1 Project Description

Contents

1.1 Introduction

Development of the “Smart Grid”, a modernized power infrastructure, is one of the key technological challenges facing the United States at the dawn of the 21st century. According to the Department of Energy (DoE) , the smart grid should: (1) Enable active participation by consumers by providing choices and incentives to modify electricity purchasing patterns and behavior; (2) Accommodate all generation and storage options, including wind and solar power. (3) Enable new products, services, and markets through a flexible market providing cost-benefit trade-offs to consumers and market participants; (4) Provide reliable power that is relatively interruption-free; (5) Optimize asset utilization and maximize operational efficiency; (6) Provide the ability to self-heal by anticipating and responding to system disturbances; (7) Resist attacks on physical infrastructure by natural disasters and attacks on cyber-structure by malware and hackers [62].

Microgrids are semi-autonomous, self-regulating electrical systems below the subsystem level that can involve small-scale storage and generation as well as consumption. Supporting all generation options implies the need to support both utility-scale central generators and distributed, small scale, variable generating resources such as behind-the-meter solar PV. Supporting all storage options implies the need to support distributed, small scale, load management resources including electric vehicle batteries, demand response (DR) and distributed generators (DG). When DG and load management options can be locally controlled, the utility of microgrids as a building block for the DoE Smart Grid becomes clear.

1.1.1 Vision

Our vision for a sustainable energy pathway begins with the creation of a *smart, sustainable microgrid* for the University of Hawaii at Manoa (UHM) campus. By “smart”, we mean a microgrid that uses environmental sensors and predictive analytics to automatically adjust loads as well as one that engages microgrid users in proactive, positive energy conservation and management. By “sustainable”, we mean a microgrid that incorporates significant renewable energy sources with the long-term goal of a net-zero energy footprint.

Our vision for a sustainable energy pathway begins with the creation of a functional, semi-autonomous, self-regulating microgrid that creates a positive energy future for the University of Hawaii at Manoa campus. Analogous to the energy grid, the state and campus are currently facing severe energy challenges. For

UHM, while energy consumption per square foot is among the lowest across campuses in the nation (at approximately 65K BTU per square foot), the cost of energy per square foot is among the highest in the nation (approximately $4.50 per square foot), as is the cost of energy per student FTE (approximately $1,300 per student FTE).

Making matters more complicated, an aggressive retrofitting of mechanical systems at the University over the past 10 years has largely exhausted the traditional avenue to energy cost reduction. In addition, because the State of Hawaii depends on fossil fuels for almost 90% of its energy, it is possible, if not probable, that the cost of energy in Hawaii, already the highest in the nation, will rise substantially in the next 20 years. The current high cost of energy and the probability of it rising even higher, combined with the exhaustion of traditional approaches to energy cost reduction, has led David Hafner, Assistant Vice Chancellor at the University of Hawaii to state, *"the cost of energy represents an existential threat to the University of Hawaii as a Research I university"* [20].

We present this background to emphasize that our choice to focus on a sustainable energy pathway for the University of Hawaii at Manoa (UHM) campus is not because it would be "nice to have", it is because the status quo is quite literally unsustainable. To retain its current quality of campus life, the University is pursuing strategic options including conservation measures and self-generation in support of energy cost reductions. We envision the UHM smart sustainable microgrid as a focal point for industrial and academic collaboration that creates a "climate of energy conservation" both on the campus and the larger community.

Our vision involves the transformation of the campus from a passive to an active contributor of its energy needs, Plans include operating the campus as a microgrid with up to 5 MW of solar generation, short term, small scale storage, automated demand response for the major on-campus HVAC systems, and consumer facing information technology to engage campus members in support of the microgrid and its goals. This vision requires innovation in transmission, distribution, efficiency, and use. Our research and development plan involves five interrelated research components, summarized as follows:

1. *Sensing, monitoring, and data gathering.* A responsive microgrid requires the ability to assess its current state and estimate its future state. To enable these capabilities, this component will design and install a network of strategically located power and environmental sensors into the UH campus as well as into the neighboring vicinity. This raw data will be collected and stored in a server for use in modeling and analysis. (Section 1.2.1)

2. *Modeling and analysis.* This component takes the raw power and environmental data and applies stochastic modeling techniques to gain insight into both the current and near-future state of the UHM microgrid. This component provides the information necessary for control and optimization. (Section 1.2.2)

3. *Control and optimization.* This component uses models and analyses to support voltage and frequency regulation, load management, peak shaving and peak shifting. By maintaining quality of service while reducing load disruptions and ramp events, the University microgrid can serve as a model to help inform strategies for reducing overall variability impacts of solar resources. (Section 1.2.3)

4. *Social, economic, privacy, security, and policy implications.* It is explicitly not our goal to create a grid that operates separately and invisibly from its users. Indeed, we believe that part of the problems with our current electrical infrastructure results from lack of public awareness concerning the problems of reliable, sufficient, and sustainable energy production. This component investigates the information technology necessary to develop bi-directional awareness to 1) inform campus members about the capabilities of the microgrid; 2) elicit action that lets them actively participate in achieving cost reduction goals; and 3) interface campus microgrid capabilities to provide grid-friendly services

in support of the larger grid. In so doing, we must confront and address the privacy and security issues that result, both with respect to the security of the grid itself and the ways the microgrid sensing and monitoring infrastructure could be used to inappropriately monitor campus member behaviors. (Section 1.2.4)

5. *Education and workforce development.* All of the PIs on this project and industry partners are also active participants in the Center for Renewable Energy and Island Sustainability (REIS), a project with a central focus on workforce development in renewable energy. As a natural result, our vision includes the development of curriculum materials about microgrid design, implementation, and evaluation, and students with real-world experience in development of the microgrid. Leveraging the REIS program helps ensure that workforce development will span multiple disciplines including computer science, engineering, economics, urban planning, law, biology, and other disciplines. (Section 1.2.5)

Our vision begins, but does not end, with addressing the energy challenges facing the University of Hawaii at Manoa campus. First, the creation of a functional microgrid for the UH Manoa campus will create technology, data, and workforce training essential for the development of similar strategies for other educational, government, and military campuses across the Hawaiian islands. Replication of the approach will yield important insights into the transformation of a single centralized, top-down grid into multiple, decentralized microgrids (that capture the benefits of distributed generation (DG) and demand response (DR)) .

Second, while the mainland US does not yet feel the level of energy pressure faced by Hawaii, we believe these pressures will rise across the country in coming years as the price of oil rises or if a commitment to sustainable energy pathways is made. We believe the science and engineering and industrial partnerships developed through this research will provide significant aid to microgrid development outside Hawaii, and thus provide an important building block in service of the Department of Energys goal of a nationwide Smart Grid.

