# Technologies for Energy Efficient Buildings

**Prepared for the**

**U.S. Department of Energy**
**Office of Electricity Delivery and Energy Reliability**

**Under Award No. DE-FC26-06NT42847**
**Hawai‘i Distributed Energy Resource Technologies for Energy Security**

**Subtask 8.4 Deliverable**

**By**

**GE Global Research**
**Niskayuna, New York**

**And**

**Hawai‘i Natural Energy Institute**
**School of Ocean and Earth Science and Technology**
**University of Hawai‘i**

**December 2009**

*Acknowledgement:* This material is based upon work supported by the United States Department of Energy under Award Number DE-FC-06NT42847.

# Table of Contents

## TABLE OF FIGURES



## TABLES

# 1. Executive Summary

The scope of this project [1] is to develop and demonstrate in a laboratory environment a specific portfolio of technologies that enhance the functions and features of the Energy Optimization System (EOS) developed at GE Global Research. This is in support of Hawai‘i Natural Energy Institute’s (HNEI’s) contribution to the Hawai‘i Clean Energy Initiative (HCEI) to improve overall end-use energy efficiency by improving building system and appliance operating efficiencies, as well as by reducing peak demand through usage monitoring and demand response equipment installed in residential and commercial structures. GE’s EOS program is focused at the residential level on the following three areas: 1. Defining system requirements and specifications; 2. Developing advanced / enhanced functions and features of the energy management / optimization system; and 3. Performing laboratory validation tests and analysis.

The first focus area is on development of functional requirements and conceptual designs for the different component technologies that comprise the EOS. Three EOS conceptual system architectures (distributed, centralized, and hybrid) have been developed, compared and evaluated with emphasis on the distributed architecture for laboratory validation. Functional requirements and specifications for all key EOS component technologies / modules have been defined. These key components are self-learning and adaptive home models through system identification, utility feedback analytics, and direct load control and smart appliances coordination. Highlights of requirement specifications are summarized in this report. Details of the requirement specifications are documented in a separate specification document [2], referenced by this report.

The second focus area is development of enhanced functions / features of the EOS. Specifically, advanced functions / features include self-learning and adaptive home models, utility feedback analytics, and direct load control and smart appliances coordination. A home thermal model was developed to allow the EOS to predict how the home will react to stimuli such as weather, HVAC operation, homeowner occupancies. The model was constructed and updated using a system identification technique to enable self-calibrating and updating the model automatically for new and retrofit homes. The model can also be used to track changes to the home structure over time as a tool for monitoring / diagnostics. Utility feedback analytics were also designed to provide the utility with valuable information such as sheddable load and available DG generation (solar PV and wind, etc.). Direct load control and smart appliances coordination algorithms were developed and validated in GE Global Research’s Smart Grid Laboratory.

The third focus area is on the laboratory testing, validation and analysis. Three most applicable test scenarios were tested in the Lab with a stressed power grid condition simulated with high electricity price. The three test scenarios are: direct load control (DLC) for emergency load shedding; peak power reduction in response to critical peak pricing (CPP) signal; and energy optimization for energy reduction and utility bill savings. Test results met expectations. All three scenarios can be applied with pre-defined priorities per utility and consumer’s needs and preferences. They are complimentary energy management techniques / algorithms that can be implemented / deployed individually or in any combination of the three.

This report is organized as follows. Section 1 will provide an overview of the background and accomplishments of the program. Section 2 will summarize the status of the project with regards to the deliverables and milestones. Section 3 will detail technical results of all the six tasks and deliverables. Section 4 provides reference material and archival locations of detailed documentation developed throughout the course of executing the program.

## 2. Background

An objective of the Hawaii Natural Energy Institute's (HNEI) contribution to the Hawaii Clean Energy Initiative (HCEI) is to improve overall end-use energy efficiency by improving building system and appliance operating efficiencies, as well as by reducing peak demand through usage monitoring and demand response equipment installed in residential and commercial structures. Toward this goal, HNEI is examining new technology development for home energy management systems, which can coordinate demand side management, peak demand response, and end use energy efficiency.

Through expanded collaboration with GE Global Research, development was undertaken to develop control algorithms necessary to efficiently manage energy utilization in the home. This effort is instrumental in supporting present and future projects for home and community energy management such as the on-going Maui Smart Grid Demonstration project.

Smart home energy management technologies have been developed that have the capabilities to:

a. Balance on-site home energy generation, energy storage with load energy usage;

b. Coordinate operation of energy generation, energy storage and load usage to minimize utility energy cost while adhering to homeowner preferences;

c. Receive and utilize utility electricity rate tariff (direct and market-based) along with forecast weather and environmental information to perform the energy and cost optimization function;

d. Interface with advanced meters to provide trending and reporting; and

e. Interface with smart appliances and coordinate their operations in various energy savings scenarios.

The energy optimization system (EOS) consists of an energy management platform, which interfaces to smart meters, smart loads within the home as well as smart energy generation and energy storage components. The homeowner interfaces with the EOS system through a user interface display. The central element of the EOS system is an energy-optimizing engine, which is based on model-based predictive controls. The energy optimizing engine utilizes forecast weather, solar insolation and utility electricity tariff, coupled with sensors within the home, along with a thermal and energy model of the home to plan the optimal usage of the thermostat, control the storage level of energy storage and manage the operation of the smart appliances. The key value to the homeowner is the real-time estimate of energy uses and monthly savings, as homeowners make adjustments to their preferences on the user interface display. The key value to utility is the validation and quantification of actions from demand response events and the estimation of home actions in the event of utility demand response request.

The energy-optimizing engine could be utilized in many different conservation or incentive programs and scenarios. It can be used for many different functions such as energy home automation to education and informational to tracking and reporting. The EOS system enables homeowner and the utility to capture a significant entitlement of smart grid ownership and smart appliances ownership as it allows the various subsystems to work in unison as a single system.

### 2.1 Prior Energy Management Technology Development

With regard to home energy automation functions, the EOS system automates the energy savings, empty house setbacks, pre-cooling of the house for peak load reduction, and peak load reduction operation of all the major loads including appliances, heating, ventilating and air conditioning (HVAC), water heating, lighting, and miscellaneous electric loads. The EOS system receives pricing signals from the utility smart meter, such as time-of-use rate tariff, real-time pricing tariff or critical peak pricing, and parses it for usage in the optimizer engine. The EOS system also receives forecast weather and solar insolation from weather servers, which resides on the web and parses it for usage in the optimizer engine. The EOS system interfaces with all major loads via a wireless interface, e.g., Zigbee, and is able to command the appliances to temporarily enter into a reduce power state or shift to later operation where possible.

With regard to education and informational function, the EOS provides real-time estimates on the user display of energy usage and utility cost. The estimates can be showed for what is saved at the end of the month or for the next billing cycle (30 days from now). The EOS system utilizes the energy optimizer engine along with historical trends and forecast weather information to make this estimate.

With regard to tracking and reporting, the EOS system reports on the user display real-time usage of electricity. The information is stored and is trended over various time intervals (in days, weeks, months, and years). A similar tracking and reporting scheme can be easily implemented for water usage, natural gas usage as well as solar power production, if the inclusion of those systems were made to the EOS system.

### 2.2 Project Objectives

Enhanced functions and capabilities to its Energy Optimization System (EOS) were developed including:

a. Adaptive and self-learning energy optimizing engine
b. Utility feedback functions such as direct load control analytics and critical peak pricing analytics
c. Negotiator with discrete operation smart appliances - Planning algorithm.

GE will also establish functional description of capability and functionality of the above enhancements to EOS system.

Six tasks were undertaken to achieve the set objectives. The tasks are: 1. Define system requirements; 2. Develop self-learning and adaptive algorithms; 3. Develop utility feedback analytics; 4. Coordinate EOS with smart appliances; 5. Perform laboratory tests and analysis; and 6. Manage project and write progress and final project reports. Accomplishments and detailed results of all the six tasks are discussed in the following Sections.

## 3. Technical Results of Tasks and Deliverables

### 3.1 Requirement Definition

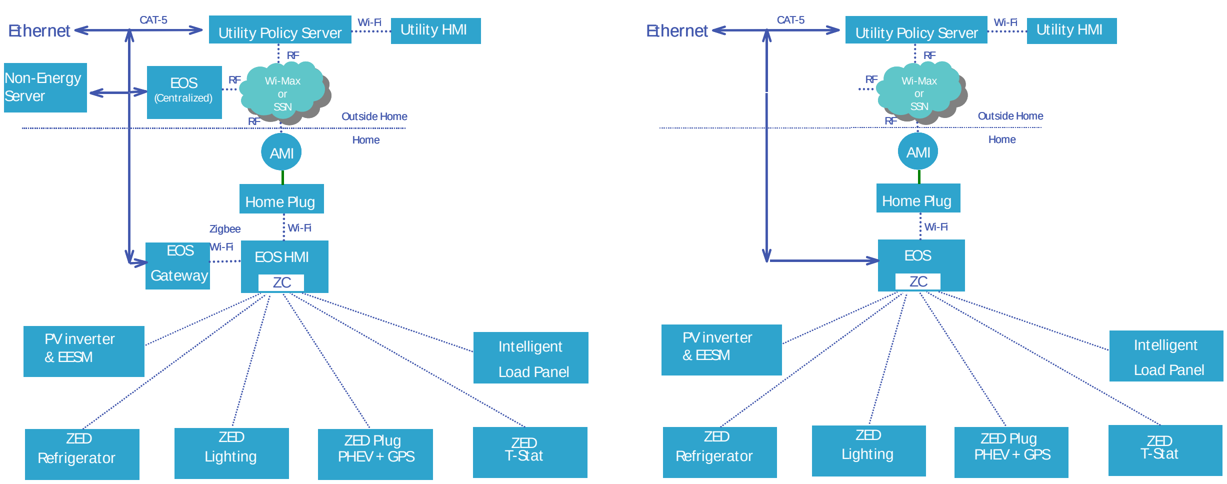
#### 3.1.1 System Communication and Controls Architecture

There are four major functional subsystems or modules for the EOS[1] system: the energy management engine (energy optimizer), connectivity to the grid / utility, connectivity to (and control of) appliances, and the user interface / human machine interface (UI / HMI). The energy

[1] EOS and EHEMS are used interchangeably in this document and references.

optimizer is the "brain" of the system.  Depending on where the optimizer is physically located, there are three major configurations for EOS: centralized, distributed and hybrid.  All three major architectures / technologies shall be available to customers with the default or preferred configuration being the hybrid architecture.

Figure 1 (A) shows a centralized EOS where the optimizer is located outside the home / user premise on a centralized server.  In this configuration, one server or energy optimizer shall control / manage a number of homes. All the energy optimization / management intelligence resides in the centralized server.  The server can be in the utility monitoring and control center; can be in a GE supervisory center; or can be in a third party managed service center.  The centralized architecture has potential lower hardware cost, lower service cost, and better maintainability (e.g., software and hardware upgrade).  It can also be better (more seamlessly and securely) integrated with other energy management systems (at transmission and distribution levels) within the entire smart grid.  Although the optimization algorithms are located outside the home on a centralized server, the end-users shall still have full access and control to the EOS.  In other words, the user shall be able to log on to his / her individual account on the server and input preferences, overwrites, or bypasses.  The limitation or drawback of the centralized EOS is elevated Internet / network traffic since the server has to communicate via Internet network with multiple homes.




Centralized EOS System Functional Block Diagram (A)

Distributed EOS System Functional Block Diagram (B)

Figure 1 EOS System Functional Block Diagram

Figure 1 (B) shows a distributed architecture of the EOS where the energy optimizer resides in individual homes.  Each home has its own dedicated energy optimizer implemented in a computer or embedded / specialized controller.  The energy optimizer may also reside in smart thermostat, cable set-top box, "smart" in-home display, or other computing / smart devices with sufficient computing capability and memory in order to perform optimization and with ability to display parameters and accept user inputs.  In contrast to the centralized EOS, the distributed architecture has all the energy management functions and intelligence installed on a personal PC in the home. It communicates and interfaces with all the other key smart home components (such as smart meter and appliances) right in the home. It, therefore, does not require / demand a lot of network traffic. The downside of the distributed EOS is that it potentially has higher overall system (capital) cost, it also puts burdens / relies on the end consumers for upgrade and maintenance.

The hybrid architecture has the same hardware / communication configuration as the centralized one as shown in Figure 1 (A). The difference between the centralized and hybrid architectures is that energy management functions / intelligence all reside in one server for the centralized configuration; whereas the management function / intelligence is split between the server and the smart panel in the home for the hybrid architecture. This hybrid approach of distributing energy management / optimization algorithms / intelligence between server and in-home smart panel / other in-home control device is more evident in the software architecture in Figure 2 which will be discussed in the software architecture Section.

In the connectivity to the grid / utility, Wi-Max and Silver Spring Network (SSN) was used to connect the meter with the utility policy server for illustration only. The architecture shall be and is flexible to adapt to other types of radio frequency (RF) networks, for example Sensus Flexnet or Itron AMI network. For SSN network (connection), Zigbee rather than Home Plug will be the media to connect meter to the rest of the EOS (for example UI/HMI) within the home.

Similarly in the connectivity to the (smart) appliances, Zigbee was used for illustration purpose; other wireless and wireline communications, such as Wi-Fi, Z-wave and Home Plug, can and shall be adapted to the architecture. Wireless communications are preferred / default protocols for better mobility. In homes with the intelligent load panel, some of the appliances shall be linked to the intelligent load panel to simplify the system (hardware / physical wiring).

In the user interface or human machine interface module, the preferred communication protocol of the UI / HMI to the rest of the EOS is the Wi-Fi wireless connection. This allows the user to freely move the UI within the home premise.

### 3.1.2 Software Architecture / Hierarchy

Figure 2 shows a software architecture for all the three possible system configurations: distributed, centralized and hybrid architectures. While the location of the intelligence is relatively straightforward for the distributed and centralized configurations, the split of the intelligence for hybrid architecture is application dependent. One example of this hybrid approach of distributing energy management optimization algorithms and intelligence between server and in-home smart panel or other in-home control device is that the data pre-processing (such as data filtering and averaging), diagnostics and prognostics reside within the home; and all the other computing and memory intensive optimizations reside on the centralized server. This hybrid architecture can best utilize all the local and global (central) resources effectively to minimize the network data traffic and maximize the system efficiency and speed.

