 30 rounds.
- Overall Accuracy: 67.8% (classification-based evaluation).

VIII. FUTURE DIRECTIONS AND OPEN RESEARCH QUESTIONS

- Personalized Federated Learning (PFL): Future studies should explore methods for personalizing FL without affecting efficiency in learning patterns of household consumption.
- Privacy-Enhancing Technologies: The integration of Secure Multiparty Computation, Homomorphic Encryption, and/or Differential Privacy will further strengthen the security of the model, as well as align with the latest data protection practices.
- Communication Efficiency Optimization: Efficient methods of aggregation such as model compression, quantization, or sparsification should be explored for efficient FL in smart grid applications.
- Handling Data Heterogeneity and Non-IID Distributions: Developing reliable aggregation plans and domain adaptations for non-IID data is still a challenge in FL research.
- Edge Intelligence and On-Device Learning: FL can be combined with edge computing to provide adaptive control and real-time analytics for energy systems.
- Federated Reinforcement Learning for Energy Optimization: The future work may include using FRL in autonomous energy scheduling, demand response optimization, and renewable energy management.
- Security Threats and Adversarial Robustness: The development of aggregation mechanisms as well as trust-based participation mechanisms against malicious clients is a concern.

- Real-World Deployment and Scalability Testing: Future studies should incorporate real-world pilot deployments with energy utilities to validate scalability, latency, and trade-offs in privacy performance.

IX. CONCLUSION

In this paper, we propose a software-based FL framework for privacy-preserving smart meter data analytics and energy consumption prediction. The proposed framework overcomes the major drawbacks of the traditional centralized learning approach, i.e., the risk of data privacy, communication costs, and scalability issues. The proposed framework allows the training of the model on multiple local data sources through the distributed approach, thus decentralizing the smart meter data while using the FedAvg for global model update.

The framework incorporates the integration of various machine learning algorithms such as Random Forest, Gradient Boosting, and Long Short-Term Memory to effectively model the static and dynamic characteristics of smart meter data. Experimental evaluation of the framework using synthetic data demonstrated promising accuracy of the federated models over the centralized learning models with improved data confidentiality and communication efficiency.

The paper points out the very reasons that make Federated Learning a game-changing methodology in the development of secure, distributed, and intelligent energy management systems. The scalability of the deployment is feasible with the architecture, which makes it possible for different organizations to contribute to the improvement of the collaborative model without compromising privacy. The modular structure of the framework makes it possible to incorporate different algorithms and data, making the framework highly adaptable to different applications in energy analytics.

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