1.1.2 Integration

This project is designed to explore the challenges and opportunities of an informed and integrated microgrid development from multiple perspectives and multiple disciplines.

From a scientific perspective, our sustainable energy pathway will produce opportunities for the development of new analytic methods. As further discussed in Section 1.2.2, this research is expected to result in the development of new analytic methods based upon belief propagation networks and Markov models. It will also support the development of controlled and semi-controlled experiments to understand both the control issues underlying a semi-autonomous, self-regulating microgrid (as discussed in Section 1.2.3), as well as social, economic, security, privacy, and policy issues (as discussed in Section 1.2.4).

From an engineering perspective, the challenges and opportunities are obvious and manifest. The microgrid requires the specification, acquisition, and/or fabrication of hardware and software components for sensing and regulation of electrical and environmental data, as discussed in Section 1.2.1. These components must be integrated into the current electrical and physical infrastructure of the University of Hawaii campus and the utility grid in a manner compliant with all university, state, and federal regulations. Finally, the microgrid must interact with the centralized grid provided by the utility, both accepting control signals from that grid as well as providing status information back to the utility, as discussed in Section 1.2.3.

The scientific and engineering challenges will not be faced in isolation but form a natural, complementary, and synergistic pair of viewpoints. For example, the development of analytic methods will be guided by the control and optimization goals. Conversely, resolution of engineering challenges such as the optimal placement of sensors will be guided by controlled experimental procedures in relation to the existing grid

	Inside microgrid / UH	Outside microgrid / UH
Science / Engineering	Kavcic, Kuh, Johnson, Hafner	Nakafuji, Fripp
Environment / Policy	Hafner, Meder, Kuh	Mikulina, Meder, Johnson, Nakafuji

Figure 1: Team members and focal areas

infrastructure that are intended to produce methods for sensor placement useful outside of the University of Hawaii context.

1.1.3 Collaboration (Management Plan)

Our team consists of five principal investigators (Professors Aleksandar Kavcic, Philip Johnson, Anthony Kuh, and Matthias Fripp from the University of Hawaii and Dora Nakafuji from Hawaiian Electric Company and an Adjunct Professor) along with three collaborators (David Hafner and Stephen Meder, Assistant Vice Chancellors for the University of Hawaii; and Jeff Mikulina, Blue Planet Foundation). Each of the collaborators along with Hawaiian Electric Company have supplied a letter indicating their support for the project and interest in participation.

Team members were carefully chosen to provide a broad, interdisciplinary, and complementary set of skills. Professors Kuh, Kavcic, and Fripp are from the Department of Electrical Engineering and have expertise in sensing, modeling, and power systems. Professor Johnson is from the Department of Information and Computer Sciences and has expertise in software engineering and consumer-facing interfaces to the Smart Grid. Dr. Dora Nakafuji is Director of Renewable Energy at Hawaiian Electric Company and has expertise in utility-side systems. David Hafner is an Assistant Vice Chancellor and head of Facilities Management at the University of Hawaii and has expertise in UH power systems and requirements. Stephen Meder is also an Assistant Vice Chancellor and head of sustainability initiatives at the University of Hawaii. Finally, Jeff Mikulina is the Executive Director of Blue Planet Foundation, a Hawaii-based environmental advocacy group which has played a major role in renewable energy policy development in Hawaii.

For a summary of the basic roles and responsibilities of these team members, it is useful to think of the project as consisting of two dimensions. The first dimension, domain of inquiry, comprises two basic areas: science/engineering and social/environmental/policy. The second dimension, domain of application, also has two basic areas: internal to the proposed microgrid (i.e. the University of Hawaii campus) and external to the proposed microgrid (i.e. the surrounding environment). Figure 1 illustrates these two dimensions and the focal points for the team members in tabular form.

The project will be led by Dr. Kuh who will manage the work, ensure coordination among the investigators, and track milestones. The entire team will meet monthly by conference call to discuss research and education progress, with smaller meetings in focus areas occurring more frequently. A yearly summit meeting will provide an opportunity to assess overall progress and adjust milestones if necessary.

At the University of Hawaii, the PIs will hold weekly meetings with graduate students. Typically, a student or faculty member will present their research results which will be critiqued by the whole group. The meetings will ensure that work is collaborative and will give all investigators and students an opportunity to see the different phases of the research project. Dr. Nakafuji became an adjunct Professor at the University of Hawaii and will join our meeting at regular intervals.

The PIs will serve as leaders for the five research components. Professor Kuh and Dr. Nakafuji will lead sensors and monitoring, Professor Kavcic and Kuh will lead modeling and analysis, Professor Fripp will lead control and optimization, Professor Johnson will lead social, economic, privacy, security, and policy implications, and Professor Kuh will (also) lead education and workforce development.

All PIs will work together on recruiting, retention, and outreach efforts. Special attention will be given to recruiting of underrepresented students with assistance from NHSEMP and SWE, as discussed in Section 1.2.5.

1.2 Pathway to Smart, Sustainable Microgrids

Our pathway to smart, sustainable microgrids involves the development of a testbed consisting of the UH Manoa campus. This section goes into detail on the five research components introduced above.

1.2.1 Research component: Sensing, monitoring, and data gathering

In this research component, we will address the problems of sensing, monitoring, and data gathering for a microgrid with a high penetration of distributed renewable energy generation. Theoretical studies will be considered along with extensive simulations in conjunction with the development of the actual University of Hawaii at Manoa microgrid. The UHM microgrid and field data will support validation of the simulation and theoretical studies.

Today's modern electrical grid system relies on a vast web of distribution networks (D) and transmission corridors (T) to deliver power to customers. Tremendous control, visibility and communication resources and standards exist to support the "T" portion. The "D" portion has received much less attention and poses one of the weakest links to enabling wide adoption of more distributed resources. The "D" portion tends to be more disperse, less automated and non-standard across the nation. Making matters worse, the utility operators have limited or no visibility to the distributed resources emerging on their systems. The influx of customer-sited PV systems and emerging plug-in-hybrid vehicle technologies deployed at the distribution level have accelerated the need to accurately model impacts of these distributed generation (DG) resources on the electric system. On the UHM microgrid this requires design and installation of appropriate sensing equipment to monitor environmental resource data, electrical grid data, and building energy usage. This is closely tied to other aspects of the project including modeling and analysis, optimization and control, and the economic, social, and policy implications.

