Improving accuracy and convergence of federated learning edge computing methods for generalized DER forecasting applications in power grids

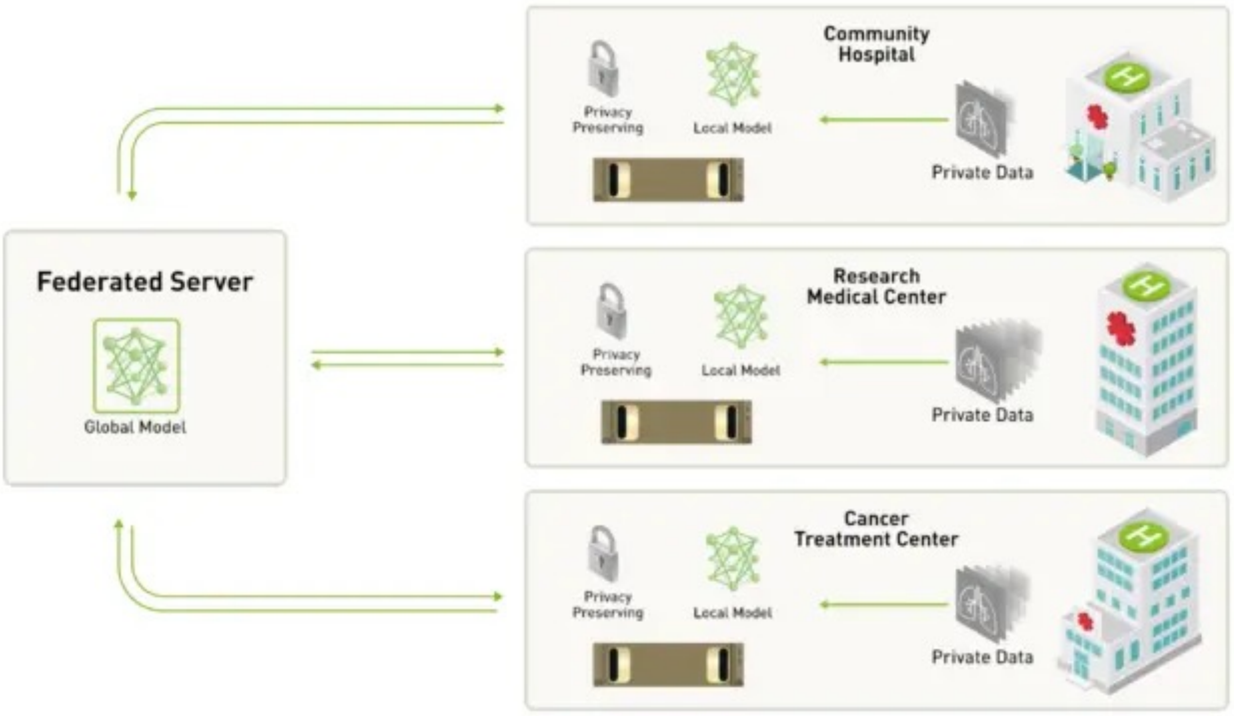
Vineet Jagadeesan Nair (jvineet9@mit.edu) & Lucas Pereira

Advisor: Dr. Anuradha M Annaswamy

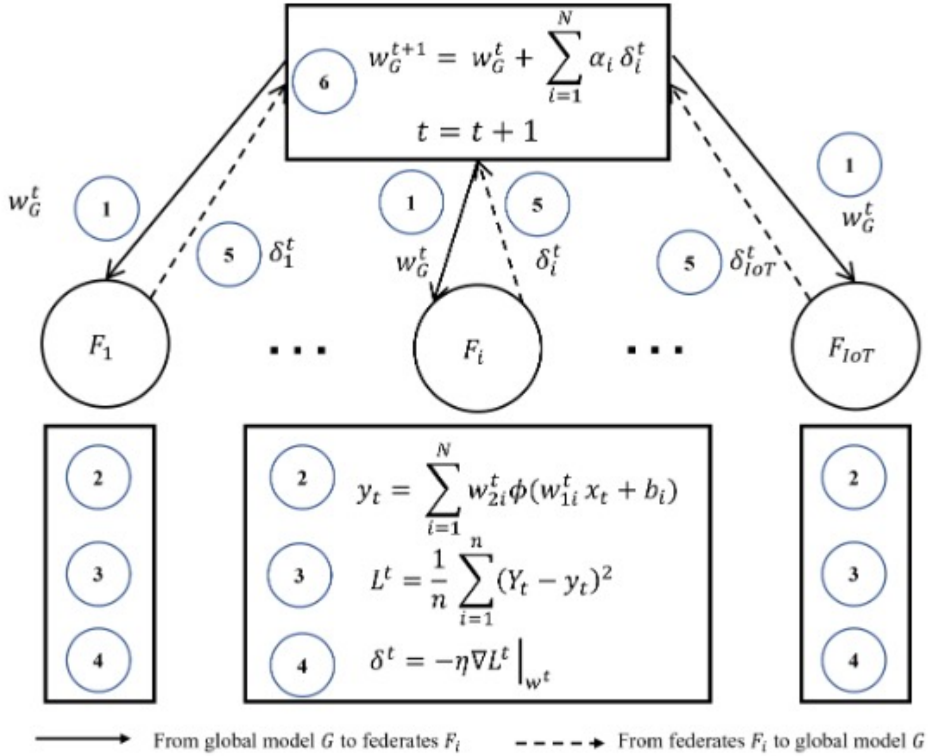
Active-Adaptive Control Laboratory

Department of Mechanical Engineering

Federated machine learning (FL)