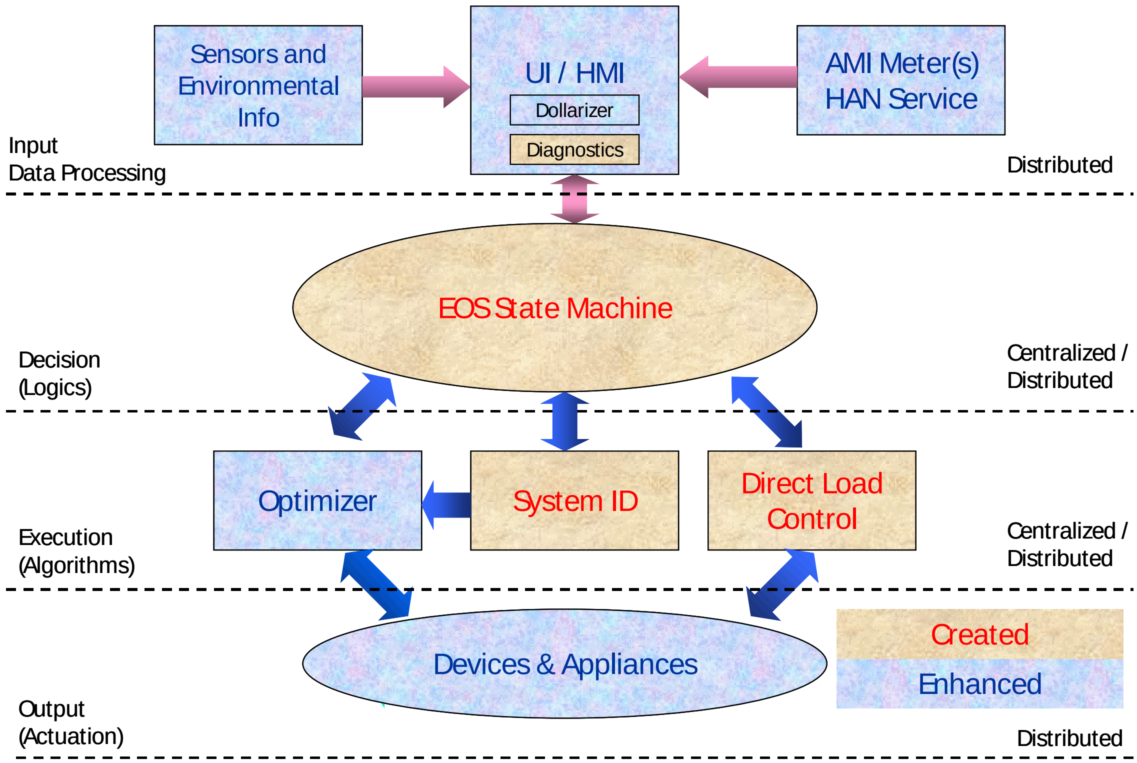



Figure 2 EOS Software Architecture / Hierarchy

### 3.1.3 System Functional Requirements

In this section, we look at requirements from the major functionality and feature perspective. In other words, we define what major functions and features the EOS shall provide and offer, respectively.

The EOS shall perform the following major functions:

- Optimize (minimize) energy consumption and cost (utility bill);
- Provide DR / DSM to enhance grid efficiency and reliability;
- Communicate in two-way mode securely with the grid and utility;
- Control appliances with secure two-way communication; and
- Provide an informative and user friendly graphical interface.

The EOS shall interface with utility advanced meters enabled with secure two-way communication, which creates and enables all other capabilities within the system. This interface may carry various data types including sensitive data, confidential data, and load control / DSM data. Specifically it shall receive and utilize utility electricity rate tariffs (direct and market-based) through the meters, along with forecasted weather and environmental information from the Internet to perform energy management functions. Appropriate levels of security must be provided for these types of communications. Security is critical. It protects consumers, utilities and (other) energy service providers' assets while enabling next-generation applications and capabilities.

It shall manage and optimize on-site home energy generation, energy storage and load usage to minimize energy consumption and utility bills, subject to external signals and homeowner preferences.

It shall interface with smart appliances via two-way secure communication and coordinate their operations in various energy saving scenarios.

It shall interface with end users to receive customers' preferences, overwrite commands / settings; and provides end users with feedback information such as cost of energy, utility bill trending, and other real-time alert messages.

#### 3.1.3.1 Energy Optimization System (EOS) Requirements

##### *3.1.3.1.1.Energy Optimization System Functional Requirements*

The Energy Optimizer (Optimization Engine) shall consist of an energy management platform, which interfaces to communicating electricity meters, residential energy generation technologies such as solar PV, on-site energy storage and interruptible smart loads within the home. A homeowner interacts with the optimizer through a graphical user interface display.

The central element of the energy optimizer is an energy-optimizing engine, which utilizes historical information, sensed information describing the present system state, and forecasted information about the future such as Time-of-Use rate information, weather and solar insolation as inputs, and then seeks to identify optimal settings for controllable energy elements within the home such as smart appliances, and interruptible thermostats and storage devices.

The optimizer shall be multi-objective in nature, and can satisfy multiple trade-off objectives such as reducing monthly utility bills and maximizing solar energy utilization, based on user preferences. The energy optimizer shall be able to provide the end users with a real-time estimate of the impact of changes in the settings of a device such as a thermostat, on their monthly utility bill or other optimization objective targets.

The energy optimizer shall provide basic trending and feedback functions that are of value to residential users. In particular, it shall trend electricity, water and natural gas consumption and shall report real-time status as well as daily, weekly and monthly consumption statistics. It shall also trend and report solar energy production and battery storage utilization, if available in the home / building. The optimizer shall also provide estimates of the monthly utility bills given current optimization engine settings.

The optimizer shall receive pricing signals through the utility meter (time-of-use rates, real-time pricing rates, etc.) and parse them for usage in the optimization engine. The system shall also receive forecasted weather and solar insolation from weather servers, which reside on the web, and parse these forecasts for usage in the optimizer.

The energy optimizer shall interface with communicating appliances, via wireless or wireline (e.g., Zigbee or Home Plug) interfaces.

Specifically, the energy optimizer shall be / contain a set of control algorithms and associated software packages / programs that optimize / minimize the total energy cost of the home / system subject to constraints and user preferences by performing the following major functions:

1. Providing the optimal thermostat Setpoints for all the thermal zones in the house / building

2. Providing the optimal water tank temperature setpoint
3. Controlling and Managing the power / energy exchange among grid, solar PV, batteries, and loads
4. Providing total electricity and minimized fuel costs.

The optimizer shall be customized to an individual home / building, and it shall be capable of adapting to a variety of homes / buildings and conditions. This includes different homes / buildings and the various conditions (e.g., aging) of the same home / building. If a home / building model is used in the optimizer it shall have the system identification capability to adjust the models to adapt to the new conditions. The optimizer shall be able to communicate both ways (taking inputs from and displaying outputs to) with the EOS user interface / human machine interface for user settings and preferences, and for displaying relevant information such as total electricity and fuel costs.

The optimizer, although capable, is not intended for direct load control purpose / functionality for modularity reason. The direct load control shall be a separate module that is specified in the next section.

The energy management system shall leverage historical energy usage statistics compiled throughout its operation to establish estimates of periodic (e.g., hourly) energy consumption, ambient temperature, solar insolation and other variables that can be used for planning how to best operate the controllable elements throughout the day. Where possible, forecasted data shall also be used to help the control system planning. Forecasted data may include time-of-use (TOU) electricity rate profiles, including peak-activated rates; solar insolation forecasts; and ambient temperature and wind forecasts. A block summary diagram of the energy optimizer is shown in Figure 3.

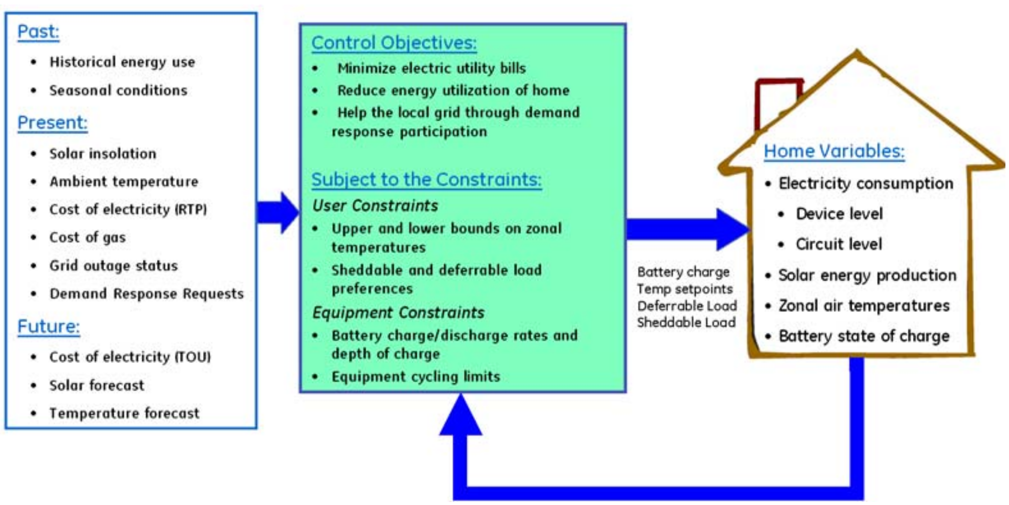



Figure 3 Energy Optimizer Functional Block Diagram

#### *3.1.3.1.2. Constraints and Objective Functions*

The energy optimizer optimizes (minimizes or maximizes) objective functions subject to physical, practical and economic constraints. Specifically the EOS energy optimizer is designed to optimize energy utilization to meet end-user / consumer objectives [8], such as:

- Minimizing energy consumption and cost / bills (electric, gas, oil);
- Reducing wasteful energy utilization in the home; and
- Stabilizing the local community grid through demand-response participation.

Of course, the objectives for each home will be different, as they will be determined by homeowners through input to a human machine interface – EcoDashBoard panel. Along with these objectives, homeowners can also specify home operation constraints, such as upper and lower bounds on zonal temperatures, and deferrable and sheddable load preferences.

Certain classes of equipment will also introduce constraints on the control, such as,

- Battery depth of charge and charge/discharge rates
- Equipment cycling limits.

Table 1 lists typical constraints for the optimization engine. There are two sets of constraints: hard constraints that must be met; and soft constraints (in *italic*) that are nice to have. The soft constraints shall be formulated into the objective function(s) with a weighted penalty factor (or slack variable). The penalty weighting factors are part of the critical specifications listed in Table 6; and shall be specified / input by the installer at commissioning of the system.

Table 1 Optimizer Constraints

<table>
<tr><th>T-stat - HVAC Constraints</th><th>DHW Constraints</th><th>Battery Constraints</th><th>PV Dispatch Constraints</th><th>Load Dispatch Constraints</th></tr>
<tr><td rowspan="2">Power within bounds</td><td rowspan="3">Power within bounds</td><td>Power balance among grid, DG / PV, EESM, and load</td><td rowspan="3">Power / energy balance</td><td rowspan="3">Power balance at the load (demanded – sheddable) = net power provided to load</td></tr>
<tr><td>Physical non-negative power</td></tr>
<tr><td rowspan="2">Temperature within bounds</td><td>Maximum power exchange with battery within limits</td></tr>
<tr><td rowspan="3">Temperature within bounds</td><td>Penalty on excessive cycling (charge and discharge)</td><td rowspan="3">Physical non-negative power</td><td rowspan="3">Non-negative sheddable loads and within bounds</td></tr>
<tr><td rowspan="2">Penalty on deviating from desired temp</td><td>Charge SOC / energy upper limit</td></tr>
<tr><td>Discharge SOC / energy lower limit</td></tr>
</table>

### *3.1.3.1.3. Inputs and Outputs of the Energy Optimizer*

Inputs and outputs of a system / subsystems are relative and depend on the boundaries of the system / subsystems of interest. In this document, we look at the inputs and outputs from a software architecture perspective. Specifically the inputs and outputs shall refer to the ones defined by the subsystems / modules outlined in Figure 2.

The inputs and outputs of the optimizer are the critical parameters of the module. Figure 4 illustrates the input and output relationships. There shall be three groups of inputs fed into the optimizer: user inputs (from UI / HMI dashboard), acquired (e.g., from weather web server), or predicted inputs and measured (e.g., from sensors) or observed inputs. Tables 2 to 4 list the details of the inputs in each respective group. Table 5 lists the outputs from the optimizer [8].

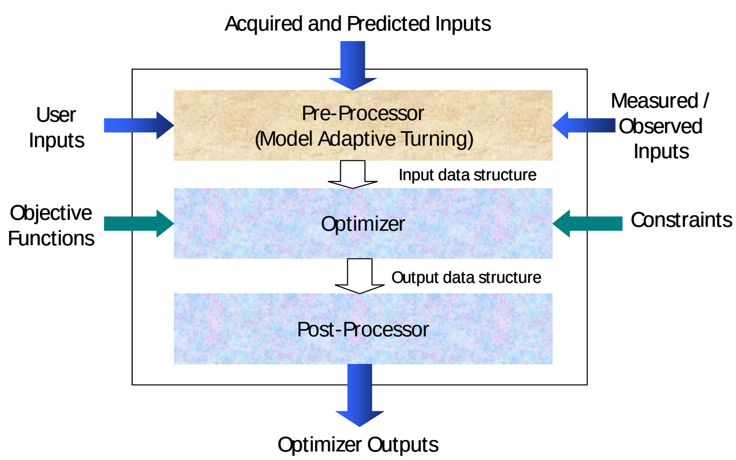



Figure 4 Optimizer Input Output Diagram

In order for the optimizer to function, the critical specifications that define the physical property of the EOS system (house) have to be specified to the optimizer. Table 6 tabulates all the critical specifications for the optimizer.