This research considers both theoretical and practical aspects of gathering data from sensor and monitors and maintaining a series of sensor networks. Multiple data types will be gathered requiring construction of sensor networks and data fusion from the multiple sensor networks. A key is to deploy enough monitors and sensors so that important information can be gathered and processed. Information needed include parameters and events that can impact the operation of the grid like ramps due to changing weather conditions (from cloudy to sunny or vice versa) and faults that can occur on the electrical grid. With sufficient sensor networks deployed intelligent control and optimization strategies can be made to reduce energy usage in buildings subject to economic considerations and energy requirements made on labs, classrooms, and offices in the building. In this subsection we discuss the data types, data collection, building sensor networks, and gathering information from the data (sensor fusion, compression, and data mining).

Data types. To accurately model and analyze the microgrid along with designing optimization and control strategies for the grid several sets of data need to be monitored. We also need to consider measuring data both spatially and temporally. The data that we consider in this proposal are environmental resource data, electrical grid data, building energy usage, and data gathered from users of energy on the microgrid. Actual grid data will be gathered from our test-bed, the UHM micro-grid. Environmental resource data is monitored so that we can better forecast the energy generation of distributed renewable energy sources such as solar PV panels located on the campus. We shall build and deploy custom and industry-grade resource sensor stations that measure solar irradiation, wind speed and direction, temperature, and humidity. These sensors and monitors will be placed on rooftops of UHM buildings with key considerations being how fast we sample data, how many sensors do we deploy, and where do we place sensors.

Electrical load grid data will also be gathered from existing building and microgrid power quality meters. Additional monitors will be placed at key locations on buses and electrical lines. Currents, voltages, complex power, and energy usage will be measured. Key considerations include how fast we sample data, where to deploy monitors and meters, and what sensors types are most cost effective and what devices are already on the grid.

We need to characterize campus circuit profiles and load data using data gathered from field sensors and monitors in buildings. Here we can monitor energy usage by deploying sensors to measure energy usage in rooms from air conditioning, electrical equipment, and lighting. The data will be stored in WattDepot, an open source platform for energy data collection, storage, analysis, and visualization developed by PI Johnson's software development laboratory [10].

Data collection. There are several issues to be considered when getting data from sensors, monitors, and meters. How much information is to be gathered, how do we collect this data, and how do we organize this data? The first issue is discussed here with the other two issues discussed in subsequent subsections.

Where do we place the sensors? There has been substantial research on the sensor placement problem from researchers studying sensor networks with applications for environmental monitoring [17, 16], monitoring the electrical grid with PMUs [29, 74], 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. Optimal algorithms are computationally infeasible for large m and n, but greedy algorithms that run in polynomial time of m and n often give good approximations to optimal algorithms [53, 48]. Some key aspects of the optimization include properties of submodularity and monotonicity [63]. We study these algorithms as it applies to our algorithm for both static and dynamic cases. A state space model can be used to model the dynamics of different parameters with a linear state space model given by

$$x(k+1) = Ax(k) + Bu(k)$$

$$y(k) = C(x(k) + v(k))$$

where $x(k)$ is the state of the system (e.g. on the electrical grid, current phasor at n different nodes). A goal is to determine the best C matrix which is a binary 0/1 matrix with at most one 1 in any column and exactly one 1 in every row.

We must also determine how often to sample data. The sensor placement problem and sampling problem depend on the information we need to control and optimize the micro-grid. This depends on the modeling and analysis of the micro-grid and also what events we are trying to detect. Other factors that come into play are the economics associated with placing sensors, monitors, and meters. A goal is to place and sample sensors so that they give the most useful information subject to placement constraints. For the field deployment we would consider placing sensors on high penetration feeders with unique load signatures on the grid and monitor the environment resource conditions for the DGs. . This will give us a better understanding of effects of renewable energy generation, how we can model this, and designing control and optimization algorithms that can mitigate intermittency subject to available resources, usage needs and management capabilities (battery storage, demand response (DR)).

Sensor network implementation. We will create two sensor networks at the micro-grid level. One sensor network will consist of environmental resource data collected from student-built solar powered monitoring platforms that measure solar irradiance, wind speed and direction, temperature, and humidity. There will also be utility compatible, off-the-shelf sensors such as solar resource locational monitors (e.g. LM2 monitors) currently used by the utility. A goal is to monitor environmental resource data both spatially and temporally on the UHM campus. Most of these sensors will be placed on top of UHM buildings currently projected to have PV. This will offer a perspective on pre- and post-DG conditions and capture value of energy produced by distributed PV sources placed around the campus. Wireless networks will be used to gather this data to a central server and storage system.

A second sensor network will monitor the electrical grid. This will consist of sampling existing HECO utility meters and deploying demand side load monitors (e.g. AMI and PMI type devices) and PMI field device data concentrators. These sensors will be connected together via a wireless network and again sent to a WattDepot server for storage, analysis, and visualization.

Information gathering. We are investing in a Smart Campus Energy Laboratory (SCEL) in 493 Holmes to collect the data from different sensor networks. This facility will house the data server and storage system running WattDepot [10]. Time stamped data will be gathered from sensor networks monitoring environmental resource data, electrical grid data, and sensor networks in buildings monitoring energy usage. In addition, as discussed in Section 1.2.4, there will be data collected from students, staff, and faculty on campus about their energy usage. A goal of data collection is to enable data fusion so that information can be obtained to assist in detecting key events that happen on the microgrid (e.g ramps in energy produced by distributed solar PV and faults that occur on the electrical grid).

Tools are needed to organize and fuse the raw data from sensor networks. This includes using filtering, sensor fusion, source coding, compressed sensing, and machine learning to process the data to extract useful information from the data. Once this is done models can be created of the microgrid to analyze and simulate the behavior of the grid. Then control and optimization algorithms can be tested on simulation networks to deal with events such as ramping and faults. Software packages such as Powerworld, Matlab, and PSCAD will be used along with visualization tools such as TREX designed by Referentia, a Hawaii-based high tech business.

1.2.2 Research component: Modeling and analysis

Given appropriate data, the next step is to apply analytic techniques to create real-time and historical information useful for control and optimization of the microgrid.

Two important contributions of this part of the research will be: (1) analytic techniques that enable us to adequately characterize the current state of the microgrid while minimizing cost-prohibitive deployment of sensing equipment, and (2) analytic techniques that enable short-term prediction of various useful attributes of the micro-grid (such as future potentially peak load and ramp) and the surrounding environment (insolation, wind speed and direction, etc.)

It should be noted that there is an interdependence between the "sensing and monitoring" subproject and the "modeling and analysis" subproject: we will "tune" the installation of sensing equipment in order to obtain acceptable quality of analytic outcomes for the next step, control and optimization. Furthermore, the chosen models and analytical tools cannot only be good descriptors of the underlying physical processes, but also need to be matched to the signal processing (detection and estimation) methods, or else the signal processing methods will not be of much use.

