SIGNAL AND INFORMATION PROCESSING APPLICATIONS FOR THE SMART GRID

Anthony Kuh

Dept. of Electrical Engineering
University of Hawaii
Honolulu, HI 96822
kuh@hawaii.edu

ABSTRACT

This paper discusses using signal processing to assist in processing of information for the smart grid. This consists of getting information about the electrical grid and environment via sensor networks, interpreting information received via signal processing and machine learning, and then using the information to make intelligent decisions about the grid using control and optimization algorithms. The focus is on the electrical grid beyond the last substation, the distribution grid. For the smart distribution grid there is an increasing amount of distributed renewable energy sources and possible distributed storage. This necessitates gathering more information about the electrical grid, environmental data, and building energy usage. With this information we can forecast distributed renewable energy sources and develop algorithms for distributed state estimation. We can then develop demand response algorithms to control loads (e.g. appliances, thermostats, air conditioners, hot water heaters).

***Index Terms*—** smart grids, sensor networks, distributed estimation, demand response

1. INTRODUCTION

The electrical grid is undergoing some major changes as we transform to an electric grid with large shares of renewable energy sources, gathering detailed spatial and temporal information about the electrical grid and environment affecting grid operations, and distributed decision making controlling load usage. This paper focuses on some of the changes occurring at the distribution level beyond the last substation. Here we give an overview and discuss some of our work in each of these three areas where signal and information processing plays a major role: gathering data, data interpretation, and making intelligent decisions based on the interpreted data.

The US government has defined features of the smart grid in [1] which include enabling active participation of customers, accommodating all forms of generation and storage options, optimizing assets and efficient operations. Facilitating these features requires implementation of digital technologies and concepts from information theory, communications, signal processing, and control that have been used to advance information technologies and communications.

In recent years there has been significant attention given to applying signal and information processing to smart grid and energy problems. The *IEEE Signal Processing Magazine* had a special issue on “Technical challenges of the smart grid: from a signal processing perspective” that appeared in September, 2012. The articles in the special issue addressed some of the signal processing methodologies that are important in the design and operation of the future smart grid [2]. In December, 2014, the *IEEE Journal on Selected Topics of Signal Processing* had a special issue on “Signal processing in smart electrical power grid” with twelve articles discussing using signal processing for a variety of topics including state estimation, electric vehicle charging, demand-side management, fault detection, electricity market balancing, energy consumption models, and power balancing [3]. The *APSIPA Transactions on Signal and Information Processing* have also had a special issue articles devoted to signal and information processing for the smart grid, [4]. There have also been special sessions at both the *IEEE International Conference on Acoustic Speech and Signal Processing* and the *Asia Pacific Signal and Information Processing Annual Summit and Conference* devoted to applying signal processing methods to smart grid and energy problems. Other recently created IEEE Journals that focus on the smart grid and sustainable energy are the *IEEE Transactions on Smart Grid* and the *IEEE Transactions on Sustainable Energy*. These two journals and others from the IEEE Power and Energy Society often use algorithms and approaches from signal and information processing.

Here we focus on the electrical grid beyond the last substation, the distribution grid. In the traditional legacy grid the power is passed through the last substation and the distribution grid steps down the voltage through transformers to eventually reach the customers (residential, commercial, industrial). This is changing with the introduction of distributed renewable energy sources located at customer premises, energy storage devices, and electric vehicles hooking up to the distribution grid. The distribution grid can be a residential community, military base, or a University campus. In fact many Universities around the US and globally are looking at their distribution grid and looking at transformations to convert this to a smart microgrid [5, 6, 7, 8]. Smart microgrids are defined by the Galvin Electricity Initiative as modern smaller scale versions of today's electricity grids [9]. These can be distribution grids that not only generate, distribute, and regulate the flow of electricity, but can still function when separated from the main grid [9]. It is envisioned that the future electric grid may be decomposed into a hierarchical structure with microgrids playing an important role and each hierarchical entity have some degree of autonomy and independence [10]. In many cases these microgrids are owned by the community (e.g. University). Signal and information processing play an important role in moving distribution grids to smart microgrids with three key components listed below.

A smart microgrid needs a wide variety of data in order to make intelligent decisions. This necessitates closer monitoring of not only the distribution grid (voltage, current, and frequency), but also other sources that will affect the distribution grid. This includes environmental conditions that affect distributed renewable energy resources and energy consumption in buildings. A key to getting good data is implementation and placement of different sets of sensor networks. For the electrical grid, smart meters that provide two-way communications such as Advanced Metering Infrastructure (AMI) can be deployed. The number of sensors and their placement is a resource allocation problem that can be formulated as an integer programming problem [11, 12, 13].