Table 2 User Inputs from UI / HMI

| Input Description | Units | Size | Data Type |
|---|---|---|---|
| Preferred Temperature Setpoints | F | $n_z \times N$ | Float Matrix |
| Temperature Lower bounds | F | $n_z \times N$ | Float Matrix |
| Temperature Upper Bounds | F | $n_z \times N$ | Float Matrix |
| Water Tank Temperature Lower Bounds | F | N | Float Vector |
| Water Tank Temperature Upper Bounds | F | N | Float Vector |
| Allowable Load Shedding Tier1 | W | N | Float Vector |
| Allowable Load Shedding Tier2 | W | N | Float Vector |
| Allowable Load Shedding Tier3 | W | N | Float Vector |

Table 3 Predicted or Acquired Inputs

| Input Description | Units | Size | Data Type |
|---|---|---|---|
| Ambient Temperature | F | N+1 | Float Vector |
| Internal Heat Gains | W | $n_z \times (N+1)$ | Float Matrix |
| Predicted Outflow from Tank | Gal/min | N | Float Vector |
| Predicted Solar PV | W | N+1 | Float Vector |
| Load Demand Tier1 | W | N+1 | Float Vector |
| Load Demand Tier2 | W | N+1 | Float Vector |
| Load Demand Tier3 | W | N+1 | Float Vector |
| Load Demand Tier4 (critical) | W | N+1 | Float Vector |
| Buy Price from Grid | Cents/kWh | N | Float Vector |
| Sell Price to Grid | Cents/kWh | N | Float Vector |
| Heating Price | Cents/kWh | N | Float Vector |
| Cooling Price | Cents/kWh | N | Float Vector |
| Water Heating Price | Cents/kWh | N | Float Vector |

Table 4 Measured and Observed Inputs at Present Time Instant

| **Input Description** | **Units** | **Size** | **Data Type** |
|---|---|---|---|
| Current Temperatures | F | $n_z$ | Float Vector |
| Battery State of Charge | W | 1 | Float |
| Power Flow from Grid to Batteries | W | 1 | Float |
| Power Flow from PV to Batteries | W | 1 | Float |
| Power Flow from Batteries to Loads | W | 1 | Float |
| Power Flow from PV to Loads | W | 1 | Float |
| Power Flow from PV to Grid | W | 1 | Float |
| Power Flow from Grid to Loads | W | 1 | Float |
| Current Supplied Load, Tier1 | W | 1 | Float |
| Current Supplied Load, Tier2 | W | 1 | Float |
| Current Supplied Load, Tier3 | W | 1 | Float |

Table 5 Optimizer Outputs

| **Output Description** | **Units** | **Size** | **Data Type** |
|---|---|---|---|
| (Actual) Temperature Setpoints | F | $n_z \times N$ | Float Matrix |
| Hot Water Temperature Setpoints | F | N | Float Vector |
| Power Flow from Grid to Batteries | W | N | Float Vector |
| Power Flow from PV to Batteries | W | N | Float Vector |
| Power Flow from Batteries to Loads | W | N | Float Vector |
| Power Flow from PV to Grid | W | N | Float Vector |
| Power Flow from PV to Loads | W | N | Float Vector |
| Power Flow from Grid to Loads | W | N | Float Vector |
| Grid Generation (Net) | W | N | Float Vector |
| Total Electricity Cost | $ | N | Float Vector |
| Total Fuel Cost | $ | N | Float Vector |

Table 6 Critical Specifications of the Optimizer

| Critical Specification Description | Units | Size | Data Type |
|---|---|---|---|
| Number of Time Steps (N) | | 1 | Int |
| Time Step of Calculation (Ts) | Min | 1 | Float |
| Number of Thermal Zones ($n_z$) | | 1 | Int |
| Thermal Model Matrix1 | | $n_z \times n_z$ | Float Matrix |
| Thermal Model Matrix2 | | $n_z \times 1$ | Float Matrix |
| Thermal Model Matrix3 | | $n_z \times n_z$ | Float Matrix |
| Thermal Model Matrix4 | | $n_z \times n_z$ | Float Matrix |
| Thermal Model Matrix5 | | $n_z \times n_z$ | Float Matrix |
| DHW Model Matrix1 | W | $1 \times 1$ | Float Matrix |
| DHW Model Matrix2 | W | $1 \times 1$ | Float Matrix |
| DHW Model Matrix3 | W | $1 \times 1$ | Float Matrix |
| DHW Model Matrix4 | W | $1 \times 1$ | Float Matrix |
| Battery Time Constant | | 1 | Float |
| Max HVAC Consumption, Heating | W | 1 | Float |
| Max HVAC Consumption, Cooling | W | 1 | Float |
| Max DHW Power Consumption | W | 1 | Float |
| Max Battery Charge Power | W | 1 | Float |
| Max Battery Discharge Power | W | 1 | Float |
| Max Energy Capacity of Batteries | Wh | 1 | Float |
| Min Energy Level Batteries | Wh | 1 | Float |
| Weight on Violation of Temperature Bands | | 1 | Float |
| Weight on Deviation from Desired Temperature | | 1 | Float |
| Weight on violation of DHW Temperature Limits | | 1 | Float |

| | | | |
|---|---|---|---|
| Weight on violation of SOC limits | | 1 | Float |
| Penalty on Load Shedding, Tier1 | | 1 | Float |
| Penalty on Load Shedding, Tier2 | | 1 | Float |
| Penalty on Load Shedding, Tier3 | | 1 | Float |

#### 3.1.3.2 Requirements of Self-learning and Adaptive Home Models Integrated into EOS

*3.1.3.2.1. System Identification Functional Requirements*

If the energy optimizer relies on a set of mathematical models that represent the physics of the house / residence, the system shall have the capability / ability to self-identify, construct, and update periodically the models by initiating a set of runs that are non-invasive / non-intrusive to the customers / users. The complete and comprehensive system identification shall be run at EOS commissioning and at any major house modifications that would significantly impact on the thermal property of the premise. In addition, the system shall be able to adapt to seasonal climate changes with fine tuning of the models by self initiating a subset of the system identifications runs. The system ID algorithms shall have the intelligence to detect abnormal conditions (such as open windows and doors) to prevent the system ID from running. Such conditions would, otherwise, have skewed the system ID and mathematical models.

The interactive relationship of the system ID function with the energy optimizer and other functional modules of the system is illustrated in Figure 2.

*3.1.3.2.2. System Identification Inputs and Outputs*

From the software architecture shown in Figure 2, the EOS energy optimizer uses a set of models to optimize and control the energy system. The models allow the energy optimizer to predict how the home reacts to stimuli such as weather, HVAC operation, homeowner occupancy. The models shall be constructed and updated automatically by the energy management system using system identification (ID) technique to enable self-calibrating / updating the models with minimum user interaction for easy and low-cost installation for both new and retrofit homes. They may also be used to track changes to the home structure over time as a means to do monitoring and diagnostics.

The system identification for the thermal model used for HAVC system monitors the thermal inputs to the home and the resulting variation in temperature to estimate a model that captures the zonal temperature response. Then this estimated thermal model is passed to the optimizer block to compute optimal setpoints for the rest of the energy management system.

The inputs and outputs of the thermal model system identification are tabulated in
Table **7**, Table 8 and Table 9.

Table 7 Outputs of the System ID

| Output Description | Units | Size | Data Type |
|---|---|---|---|
| Thermal Model Matrix1 | | $n_z \times n_z$ | Float Matrix |
| Thermal Model Matrix2 | | $n_z \times 1$ | Float Matrix |
| Thermal Model Matrix3 | | $n_z \times n_z$ | Float Matrix |
| Thermal Model Matrix4 | | $n_z \times n_z$ | Float Matrix |
| Thermal Model Matrix5 | | $n_z \times n_z$ | Float Matrix |

Table 8 Critical Specifications of the System ID

| Critical Specification Description | Units | Size | Data Type |
|---|---|---|---|
| Time Step of Calculation ($Ts_{id}$) | Min | 1 | Float |
| Number of Thermal Zones ($n_z$) | | 1 | Int |
| Max HVAC Consumption, Heating | W | 1 | Float |
| Max HVAC Consumption, Cooling | W | 1 | Float |
| Initial estimate of error covariance | | $(4n_z+1)\times (4n_z+1)$ | Float Matrix |
| Initial estimate of thermal model matrices | | $n_z\times (4n_z+1)$ | Float Matrix |
| Forgetting factor in least square estimator, $0<\gamma<1$) | | 1 | Float |
| Forgetting factor in least square estimator, $\alpha=1-\gamma$ | | 1 | Float |

Table 9 Inputs of the System ID

| Input Description | Units | Size | Data Type |
|---|---|---|---|
| Ambient Temperature | F | 1 | Float |
| Internal Heat Gains | W | $n_z \times 1$ | Float Matrix |
| Current Temperatures | F | $n_z$ | Float Vector |
| HVAC Heating Load | W | 1 | Float |
| HVAC Cooling Load | W | 1 | Float |

#### 3.1.3.3 Functional Requirements of Utility Feedback Analytics

The EOS shall be connected securely with two-way communication to the electrical grid / utility server. This two-way communication shall provide means / physical media for information exchange between the EOS and the utility. Both AMI wireless RF networks, such as Wi-Max and Silver Spring Networks (SSN), and wireline broadband connection (if existing) shall be made available to connect the EOS and the utility server. The broadband connection is especially critical to the early EOS adoption since it is widely (60%-70%) available now / already in North American households.

This connectivity shall provide various types of communication to support anticipated market growth. Three communication type examples include public pricing signaling, consumer specific signaling, and control signaling. Public pricing is the communication of material, which is publicly available. Consumer-specific signaling would be signaling that supports a home energy management system. Control signaling are those signals used to support load shedding.

Each signal type warrants individual security and privacy analysis and treatment. In particular, consumer-specific information signaling shall have additional privacy measures and methods.

The EOS shall provide back to the smart meter and then to utility server the following feedback analytics information upon a query request initiated from the meter / server:

- Shedable electrical loads and status / mode
- Distributed (e.g., solar PV) power / energy generation
- Local energy storage
- Plug-in Hybrid Electric Vehicle (PHEV) ID
- PHEV electrical energy consumption / generation
- User preferences / acceptance on direct load control.

This function establishes the load state of the home and estimates the sheddable elements, which are prioritized, based on electricity price and the load shedding signaling severity. The load state and sheddable load profile can be communicated to the utility's demand response (DR) back-office application to reduce uncertainty of sheddable load and improve DR system effectiveness and reliability.

#### 3.1.3.4 Requirements of Planning Algorithms for Smart Appliance Coordination

##### *3.1.3.4.1. Smart Appliance Coordination Functional Requirements*

The smart appliances in a home or premise are controlled and coordinated in two groups / modules. As discussed in Section 0, the EOS controls and coordinates the thermostat / HAVC, water heater, and Solar PV and battery storage. All the other smart appliances are controlled and coordinated via the direct load control module as discussed in detail in Section 0.

The direct load control functionality enhances the EOS by complimenting the energy optimizer. It shall include direct load control analytics, the utility feedback analytics, load scheduling, usage planning and negotiation. It provides a channel for the utility's DSM to control (e.g., turn off) the loads that are not managed by the optimizer. The directly controlled loads, including the priority / order in which the loads are turned off, shall be specified and agreed by the users. The user shall also have the ability / option through the user interface to allow or disallow / overwrite the direct load control functionality.

Direct load control analytics integrate the utility's direct load control signaling into the EOS and gives the utility control of home loads in the event of a utility direct load control signal.

The direct load control module shall negotiate and plan usage for discrete-operation smart appliances. This function plans and coordinates the operation between smart appliances based on the appliance's constraints, user preferences and priority, and cost of operation.

The interface between the EOS and the smart appliances defines controls, measurement and monitoring applications. The control commands flow from the EOS to smart appliances while the measurement and monitoring information is fed back from the appliances and measurement devices to the EOS.

Most of the functions and information flow defined and described below apply to smart appliances. For existing traditional appliances, the control application will be predominately discrete on and off controls with a smart outlet plug.

#### 3.1.3.5 EOS to Smart Appliances

Control applications respond to control signaling / command from the EcoDashBoard and / or the EOS. There are typically two types of commands:

1. Set a control reference target / setpoint for an appliance or equipment, such as the T-stat Setpoint for HAVC and temperature Setpoint for DHW. They are part of the outputs from the energy optimizer
2. Command a device or appliance to turn on, off, or cycle at configurable time intervals or thresholds, or enter into an energy saving (Eco) mode. These are outputs from the direct load control module.

Specifically, the following functions / information exchange are required for this application interface [9]:

1) Appliance and device shall accept control signals from EcoDashBoard and EOS
2) Appliance and device shall respond to requests to cease operational state (e.g., open contact, turn off device)
3) Appliance and device shall respond to requests to resume operational state (e.g., close contact, turn on device)
4) Appliance and device shall respond to requests to cease operational state (e.g., open contact, turn off device) at a specific time
5) Appliance and device shall respond to requests to resume operational state (e.g., close contact, turn on device) at a specific time
6) Appliance and device shall delay restoration of operational state based on a pre-configured time (e.g., random number)
7) Appliance and device shall respond to request to cycle operational state (i.e., duty cycle)

8) Appliance and device shall respond to request to limit operational mode based on thresholds, setpoints, and / or triggers (e.g., price points)
9) Appliance and device shall respond to requests for variable output (e.g., load limiting, energy saving mode).

#### 3.1.3.6 Smart Appliances to EOS

Measurement and monitoring applications provide internal data and states / status, that include DG (e.g., solar, wind, and fuel cell), metering of devices within the premise (e.g., consumer PHEV), monitoring of local conditions (e.g., temperature, humidity, time, airflow, ambient light level, motion), and monitoring of a device state. These applications provide inputs to the EOS and enable processing, optimization, and action based upon the inputs.

Detailed and specific functions / information flow from appliances and devices to EcoDashBoard are listed below [9]:

1) Appliance and device shall acknowledge receipt of control signal
2) Appliance and device shall acknowledge execution of control signal
3) Appliance and device shall notify execution failure of control signal
4) Appliance and device shall signal any consumer-initiated overrides from the appliance
5) Appliance and device shall measure and report instantaneous power demand
6) Appliance and device shall measure and report total accumulated energy consumption
7) Appliance and device shall measure and report total accumulated energy production / DG
8) Appliance and device shall measure and report periodic accumulated energy consumption for a configured time interval (e.g., Wh, BTU, HCF)
9) Appliance and device shall measure and report accumulated energy production / DG for a configured time interval
10) Appliance and device shall store interval measurement (e.g., 30 days of interval reads)
11) Appliance and device shall allow interval configuration (e.g., 15 minutes)
12) Appliance and device shall monitor and report energy state (e.g., state of charge)
13) Appliance and device shall measure and report available capacity (e.g., W, Volt-Amps)
14) Appliance and device shall monitor and report device state (e.g., operational, stand-by, maintenance)
15) Appliance and device (e.g., inverter) shall monitor and report the operational mode (e.g., charging, discharging)

16) Appliance and device shall measure and report power quality (e.g., frequency, neutral voltage, harmonic content)

17) Appliance and device shall monitor and report environmental state (e.g., temperature, motion, wind).

*3.1.3.6.1. Direct Load Control Module Inputs and Outputs*

Table 10 Outputs to Appliances from EOS

| **Output / Appliance** | **Mode / Range** | **Signal Type** | **(Parent) Module** |
|---|---|---|---|
| Refrigerator | Eco | Digital (D) | Direct Load Control (DLC) |
| | Normal | Digital (D) | DLC |
| Lighting | Dimmable (0-100%) | Analog (A) | DLC |
| | On / Off | D | DLC |
| Thermostat | T Setpoint | A | Optimizer |
| | On / Off | D | DLC |
| Hot Water Heater | T Setpoint | A | Optimizer |
| | On / Off or Eco/Normal | D | DLC |
| Washer | On / Off or Eco/Normal | D | DLC |
| Dish Washer | On / Off or Eco/Normal | D | DLC |
| Dryer | On / Off or Eco/Normal | D | DLC |
| Pool Pump | On / Off or Eco/Normal | D | DLC |
| PHEV | On / Off or Eco/Normal | D | DLC |

## 3.2 Self-learning and Adaptive Algorithms

For Task 2 of the enhanced energy optimization system project, GE's committed effort was to develop, implement and test a system identification (ID) algorithm that is complementary to the energy optimizer by periodically identifying and adjusting the home models to adapt to the changing conditions (such as seasonal change and house aging).

