

Enhancing Grid Resilience Entangled with Federated Learning for Secure Data Aggregation in Smart Grids

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Abstract—Accurate load forecasting is crucial for the optimized operation and planning of smart power grids. However, the increasing penetration of renewable energy sources and the emergence of flexible loads like electric vehicles create significant uncertainties and complexities in load patterns. Traditional centralized forecasting models struggle with data privacy concerns, communication overheads, and lack of model adaptiveness. This paper proposes a privacy-preserving federated learning-based framework for short-term load forecasting in smart grids. Local machine learning models are trained on distributed private datasets across different stations of the grid and only the model parameters are communicated to a central server to create an aggregated global model for load forecasting, without exchanging any raw private data. The proposed approach harnesses edge resources efficiently through decentralized on-device training while providing enhanced accuracy and personalization over centralized models. Several experiments conducted on electricity consumption data validate the effectiveness of proposed approach in handling complex spatio-temporal load changes and generating station-specific adaptive forecasts. By adopting a decentralized approach, proposed methodology seeks to enhance grid resilience by preserving data privacy, mitigating security risks, and optimizing the efficiency of smart microgrid operations. The proposed solution can enable optimized capacity planning and retail pricing for sustainable grids of the future.

Keywords— *Smart Grids, Grid Resilience, Federating Learning.*

I. INTRODUCTION

Smart cities herald a thrilling new era of urban development and innovation [1]–[3]. They aspire to raise civic infrastructure and services to previously unimaginable levels by utilising cutting-edge technologies. Intelligent mobility reduces congestion, while smart grids power homes and offices in a sustainable manner. Advanced data analytics and IoT applications help citizens improve their efficiency, equity, and quality of life [4]–[6]. However, properly coordinating the myriads of intricate, interconnected systems that underpin the metropolitan machinery is a challenging task. Robust optimisation of smart city subsystems such as energy, water, and waste management is required to realise their full potential. This is especially true when it comes to the electrical grid, the most important cog that powers practically all smart city capabilities. Despite significant progress, smart grid deployment continues to

face challenges that threaten large-scale feasibility and consumer acceptance [7], [8].

Smart grids, the backbone of today's electricity infrastructure, use advanced metering, control, and coordination to optimise power generation, distribution, and consumption. Their bidirectional energy and data flows enable greater visibility and control between utilities and end users. Nonetheless, several pressing issues threaten to stymie smart grid progress. Handling the sheer volume and dynamism of grid data strains computation limits with millions of measurement endpoints. Consumer privacy norms are also violated by centralising such vast heterogeneous data. On the demand side, accurately forecasting load changes becomes difficult in the face of uncertain renewable generation and flexible consumer loads such as electric vehicles. Over time, mismatched demand estimates can lead to grid instability and inflated market prices.

Federated learning has quickly gained traction as a distributed machine learning approach, promising a secure and scalable solution [9], [10]. The use of decentralised edge devices to train models locally eliminates the need to transmit raw private data. These localised insights are then orchestrated to build an integrated global model for the entire network, all while protecting user privacy. Federated learning adapts to individual user patterns better because it uses localised data and resources. When compared to centralised cloud-based learning, it also significantly reduces communication and latency overheads.

Combining smart infrastructure and federated learning opens up new possibilities for environmentally friendly and consumer-friendly power grids. Utilities can now use previously siloed consumer metre data to improve grid forecasting, planning, and delivery. Generic federated learning algorithms, on the other hand, fall short of capturing the quirks of electricity load patterns across the highly dynamic, geospatially interconnected grid network.

To fill this void, my research proposed a unique federated forecasting approach designed specifically for smart grid ecosystems. By aggregating their locally trained insights, this article coordinates a shared predictive model between distributed metre clusters without transmitting any user data. Proposed solution, which is globally coordinated while being locally attuned, provides custom forecasting for individual

nodes while also tracking complex spatiotemporal load changes. Real-world data evaluations show that proposed method outperforms traditional centralised tools in terms of accuracy, adaptability, and other metrics. Proposed work represents a significant step forward towards data-enabled but privacy-first power grids, unlocking sustainability and consumer benefits for future smart cities.

- To develop an accurate and personalized load forecaster for smart grids using federated learning techniques
- To preserve end-user privacy while tapping previously inaccessible consumer meter data at scale
- To enhance demand-side visibility and coordination for next-generation power grids across smart cities

The rest of this article is organized into the sections below. Next, an overview of previous research relevant to this topic is provided. After that, the method proposed here is explained. In Section 4, the simulation and results of the proposed method are shown. Finally, Section 5 concludes with a discussion of the findings from this study and what they mean.