Once we have gathered data about the electrical grid, environmental conditions, and building energy consumption we can then interpret the data before making decision about using energy resources and performing demand response. This includes forecasting of energy for distributed renewable energy resources and estimating the state of the distribution grid. Good survey articles include [14, 15] which give overviews of state estimation and some of the challenges presented for the future electrical grid.

Once information has been assessed, then decisions can be made concerning the distribution grid. This involves controlling available resources including energy generation and storage along with using demand response to intelligently control loads. For demand response a wide variety of optimization approaches have been used ranging from using linear programming [16], game theory [17, 18] and approximate dynamic programming [19, 20, 21].

This paper proceeds to give an overview of some of the research activities in signal and information processing in the Smart Campus Energy Lab (SCEL) at the University of Hawaii. Section 2 discusses issues associated with sensor network implementation and placement. Section 3 discusses issues associated with performing distributed state estimation given more distributed renewable energy sources, Section 4 introduces using optimization and control algorithms to do demand response to control appliances. Finally, Section 5 summarizes the results of this paper and discusses directions for further research.

2. SENSOR NETWORK IMPLEMENTATION AND PLACEMENT

For the electrical grid there are a wide variety of smart meters including AMI that provide two-way communications that can receive information about pricing and energy usage from the utility company. To monitor the environment there are a number of professional weather stations that can be used including those from Campbell Scientific [22], and Libelium [23], however they are quite expensive. At a University campus such as the University of Hawaii at Manoa (UHM) there are varying environmental conditions because of the way the campus is situated at the front of Manoa valley. Cloud and wind conditions can vary dramatically within a few hundred meters. This requires a fairly dense placement of weather stations/ boxes to get both spatial and temporal coverage of environmental conditions. Similarly, sensor networks can be deployed to monitor energy usage in buildings. Our focus here is on monitoring environmental conditions.

Building and deploying low cost weather boxes has turned into an excellent undergraduate project for our students. The students are tasked to build a low cost self-powered weather box that is durable, reliable, provides accurate data, and is energy efficient. The students have used a dedicated microcontroller, XBee wireless communication device, discrete sensors (including pyranometer), lithium ion battery, and a solar panel to charge the battery [24]. Most of the key parts are located on two PCB boards and the box is built using a 3-D printer made of Acrylonitrile Butadiene Styrene (ABS) [24]. These weather boxes are self-powered and built to transmit data even with several consecutive cloudy days at a fraction of the cost of professional weather stations. Eventually, there will be a network of these weather boxes deployed on rooftops of the UHM monitoring environmental conditions such as solar irradiance, temperature, humidity, pressure, and wind speed and direction. The goal is to provide good temporal and spatial resolution around the UHM campus so that this information can be used for forecasting of distributed renewable energy sources (such as distributed solar Photovoltaics (PV)).

The cost of these weather boxes is around \$400 [24], so there is still the key question about how many weather boxes are needed and where should they be placed to get good spatial and temporal resolution of environmental conditions. This problem is a resource allocation problem that can be formulated in a number of ways. We could consider that the weather boxes form a sensor network and we would like to sample a subset of the weather boxes and estimate the state of all the weather boxes given some information about the spatial correlations between data. This problem can then be formulated as a sensor placement problem.

There has been substantial research on the sensor placement problem from researchers studying sensor networks with applications for environmental monitoring [25, 26], monitoring the electrical grid with Phasor Measurement Units (PMU)s [27, 28], and biomedical monitoring. Tools from signal processing, statistics, and machine learning are used. The problem is often framed as an optimization problem of minimizing some error criterion or maximizing some information criterion. Once space has been discretized it can be formulated as placing m sensors among $n > m$ possible locations. In [11], PMU placement is considered where observability is assumed and the goal is to optimize a given cost function. The solution involves solving an integer programming problem, which is NP-complete. However, an approximate greedy solution is found that gives good results and runs in polynomial time. The greedy algorithm is tied to submodular and monotonic functions where bounds can be obtained to the greedy algorithm in relationship to the optimal algorithm [13]. In [29] a sensor selection problem is considered for wireless sensor networks. A cost criterion is formulated based on the Kullback-Liebler (KL) divergence and Chernoff distances. The problem is also NP-hard, but the authors propose a greedy approach to solve the problem suboptimally.