The system ID algorithms have been developed, implemented and tested for convergence and robustness. The detailed results are described in the following sections.

### 3.2.1 Background

System identification is the process of building a mathematical model of a dynamic system based on measured data from the system that is being identified.

In the context of the home energy management system, system ID is used within the optimizer to estimate the thermal model of the home. The following discrete-time, first order home thermal model is being used:

$$T(k+1) = AT(k) + B_1 T_a(k) + B_2 Q_t(k) + B_{3h} u_h(k) - B_{3c} u_c(k)$$

Where

1. $k$ is the index of a given time step
2. $T \in R^{n_z}$ is the vector of temperatures in each zone ($n_z$ : number of zones)
3. $T_a$ is the ambient temperature
4. $Q_t \in R^{n_z}$ is the vector of heat gains (internal, from people or equipment)
5. $u_h(k) \in R^{n_z}$ is the HVAC heating load, and $u_c(k) \in R^{n_z}$ is the HVAC cooling load
6. $A \in R^{n_z \times n_z}, B_1 \in R^{n_z}, B_2 \in R^{n_z \times n_z}, B_{3h} \in R^{n_z \times n_z}, B_{3c} \in R^{n_z \times n_z}$ are matrices of parameters that need to be identified.

The system ID monitors the thermal inputs to the home and the resulting variation in the zonal temperatures. The inputs to the system ID model are the measured room temperature (T), measured ambient temperature ($T_a$), prescribed internal heat gain ($Q_t$), measured heating load ($u_h$), and measured cooling load ($u_c$). Using this input data the system ID updates the estimated thermal model of the home, the A, $B_1$, $B_2$, $B_{3h}$, and $B_{3c}$ matrices, using the least squares error method. In order for the optimizer to work effectively, the response of the system ID model must closely predict the thermal response of the house. To achieve this goal, a recursive system ID algorithm has been used; the thermal model is updated online as the input data is received, thereby allowing it to follow changes in the thermal response of the home caused by seasonal changes, structural changes, open windows, etc.

The optimizer uses the thermal model to calculate the optimum temperature set point for all zones in the house so as to minimize the cost of heating or cooling required for maintaining the temperatures within a user defined comfort zone.

### 3.2.2 System Identification Algorithm

The following system ID algorithm has been implemented in the optimizer:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + L(k) * \left[ T(k) - \hat{\theta}^{T}(k-1) * \varphi(k) \right]^{T}$$

$$L(k) = \frac{1}{\gamma} * \left[ P(k-1) * \varphi(k) \right] * \left[ \frac{1}{\alpha} + \varphi^{T}(k) * \frac{P(k-1)}{\gamma} * \varphi(k) \right]^{-1}$$

$$P(k) = \frac{1}{\gamma} * \left[ I - L(k) * \varphi^{T}(k) \right] * P(k-1)$$

Where,

$$\hat{\theta} = \left[ A B_1 \; B_2 \; B_{3h} \; B_{3c} \right]^{T}$$

$$\varphi = \left[ T \, T_a \; Q_t \; u_h \; u_c \right]^{T}$$

$$\gamma = \text{forgettingfactor}$$

$$\alpha = 1 - \gamma$$

### 3.2.3. Results

Recent work on the system ID portion of the optimizer focused on three areas:

- Assess the benefit of system ID
- Improve system ID performance
- Test system ID robustness.

#### 3.2.3.1. <u>Assess the benefit of system ID</u>

To assess the benefit of system ID, we simulated the optimizer with five different amounts of mismatch between the actual home model and the estimate. System ID was not used for these simulations so the initial model estimates were not updated. Each simulation was run for a time segment from July 1 to July 10 using California as the geographic area. Results are shown in Table 11.

Table 11 Benefits of System ID

| Simulation Description | | Results | | |
|---|---|---|---|---|
| Case # | a11 and a22 mismatch | Cost of Electricity and Gas($) | Electrical Energy Consumed (kWh) | Temp. Bounds Violation |
| 1 | 0 | 47.37 | 321.0 | No |
| 2 | +10% | 45.35 | 317.2 | Yes |
| 3 | -10% | 52.31 | 338.0 | No |
| 4 | +20% | 45.40 | 319.1 | Yes |
| 5 | -20% | 67.88 | 430.2 | Yes |

The above was compared to a simulation run using system ID for the same time segment and geographic location. The following initial estimate was used:

$$\mathbf{A} = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \qquad \mathbf{B}_1 = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} \qquad \mathbf{B}_2 = \begin{bmatrix} 0.001 & 0 \\ 0 & 0.001 \end{bmatrix}$$

$$\mathbf{B}_{3h} = \begin{bmatrix} 0.005 & 0 \\ 0 & 0.005 \end{bmatrix} \qquad \mathbf{B}_{3c} = \begin{bmatrix} 0.001 & 0 \\ 0 & 0.001 \end{bmatrix}$$

The actual model parameters determined from the Doe-2 simulation are:

$$\mathbf{A} = \begin{bmatrix} 0.78 & 0.006 \\ 0.07 & 0.65 \end{bmatrix} \qquad \mathbf{B}_1 = \begin{bmatrix} 0.214 \\ 0.28 \end{bmatrix} \qquad \mathbf{B}_2 = \begin{bmatrix} 0.0016 & 0.0001 \\ 0.0001 & 0.0016 \end{bmatrix}$$

$$\mathbf{B}_{3h} = \begin{bmatrix} 0.00117 & 0.0002 \\ 0.0002 & 0.0013 \end{bmatrix} \qquad \mathbf{B}_{3c} = \begin{bmatrix} 0.004172 & 0.0005 \\ 0.0005 & 0.00637 \end{bmatrix}$$

The results obtained from this simulation are:

- Cost of electricity and gas: $47.37
- Electrical energy consumed: 321.0 kWh
- No temperature violations after initial transient.

The above results show that running the optimizer without system ID can result in temperature violations and/or increased cost depending on the degree of model mismatch as the data shaded yellow in Table 11. It is clear that system ID must be a part of the optimizer to make an accurate estimate of the home thermal model, so as to stay within the temperature bounds and minimize cost. Additionally, the system ID algorithm must be recursive so as to track the changes in the thermal model which occur when there are seasonal, structural and home occupant induced changes.

#### 3.2.3.2. Improve system ID performance

The performance of the system ID algorithm is characterized by (1) the time it takes the algorithm to converge to the actual model and (2) the sensitivity of the algorithm to measurement noise. Both of these characteristics are strongly impacted by the choice of forgetting factor.

The forgetting factor in the recursive least squares algorithm acts as a knob that the designer can use to adjust the performance of the algorithm. The forgetting factor must be between 0 and 1. A small forgetting factor results in an algorithm that quickly forgets the previous parameters. This is good for fast tracking of the model parameters, but causes the algorithm to be highly sensitive to noise. A large forgetting factor results in an algorithm that remembers the pervious parameter values, resulting in slow tracking of the parameters, but has the advantage of being less sensitive to noise.

We started the system ID performance analysis by running the optimizer without measurement noise on the inputs. Initially, the system ID was run with a forgetting factor of 0.98. This resulted in a slow rate of convergence. To improve the rate of convergence, forgetting factors of 0.5 and 0.05 were evaluated. Additionally, considering that a low forgetting factor is sensitive to noise, we also evaluated a variable forgetting factor that changes in value over time, as shown in the following figure.

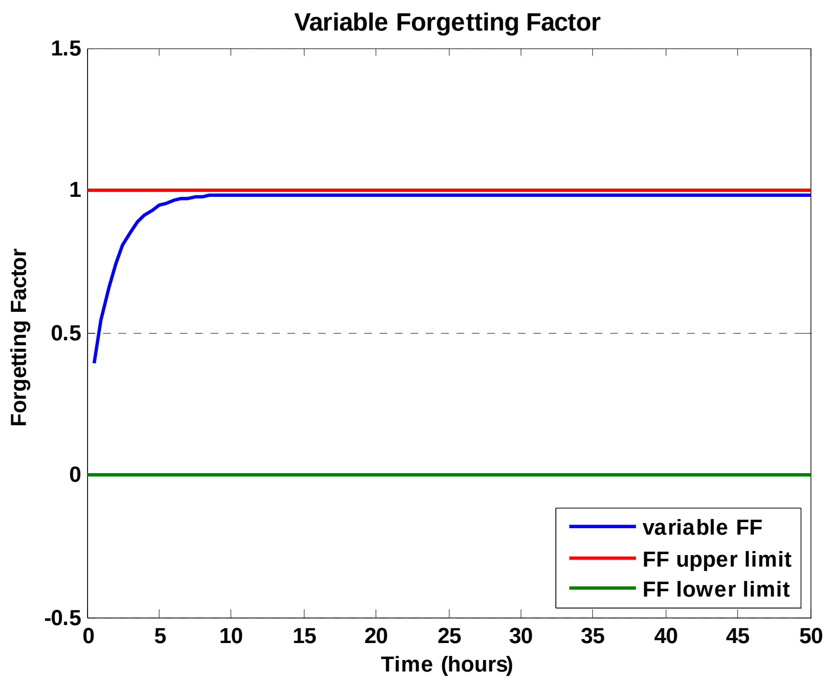



Figure 5 Variable Forgetting Factor

The profile for the variable forgetting factor was chosen so that at the beginning of the simulation, when the estimate of the model is starting at some initial values far from the actual values, the forgetting factor is small so the algorithm can quickly track the model parameters. As time passes, the forgetting factor increases towards unity, making the algorithm less sensitive to noise.

The time segment for each simulation was from July 1 to July 10, using California as the geographic location, and the results are summarized in Table 12.

Table 12 Simulation Results Summary

| Forgetting Factor | Time to Converge (hrs) | Error in Model Estimates (%) | Total Cost ($) | Electrical Energy Consumed (kWh) |
|---|---|---|---|---|
| 0.98 | 229 (9.5 days) | 0.0034 | 47.37 | 321.0 |
| 0.5 | 6 | 2.2e-12 | 47.37 | 321.0 |
| 0.05 | 6 | 1.6e-9 | 47.47 | 321.2 |
| Variable | 21 | 4.4e-5 | 47.37 | 321.0 |

The time to converge is defined as the time it takes for the slowest parameter to converge within ± 1% of the actual value for at least 2.5 hours.

The results, as expected, show that a forgetting factor of 0.98 converges the slowest, while the other forgetting factors converge faster with similar rates. Additionally, the temperature profiles obtained for all forgetting factors were similar. The temperature stays within bounds after an initial transient, which is caused by a mismatch between the estimated and actual model parameters, as shown in reference [10] for temperature zone 1. Zone 2 temperature profiles are similar and are therefore not shown.

We then introduced Gaussian white noise onto each input measurement and simulated with the four forgetting factors again. In the presence of noise, low values of the forgetting factor (0.05 and 0.5) cause significant model mismatch which results in very large temperature violations, as shown in reference [10] for zone 1 temperature profiles. Zone 2 temperature profiles are similar and are therefore not shown. The low forgetting factors (0.05 and 0.5) were not used for the rest of the analysis.

Based on the above results, the 0.98 forgetting factor and the variable forgetting factor are the only appropriate choices in the presence of noise. The variable forgetting factor yields improved performance because of faster convergence.

#### 3.2.3.3. Test system ID robustness

In order to thoroughly check that the system ID portion of the optimizer will be robust to different noise levels, different initial conditions, and different model parameters, we performed an exhaustive system ID robustness evaluation. The following summarizes the evaluation effort:

- Simulations were run for 144 different home models. These models were generated by sweeping the critical model parameters around the original model parameters that were generated by the Doe-2 simulation tool
- Each simulation described above was started with five different sets of initial model estimates
- The above results in a total of 720 simulation runs. These 720 simulation runs were performed for 2 different scenarios, summer with a low noise level (variance of 0.01 on temperature measurements) and winter with a large noise level. (variance of 0.1 on temperature measurements).

The system ID algorithm turned out to be highly robust. For both scenarios, all 720 simulations converged (the convergence criteria is based on the amount of noise applied to the measurements). The average time to converge for each scenario is less than a day. Histograms for convergence times of these scenarios are shown in References [6][10].

These two scenarios were run with no noise on the room temperature and the results were very good. For further improvement, we are in the process of running simulations with noise applied to the room temperature measurements. Additionally, we may implement noise filtering to reduce the amount of measurement noise and improve the system ID performance. Example plots for the system ID algorithms results are given in References [6][10].

### 3.3. Feedback Analytics

For task 3, GE committed to develop the feedback analytics that quantify and verify the aggregated home response, including pre-cooling the house, responding to a load shedding and pricing signal from the utility.

GE's team has defined and developed the feedback analytics that will provide feedback information from the EcoDashBoard to the smart meter and then to the utility server. The details of the analytics are described in the following section and are summarized in Tables 13 and 14.

The smart meter and the EcoDashBoard interface shall be a secure two-way communication thru a wireline or wireless connection. Wireless (e.g., Zigbee or Wi-Fi) connection is the preferred / default offering / option since it allows the EcoDashBoard to be moved freely within the home. This interface shall serve as the key “information channel” for exchanging critical information between the smart meter and the EOS. For security reasons, the information shall flow primarily from the meter to the EOS dashboard. A minimum set of absolutely must-have feedback analytic information shall be transferred from the EOS dashboard to the meter and then to the utility server.

To manage / limit the data transfer rate, the data exchange / flow shall be initiated by queries on the receiving end. In other words, the receiver shall initiate a query in order to get information from the sender. As results, the sender will respond to the request by returning relevant text strings containing the requested data.  The general format of the query request shall be [11]:

http://HOST_ID/query/QUERY_TYPE

where *HOST_ID* is either an IP address (xxx.xxx.xxx.xxx), a URL (host.ge.com) or, “localhost” if the home area network (HAN) service and the EcoDashBoard are on the same physical media / device. *QUERY_TYPE* is specific to each data type as discussed in the following sections.

The EOS dashboard shall provide back to the smart meter and then to the utility server the following feedback analytics information upon a query request initiated from the meter / server:

- Shedable electrical loads and status / mode
- Distributed power / energy generation (solar PV) generation
- Local energy storage
- Plug-in Hybrid Electric Vehicle (PHEV) ID
- PHEV electrical energy consumption / generation
- User preferences / acceptance on direct load control.