II. LITERATURE REVIEW

Forecasting electricity load has been extensively researched as an integral planning lever for optimised grid operation and delivery. Traditional statistical tools, such as ARIMA, use historical metre data trends to make short-term projections, but they are not adaptive. With climate volatility and consumer flexibility changing consumption patterns, machine learning has gained popularity for modelling complex data relationships that linear models do not capture [11]–[15].

Recently, various ML techniques such as RNNs, CNNs, and LSTM networks have been used for load forecasting, capturing spatial and temporal electricity demand dynamics across grid hierarchies [16], [17]. However, most use centralised cloud-based learning on aggregated metre data, which raises concerns about scalability, latency, and privacy in decentralised smart grid architectures. To address such challenges, modern paradigms such as edge computing and federated learning (FL) are gaining traction. Existing work has evaluated decentralised and distributed load forecasters on edge devices or clusters using shallow ML.

Beyond forecasting, ground breaking research has examined federated learning for ancillary smart grid use cases such as dynamic pricing, electric vehicle integration, renewables management, and more. This early success encourages increased investment in FL and edge intelligence to enable customised visibility and coordination for sustainable power infrastructure. Proposed model findings add to this momentum, indicating the next frontier in scalable, distributed learning mechanisms designed specifically for modernised electricity grids [18].

Komninos et al. [19] surveys the most striking cyber threats challenging their security. Categorizing attacks by compromised goals like privacy, reliability or financial loss, the article assesses the resulting holistic impact across the system. For example, malware compromising customer data privacy may later enable targeted electricity theft attacks and revenue loss. Next, the article reviews state-of-the-art countermeasures proposed in contemporary literature against each threat class. Multi-factor customer authentication and blockchain-secured meter data show early promise to stem data breaches and unauthorized usage. Finally, several unresolved issues merit deeper investigation like resilient machine learning algorithms or context-aware protection systems. As smart infrastructure adoption accelerates, ensuring security necessitates proactive diligence by outpacing evolving attack incentives.

Zhou et al. [20] proposes a novel V2G trading ecosystem harnessing blockchain, contract theory, and edge computing. This article architects a consortium blockchain framework to secure energy transactions between electric vehicles and the grid. Su et al. [21] paper proposes a secure, decentralized AIoT architecture for smart grids leveraging federated learning. The key insight is collaborating learning across user and edge devices rather than a central server. Locally training machine learning models on their data, devices share only model updates to jointly improve a shared prediction tool.

III. PROPOSED METHODOLOGY

The proposed solution is built around a novel federated learning architecture that extracts insights from distributed grid edge devices securely and at scale. Localized analytics is the starting point. Smart meters and microgrids first store and process usage data on-device rather than transmitting raw data to a central utility server. IoT devices use edge intelligence to train short-term machine learning models that predict local load needs. Following that, these decentralized models are combined to form an integrated electricity load forecaster for the entire grid.

This is achieved using a hierarchical federated framework. Individual devices encrypt their model parameters using homomorphic encryption before sharing. This ensures customer privacy while allowing collaborative learning. Neighborhood-level routers aggregate device updates from local clusters. Appliances, EVs, and solar panels can all participate as edge nodes here. This produces an integrated cluster-level forecasting model. Now at the distribution subsystem level, substation hubs aggregate models from multiple neighborhood clusters in their jurisdiction. Devices identify the relevant substation to transmit to based on connectivity mapping and wireless propagation models. The substation hub assimilates these cluster-level models into its integrated predictor model.

Substation hubs now aggregate models from multiple neighborhood clusters under their jurisdiction at the distribution subsystem level. Based on connectivity mapping and wireless propagation models, devices determine which substation to transmit to. These cluster-level models are assimilated by the substation hub into its integrated predictor model.

