**Introduction and Problem Statement:** Renewable generation is going to be the leading form of energy generation in the future, but the current electrical grid was not designed to handle bi-directional flow and variable generation. Utilities’ electric grids are very expensive and aging; most utilities were formed in the early and mid-1900s. So, utilities are now scrambling to update their grids and implement the tools that will allow them to safely operate and manage their asset.

Currently there is a limit to how much renewable generation can be added to a distribution circuit before safety concerns arise. Based on the current practices, a customer cannot install renewable generation at their home or business if the hosting capacity has already been exceeded for their circuit. Energy storage can be used to offset the safety concerns on distributed generation (source), and is currently being used to safely operate renewable energy generation project, but the limited projects that have been completed are large scale and/or in areas that are remote and have limited or expensive access to other energy sources (Hawaii, Alaska sources). With California and Hawaii setting goals to be 100% renewable energy powered by 2045, behind-the-meter batteries will become a necessary commodity in the United States.

There are currently only (small% -source needed) homes with grid connected batteries in the United States, but with the evolving policies and dropping prices, this is expected to increase dramatically. Some utilities do not have the regulation or policies in place to identify when a customer adds grid connected PV or battery systems to their home, much less the normal operation of the devices. Policy could be changed to require more customers to give utilities access to the use data, but policy moves slower than technology and implementing communication networks and procedures to collect and organize the new data is time consuming, complicated, and very costly. Machine learning has already been shown to be useful to extrapolate useful information from data already available at utilities (yang source) and has the potential to be used to identify and parameterize behind-the-meter devices.

Whereas pen and paper sufficed to do simple power system analysis, circuit models are now required to include bi-directional flow and the variability of renewable. Utilities such as DLC are rushing to build a GIS system of all their assets in the distribution grid. But a perfectly accurate GIS system is very costly and likely infeasible because of the quantity of assets, and the nature of the distribution grid to rapidly change. Research has shown that circuit models can be reconstructed without GIS data (my paper, yangs paper). Using machine learning, AMI data can also be used to identify behind the meter devices.

**Hypothesis:** Using machine learning, AMI data can be analyzed to identify customers who have behind the meter generation or storage devices and the device’s normal operation parameters. Knowing the topology of the system and the behind-the-meter devices, utilities will be able to safely improve the operation and increase the hosting capacity of renewable generation on the grid.

**Methodology and Testing:** A machine learning algorithm will be created to identify normal customers and highlight outlier customers, those with PV and batteries installed at their homes (yang PV source). Unfortunately, behind the meter battery systems are not common so some of this data will have to be created based on simulations.

There are many different types of control algorithms for behind-the-meter energy storage systems. Most of them can be classified by the different goals of that the algorithm is trying to use the battery: lower peak load, back-up power for outages, and/or voltage regulation. So even though there is a lack of customers with these systems, generic battery control algorithms can be created based on the strategies they are trying to implement (source?). Then the algorithms can be tested on the database of AMI data, with varying sizes of battery systems and PV systems. After running the generic battery control algorithms on a variety of customers, enough new data could be generated to cover the entire possibility spectrum.

Using the original AMI data, knowledge of the customers, and the generated data, a machine learning program can be trained to differentiate between different types of customers. Further, once the machine learning algorithm can confirm the behind-the-meter device(s) at a customer location, the capability to identify different stages of operation of those devices could be extracted from the data. When does the battery normally charge, discharge, regulate the voltage, or do nothing? By identifying the modes of operation the primary parameters that control the operation of the device can be estimated (such as size, primary purpose, night charging time, charging rate, etc). These parameters can then be added to a distribution circuit model so that the engineers in a utility can accurately assess how the circuit is being impacted by the addition of the battery and/or PV system that has been identified.

**Expected Significance and Broader Impact:** The capability this project provides plays a critical role in the utility of the future. Not only will it improve operation and increase the PV hosting capacity of a circuit, but it has the potential to increase customer satisfaction, educate customers, and provide utilities the ability to offer new types of services. Services could involve tweaking control parameters of your battery system and providing a small incentive to do so. One example would be to suggest a different starting time for a battery to begin charging at night to smooth out the load seen by the power companies. Another example would be to keep the battery capacity empty until the day to prevent an overvoltage during peak solar generation hours because all your neighbors have solar, but you have the only battery. This would require customer interaction, so a before and after simulation of the state of the system could be sent to the customer to educate energy involved customers on their local grid operations. The incentives could involve lower rates for a month, credit toward the electric bill, and/or credit towards an upgraded battery system. The involvement would be optional, so customers would retain control over their system, but whether the customer made the adjustments could be calculated automatically using my propand took me to places I never dreamedosed algorithm.