The query commend shall have the format:

http://HOST_ID/query/FBLoad

The response of the query shall be a text string filled with fields of characters and values as follows:

[{“title”:”load name”,“date”:”yyyymmdd”,”time”:”hhmm”,“type”:”sheddable load”,“id”:”ip address”,“status”: status value,”sheddableload”; sheddable power,”msg”:”Sheddable Load”,”advertUrl”:””}]

Table 13 Data Fields for Load Feedback Analytics

| **load name** | **status value** | **sheddable power** |
|---|---|---|
| T-stat | 1 / 0 | pppp / 0 |
| Domestic Hot water | 1 / 0 | pppp / 0 |
| Pool Pump | 1 / 0 | pppp / 0 |

| | | |
|---|---|---|
| PHEV | 1 / 0 | pppp / 0 |
| Dishwasher | 1 / 0 | pppp / 0 |
| Dryer | 1 / 0 | pppp / 0 |
| Washer | 1 / 0 | pppp / 0 |

where the status value “1” means the load is on and “0” indicates off.

One specific example of dishwasher is:

[{“title”:”dishwasher”,“date”:”20090101”,”time”:”0000”,“type”:”sheddable load”,“id”:”192.35.34.16”,“status”: 1,”sheddableload”; 800,”msg”:”Sheddable Load”,”advertUrl”:””}]

For distributed generations (DG) such as solar PV, electrical energy storage module (EESM), and PHEV, the feedback analytics shall /can be queried as

http://HOST_ID/query/FBDG

The response of the query shall be defined as:

[{“title”:”load name”,“date”:”yyyymmdd”,”time”:”hhmm”,“type”:”DG FB analytics”,“id”:”ip address”,“status”: status value,”capacity”; capacity value,”msg”:”DG status”,”advertUrl”:””}]

Table 14 Data Fields for DG Feedback Analytics

| **load Name** | **status value** | **capacity value** |
|---|---|---|
| Solar PV | 1 / 0 | aaaa / 0 |
| EESM | 1 / 0 | bb% |
| PHEV | 1 / 0 | cc% |

Where the status value “1” means generating / discharging and “0” represents consuming / charging; aaaa is solar PV power generated; bb% and cc% are the remaining capacity in percentage (state of charge for batteries).

One specific example for solar PV is:

[{“title”:”Solar PV”,“date”:”20100101”,”time”:”0102”,“type”:”DG FB analytics”,“id”:”192.35.34.16”,“status”: 1,”capacity”; 5000,”msg”:”DG status”,”advertUrl”:””}]

While the feedback analytics were developed, we were not able to validate the algorithm in the Lab. This was because that the PolicyNet server was provided by a third party vendor, GridNet. Accessing the proprietary software was beyond the scope and budget of this project.

## 3.4 Smart Appliance Coordination

### 3.4.1 Direct Load Control and Smart Appliance Coordination Algorithms

The smart appliances are coordinated and controlled by the direct load control module and the utility feedback analytics. Task 4 addresses the direct load control from the EOS DLC module to the appliances, while Task 3 – Utility Feedback Analytics, discussed and reported in Section 0, provides feedback information from the appliances to the DLC module in the EOS.

Specifically, the direct load control (DLC) module in the EOS controls and manages the following major home appliances in the pre-defined default order of priority:

1. T-stat – HVAC
2. Domestic water heater (DWH)
3. Pool Pump
4. Washer
5. Dryer
6. Dishwasher
7. Large LCD / Plasma TV
8. Plug loads (computers, computer peripherals / accessories, fax machine, power supplies)
9. Refrigerator (smart or traditional)
10. Lighting (dimmable or on/off non-dimmable traditional).

These are mostly discrete types of appliances that have on/off, eco-mode/normal mode, or multiple discrete power saving modes (e.g., dimmable lighting). The current typical major energy intensive appliances (excluding PHEV in the future) are HVAC and water heater that are controlled and managed by the EOS. The rest of the appliances listed above are ranked in the order of descending energy consumption from the top to the bottom. This is also the default priority ranking for the DLC module when a load shedding command is received from the utility and the DLC function is enabled by the consumer. The default priority list also takes into account the nature of the appliances, the comfort of the consumers, and criticality of the appliances (e.g., the refrigerator cannot be simply turned off due to potential food / health hazards). Of course, the priority ranking can be overwritten by the consumers / system owners per their specific preferences and choices.

The DLC initiated from the utility is most commonly used for peak load reduction, especially for emergency load shedding. It provides an effective and economic tool for the utility to manage its load / power demand with optimally dispatched or minimized generation resources / spinning reserves. It also enhances reliability of the electric power system to avoid power outages and thus improve customer satisfaction. In addition to the benefits utilities enjoy from DLC, end use customers also benefit from the savings DLC generates. DLC is also relatively simpler to implement and adopt compared with other energy management / optimization algorithms. It was therefore designed in the EOS as a high priority algorithm to execute. The algorithms that coordinate the direct load control for smart appliances are illustrated in Figure 6.

The following Sections discuss the functional capabilities of DLC algorithm and the smart appliance coordination.

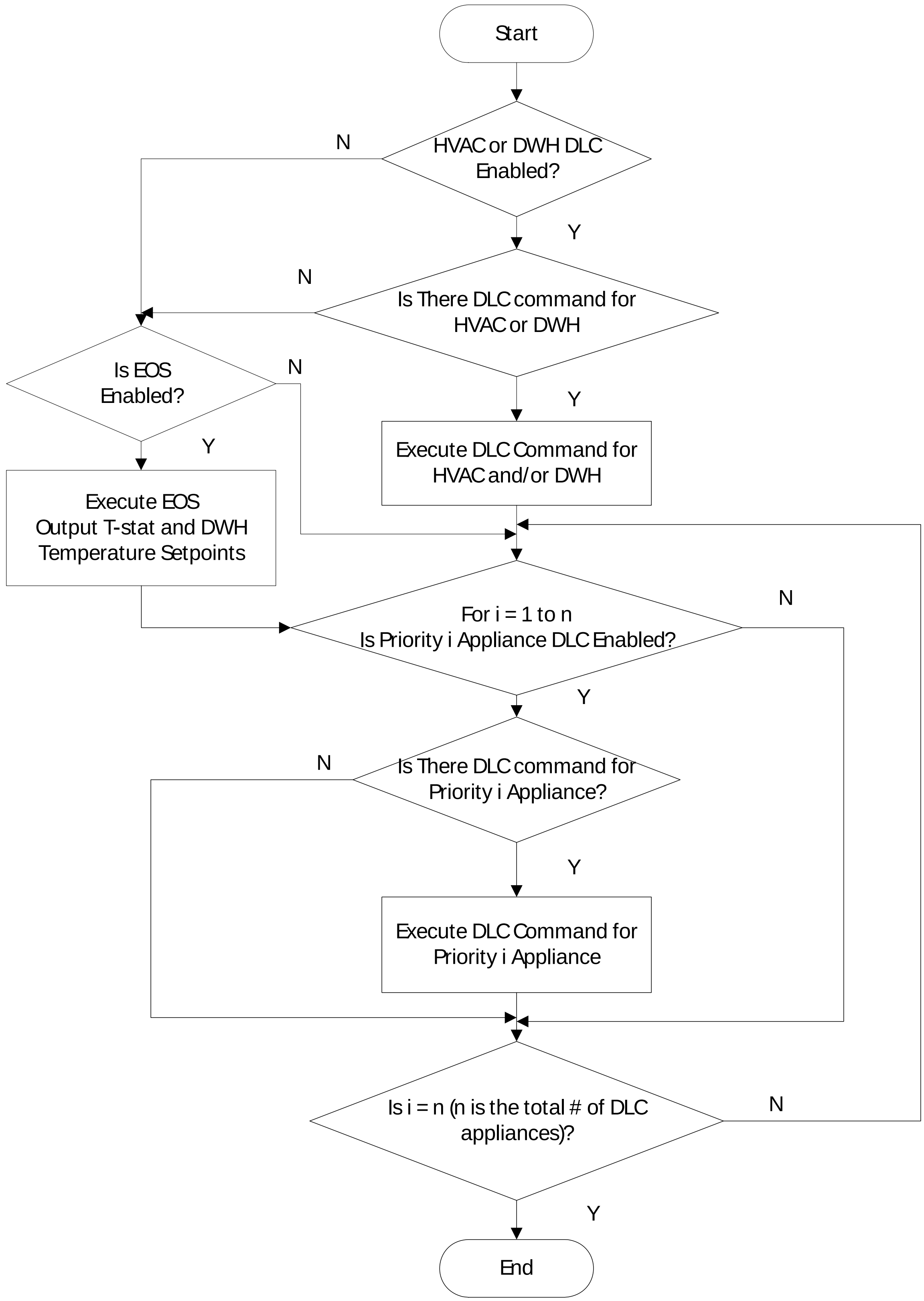



Figure 6 Flowchart of Direct Load Control for Smart Appliance Coordination

### 3.4.2 Smart AMI Meter and EOS Communication Interface Implementation

One of the key technology enablers of DLC and smart appliance coordination is the HAN communication. In order to pass DLC commands from the utility server, a communication channel / means is required from the utility server via the AMI meter to the EOS and then to the appliances. This section discusses the communication interface that links the AMI meter and the EOS appliances.

The smart meter and the EcoDashBoard interface shall be a secure two-way communication through a wireline or wireless connection. Wireless (Wi-Fi) connection is the preferred / default offering / option since it allows the EcoDashBoard to be moved freely within the home. This interface shall serve as the key “information channel” for exchanging critical information between the smart meter and the EOS. For security reasons, the information shall flow primarily from the meter to the EOS dashboard. A minimum set of absolutely must-have feedback analytic information shall be transferred from the EOS dashboard to the meter and then to the utility server.

To manage / limit the data transferred rate, the data exchange / flow shall be initiated by queries on the receiving end. In other words, the receiver shall initiate a query in order to get information from the sender. As results, the sender will respond to the request by returning relevant text strings containing the requested data. The general format of the query request shall be:

http://HOST_ID/query/QUERY_TYPE

where *HOST_ID* is either an IP address (xxx.xxx.xxx.xxx), a URL (host.ge.com) or, “localhost” if the HAN Service and the EcoDashBoard are on the same physical media / device. *QUERY_TYPE* is specific to each data type as discussed in the following sections.

The smart meter shall provide the following information to the EOS dashboard upon a query request from the EOS:

- Direct load control request / command, including programmable communicating thermostat (PCT)
- Critical peak pricing (CPP)
- Total electrical energy consummation
- Consumer alert message
- Meter ID (e.g., IP address), sub-metering for solar PV and PHEV
- Utility billing and payment (this can come from the “dashboard and Ethernet interface” as an alternative)
- Power outrage / grid status
- Rebate and other incentives – e.g., peak time rebate (PTR)
- Real-time pricing (RTP)
- Time of use (TOU).

Detailed formats of the above exchanged parameters are defined in the following subsections.

#### 3.4.2.1. Direct load control (DLC) request / command, including programmable communicating thermostat (PCT)

The DLC command shall be issued via the following query:

http://HOST_ID/query/DLC

Unlike the other queries where the response returns a vector filled with values, the direct load control command from the utility / smart meter to the EOS dashboard shall have a format of fields defined as [11]:

[{“title”:”title content”,“date”:”yyyymmdd”,”time”:”hhmm”,“type”:”type content”,“id”:”ip address”,“action”: true or false answer,”variable name”; variable value,”msg”:”msg content”,”advertUrl”:””}]

where yyyymmdd is the year month and date; and hhmm is the hour and minutes when the direct load control command is issued. The “title”, “type”, and “id” are defined in Table 15. The “action”, “variable name”, and “variable value” are specified for respective major house load / appliance in Table 16. The msg content is “Mandated Direct Load Control.” The “id” shall be an IP address that links to the appliance / load

Table 15 Appliance Direct Load Control Command Field 1

| Appliance | title content | type content | Id value |
|---|---|---|---|
| T-stat | T-stat temperature changed | PCTChange | T-stat id/IP |
| Domestic Hot water | Domestic Hot water OFF/ON | DHWOFF/ON | Water tank id/IP |
| Pool Pump | Pool Pump OFF/ON | PoolPumpOFF/ON | Pool Pump id/IP |
| PHEV | PHEV charging OFF/ON | PHEVOFF/ON | PHEV outlet id/IP |
| Dishwasher | Dishwasher OFF/ON | DishwasherOFF/ON | Dishwasher id/IP |
| Dryer | Dryer OFF/ON | DryerOFF/ON | Dryer id/IP |
| Washer | Washer OFF/ON | WasherOFF/ON | Washer id/IP |
| Refrigerator | Refrigerator to EcoMode | RefrigeratorEco | Refrigerator id/IP |
| Lighting | Dim lighting | DimLighting | Lighting id/IP |
| Plug loads | Plug Loads | PlugloadOFF/ON | Plug load outlet id/IP |

Table 16 Appliance Direct Load Control Command Field 2

| **Appliance** | **action** | **variable name** | **variable value** |
|---|---|---|---|
| T-stat | fixedSetback | degreeSetback | 0 – 20 |
| Domestic Hot water | DHW OFF/ON | DHWDLC | 0 / 1 |
| Pool Pump | Pool Pump OFF/ON | PoolPumpDLC | 0 / 1 |
| PHEV | PHEV charging OFF/ON | PHEVDLC | 0 / 1 |
| Dishwasher | Dishwasher OFF/ON | DishWasherDLC | 0 / 1 |
| Dryer | Dryer OFF/ON | DryerDLC | 0 / 1 |
| Washer | Washer OFF/ON | WasherDLC | 0 / 1 |
| Refrigerator | Refrigerator EcoMode OFF/ON | RefrigEcoModeDLC | 0 / 1 |
| Lighting | Dim lighting | DimPercentage | 0-100% |
| Plug loads | Plug loads OFF/ON | PlugLoadsDLC | 0 / 1 |

Where the plug loads shall be grouped onto designated smart outlet plug(s) ; or onto the designated circuit in the intelligence load panel.

Here are four specific examples for PCT, Pool Pump, Refrigerator, and Lighting.