In [12, 13] we formulated the static sensor placement problem using a mean square error criterion and showed the problem reduced to an integer programming problem that becomes infeasible when the number of locations, n and sensors, m become large. We found families of greedy algorithms that run in polynomial time and also found upper and lower bounds to optimal performance. These bounds are based on generalized eigenvector decompositions and using matrix pencils. The problem is broadly applicable in a number of domains including placement of weather boxes at discrete locations, PMU placement, and placement of AMI on a distribution grid. In [13] we conducted a number of simulations on randomly generated data and also on an IEEE 57-bus test system. The simulations showed that greedy algorithms that run in polynomial time give good approximations to optimal algorithms and that we could find reasonably tight lower and upper bounds to optimal algorithms. The cost criterion used is the overall mean squared error at all n locations (measurements are application dependent and could be in terms of solar irradiation, voltage, or current).

3. DISTRIBUTED STATE ESTIMATION FOR A SMART MICROGRID

Once we have gathered data from the electric grid, the environment, and information about energy usage in buildings we can then interpret data using signal and information processing. There is a variety of tasks that can be performed including spatial and temporal forecasts of distributed PV energy generation and distributed state estimation. This Section focuses on distributed state estimation for a distribution grid.

The electrical distribution grid beyond the last substation consists of feeder lines that distribute power to customers. It can usually be modeled as a radial network. Our goal is to measure both voltages and currents on the radial network. As we move towards a smart microgrid the radial network will have smart meters deployed on the radial network and also have distributed renewable energy sources such as wind and solar PV energy generation. A simple radial network is shown in Fig. 1. There may also be additional wireless communication capabilities on the radial network.

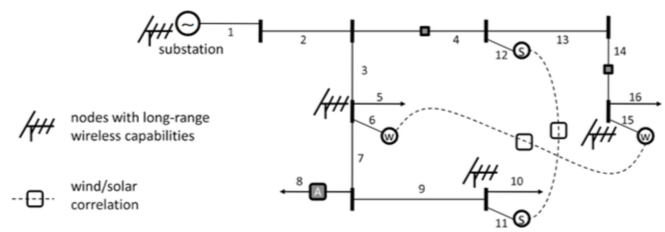

Fig. 1. Model of radial network with distributed renewable energy sources and metering

We would like to perform state estimation for this radial network finding voltages at nodes and currents at branches. Here the circles represent distributed renewable energy generation (solar PV and wind) and the shaded squares represent meters taking measurements. We can convert the radial network into a factor graph as shown below in Fig. 2 [30].

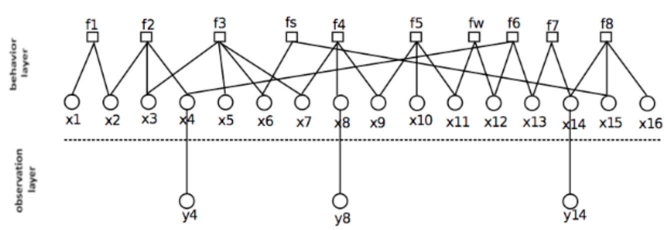

Fig. 2. Conversion of radial network in Fig. 1 to a factor graph

For this example there are three meters representing three observations which are described by three nodes at the bottom layer. The middle layer consists of nodes representing the state of the radial network. The upper layer consists of functional relationships giving the physical connections of the radial network and also describing the correlations between the distributed renewable energy sources denoted by f_s for solar and f_w for wind.

For real distribution grids the radial networks are often very large consisting of many nodes and connections in the factor graph. For most radial networks the factor graph representation is a tree if there are no distributed renewable energy sources. For these networks distributed state estimation algorithms such as message passing and belief propagation work well and converge [31]. When we have distributed renewable energy generation such as solar PV, loops are created in the factor graph. The distributed solar PV generation is highly correlated at close distance and is stochastic and intermittent. We have performed belief propagation on factor graphs modeling simple distribution grids with distributed renewable energy generators (DREG) and show that the algorithms converge to good solutions [30, 32].

Currently, distributed solar PV generation is becoming popular. Hawaii has the highest penetration of rooftop solar in the United States with an average of 12% penetration in residential communities in Honolulu, [33]. Because of this, the local utility company, Hawaiian Electric Company is concerned about the stability of the grid on certain feeder lines with high percentage of rooftop solar. We can model these distribution grids and feeder lines using the approach above. However, with large amounts of distributed solar PV generation it becomes difficult. This is because there are many loops to the factor graph resulting in difficulties when using algorithms such as message passing and belief propagation [31].