Belief Propagation. Through or previously funded NSF project (ECCS-1029081), we have already established that the factor-graph approach is well-suited to modeling the electrical connections of a microgrid. Figure 2 shows a schematic view of a factor-graph associated with a fictitious microgrid. The nodes in the mocrogrid are divided into three layers: 1) the observation layer (sensors, measurement equipment), 2) the behavior layer (collection of network nodes, loads and microgenerators) and 3) the communication layer. We demonstrated that, with only a few well placed sensors in the grid, we are able to track slowly evolving

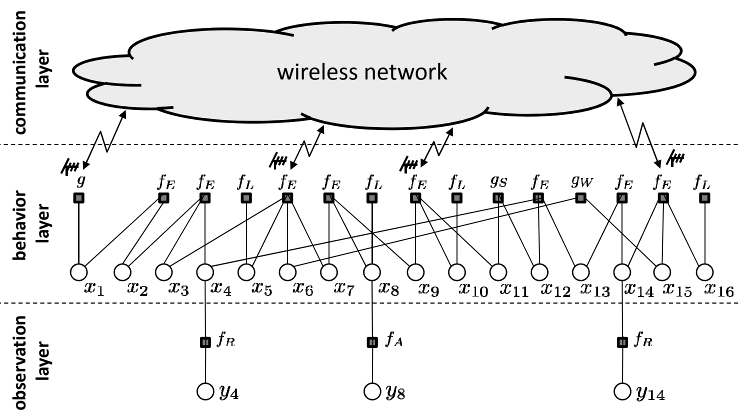

Figure 2: Factor graph - an abstraction of the microgrid. The factor graph consists of the behavior layer and the observation layer. The communication layer provides additional global communication features. In this figure, the state variables are denoted by x_i and available observations (sparse measurements) are denoted by y_i. The belief-propagation algorithm is a monitoring algorithm that works by passing only *local* messages along the solid edges of the graph, yet achieves *global* monitoring.

behaviors of the grid as well as with more elaborate exact maximum-likelihood estimators [24, 26, 25]. This is mainly because the electrical grid is typically a *tree* graph, where correlations among renewable sources create rare loops with large diameters.

In this research, we plan to use belief propagation as a tool that would also enable 1) tracking the grid in transitional modes (e.g., if a large number of users and/or renewable microgenerators enter and/or drop from the microgrid abruptly) and 2) short-term future prediction of the grid behavior at node-levels. To this end, we will develop the necessary modeling and prediction tools.

Modeling demand. Often, the demand in grid networks is described using historical *histograms*. However, historical histogram patterns do not reveal the true spatiotemporal character of the demand. It is obvious that spatial and temporal correlations will need to be exploited in order to arrive at a model that would be useful for spatiotemporal demand prediction, i.e., prediction that can predict the demand, say, five minutes in advance at any given set of spatial location locations in the microgrid. Furthermore, in order to utilize the belief-propagation tool, we will seek to model the demand among various nodes in the microgrid as a spatiotemporal Markov process with as few loops as possible (because it is the loops that adversely affect belief propagation [72, 49, 60]). We note that simple Gauss-Markov process modeling will likely not suffice because Gaussian processes are well-suited only for tracking slow changes. Yet, demand in campus environment can be spatially and temporally bursty (because of correlation to class-time starts, lab-clusters, weather/heat conditions and distributed renewable microgenerators). For this reason, we plan to leverage our experience in modeling Gauss-Markov processes [43] and finite-state machines [76, 70] to develop a comprehensive double-layer Gauss-Markov/finite-state spatiotemporal demand model. We will extrapolate, calibrate and test the model using measurement data from sensors distributed around the campus.

Modeling renewable sources. Much like the loads (demand) are spatially and temporally distributed, so are the renewable micro-generators. The UH campus already has several photovoltaic (PV) systems and two small wind turbines (used for experimental purposes) dispersed around campus. Therefore, we will need to begin by modeling their energy outputs using spatiotemporal Markov processes (with as few loops as possible) that are capable of modeling both slowly varying effects as well as (spatially and temporally) localized bursts. Again, we will utilize a layered Gauss-Markov/finite-state modeling approach to capture both effects. However, unlike modeling demand, here we will need to heavily correlate the model to weather conditions (night/day, cloud-cover, wind speed and direction). We will extrapolate, calibrate and test the model using weather measurement data from irradiance sensors, wind velocity sensors and cloud cameras distributed around the campus.

Prediction. It is a well-known fact that the Kalman predictor is the optimal predictor of spatial and temporal Gaussian processes [41, 42, 39]. When the Gaussian process further possesses a Markov structure (i.e., a Gauss-Markov process), the Kalman predictor is computationally less intensive [49, 60]. In our case, we will likely have a two-layer spatial and temporal Gauss-Markov/finite-state process to track. The optimal tracker of this process would be a spatiotemporal combination of a Kalman predictor [41, 42] and a forward recursion of the Baum-Welch algorithm [4, 2]. However, this approach will likely be too computationally intensive to be practical. Therefore, we will ignore the loops in the model, and implement the predictor using belief propagation derived for a tree-like double-layer (Gauss-Markov/finite-state) graph, but applied to the exact loopy microgrid graph.

We envision that the developed prediction tool will be used to indicate where and how the control mechanisms (e.g., peak-shaving, gray-outs, etc.) should be applied. However, we must consider the sensitivity of certain locations when applying control. For example, it would be detrimental to shut off the air conditioner in a sensitive climate controlled laboratory, or in computer server clusters that must remain cool. For this reason, it is desirable to have a prediction method that will account for these sensitivities. It is well-known that any prediction method suffers form uncertainly, misdetection and false alarms. Grossly false estimation or prediction of the state of certain sensitive nodes may adversely affect the stability of the network or sensitive campus locations. This can be minimized in two possible ways. Firstly, we may choose to place sensors in the vicinities of highly sensitive nodes, and thus minimize the risk of misprediction. Secondly, we may choose to dampen the belief-propagation algorithm to prevent wild belief swings in the vicinities of highly sensitive nodes. This amounts to placing weights (or other types of constraints) on beliefs corresponding to highly sensitive nodes. We shall term this approach *sensitivity weighted* belief-propagation. To our knowledge, no such approach has been attempted in smart-grid networks, although similar strategies are available in the communications and error-control coding literature [71, 30, 69].

Analysis. The final piece of the modeling and analysis effort is the actual analysis of the proposed models and tracking methods. In tracking mode, we will utilize statistical signal processing techniques to analyze the performance of the trackers. For example, under stationarity conditions, we can easily bound the performance of maximum-likelihood estimators of Gaussian processes. We will extend these techniques, and combine them with bounding techniques typical for finite-state processes [28], to develop bounds for tracking the layered Gauss-Markov/finite-state process under certain stationarity assumptions.