Example 1 – PCT

[{“title”:”T-stat temperature changed”,“date”:”20081029”,”time”:”1530”,“type”:”PCTChange”,“id”:”132.618.6.6”,”fixedSetback”: false,”degreeSetback”; 2,”msg”:”Mandated Direct Load Control.”,”advertUrl”:””}]

Example 2 – Pool Pump

[{“title”:”Pool Pump OFF/ON”,“date”:”20081030”,”time”:”0830”,“type”:”PoolPumpOFF/ON”,“id”:”132.618.6.7”,“Pool Pump OFF/ON”: true,”PoolPumpDLC”; 0,”msg”:”Mandated Direct Load Control.”,”advertUrl”:””}]

Example 3 – Refrigerator

[{“title”:”Refrigerator to EcoMode”,“date”:”20080908”,”time”:”1430”,“type”:”RefrigeratorEco”,“id”: “192.168.3.121”,“Refrigerator EcoMode OFF/ON”: true,”RefrigEcoModeDLC”; 1,”msg”:”Mandated Direct Load Control.”,”advertUrl”:””}]

Example 4 – Dimmable Lighting

[{“title”:”Dim lighting”,“date”:”20080816”,”time”:”1130”,“type”:”DimLighting”,“id”:”192.168.3.122”,“Dim lighting”: true,”DimPercentage”; 60%,”msg”:”Mandated Direct Load Control.”,”advertUrl”:””}]

The priorities for load shedding shall be in the order defined in Tables 15 and 16 based on consumer power consumption statistics and the impact on quality of life of the consumer.

### 3.4.2.2. Critical peak pricing (CPP)

The CPP shall be a representative critical peak pricing structure that can be used by the utility to leverage / influence demand side management. A text string composed of alphabetic and numeric letters shall be used to communicate the information [11]. For the following illustrative example, 192 price data points are used for total of 48 hours with 15-minute time interval between two adjacent data points. The first 96 data points are for the previous 24 hours inclusive; and the last 96 data points for the upcoming 24 hours. The general data format is defined as:

{“startDate”:”mmdd”,”startTime”:”hhmm”,”value”:[$v_1$,$v_2$,$v_3$,……,$v_{191}$,$v_{192}$]} (1)

The content of the text string is listed in Table 17.

Table 17 CPP data structure and format

| Content | Format | Range | Scaling | Interval | Default |
|---|---|---|---|---|---|
| Header | mmdd | mm = 01, 02, …, 12; dd = 01, 02, …, 31 | 1 | N/A | mmdd = -1 |
| Header | hhmm | hh = 00, 01, …, 23; mm = 00, 01, …, 59 | 1 | N/A | hhmm = -1 |
| Value | $v_i$ (i=1,2,…,129) | $v_i$ = 0, 1,…… (integer) | $0.001 | 15 minute | $v_i$ = -1 |

It is worthwhile noting that –1 has been used to indicate the current setting.

One specific example is shown below:

{"startDate":-1,"startTime":"0952","values":[-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-
1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-
1,900,900,900,900,900,900,900,900,900,900,900,900,900,900,900,900,900,900,900,900,900,900
,900,900,900,900,900,900,900,900,900,900,400,400,400,400,400,400,400,400,400,400,400,400,
400,400,400,400,400,400,400,400,**400,**400,400,400,400,400,400,400,10, 10, 10,10,-1,-1,-1,-1,-
1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-
1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-
1,-1,-1,-1,-1,-1,-1,-1,-1]}

In this sample, there are three tiers. The first is 8 hours @ $0.90 / kWh. The second is 8 hours @ $0.40 / kWh and the last is 1 hour @ $0.10 / kWh. For any reporting interval where the default contract price is in effect, the element of the vector is ‘-1’. The current time interval pricing of $0.40 / kWh is indicated in bold.

The CPP information can be obtained by initiating the following query command from the EOS:

http://HOST_ID/query/pricing.

### 3.4.2.3. <u>Total electrical energy consumption</u>

The total electricity consumption shall be reported in a similar data format as CPP (formula (1)) with the pricing information replaced by electrical energy consumption in 0.001 kWh for a fixed time interval. This matched data format will enable rapid / synchronized data processing and analysis. Since only the past / historical consumption is measured and known, the current and future reporting periods will always hold '-1' indicating the unknown and to be determined consumption. An example energy consumption for 48 hours with 15-minute time interval is shown below [11]. The current reporting interval is bolded.

{"startDate":”0118”,"startTime":"0438","values":[70,65,65,65,65,65,65,65,65,65,565,1490,1415
,865,745,740,740,740,740,740,745,740,520,425,420,550,770,770,775,575,65,65,410,760,760,76
5,765,755,760,1155,1525,1535,750,65,65,65,65,65,65,60,65,65,65,65,65,65,65,65,65,60,65,65,6
5,65,65,65,65,65,65,65,65,65,65,65,60,65,65,65,65,65,65,65,65,65,65,60,65,65,65,65,65,65,65,6
5,**-1**,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-
1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-
1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1]}

The electricity consumption query shall be initiated by the EOS using the following command:

http://HOST_ID/query/usage

### 3.4.2.4. <u>Consumer alert messages</u>

Consumer alert messages prompt users with significant event or pricing changes. They shall provide users useful information that can be used to make decisions on reducing energy consumption, increasing efficiency or improving system reliability. The alert messages can be obtain via query command initiated from the EOS dashboard:

http://HOST_ID/query/alerts

The response of the query command shall have the generic format [11]:

[{“alert”:”alert content”,“date”:”yyyymmdd”,”time”:”hhmm”,“type”:”type content”,“id”:”NULL”,“alert”: true,”variable name”; variable value,”start time”:”mmddhhmm”,”end time”:”mmddhhmm”}]

where the variable data fields are defined in Table 18.

Table 18 Data Fields for Alert Messages

| **alert content** | **type content** | **variable name** | **variable value** |
|---|---|---|---|
| RTP Price | RTP | RTPPrice | aaa |
| TOU Price | TOU | TOUPrice | bbb |
| Expected Peak Load | Peak Load | PeakLoad | cccc |
| Grid Outrage | Outrage | Outrage | 1 |
| Price Rebate | Rebate | RebatePrice | ddd |
| Monthly Billing | Billing | Billing | $ffffff |
| Payment | Payment | Payment | $gggggg |

One specific example of RTP price is:

[{“alert”:”RTP Price Change”,“date”:”20081105”,”time”:”1800”,“type”:”RTP”,“id”:
“NULL”,“alert”: true,”RTPPrice”; 400,”start time”:”01111900 ”,”end time”:
”01182000”}]

where the new electricity price is 40 c/kWh. Note that unit of 0.001 c/kWh applies to the electricity pricing and $0.01 applies to the billing and payment values.

## 3.5. Laboratory Testing and Analysis

For Task 5 of the enhanced energy optimization system project, GE’s committed effort was to perform a laboratory validation test, and to write a report to describe the performance and characterization of the overall system operation under stressed grid conditions.

Lab tests have been performed at GE Global Research’s Smart Grid Lab in three different system scenarios and grid conditions. They are: 1. Bypassing the energy optimizer, and executing direct load control (DLC) commands for emergency load shedding and peak power reduction; 2. Utilizing the critical peak pricing signal to manage / reduce peak power consumption and reduce utility bill / electricity cost; and 3. Running the energy optimizer for minimizing energy consumption by controlling the thermostat, hot water heater, solar PV, and energy storage. The grid stressed conditions are simulated in the form of high critical peak pricing signal indicating that the system is overloaded or close to its designed peak load.

**Table 19** summarizes the test scenarios and test results.

Table 19 Summary of Test Scenarios and Results

| Scenario | Assumption | Setup | Results | Comments |
|---|---|---|---|---|
| **1. DLC for Emergency Load shedding** | • DLC is generated by utility based on peak power overloading situation<br>• PCT DLC is used for tests<br>• Agreement / contract available between utility and consumer<br>• Utility offers fixed contractual incentive | • PCT DLC command generated by PolicyNet server<br>• PCT command deployed to EcoDashBoard via AMI meter<br>• EcoDashBoard sent the command to T-stat<br>• Command executed by T-stat offsetting temperature setpoint to stop / cycle HVAC | • T-stat temp offset / changed accordingly on T-stat per PCT DLC command<br>• Offset T-stat temp setpoint will stop / cycle HVAC | • Demo was on PCT DLC<br>• Concept applies to DLC for all appliances<br>• Load shedding can be appliance off or eco-mode / energy saving mode operation<br>• Other DLC commands defined for PolicyNet and implemented in HEM<br>• Highest priority |
| **2. Peak load / power reduction using CPP** | • Available variable pricing signal<br>• 48 hr 3-tier CPP<br>• Generated by utility based on overloading or peak power situation | • CPP generated by PolicyNet server<br>• Consumer defines / controls threshold<br>• Higher than threshold CPP triggers eco-mode operation<br>• Eco-mode operation save energy and cost | • Higher than threshold CPP triggered dryer to eco-mode from normal mode<br>• Reduced Power by ~3 kW | • Incentive based (via variable pricing signal) voluntary load shedding<br>• Smart appliances also improved energy efficiency<br>• Pro-active peak load reduction to avoid emergency situation<br>• Second highest priority |
| **3. Energy Optimization** | • No need for emergency mandatory and incentive based voluntary peak reduction<br>• Target for Energy reduction<br>• Weather info was fed via data file | • MPC based Closed loop control<br>• Optimize T-stat / HVAC, Hot water heater, PV and Energy Storage<br>• Minimize energy and cost | • T-stat temp setpoint set accordingly by optimizer on the EcoDashBoard display<br>• T-stat temp setpoint was set by Eco-Dashboard | • Lowest priority<br>• Aimed at improving energy efficiency and utility bill reduction<br>• Energy reduction rather than peak power reduction |

The following sections of the report describe and document the details of the laboratory test setup and results of all the three test conditions.

### 3.5.1 Laboratory Test Setup

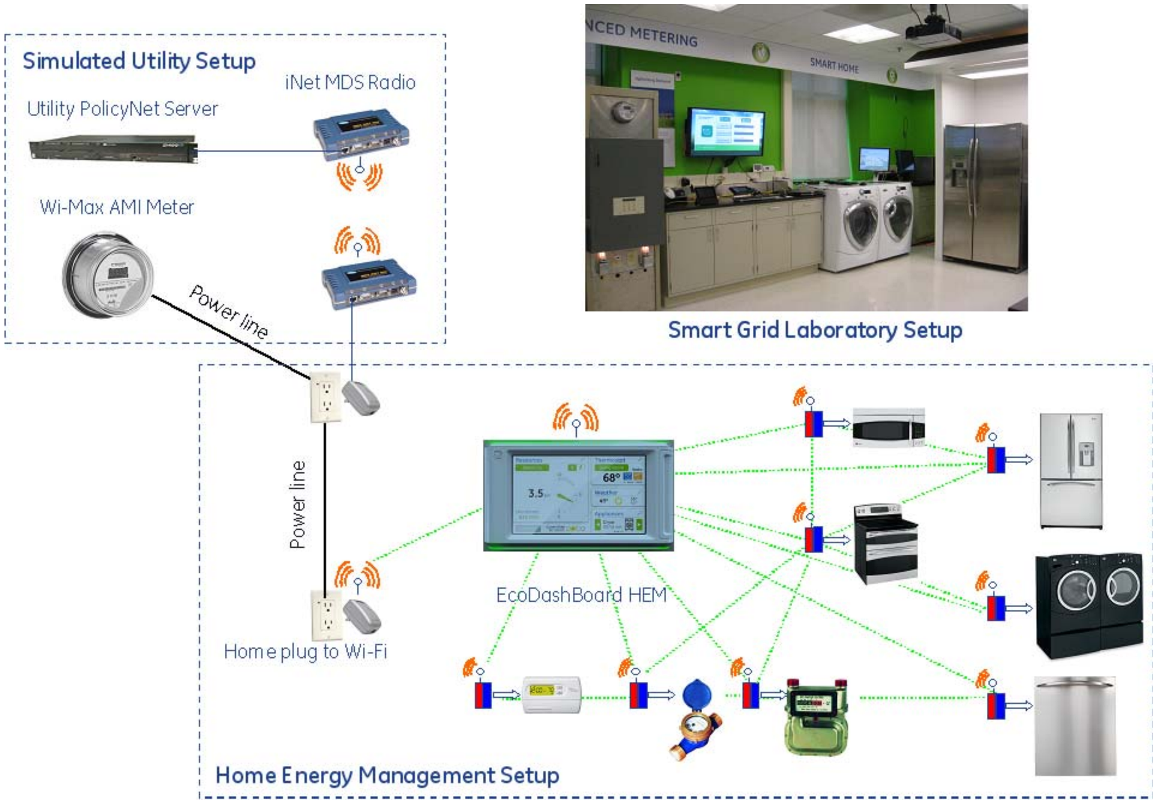



Figure 7 Lab Test Setup and Functional Block Diagram

Figure 7 shows a functional block diagram and the actual / physical laboratory setup for the tests performed at GE Global Research's Smart Grid Lab.

In this setup, there are two major functional areas / subsystems: utility energy management and smart home energy management.

**Utility EMS** was simulated with a GridNet Policy Server, a GE Wi-max AMI meter and a couple of GE microwave data system (MDS) radios. The GridNet policy server has three main functions: 1.) Generating direct load control command, specifically, programming communication thermostat (PCT) to control T-stat / HVAC for emergency load shedding; 2.) Generating, managing, and deploying dynamic / variable pricing signal / policy (e.g., critical peak pricing / CPP) to incentivize peak load reduction; and 3. Sending alert and warning messages (e.g., electricity price change and / or outage notifications) to consumers. The PolicyNet server has a web portal interface with a secure authorized user login. The communication between the utility PolicyNet server and the AMI meter is simulated with a GE iNet 900 MHz MDS radio network in the laboratory as shown in Figure 7. This simulated wireless RF connection is to avoid the relative high cost of building a Wi-Max station for the test. Similarly, for cost reason, power line carrier (Home Plug) is used for the experimental setup of the AMI meter connection with the home area network (HAN). The GE Wi-Max meter was used as a communication gateway that connects the utility EMS function and the Home energy management system.

**Home EMS** was setup based on the GE Consumer & Industrial's smart appliances and home energy manager products. As shown in Figure 7, smart appliances used in the experimental setup include washer, dryer, refrigerator, dishwasher, range, and microwave. Also included in the setup were a smart thermostat and a simulated water meter measurement. A tablet PC was used as the EcoDashBoard HEM that provided an interface with the consumer for inputting preferences and for displaying energy related information. The tablet PC was also used as a host of the energy optimization algorithms. The EcoDashBoard HEM communicates with the smart appliances via a meshed Zigbee (smart energy profile [12]) network. The EcoDashBoard communicates with the AMI meter via a Wi-Fi signal converted from a Home Plug power line carrier signal. The smart appliances have two modes of operation: normal mode and eco-mode (power/energy saving mode). In eco-mode operation, the appliances consume only a fraction of the power at normal mode. For example, for the dryer, eco-mode consumes about 30% of the power at normal mode. The appliances receive a mode control signal from the EcoDashBoard HEM. This mode control signal can be derived from either a direct load control signal or a critical peak pricing (CPP) signal. Both direct load control and CPP signals come from the utility energy management policy server. For the smart thermostat, the optimum temperature setpoint comes from the energy optimizer that minimizes the energy consumption and the cost of utility bill.