Source: [NVIDIA AI blog]()



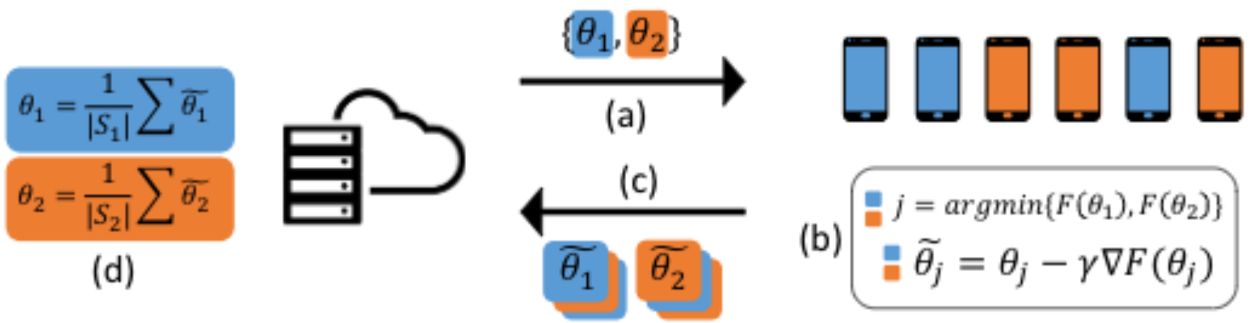
Source: Venkataramanan, V. et al.
IEEE Internet of Things Journal (2022).

Challenges & limitations of FL

- Relatively poor test set performance of FL in terms of prediction accuracy compared to traditional centralized ML methods
- Applications where data is not independently and identically distributed (IID) across different FL clients
- Long training times for aggregated global model to converge due to diverse weights & parameters across clients
- Privacy vs Accuracy tradeoff
- Communication costs and sample efficiency

Variants & extensions of FL

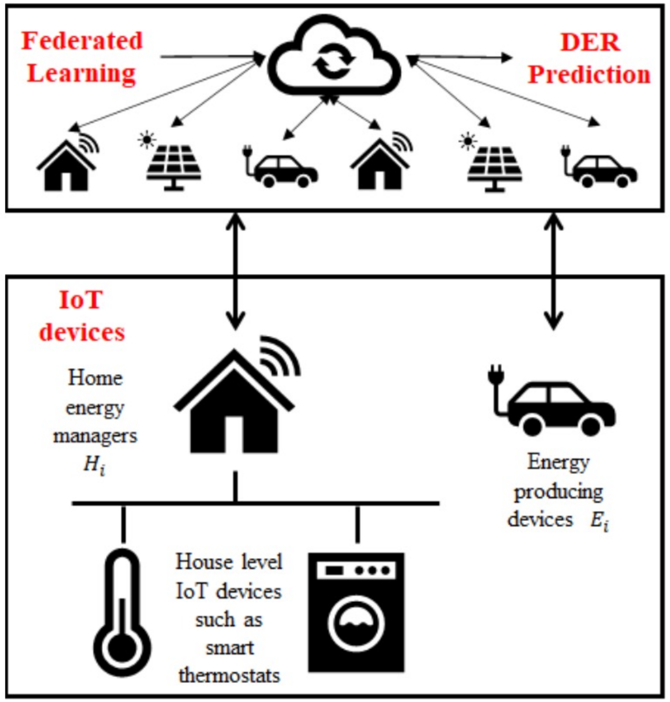
- **Clustered & hierarchical FL:** Divide similar local clients into clusters
  - Learn both a joint global model (via local updates)
  - As well as cluster-level models by aggregating private data within each cluster
  - Gradient averaging, model averaging approaches
- **Dynamic regularization:** Update local loss functions dynamically so device-level optima coincide with globally optimal model parameters
- **Model personalization & fine-tuning**
  - Personalize global meta-model locally for each device
  - Debiase local updates via gradient correction methods
  - Transfer learning
  - Heterogeneous FL training frameworks



Source: Ghosh, A. et al. NeurIPS 2020.