Under extremely non-stationary, non-Gaussian conditions, however, it will be extremely difficult to come up with analytical tools that will be able to bound the performance of the estimator/tracker. Indeed, in the signal processing literature, response to extreme non-stationarities are typically demonstrated by simulations [75, 67]. For this reason, it is actually very important to design a robust model that will not only be useful for designing the detector, but also for designing the simulator. The usefulness of this approach will be extremely important when determining the response to *rare or contingency events*. Rare events are events that are rarely (or never observed) in practice until they happen in reality (e.g., black-outs, shut-downs, catastrophic failures, storms). The only way to understand how such events would affect the system is through simulations. We will conduct analysis studies of these rare, extremely non-stationary events through the means of simulations using the developed process models.

1.2.3 Research component: Control and optimization

The primary goals of a smart, sustainable microgrid are to use electrical energy as efficiently as possible, maximize the amount of energy coming from renewable resources, and minimize the overall cost of energy while retaining acceptable levels of reliability and quality. The optimization and control module of this project will study how well these goals can be met by scheduling electricity production and consumption using data and forecasts from the modeling and analysis module.

Some of the important capabilities of the microgrid control system will include peak shaving/shifting, ramp-rate management, and lowered overall consumption. The initial approach will focus on cooling loads, which make up most of UHM's electricity demand. Later in the project we will develop optimal control strategies for other time-shiftable loads, such as water heating, energy-intensive scientific research, and eventually electric vehicles. The control effort will also manage UHM's many individual backup generators as a coordinated asset, making them available for peak shaving and ramp rate management. All these efforts will improve the demand profile presented to the electric utility and reduce the campus's electricity bills.

This research will study power control techniques with varying degrees of user interaction, from direct automation through voluntary user responses to campus alerts. Automation is most suited for systems that don't directly affect users or for complex systems. For example, electricity demand for chillers and water heaters can be deferred several minutes or hours by adjusting their temperature setpoints slightly. Automation allows consistent and fine-grained adjustments that would not be possible with user responses alone (e.g., simultaneously adjusting many different lights or parts of the cooling system) [61, 65]. Automation can also provide faster and more frequent responses than users alone, which will be essential for integrating renewable power both at UHM and in the larger power system [66, 13]. In contrast, many peak-reduction programs set financial incentives a day in advance in order to involve users more easily [8, 66], which reduces their suitability for renewable integration. However, rich user engagement will also be essential to obtain the greatest possible benefit from the microgrid. This will require innovation in the presentation of energy information to users and the design of interfaces that blend automation and user control - work which is described in more detail in the next section.

The core of the microgrid optimization system will be a multi-period stochastic linear optimization model [40] that chooses how to control loads and generators in order to minimize the total cost of providing power to the campus in coordination with the system grid . The objective (cost) function of this model will use a broad definition of the total cost of power, including the time-varying cost of electricity, utility charges based on the peak load and ramp-rate for the month, the cost of operating backup generators as peak- or ramp-shaving units, and the "costs" of load control itself – inconveniencing users or depleting their interest in future load control measures. During each optimization cycle, the model will consider several alternative scenarios, each defined by specific values for future loads, renewable power production and electricity costs, over periods ranging from the next few minutes to the next 24 hours, as well as forecasts of the month's peak load and ramps. Scenarios will be generated that cover the forecasted values for each of these future parameters, as well as the uncertainty range of these forecasts. The optimizer will choose a control strategy that minimizes the expected cost of power over all these scenarios. Voluntary user responses tend to be strongest for infrequent events [8] [18, 66] and vary from user to user, so we will also seek to optimize the frequency with which we call for action from each user.

In addition to developing the software and hardware systems required for control and optimization, we will measure the effectiveness of these control strategies in the field. This will serve two purposes: First, it will provide valuable information on the magnitude and duration of energy time-shifting (real or virtual storage) available from a wide variety of building energy systems, as well as estimates of how this capability changes over time as user interest increases or decreases. Second, this information will be used to fine-tune the optimization and control algorithms, to more precisely achieve the desired level of load control.

We will also explore tradeoffs between efficiency and peak-management in the operation of the campus power system. For example UHM's smart grid and smart chiller water distribution system will allow the campus to run many generators or chillers at once, giving a strong peak-shaving or ramp-shaving capability. However, either of these strategies would increase total power consumption, since chillers and generators are less efficient when they are run at part load. Similarly, if chiller water is cooler than needed to maintain building comfort, there is some leeway to allow temperatures to rise (reducing electricity demand) during a peak-load event. However, overall efficiency can be improved by maintaining chiller water at a higher temperature from the outset [61].

1.2.4 Research component: Social, economic, privacy, security, and policy implications

As discussed in the introduction, one of the key properties of the Smart Grid according to the Department of Energy is to "enable active participation by consumers". We believe that this is especially important for our smart, sustainable microgrid, and that it would be naive to assume it could be implemented transparently and invisibly to its users. Many people are used to virtually unlimited, low-cost, and reliable electrical energy produced in an unsustainable, environmentally harmful manner and do not yet understand why this cannot continue.

In this research component, we will investigate the social, economic, privacy, security, and policy implications that arise during the transition to a smart, sustainable microgrid. We intend this research to produce insight into how to best engage citizens in the process of weighing the trade-offs associated with microgrid development, as well as how to best enable them to become active participants in microgrid management. Active participation has the potential to create efficiencies not possible through automated techniques alone, but this will require providing users with new forms of information along with the incentives and engagement necessary for users to act on this information in a timely, effective, and positive manner. Finally, this research component will investigate what kinds of data must be gathered in order to support broader policy decisions by local government that can make future smart, sustainable microgrids easier to develop and deploy.

Social and policy issues. There is a growing body of research regarding social engagement in energy use and conservation [21, 66, 14, 1, 15, 21, 18, 22]. Engagement can range from passive (e.g., tolerating automated building temperature adjustments) to active (e.g., scheduling energy-intensive research for off-peak times). Much of the prior research on user behavior has focused on residential environments or other circumstances where direct financial incentives apply. In contrast, we will need to actively engage users in energy conservation and management in an environment where they have only an indirect financial stake in the outcome. Fortunately, we have already established a research program called the Kukui Cup which investigates the use of real-time feedback, incentives, education, and game mechanics to obtain sustained, positive changes in energy behaviors among dorm residents [9, 12]. In the Kukui Cup, direct financial incentives also do not apply.