### 3.5.2 User Control Options of the Test Scenarios

The EcoDashBoard HEM provides high-grained control of the end user load by both the energy provider and the user. End users, however, are unlikely to respond positively to a system in which the end user cannot disable features at will. Thus, the EcoDashBoard HEM includes switches / buttons with which the user can choose to perform manual operation, or, at their discretion, allow any combination of Optimizer, DLC and CPP responses [13].

Figure 8 [*]shows a screenshot of the EcoDashBoard display that has the switches on the left-side which end users can use to select control features. A manual switch can be used to enable or disable all non-manual advanced control features. In Figure 8, the switches are all in the "off" position. The actual default is "off" for the manual switch and "on" for the other three. The majority of the state changes based on electricity price or DLC are triggered by messages from the message dispatcher – one of the software modules. Although these may occur on a regularly scheduled basis, users expect a "real-time" response to their input. Thus, a change in the switches will trigger a state update. For example, if a DLC is in effect and the DLC response is disabled, the DLC state will be negated. Similarly, if a DLC is in effect and the DLC response is enabled, the DLC will be instituted. The same is true for the CPP, Optimizer and manual switches.

Table 20 summarizes all the possible combinations of control options. It is worth noting that there are a number of control options that are very beneficial to the engineers who are developing the technology. However, they could be confusing to some consumers for practical deployment. For commercial applications / implementations, control options will be either automated or limited to ensure easy use and simplicity. The three combinations high-lighted in Table 20 are the three test scenarios used in the laboratory validation for this project, and they are discussed in the following subsections.

---

[*] The "Energy Bill Saving" and the "Appliance Power Usage" bar display in all the screenshots of the test results were not kept updated to match the exact test conditions since the power usages of the individual appliances were not measured in the setups.

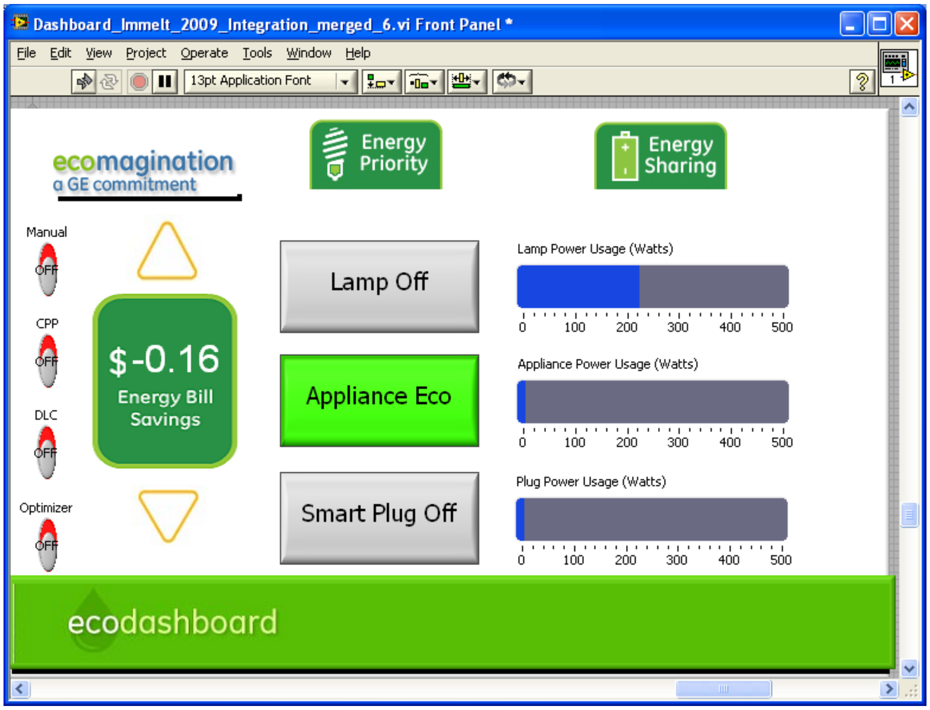



Figure 8 User Control Options of Test Scenarios

Table 20 Available / Possible User Controls Combinations

| **Control & state** | **FEATURE** | | |
|---|---|---|---|
| | **Optimizer** | **Direct Load Control (DLC)** | **Critical Peak Pricing (CPP)** |
| **DLC ON** | Disabled | ON | N/A |
| **DLC OFF** | Optimizer switch | OFF | N/A |
| | | | |
| **CPP ON** | N/A | N/A | ON |
| **CPP OFF** | N/A | N/A | OFF |
| | | | |
| **Optimizer ON** | Subject to DLC state | N/A | N/A |
| **Optimizer OFF** | OFF | N/A | N/A |
| | | | |
| **Manual ON** | OFF | OFF | OFF |
| **Manual OFF** | Optimizer switch | DLC switch | CPP switch |

### 3.5.3 Direct Load Control for Emergency Load Shedding

Direct load control (DLC) has the highest priority among the three test scenarios / operation modes we evaluated in the Lab. It is designed for emergency load shedding. When the peak power of a power system is approached or exceeded, actions must be taken to relieve the power system overloading condition. Before starting the expensive and time-consuming (to startup) peaker generators, the preferred option would be to reduce / drop the non-critical loads to balance the generation and demand. This is typically accomplished via utility commanded DLC. To implement this control scheme, the utility company will have an agreement or contract in place with end-users who would allow the utility to control some loads directly as needed. One hypothetical example is that the consumers would allow the utility company to turn off / cycle the HVAC system five times a month for 30 min each. In return, the consumer could get a $5/month credit off the utility bill.

We used HVAC as the load in this DLC lab test since it represents 40-50% of the electrical loads for a typical household.

In the Lab test, a PCT DLC command was generated in the utility PolicyNet server as shown in Figure 9. This PCT command offsets the T-stat temperature setpoint by predefined / specified degrees. An offset of +2 $^{\circ}$F was used in the Lab test. This DLC was deployed from the utility PolicyNet server to the AMI meter through an iNet RF radio. Then the command was passed from the AMI meter to the EcoDashBoard via the PLC / Home Plug and Wi-Fi communication as shown in Figure 7. The received DLC command was displayed on the EcoDashBoard display as shown in Figure 10. Figure 10 also shows a comparison of the T-stat temperature setpoint display before and after the DLC command was issued. Figure 11 shows that the PCT DLC command was successfully executed from the EcoDashBoard to the actual device (T-stat) by offsetting the temperature +2 $^{\circ}$F degrees higher. Since both DLC and the energy optimizer have the ability of setting the thermostat, to avoid conflict, when a DLC command is in effect, the energy optimizer is disabled or bypassed.

### 3.5.4 Reducing Peak Power Demand by Utilizing Critical Peak Pricing Signal

This peak load reduction control is designed to be an incentive based voluntary program that helps consumers reduce utility bill / energy cost while helping the utility company reduce peak load and relieve power system overloads. The goal of this approach is to take pro-active measures when peak demand / load is approaching the limit. This would help either avoid the re-active emergency load shedding situation; or help better plan / predict ahead of time for emergency load shedding. Both the utility company and the consumers will benefit from this "less intrusive" program. It is totally voluntary for consumers. The consumer have total / full control of the optional program by enabling / disabling this feature, by defining CPP threshold and by defining / specifying other preferences.

To validate this peak load management method, a CPP policy was generated in the PolicyNet server as shown in Figure 12. There were two tiers (one hour time period for each tier) of CPP (25 cents/kWh and 15 cents/kWh) in Figure 12. The higher than normal electricity price is used to simulate / respond to the peak power demand. On the EcoDashBoard, the user can define a threshold that represents the tolerance / willingness of the consumer to participate in the voluntary peak power reduction program. In the test, this threshold was set to 10 cents / kWh. In other words, the customer chooses to reduce his/her power demand if the CCP is greater than 10 cents/kWh. The power demand / load reduction is done by turning the appliances to eco-mode (energy saving mode) of operation.

In the test, a cloth dryer was used to demonstrate the peak power reduction . Figure 13 shows the CPP policy was deployed from the utility policy server to the AMI meter. Figure 14 shows that the EcoDashBoard HEM has received the CPP info, compared it with the user-defined threshold (10 cents/kWh), and then decided to turn the dryer into eco-mode of operation. Figure 14 shows the change of appliance operation mode from “normal to Eco” before and after the CPP command was executed. Figure 15 shows the actual power demand / consumption drop from ~3 kW (normal mode) to ~1 kW (eco-mode) of the cloth dryer.