We have examined solar PV data at different spatial locations and looked at the correlation matrix of solar irradiation. The correlation matrix can be described via a graph with nodes representing locations and edges representing the normalized inverse of the correlation matrix. These graphs are often fully connected, but in some cases we can make approximations with sparser graphs. In [34] we explored using a regret function and found a Markov chain approximation to the graph. The approach was suboptimal and used an incremental Cholesky factorization. In [35] we considered using tree apronximations for the correlation matrix graph. Here we use the KL divergence as a cost function. The advantage here is that there are efficient algorithms such as the Chow-Liu algorithm that can easily be deployed when data is assumed to be Gaussian [36]. We found that for graphs with larger number of nodes, tree approximations were not always accurate, but that the KL divergence could vary widely depending on the tree approximation used. Using the Chow-Liu tree gave reasonable approximations and could then be used in the factor graph describing the distribution grid.

4. DEMAND RESPONSE FOR APPLIANCES USING APPROXIMATE DYNAMIC PROGRAMMING

A fundamental equation of the electric grid is that energy generation must equal energy consumed. In fossil fuel power plants and nuclear power plants the amount of electricity generated is deterministic. For the legacy grid energy generation is known and can be added depending on loads. Loads are random, but aggregate loads follow certain usage patterns depending on time of day and time of year. Utility operators can usually determine when to add and remove energy generation from power plants depending on the predicted loads to supply sufficient amounts of power while optimizing assets. The equations change when renewable energy sources such as wind and solar are introduced. Wind and solar energy are intermittent and stochastic. When there are large shares of renewable energy on the grid, especially the distribution grid we need good forecasting and ways of balancing energy generation and energy usage. Some ways include energy storage, but storage is often expensive. Other methods combine forecasting, energy storage, and demand response.

Demand response can occur in homes by controlling appliance usage, setting thermostats and hot water heaters, and controlling when electric car batteries are charged. The optimization approach that is used depends on how the problem is defined. Things to consider include the cost of electricity, where energy is coming from (renewable sources or firm sources), storage options, user load profiles, and comfort indices. As mentioned in the introduction there has been many different approaches to demand response including using linear programming, non convex programming, dynamic programming, game theory, and approximate dynamic programming (ADP). In this Section we focus on ADP as this allows systems to learn load profiles and forecast renewable energy production. This involves both exploring and exploiting the state space to come up with good solutions. Conditions can also change with time due to load profile changes and seasonal weather changes. In previous work [19, 20, 21] use ADP is used to control appliances, thermostats, and when to charge or discharge an electric car battery.

Here we briefly discuss a current research project of controlling a hot water heater using ADP. Water is a storage medium for energy. Hydroelectric power is generated by moving water from a high elevation to a lower elevation. Cooled and heated water also contains energy that can be used as storage. Our work is ongoing and based on [37]. The problem consists of minimizing a combination of costs to heat water in the hot water heater and the discomfort of the customers when they do not get enough hot water. These are modeled as a Markov Decision Process (MDP). The MDP could be solved using a finite horizon dynamic programming model however, we do not know the state and action transition probabilities. A key is to determine when to turn on the water heater and when to turn off the water heater. Models are formulated for how the water in the water is heated when the water heater is turned on and how the water in the water heater cools when the water heater is turned off. In addition in our research lab we have a twenty gallon water heater with sensing devices on the heater to conduct experiments on how water in a water heater both warms up and cools down.

For this problem we need to find information about how residents use hot water. This consists primarily of taking showers and using hot water for cleaning. This can be learned from conducting surveys and also observing households over a period of time. A finite horizon ADP problem can be then formulated with the horizon being one day. Both time and temperature of the hot water heater are discretized. Since there are a large number of states, we aggregate both discrete time and temperature. The ADP is shown to converge and give a significant improvement over water heaters that have fixed set points determined by time of day. Using ADP results for the hot water heater involves predicting when a user will take a hot shower. The ADP algorithm will typically turn on the hot water heater well before the anticipated shower takes place. Extensions include developing models for solar water heaters to also predict solar energy and aggregating multiple water heaters in a community to serve as distributed energy storage.

5. SUMMARY AND FURTHER DIRECTIONS

This paper has discussed the gradual transformation of our electric power grid into a smart grid. We have focused on the distribution grid beyond the last substation which is moving towards a smart sustainable microgrid. Here we show that signal and information processing will play an important role in this transformation. This paper gives an overview of areas that my research lab has worked on to get and assess energy and environmental data and to then use optimization tools to perform demand response. This work is ongoing and will provide for a wide range of opportunities for signal and information processing researchers interested in transforming our electrical grid to a future smart grid.

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