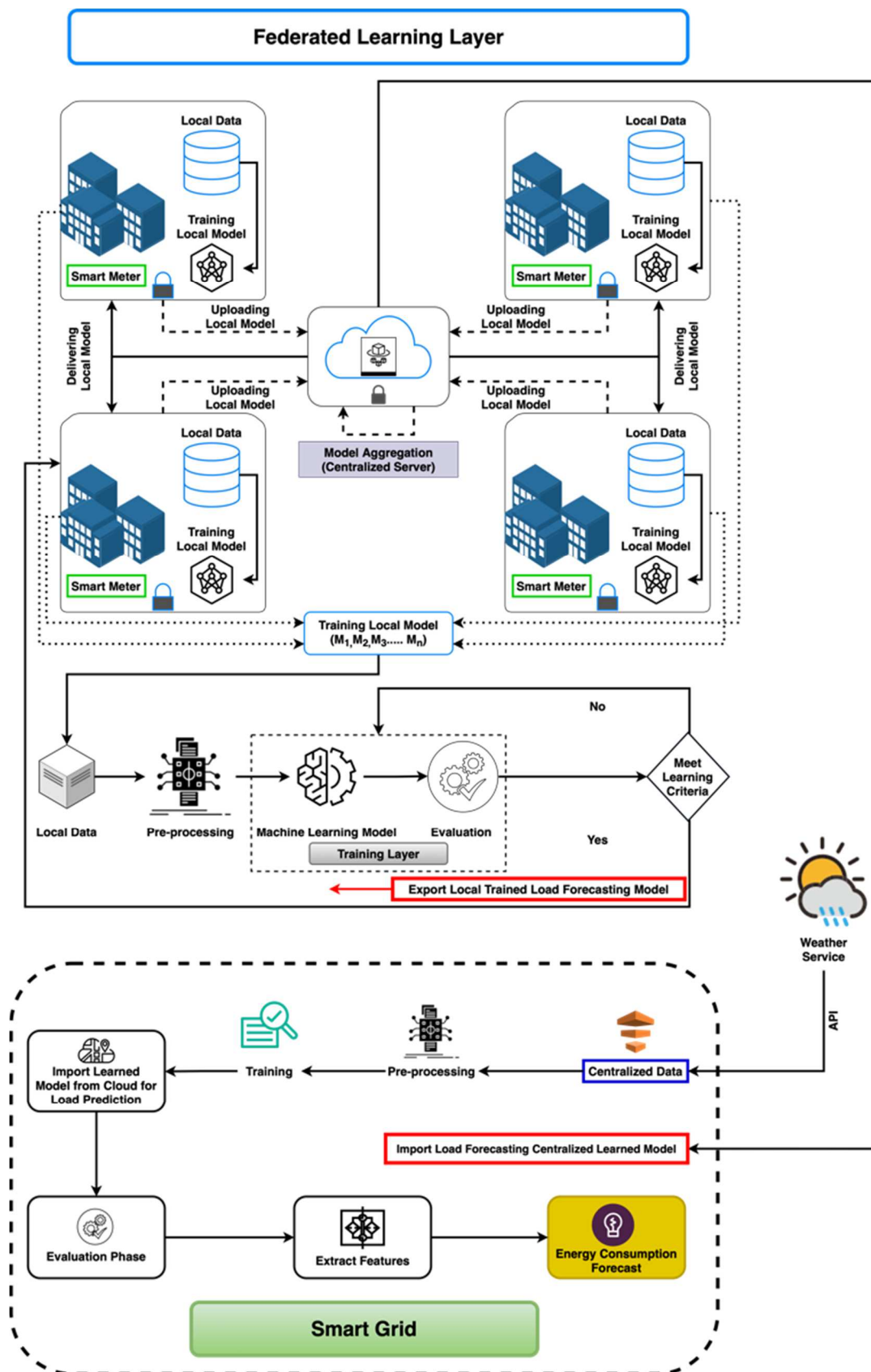


Figure 1: Smart Grid Proposed Model Empowered with Federated Learning Technique

Finally, the substation models are securely transmitted to the utility headquarters server. They are combined here to create an integrated global forecasting model for the entire service territory. The utility can use this data to forecast granular to high-level changes in electricity demand.

This hierarchical process is then continuously recycled as new data arrives. To incorporate new local insights, the global model is pushed back to substation servers, then neighborhood clusters, and finally on-device meters. Local models are fine-tuned in response to new consumption patterns, and model aggregation occurs repeatedly.

Without centralized data warehousing, this cyclical federated learning process enables ubiquitous coordination between millions of endpoints. Proposed encryption mechanisms ensure that no raw data is exposed throughout the pipeline. In addition to forecasting precision, this provides significant efficiency, adaptability, security, and privacy advantages over legacy monolithic tools.