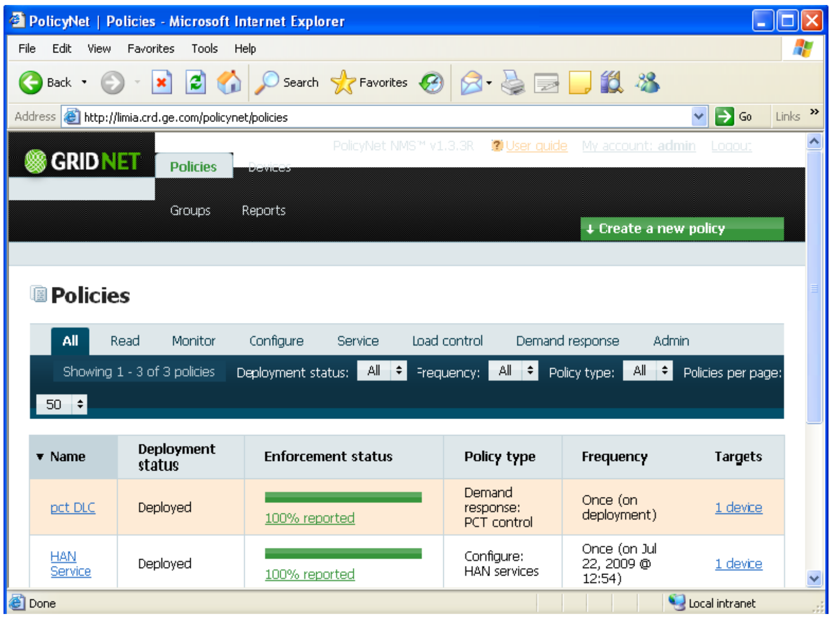



Figure 9 Programmable Communicating Thermostat (PCT) DLC Command

\


(a) Before (b) After

Figure 10 PCT DLC Display on EcoDashBoard


(a) Before (b) After

Figure 11 PCT DLC Commands Executed in T-stat

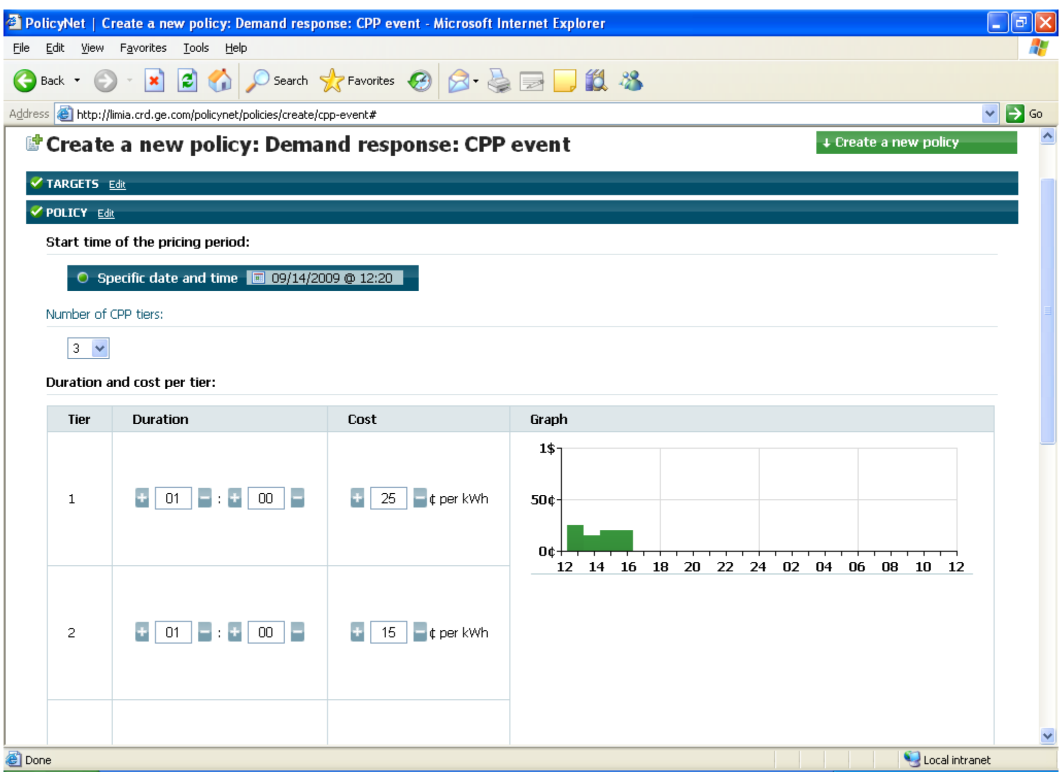



Figure 12 CPP Policy Generated in PolicyNet

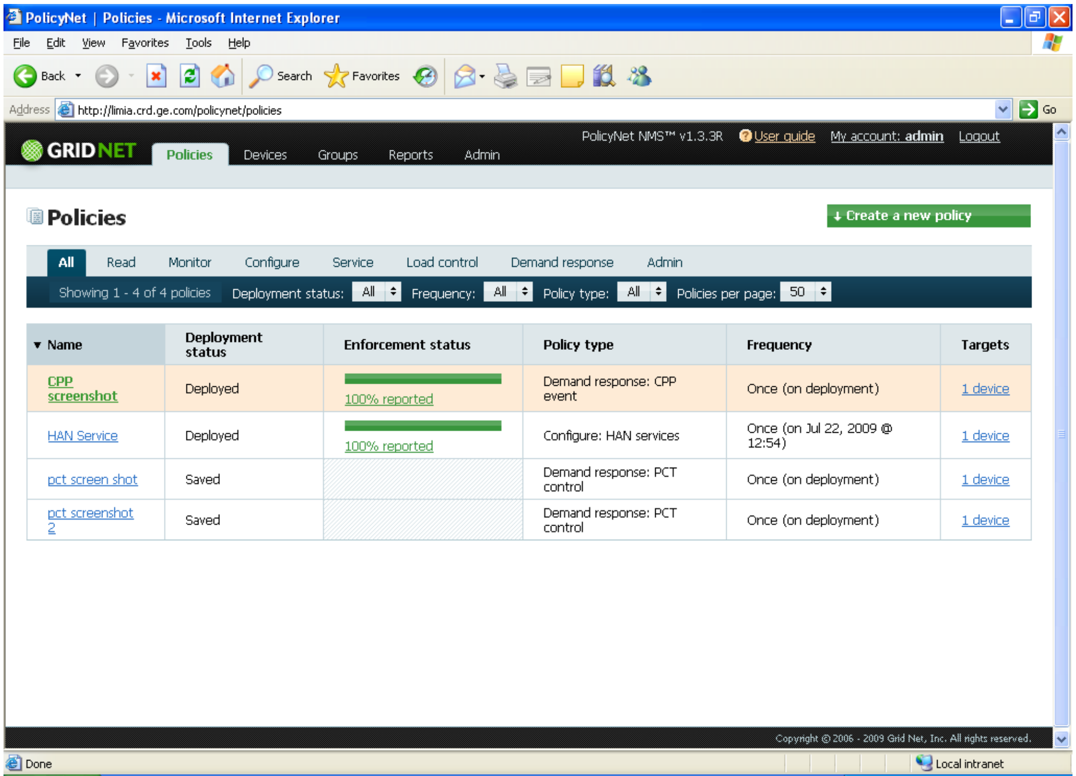
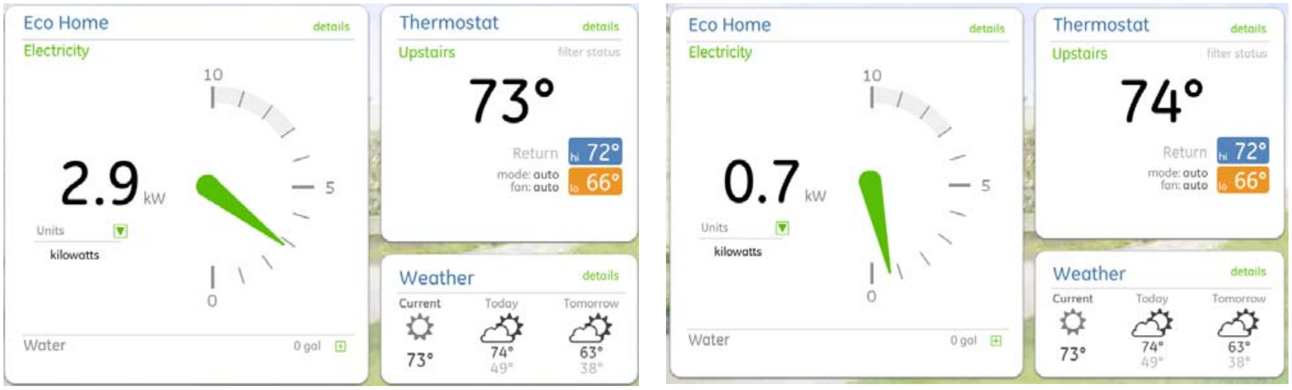



Figure 13 CPP Policy Deployed from the PolicyNet


(a) Before (b) After

Figure 14 Peak Power Reduction in Response to CPP



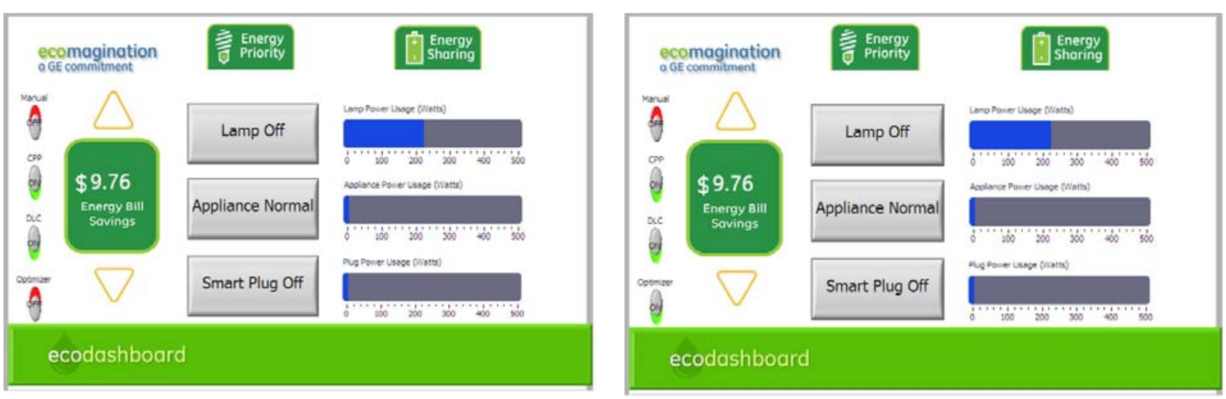

(a) Before (b) After

Figure 15 Peak Power Reduction Results for Dryer

### 3.5.5 Energy Optimization by Running the Energy Optimizer

In addition to peak power reduction, base energy load reduction is also an objective of this project. This is accomplished by running an energy optimizer on the EcoDashBoard HEM that optimally sets the T-stat and hot water heater temperature setpoints, optimally dispatches solar PV generation and manages energy storage. This is a closed-loop optimal control that minimizes energy consumption and utility bill subject to a set of constraints (user defined and/or system / equipment imposed). The consumers will benefit from this via a utility bill / electricity cost reduction.

In the specific Lab test, we run the optimizer to set the T-stat temperature setpoint. The input data required by the optimizer, such as historical energy consumption data, ambient temperatures, solar insolation forecasts were fed to the optimizer by the data measured from an employee's house. The optimizer also has a system identification module that identifies and updates the thermal model of the house. Figure 16 shows the optimizer being turned on from the off state. Figure 17 shows the optimal T-stat temperature was calculated and set on the EcoDashBoard and on the actual device for the morning duration from 8 am – 10 am.




(a) Before (b) After

Figure 16 Energy Optimizer Turned Off and On


(a) Temperature Set on EcoDashBoard (b) Temperature Set in T-stat

Figure 17 Energy Optimizer Setting the T-Stat Setpoint

### 3.6. Project Benefits

The direct benefits of the energy optimization system are two fold: 1. Peak load reduction by emergency load shedding and by utilizing a dynamic / variable electricity pricing signal; and 2. Energy and cost / utility bill savings via energy optimization.

The peak load reduction benefits the utility companies most while the energy savings are more for consumers. It has been demonstrated in the laboratory tests that at the individual appliance / load level, for example the cloth dryer, the peak power reduction can be as much as 70% of the normal power consumption of the appliance. While this project is not set up to prove / validate the actual / practical peak power reduction capability of the energy optimization system, analysis has shown that at a holistic residential level, 15%-25% of peak power reduction is achievable by implementing the energy optimization / management technology. Utility companies will benefit from this significant peak power reduction by deferring capital investment on spinning reserve generation capacity, transmission and distribution infrastructure build-up, etc. This will also improve power system reliability and customer satisfaction by reducing and minimizing the number of power outages. Utility companies can and should share the benefits / profits with customers, thereby encouraging active and large-scale customer participation.

On the other hand, the consumers will benefit the most from the energy savings through the energy optimization system. This would be evident from the monthly utility bills. The energy optimization system is set up as an optimization problem with the objective functions of minimizing energy consumption and utility bills. GE project team has performed DSM benefit analysis using DOE EIA RECS 2001 data. The results indicated that 13-27% energy efficiency improvement is achievable by implementing DSM and energy management technologies. Specifically, the benefit of the energy optimization system developed in this project was simulated using a California home as an example. The assumptions for this California home are:

- One thermal zone
- Internal heat gain from loads, people
- Natural gas (NG) boiler heating: 13.7 kW, efficiency = 75%
- Electric AC: 2 kW

- Electric hot water heater: 4.5 kW
- Battery storage: 1.5 kW, 10 kWh
- 2 kW of roof-mounted solar PV
- State-space model: thermal capacitance and resistance.

The yearly sourced energy savings (electricity and NG) were simulated using the model predictive control (MPC) based energy optimizer with banded temperature setpoints for the thermostat defined as in Figure 18. The upper and lower temperature bands / bounds were designed to accommodate the consumers' comfort level while allowing the setpoint to flow to enable energy and cost savings. Figure 19 shows the estimated potential energy and cost savings from the simulation. There are five incremental cases / scenarios simulated:

1. Base-line without energy optimization
2. Manually adjusted thermostat without any automation / optimization
3. MPC based energy optimization with banded thermostat temperatures
4. With solar PV
5. With energy storage.

The energy consumption in kWh for all the five different scenarios were plotted in Figure 19a. Figure 19b showed the incremental energy and cost savings in the format of a pie chart. One can see from Figure 19b that there were 3.5% energy and 3.3% cost incremental savings of the adjusted thermostat from the baseline; 24.1% energy and 18.1% cost incremental savings of the energy optimization from the adjusted thermostat; 6.9% energy and 14.6% cost incremental savings by adding solar PV into the optimization; and 0.1% energy and 3.3% cost incremental savings by adding the energy storage. The biggest gain on energy and cost came from the energy optimization. It is worth noting that this was only ONE hypothetical example used to illustrate the potential of the energy optimization on energy and cost savings. The actual energy and cost savings depends on the specifics of the use cases / applications. Nonetheless, the simulations showed that energy optimization could potentially provide significant energy and cost savings directly to consumers.

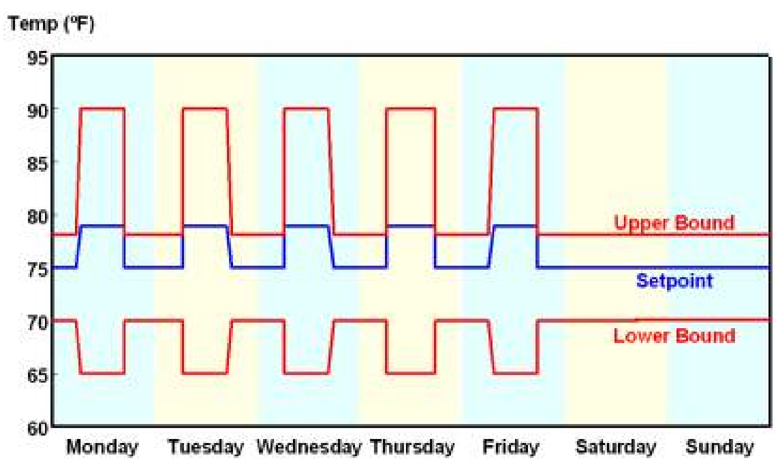
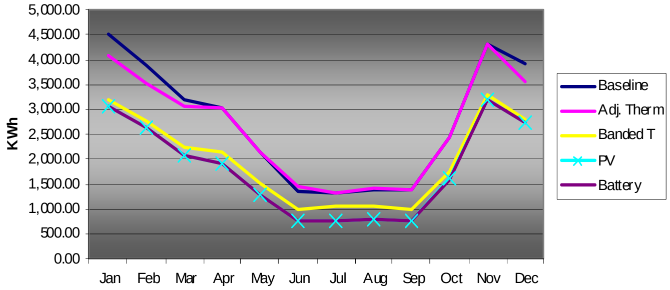
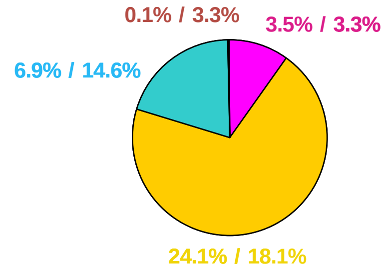



Figure 18 Banded Thermostat Temperature Setpoint




(a) Energy Saving Scenarios

(b) Energy Saving / Cost Saving

Figure 19 Potential Energy Savings by the Energy Optimization

Indirectly, the energy saving will also translate to $CO_2$ footprint reduction and environmental benefit. It would reduce dependence on fossil fuels and strengthen the nation's energy security.

## 4. Glossary / Acronyms and Abbreviations

CPP – Critical Peak Pricing
DG – Distributed Generation
DHW – Domestic Hot Water
DLC – Direct Load Control
DOE – Department of Energy
DR – Demand Response
DSM – Demand Side Management
EESM – Electrical Energy Storage Module
EHEMS – EcoDashBoard Home / EcoHome Energy Management System
EIA – Energy Information Administration
EOS – Energy Optimization System
GUI / HMI – Graphical User Interface / Human Machine Interface
HAN – Home Area Network
HCEI – Hawaii Clean Energy Initiative
HNEI – Hawaii Natural Energy Institute
PCT – Programmable Communicating Thermostat
PHEV – Plug-in Hybrid Electric Vehicle
RECS - Residential Energy Consumption Survey
SOC – State of Charge
Solar PV – Solar Photovatic
TOU- Time Of Use.

# 5. References

1. GE's Energy Management Technology Development Statement of Work, July 29, 2008.
2. EcoDashBoard Home Energy Management System (EHEMS) Requirements Specification, GE Global Research, September 30, 2009.
3. EcoHome Energy Management System (EHEMS), Zhi Zhou (Joe), project kickoff presentation, October 6, 2008.
4. Project Milestone and Progress Report 1 (to HNEI) – Deliverable 1 for Subcontract Z887501 of Prime Contract DE-FC26-06NT42847 – Enhanced Energy Optimization System, Zhi Zhou (Joe), April 16, 2009.
5. Project Milestone and Progress Report 1 (to HNEI) – Deliverable 4 for Subcontract Z887501 of Prime Contract DE-FC26-06NT42847 – Enhanced Energy Optimization System, Zhi Zhou (Joe), April 16, 2009.
6. Project Milestone and Progress Report 2 – Deliverables 2 and 3 for Subcontract Z887501 of Prime Contract DE-FC26-06NT42847 – Enhanced Energy Optimization System, Zhi Zhou (Joe), May 17, 2009.
7. Project Milestone and Progress Report 3 – Deliverables 5 and 6 for Subcontract Z887501 of Prime Contract DE-FC26-06NT42847 – Enhanced Energy Optimization System, Zhi Zhou (Joe), September 28, 2009.
8. Energy Management System for the EcoDashBoard, Ramu Chandra, GE Global Research, August 6, 2008.
9. Utility AMI 2008 Home Area Network System Requirements Specification, Version 1.04, August 19, 2008.
10. System Identification Update: Algorithms Improvement and Testing, Ajay Dhar and Emrah Biyik, GE Global Research, May 15, 2009.
11. The Smart Grid: End-to-End Power System Control, Earl Eiland, GE Global Research, July 2008.
12. Zigbee Smart Energy Profile Specification, Revision 14, May 29, 2009.
13. Documentation for the Upgrade of the EcoDashBoard with the Plogg and the CT80 Zigbee Thermostat, James Lopez and Earl Eiland, August 2009.