Developing a Simulated Node on the Smart Grid

1. How many students you would prefer
   1 – 2 students

2. Preferred student specialty (CS, EE, Cyber, etc.)
   CS/Cyber/CE/EE

3. Preferred academic specialty code (4IJY, 4ICY, etc.)
   Any

4. The days that you would need the students for
   Flexible

5. How many hours per day you would need the students for
   Self-paced. Plan to meet bi-weekly, but work can occur asynchronously / remote

6. A description of the project (bullet form or paragraph)

The larger research project shows how federated learning can improve the power grid's privacy, security, and resilience. Traditional machine learning techniques require data to be in some central repository. For some applications (e.g., healthcare, training), training these centralized models is difficult due to privacy and sensitivity issues. Federated Learning (FL) eliminates the need for centralized data in the ML pipeline (McMahan et al., 2017). In FL, client data never leaves the client. However, a centralized model can be updated -- the weights, parameters, and other model metadata is sent to the central model without granting access to the training data. Figure 1 represents a notional federated learning pipeline:

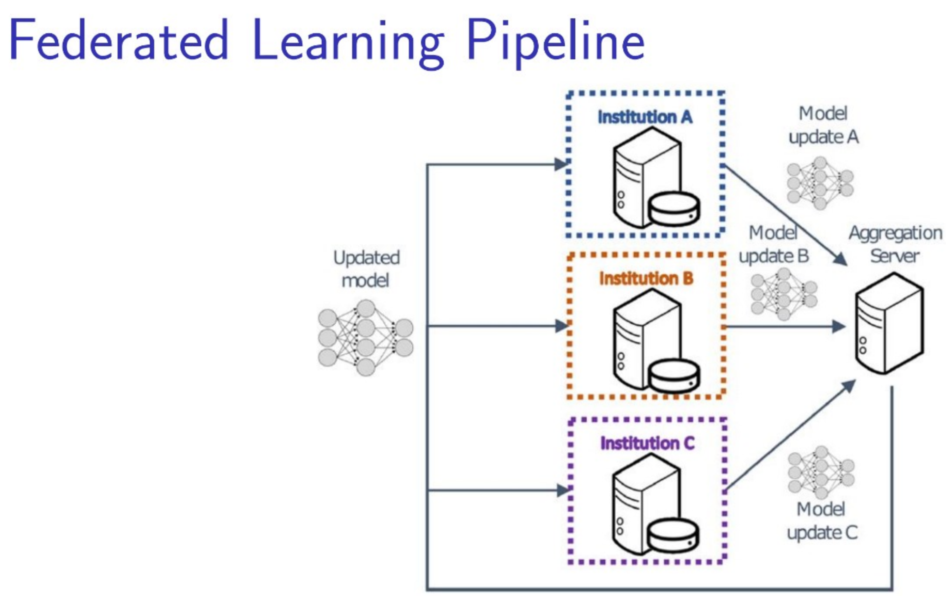

Figure 1: Federated Learning Workflow from Sheller et al. (2020).

Using FL in the smart grid would allow for the prediction of the power draw from various levels (house, neighborhood, city, region, etc.) without sharing sensitive information about actual residential usage. To begin researching in this area, realistic simulations of power grid consumer nodes are required.

The casual student will develop a Python simulated residential node on the power grid that can represent power draw from various adjustable parameters and conditions. The casual student will work with the professor and other experts to craft a plausible scenario to observe the power draw from the following adjustable parameters:

- Three-month weather patterns in the local area and their impact on HVAC.
- Quantity, wattage, use schedule, and variability of residential appliances.
- Family parameters such as family size (1 – 6), composition, schedule, and activities (e.g., telework, entertainment).
- External events (e.g., anomalous weather conditions →10-day forecast) that could increase or decrease overall power needs.
- Internal temperature settings on HVAC

Works Cited

McMahan, B., Moore, E., Ramage, D., Hampson, S., and y Arcas, B. A. (2017).Communication-efficient learning of deep networks from decentralized data. InArtificialintelligence and statistics, pages 1273–1282. PMLR.

Sheller, M. J., Edwards, B., Reina, G. A., Martin, J., Pati, S., Kotrotsou, A., Milchenko, M., Xu, W., Marcus, D., Colen, R. R., et al. (2020). Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data. Scientific reports, 10(1):1–12.