Our strategy for social engagement will include several elements. The first level will be presenting users with information on concrete measures they can take (long-term and hour-by-hour) to help the campus achieve cost savings and greater usage of renewable resources. As an additional incentive, we will study socially oriented ways of motivating actions that help the campus, building on techniques we developed for the Kukui Cup. We will also develop new interfaces such as smart phone apps to replace the in-home display typically used in residential demand response programs. We will design these interfaces to engage many different types of user and help them learn successively more about the power system and their role within it [66]. This effort will also benefit from collaboration with smart metering researchers in Oxford University's Lower Carbon Futures group (support letter attached).

We will carefully analyze the ways in which government and university policies act to promote or inhibit the successful development of the microgrid. Policy analysis must occur across a very wide spectrum.

At one end, building code policies can influence the ease of sensor installation, use, and subsequent control capabilities. At the other end, energy data access policies can influence whether users can effectively participate in grid management.

Privacy and security issues. Enabling active participation by consumers is made difficult by the fact that the collection, analysis, and usage of power and environmental data within a microgrid creates significant new security and privacy considerations. The canonical security concern is the possibility of unauthorized agents infiltrating the microgrid network and becoming capable of injecting control signals into the microgrid leading to power and/or equipment failure. The canonical privacy concern is the possibility of unauthorized agents infiltrating the microgrid network and using its data to gain insight into the behaviors of campus members and organizations, enabling them to better plan and execute robberies or other illegal activities.

Smart grid security and privacy issues can be organized into categories corresponding to primary grid components: the PCS system, smart meters, power system state estimation, smart grid communication protocol, and smart grid simulation for security analysis.

The most common PCS system is SCADA. Traditional PCS systems are designed with a defense-in-depth, firewall network protection scheme. Adding more security to PCS systems is complicated due to their real-time, low latency (sub-second), and high availability requirements [68].

Smart meters provide fine-grained, near-real time information about power use within a building or other component of the campus. Security issues include tampering with the smart meter readings to effectively "steal" power. Privacy issues include using the fine-grained data to infer the behaviors of occupants. Berthier, Sanders, and Khurana have proposed a comprehensive set of security tools for smart meters [7].

Maintaining the integrity of the grid requires power system state estimation, and yields a security risk of attackers injecting false data into the model to create system instability or for financial gain [73]. Allocating the processing overhead necessary to distinguish false from real data is problematic due to the high-availability and low-latency (sub-second) requirements for this component. Some research has been done on how many compromised sources are required to carry out an unobservable attack [45].

Network communication and their associated protocols is the backbone of the smart grid, and the security and privacy issues are diverse and dependent upon the nature of the protocols and the types of information that are being communicated. A particularly difficult issue is the need to interface with legacy systems which were not designed with support for security. Khurana et. al. have proposed a set of design guidelines for smart grid protocols to reduce the number of vulnerabilities [44].

Finally, smart grids cannot be taken down for testing, and so simulation systems are used for testing instead. While traditional grid simulation systems are focused on availability and stability concerns, smart grids will require these systems to support security and privacy assessment as well. Kundar et al have begun work on a framework that provides initial progress toward smart grid security analysis through simulation [51].

A contribution of this research project will be the evaluation of these techniques in the context of microgrid design and implementation and insights into enhanced privacy and security based upon industry standards and campus ITS requirements.

Economic issues. The final area of investigation for this research component involves the economic implications of the microgrid. Our principal focus in this area will be to determine how effectively the microgrid can serve to decrease the overall cost of energy supplied by the local utility. Currently, the University electrical rates for a given month are primarily a function of two variables: the peak demand by the University during that month, and the peak rate of increase in demand (ramp) during the month [20].

If the microgrid design is effective, then we should be able to lower peak demand in the following ways:

(1) by integrating solar generation (which reduced demand from the utility); (2) though automated demand response (which, when combined with adequate prediction, should enable the system to shut down chillers in advance of periods of high load, reducing peak requirements), and (3) through customer-facing user interfaces, which could inform campus members of periods of high loads and enable those with discretionary power loads to shift them in time to periods of lighter overall demand. We will also be able to evaluate the ability of our prediction algorithms to reduce the rate of increase in demand.

By the conclusion of the project, we will be able to produce comprehensive cost-benefit analyses of the investment required to create the sustainable, smart microgrid and the economic benefits that accrued from its implementation and use. We will provide an accounting for the savings from generation, automated demand-response, and user behavioral change.

1.2.5 Research component: Education and workforce development

The Hawaii Clean Energy Initiative (HECI) is a Memorandum of Understanding (MOU) between the state of Hawaii and the Department of Energy signed in 2008 that set goals for Hawaii so that by 2030 70% of our energy will come from clean energy sources (30% from energy efficiency and 40% from renewable energy sources). Through the Renewable Energy and Island Sustainability (REIS) goup we have developed curriculum and courses in energy and sustainability to help train this workforce that will be needed to achieve these goals. Much as HCEI will rely more on local energy sources the REIS group is working to have Hawaii more reliant on locally trained experts in energy and sustainability.

At the UHM we are developing multidisciplinary education and research programs that span the range of jobs that will be needed to supply new educated workforce in the energy and sustainability areas. We have funded workforce training programs at the University of Hawaii community college level (NSF Tribal Communities University Program (TCUP) Pre-Engineering Education Collaborative (PEEC)) and at the graduate and undergraduate level at the UHM through REIS (Department of Energy (DOE) workforce training grant). The DOE workforce training grant is developing curriculum over a broad range of energy topics considering engineering, natural and social science, and policy. Student in the graduate REIS program supported by the DOE workforce training grant take two core graduate courses in energy (one class in engineering and the other class in social science). The students then take other courses so that they can concentrate on their research which varies from studying nanocomposites for fuel cells to biofuels to wave energy to smart grid security.

This proposal goes one step further by focusing on an in depth understanding of microgrids, distributed renewable energy sources, demand response, and energy efficient management. We will work on further development of courses in the smart grid and renewable energy areas with a focus on systems, software, and policy issues. We will create a variety of graduate level courses including classes on the Smart Grid and Future Electrical Energy Systems, Advanced Software Energy Systems, and Energy Resource Assessment. These courses will all have engineering, economic, social,and policy aspects and provide background knowledge along with the two core REIS graduate courses and fundamental courses in Probability, Signal Processing, Communications and Networking, Software Engineering, and Economics. The courses are well integrated to the four research projects and will give students a good foundation to conduct their research.

In addition we are working through local funding agencies to develop a short twenty hour course on smart grids and integration of renewable sources that will be available to UHM students and faculty and also the external community. This course will be broken up into five four hour segments: grid overview, policies and standards, tools and capabilities, communications and networking and security, and integration of sources.