FL applications for power grids

- FL has been applied for mainly load forecasting
- Recent works have examined **Clustered FL** for predicting energy consumption
- Other, more recent advanced FL tools have **not yet been applied** to the grid-specific context
- **Distributed Energy Resource (DER)** forecasting - solar PV, EV, batteries, flexible loads etc.
  - Large no. of heterogeneous, independently owned devices with private, sensitive customer data

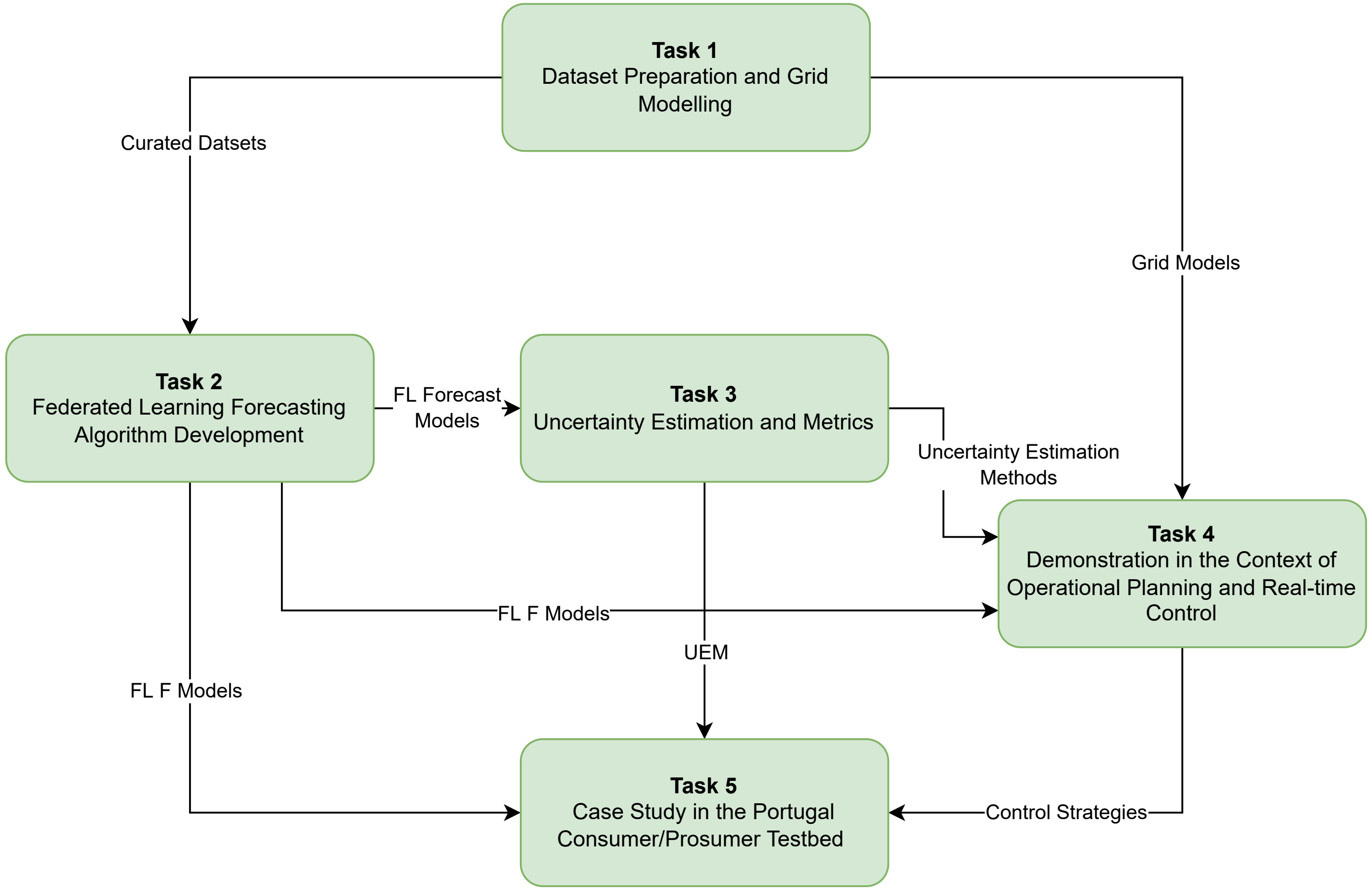


Source: Venkataramanan, V. et al. IEEE Internet of Things Journal (2022).

- Incorporate more domain-specific knowledge (e.g., DER/load models, grid physics/constraints) → Physics-informed FL?

Research proposal

- Apply advanced FL methods for DER forecasting at both individual device & aggregate levels
- Rigorously evaluate performance (accuracy, training time, efficiency) on synthetic & real data from US/Portugal
- Quantify uncertainty and DER forecast errors associated with FL predictions
- Understand impacts of improved FL forecasts (and uncertainty) on power systems operations (transmission & distribution)



Climate change impacts

- Enable more rapid integration of DERs & renewables
  → Help decarbonize power & transportation sectors

- Better grid operational planning & real-time operations
  → Maintain system stability, reliability & resilience

- Aid in market clearing and increased efficiency
  → More affordable energy access & climate justice goals

- Grid operators & utilities can plan ahead to deal with intermittency & variability with high renewables % and/or extreme weather
  → Reduce reliance on coal & natural gas peaker plants

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