Short-Term Energy Consumption Forecasting at the Edge: A Federated Learning Approach [Paper URL]

1 Summary

1.1 **Motivation:** The motivation for this study is to address the privacy and scalability issues that arise when using centralized AI-based methods for short-term residential energy consumption forecasting. The authors aim to leverage Federated Learning and Edge Computing to enable accurate forecasting while keeping sensitive data local and reducing the computational burden on centralized servers.

1.2 **Contribution:** The study introduces a new architecture combining Federated Learning and Edge Computing for short-term energy consumption forecasting. It uses local training with relevant features, capturing seasonality and other factors. The federated approach reduces training time and communication overhead, making it a privacy-preserving alternative. The strategy is adaptable to rapidly changing consumption patterns.

1.3 **Methodology:** The paper presents a methodology for short-term energy consumption forecasting using a federated learning approach. It identifies five key features for the forecasting model: weekday, hour, AVG4D (average of 4 days energy consumption), and energy cluster information. The model's parameters are tuned using a subset of the dataset, with the Mean Absolute Error (MAE) as the evaluation metric and the Adam optimizer employed with a learning rate of 0.0001. Regularization techniques are used to prevent overfitting. The dataset is divided into training and testing sets based on ACORN Clustering, K-Means Clustering, and a random selection of traces. The TensorFlow Federated framework and Keras API are used to build the LSTM model, with training occurring locally on edge devices. The federated architecture is evaluated against a centralized architecture, focusing on forecasting performance, model training time, and communication overhead. The methodology emphasizes a decentralized approach to energy consumption forecasting, leveraging local data and federated learning to enhance privacy and efficiency.

1.4 **Conclusion:** The study highlights the effectiveness of a proposed federated learning architecture for short-term energy consumption forecasting. It demonstrates effective forecasting at the edge, incorporates relevant features, and preserves privacy. The architecture outperforms centralized models in terms of training time and communication overhead. Future work includes extending the architecture and implementing real-world tests.

2 Limitations

2.1 There is a potential vulnerability of model inversion attacks, which could compromise participant privacy. In cases of unbalanced data, it may be possible for an adversary to infer sensitive information about individual users from the aggregated model parameters.

2.2 The federated learning approach, despite its scalability, may face challenges with increasing participant numbers due to communication overhead and coordination issues. The paper briefly mentions reduced overhead but lacks detailed analysis.

2.3 The federated learning model's performance relies on quality local data from edge devices, but the paper lacks any discussion on ensuring data quality for optimal forecasting accuracy.

3 Synthesis

3.1 Extending the architecture to incorporate distributed long-term energy consumption analysis. In real scenarios, long-term analysis is more required for future planning, load distribution, load-shedding scheduling, power plant management, and so on.

3.2 Evaluating the use of additional demographic and economic features that can affect the performance of the model.