A major component of education and training is conducting research while using the Smart Campus Energy Lab (SCEL) and working on the UHM microgrid. Both graduate and undergraduate students will be working on research projects in conjunction with HECO engineers and UHM facility people. There will be a close integration between the different research areas and also between education in the classroom where concepts are learned, analysis where models, algorithms, optimization, and control methods are formulated, software and hardware simulation studies, and the UHM campus environment and microgrid where analysis and simulations are confirmed. The research projects will also educate students in team work, project management, and improve their oral and written communication skills.

Integration of members of under-represented minorities This project will collaborate with the Native Hawaiian Science and Engineering Mentorship Program (NHSEMP) to broaden the participation of under-represented groups. NHSEMP is a successful program housed at the University of Hawaii funded (in part) by the National Science Foundation Louis Stokes Alliance for Minority Participation Program and the U.S. Department of Education Native Hawaiian Education Program. The program is already very successful in attracting members of the Pacific Islander minority into the undergraduate engineering program. Our next goal is to achieve a smooth transition of the most talented minority students into the best graduate programs nationwide. For example, we are already implementing an REU exchange program with our collaborators (at MIT) in conjunction with a joint project between MIT and University of Hawaii [NSF Grants ECCS-0725555 and ECCS-0725649]. Throughout 2008 and 2009, MIT hosted Hawaiian minority undergraduates from Professor Kavcic's group. Their video-documented experiences can be viewed at http://www2.hawaii.edu/˜thanhvu/Videos.html. We are also presently in the process of selecting qualified minority undergraduates to send to Pittsburgh, PA to participate in our joint project with Carnegie Mellon University [NSF Grants ECCS- ECCS-1029081]. We will continue to draw representatives of underrepresented students into our research program in conjunction with this project. UH minority undergraduates will spend their semesters working as researchers with at University of Hawaii and their summer/winter breaks as interns/researchers at HECO or visiting our research partners on the mainland.

We will also collaborate with the Society of Women Engineers (SWE) and Women inTechnology (WIT) to recruit both undergraduate and graduate students into our program. Faculty and students from the REIS group have already participated in a number of outreach activities to recruit students (especially underrepresented students into considering careers in energy). Some events such as "Wow! that's engineering" have been targeted at middle school students, other events such as the COE open houses have been targeted at high school students, and the Hawaiian Electric Company outreach event at Bishop Museum target the general community. Activities include purchasing unassembled miniature wind turbine kits and having kids and adults at these events assemble the wind turbines. Using fans, the wind turbine blades would turn and meters would show the electricity that was generated.

1.3 Project plan

Figure 3 illustrates the project timeline, organized by the five research components. The four years of this project are broken down into four phases: a six month "ramp up" phase at the start of the project, followed by two eighteen month phases in which we iteratively develop and evaluate the microgrid, followed by a six month "ramp down" phase in which we focus on documentation, evaluation, and other activities necessary to allow maximal external use of the knowledge and skills gained during this project.

The goal of the initial six month ramp up phase is to complete all of the startup activities necessary to ensure a successful Phase I implementation of the microgrid. For all research components, this involves hiring of personnel and initial meetings to review literature and become familiar with relevant issues and technologies. For the sensing and monitoring component, the ramp up period also involves the development of a simple server based upon historical data that can provide simulated data about building loads, environmental data, and grid state. This simulated data will be relatively imprecise given the short time available for implementation, but its goal is to simply enable other research components to make progress prior to complete installation of sensors. The modeling and analysis component will also create a simulator during

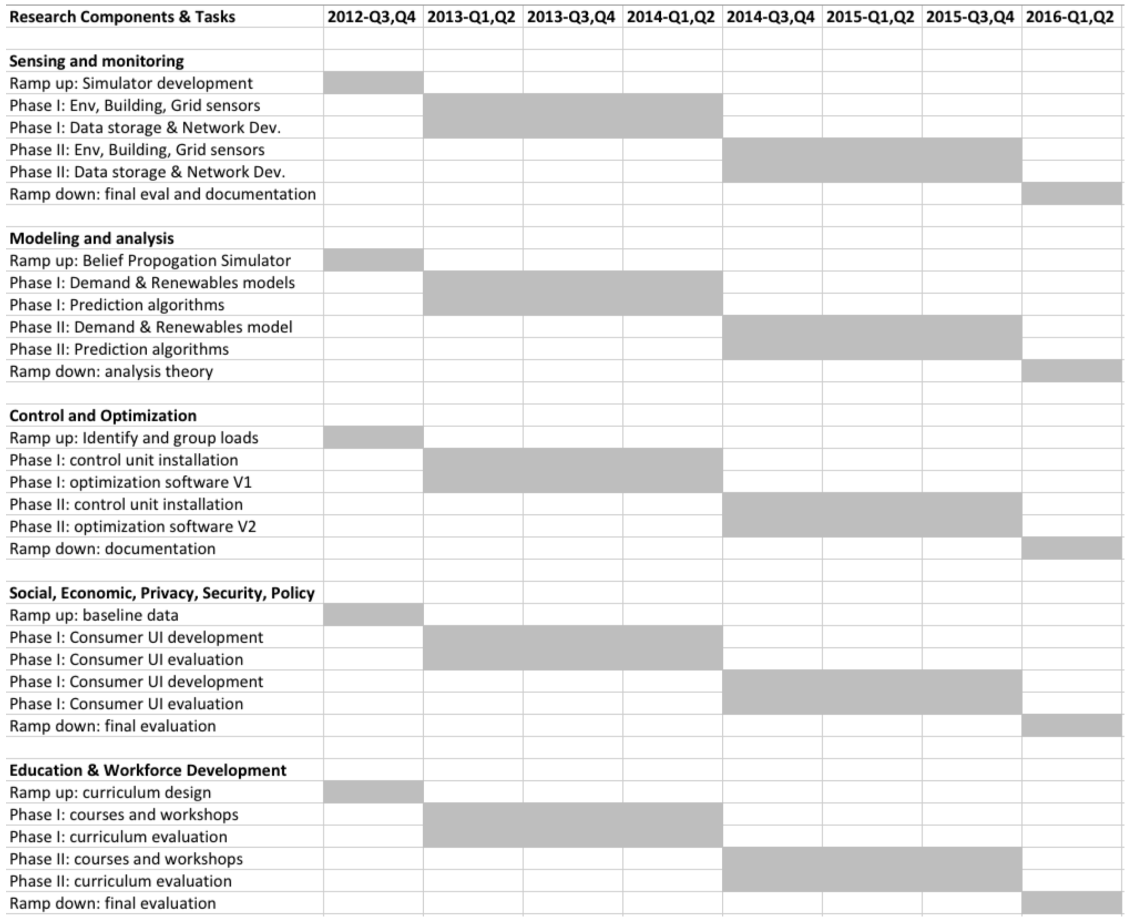

Figure 3: Work breakdown structure.

the ramp up phase, in this case for a belief propogation network appropriate to the microgrid. The control and optimization component will research historical loads and assess control unit types and applicability. The social, economic, privacy, security, and policy (SEPSP) research component will obtain baseline data regarding energy use, attitudes, and concerns among the university stakeholders. Finally, the education and workforce development research component will work on curriculum during the ramp up phase.