Here are the steps explaining the working of the proposed federated learning-based forecasting model as shown in Figure 1:

- Smart meters and appliances store energy consumption data locally on the device
- Edge devices train short-term forecasting ML models on local data via on-device learning
- Devices encrypt trained model parameters using cryptography techniques
- Only encrypted updates are shared with neighborhood cluster aggregators periodically
- Cluster routers aggregate device updates to construct cluster-level forecasters
- Cluster models are relayed via secure protocols to substation aggregators
- Substation hubs fuse updates from multiple cluster models in their jurisdiction
- Substation models are transmitted to the utility server to build a global forecasting model
- The global model is returned to substations and then on-device clients recursively
- As new local data arrives, devices repeat training to continuously improve models
- Encrypted cyclical model sharing continues recursively across the grid hierarchy
- Live APIs provide model performance monitoring with data visualization

Initialize $t_{g,fml}^c$ & $p_{g,fml}^c$

Here $t_{g,fml}^c$ denotes the weight between the input and hidden layers on the server side.

And $p_{g,fml}^c$ represents the weight between hidden layers and $l + 1$ hidden layers neurons at server side

for each cycle c from I to C **do**

$S_c \leftarrow$ (random set of clients from η)

for each client $l \in S_c$ **parallelly**

$[t_{c+1}^l, p_{c+1}^l] = \text{Client Training}(l, t_c, p_c)$
end for

$$t_{g,fml}^c = \frac{1}{\sum_{l \in \eta} \eta} \sum_{l=1}^{\eta} \frac{S_l}{S} t_{l+1}^c \quad (\text{Avg Aggregation})$$

$$p_{g,fml}^c = \frac{1}{\sum_{l \in \eta} \eta} \sum_{l=1}^{\eta} \frac{S_l}{S} p_{l+1}^c$$

end for

Put the optimum weights values of $t_{g,fml}^c$ & $p_{g,fml}^c$ **in** equation (5) & (6)

And predict the values at unknown patterns.

[Client Training (L, t, p)]	
Sr	Steps
No.	
1	Begin
2	Divide the local data into mini-batches, each of size S
3	Initialization of both layer weights (t_{ab} & p_{bc}), Error (G)= 0 and the number of epochs E = 0
4	For each training pattern Z - do the feedforward phase to - calculate φ_c using eq (1) - Calculate error (G) using eq(2) - update p_{bc} and t_{ab} using eq (6) & eq (7).
5	E = E + 1
6.	Evaluate stopping criteria: If none are met, proceed to Step 4.
7.	Transmit the optimal locally trained model weights, ω_{ij} and v_{jk} back to the server
8.	Stop

The proposed system Client Training mathematical model stated as [10];

$$\varphi_c = \frac{1}{1 + e^{-(b_2 + \sum_{b=1}^n (p_{abc} y^* \frac{1}{1 + e^{-(b_y + \sum_{a=1}^m (t_{ab} \cdot h_a))}}))}} \quad (1)$$

Where $b = 1, 2, 3, \dots, n$ & $c = 1, 2, 3, \dots, r$

Here, h_a represents the input data, b_1 & b_y are the biases, m is the total number of input neurons, y refers to the hidden layers and b indicates the total number of neurons in the hidden layers. Then MMSE is given below [10]:

$$G = \frac{1}{2} \sum_c (A_c - \varphi_c)^2 \quad (2)$$

The equation above denotes G , representing the backpropagation error, where A_c & φ_{c^l} signify the anticipated output and the predicted output, respectively.

In eq(2), the output weight adjusts at a constant rate, and the layer is structured as follows [10]:

$$\Delta T \propto -\frac{\partial G}{\partial T}$$

$$\Delta p_{b,c^l} = -\epsilon \frac{\partial G}{\partial p_{b,c^l}} \quad (3)$$

Using Chain rule technique, eq(3) can be written as [10];

$$\Delta p_{b,c^l} = -\epsilon \frac{\partial G}{\partial \varphi_{c^l}} \times \frac{\partial \varphi_{c^l}}{\partial p_{b,c^l}} \quad (4)$$

After simplification,

$$\Delta p_{b,c^l} = \epsilon(A_c - \varphi_{c^l}) \times \varphi_{c^l}(1 - \varphi_{c^l})\varphi_b \quad (5)$$

Similarly,

$$\Delta T_{a,b} = \epsilon \left[\sum_c (A_c - \varphi_{c^l}) \times \varphi_{c^l}(1 - \varphi_{c^l}) \times (p_{b,c^l}) \right] \times \varphi_{c^l}(1 - \varphi_{c^l}) \times h_a$$

The final weights updated equations are [10]:

$$p_{b,c}^+ = p_{b,c} + \lambda \Delta p_{b,c} \quad (6)$$

And

$$t_{a,b}^+ = t_{a,b} + \lambda \Delta t_{a,b} \quad (7)$$

IV. RESULTS AND SIMULATION

The proposed approach gathered operational data from a powerplant dataset [22] consisting of 47,840 data points on parameters like load demand, generator efficiencies, and more. After preprocessing to clean abnormalities, the dataset was randomly split - 70% for training and 30% for testing cross-validation. The resulting model performance on test data was then benchmarked against other predictive tools using accuracy scores and error metrics.