After ramp up, the project begins two eighteen month cycles of microgrid design, implementation, and evaluation. We designed the project so that by the end of year two of this four year project, we will have created a functional microgrid, though not complete or optimal. By the end of Phase I, the sensors and monitoring research component will have installed an initial set of environmental, grid, and building sensors and this data will be provided for use in modeling, analysis, control, and optimization. Based upon Phase I experiences, the sensors and monitoring research component will install additional sensors or modify existing ones to improve the quality of grid performance in Phase II.

A similar iterative approach is employed in the other research components. During Phase I, the modeling and analysis research component will create models of both energy demand and renewable resource production and build an initial prediction algorithm using the data provided by Phase I sensors and monitoring. The strengths and weaknesses of these initial models and the data they are based upon will be evaluated at the end of Phase I and used to construct more robust and performance models and prediction algorithms in Phase II. Similarly, the control and optimization research component will implement initial control mechanisms during Phase I, and the results will be used to generate Phase II requirements for the modeling and analysis and sensors and monitoring research components.

The SEPSP research component during Phase I and II is similarly iterative, but here the focus is on creating and evaluating user interfaces that result in active participation by campus members in the management of the grid. Finally, the education and workforce development components will focus during Phase I on more general curriculum while the micro grid is still under initial construction. During Phase II, the curriculum can be refocused to incorporate "live" analysis of the running microgrid and its operational state.

The project plan provides for a six month "ramp down" period at the conclusion of the four years. The goal during this period is to ensure that we create curriculum, publications, software, hardware, and documentation of maximal utility to others wishing to engage in microgrid development either in Hawaii or on the mainland. In addition, the final six months serves as a "buffer" period in the event that Phase I or Phase II takes longer than expected.

1.4 Results from prior NSF research

The PIs for this project have had the following NSF-supported projects during the past five years:

1. P. Johnson, *Human centered information integration for the Smart Grid*, NSF Grant IIS-1017126, 8/15/10 - 8/14/13, $381,467. The objective of this research is to design information technology and associated experimental methods to help understand what information, provided in what ways and at what times, enables consumers to make positive, sustained changes to their energy consumption behaviors. Selected publications include [10, 11, 12, 9, 52].

2. P. Johnson, *Supporting development of highly dependable software through continuous, automated, in-process, and individualized software measurement validation*, NSF Grant CCF02-34568, 9/01/02 - 8/31/07, $638,000. The objective of this research was to design, implement, and validate software measures within a development infrastructure that supports the development of highly dependable software systems. Selected publications for this project include [37, 64, 36, 35, 34, 31, 38, 19, 36, 3, 23, 33, 32, 46].

3. A. Kavcic, *Energy-Efficient Communication with Optimized ECC Decoders: Connecting Algorithms and Implementations*, NSF Grant ECCS-0725649, 09/01/07 - 08/31/10, $120,000. This was a joint project with MIT. The PI was responsible for reshaping Reed-Solomon soft decoding algorithms for VLSI implementation. Selected publications for this project include [5, 6, 57, 56, 59, 58].

4. A. Kavcic *Channels with Memory – Universal-Compression-Based Modeling Principles for Computing and Optimizing Information Rates* NSF Grant CCF-1018984, 08/01/10 - 07/31/13, $462,000. The aim of the project is to utilize compression-based modeling principles to compute information rates of long-memory channels whose memory is so long that conventional channel modeling principles fail. The following publications are available to date [54, 78, 27, 55, 77, 79].

5. A. Kavcic *Collaborative Research: Factor-Graph Approach to Monitoring and Failure Assessment in Smart-Grid Networks* NSF Grant ECCS-1029081, 10/01/10 - 09/30/13, $225,000. This is a joint project between the University of Hawaii and Carnegie Mellon University. University of Hawaii is responsible for developing the factor-graph framework for belief propagation monitoring, while Carnegie Mellon is responsible for devising microgrid control algorithms. Publications to date include [24, 26, 25].

6. A. Kavcic *Collaborative Research: Cross-Layer and Unified Signal Processing System Design for Ultra-High-Capacity Next-Generation Magnetic Storage* NSF Grant ECCS-1128705, 09/01/11 - 08/31/14,

$165,000. The aim of the project is to formulate a unified signal processing and coding framework that will integrate the magnetic and solid state memories into a single device. The project started only very recently and there are no results to report to date.

7. A. Kuh, *Incremental and Distributed Learning in Nonstationary Environments with Applications to Wind Forecasting*, NSF Grant ECCS-098344, 9/01/09 - 8/31/11, $150,251. The objective of this research is to design novel nonlinear kernel online and distributed learning algorithms for applications including wind forecasting. Research was also conducted to model the microgrid using a factor-graph framework. This was done in collaboration with Prof. Kavcic and NSF Grant ECCS-1029081. Selected publications for this project include [50, 47, 24, 26, 25].

8. A. Kuh, *US-Japan Joint Seminar Information Theory*, NSF Grant 0508025 $35,750. Funds used to support graduate students for conferences and for visit to Japan.

Profs. Johnson, Kavcic, Kuh, and Dr. Fripp also had NSF support dating back more than 5 years.

1.5 Conclusions

In this proposal, we present a vision of a sustainable energy pathway that begins with the design, implementation, and evaluation of a smart, sustainable microgrid for the University of Hawaii at Manoa campus. Our vision is that the scientific findings, technological innovation, and social and policy insights gained from this work will contribute to the ongoing body of work that facilitates the development of microgrids across the Hawaiian Islands and across the mainland in future years.

The contributions of this research will include the following: (1) Development of an integrated data collection and management system for both environmental and energy data; (2) Procedures to determine appropriate placement of monitoring equipment within a microgrid in order to best support modeling and control; (3) Analytic techniques for characterizing the current state of the microgrid without a cost-prohibitive deployment of sensing equipment; (4) Analytic techniques that enable short-term prediction of various useful attributes of the microgrid; (5) Automated techniques for peak shaving/shifting, ramp-rate management, and lowered overall consumption through control of time-shiftable loads; (6) User interfaces to enable active participation in energy conservation and management; (7) Development and evaluation of enhanced security and privacy mechanisms; (8) Analysis of the cost-benefits of microgrids involving distributed, intermittent generation; (9) Curriculum and workforce development for microgrids; and (10) Integration of members of under-represented minorities.

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