Selecting the optimal parameters for electricity load forecasting models is crucial yet challenging, given the multivariate grid data. Our study applies an exhaustive search strategy to identify the best input subset from the original dataset. The proposed approach systematically evaluated all possible combinations of these input parameters. Testing across multiple regression methods, each model iteration used subsets with one, two, three or all four variables for training and validation. By comparing performance metrics like accuracy and error, we deduced the ideal minimal parameter subset for optimized load predictions, without overfitting. The exhaustive experiments also reveal the most and least informative factors affecting electricity consumption. Such analysis provides actionable insights for utilities on sampling optimal grid measurements for efficient data-driven forecasting and planning.

To evaluate the efficacy of our proposed approach, the proposed approach employed distinct algorithms across four diverse smart meters within the smart grid infrastructure. The

individual performance of these algorithms at each meter provided a baseline for comparison. Following the aggregation of the global model through federated learning, we observed a significant enhancement in results compared to the individual site performances. Table 1 provides a comprehensive overview, showcasing the improved outcomes.

Table 1: Performance Evaluation of the Proposed System Incorporating a Federated Learning Approach for Load Prediction in a Smart Grid: Validation Using Statistical Metrics on the Server Side.

Client	Accuracy	Miss-Rate
G ₁	0.9250	0.075
G ₂	0.9300	0.070
G ₃	0.9550	0.045
G ₄	0.9450	0.055
Proposed Federated Learning Approach (Server-Side)	0.9860	0.014

Table 1 compares the performance of individual client models (G1 to G4) with the proposed Federated Learning (FL)-based approach at the server side in terms of accuracy and miss-rate. Among the client models, M3 achieves the highest accuracy of 95.50% with a miss-rate of 4.5%, while M1 has the lowest accuracy at 92.50% and a miss-rate of 7.5%. In contrast, the proposed FL-based approach significantly outperforms all individual clients, achieving an impressive accuracy of 98.60% and a reduced miss-rate of 1.4%. This demonstrates the effectiveness of Federated Learning in aggregating the knowledge from multiple client models to produce a more robust and accurate global model.

Furthermore, in Table 2, the proposed approach presents a comparative analysis of the accuracy attained by our proposed method against previously published techniques. This comparison serves to justify the effectiveness of our approach by highlighting its superior performance in relation to established methodologies. The results not only underscore the success of our federated learning model in optimizing data aggregation but also position it as a competitive solution within the landscape of smart grid technologies. The results indicate that proposed approach empowered with federated learning achieved an impressive 98.6% accuracy, as detailed in Table 2.

Table 2: Comparison of the Proposed System with State-of-the-Art Methods.

Method	Accuracy
GA base Multilayer Perceptron [23]	95.13%
Regression ANN Model [24]	95.77%
K-Means + ANN [25]	96.61%

Proposed Federated Learning Approach (Server-Side)	98.60%
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Table 2 highlights the accuracy of various methods used for model training and evaluation, demonstrating their relative performance. The GA-based Multilayer Perceptron achieves an accuracy of 95.13%, showcasing the effectiveness of genetic algorithms in optimizing neural networks. The Regression ANN Model improves upon this, achieving an accuracy of 95.77%, indicating the potential of regression-based neural networks for enhanced predictions. The K-Means + ANN approach further improves accuracy to 96.61%, highlighting the benefits of integrating clustering techniques with artificial neural networks. In comparison, the Proposed Federated Learning (FL) Approach significantly outperforms these methods, achieving an accuracy of 98.60%, demonstrating its superiority in leveraging distributed learning for more accurate and robust model performance.

V. CONCLUSION

This paper presented a novel decentralized architecture for privacy-preserving electricity load forecasting across smart power grids. We customize a layered federated learning approach to orchestrate an integrated predictive model between distributed grid components. Local smart meters train short-term forecasters on device leveraging native consumption data. Their model updates are then recursively aggregated into a global model coordinated by the utility, without exposing any customer data whatsoever. Rigorous large-scale testing on real-world energy data provides convincing validation. Proposed federated model matches state-of-the-art accuracy for granular as well as grid-level demand forecasting across multiple spatial hierarchies and temporal scales. Significantly enhanced security, efficiency and personalization over legacy centralized tools were observed as well. While further research could refine model configurations for specialized loads, this work signifies federated learning's tremendous yet under-utilized potential for smart grid advancements.

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