A DISTRIBUTED INTELLIGENT AUTOMATED DEMAND RESPONSE
BUILDING MANAGEMENT SYSTEM

Quarterly Progress Report

July 30, 2011

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1.2 Recipient:
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2 Project Title and Principal Investigators

2.1 Project Title:
A DISTRIBUTED INTELLIGENT AUTOMATED DEMAND RESPONSE BUILDING MANAGEMENT SYSTEM

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30 July 2011

3.2  Period Covered:

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5 Comparison of Project Accomplishments and Project Goals

The outlined goals of the Distributed Intelligent Automated Demand Response project for the fourth quarter (April 1, 2011-June 30, 2011) consisted of the completion of two major tasks (Tasks 3 and 5) and embarking on a third task (Task 6) that will continue into the next budget period. Task 3 is the development of a Service-Oriented Architecture (SOA) for Distributed Intelligent Automated Demand Response (DIADR) and Task 5 is the development of Demand Response Algorithms. On April 27, the teams from UC Berkeley, LBNL and Siemens (SCR) presented work to date, and demonstrated the Gateway and the central and distributed algorithms to DOE via a webcast. The following paragraphs describe the results of Tasks 3 and 5, describe progress on Task 6, and introduce work in preparation for Tasks 8 and 9.

The subtasks outlined for Task 3 this quarter consisted of testing the SOA, demonstrating with a communication protocol, and documentation. The SOA consists of the Commercial Energy Gateway, which acts as a distributed load controller. The Gateway was installed on a number of computers and UC Berkeley and Siemens worked on developing the communication between the Smart Energy Box and the Gateway, as well as between the Gateway and the loads. The JADE based control platform was further developed. The UC Berkeley and Siemens teams each demonstrated how the Gateway can be used to control distributed loads given a Demand Response signal.

The final subtask for Task 5 was documentation. In addition, the teams demonstrated the simulation-based DR optimization and control to DOE and as well as a public audience on April 27.

Task 6, DIADR local control testing in a test environment, began this quarter with work on the first subtask, local control DIADR integration. Regarding Task 8, DIADR building integration, work continued on the collecting, trending and analyzing of HVAC data. In addition work began on HVAC and lighting integration. In preparation for Task 9, Enhanced Scale Testing, contributions included load isolation, refinement of the EnergyPlus model, development of the baseline, further refinement of demand response scenarios, and development of a test plan.

6 Major Activities, Significant Results, Major Findings

The major event for this quarter took place on April 27th, as the teams met two milestones by demonstrating the Gateway functionality and presenting simulations of both distributed and central control demand response algorithms. The documentation was also submitted. We created a website to describe the work and act as a data repository. Task reports, quarterly reports, and the April 27 presentation slide decks may be found at http://i4energy.org/. Another major undertaking began this quarter regarding the occupant survey; UC Berkeley and LBNL began communication with the Center for the Built Environment at UC Berkeley to develop a web-based survey of the occupants in Sutardja Dai Hall to ensure the maintenance of occupant health, productivity and comfort during DR events.
The contribution from the UC Berkeley team primarily consisted of work on the Gateway, including the web-based user interface, data management from the building system, data visualization from the electrical power loads, and baseline load calculation.

During the current reporting period, Siemens Corporate Research (SCR) continued work in three areas. First, SCR worked with LBNL on modeling the Sutadja Dai Hall HVAC control system and creating DR control algorithms. The as-built HVAC control system was reverse engineered. Control sequences for Air Handler Unit 2A/2B and reheat VAV boxes were captured in MATLAB models. Energy Plus then was updated accordingly. Individual DR strategies on HVAC equipment were investigated using Energy Plus. Meanwhile, we continued our study on weather based DR strategies using different weather classification methods. For the Energy Plus simulation based optimization, Genetic Algorithms were studied and the experimental results show that the search time can be reduced by 70%. Second, SCR continued to work on the Siemens Smart Energy Box development to support the implementation of Demand Response control. Finally, SCR worked with UCB on the distributed load control platform and algorithm development. SEB-JADE communication was established for adaptive and market-based DR control. For adaptive DR control, central DR allocation can be made every 15 minutes based on the run-time cost models received from individual DR contributors.

LBNL continued to contribute to the DIADR project in the following areas: 1) continued to update the EnergyPlus (E+) model; 2) worked with UCB researchers to isolate the power usage of the office portion from the whole CITRIS building and meanwhile establish the base load of the office portion; 3) worked with SCR to perform the analysis of the potential demand reduction.

6.1 Task 3.0—Develop Service Oriented Architecture (SOA) for DIADR

Subtasks for Task 3 this quarter consisted of testing the SOA, demonstrating with a communication protocol, and documentation. Both the UC Berkeley and Siemens teams worked on testing.

In the past quarter, Siyuan Zhou of SCR worked on the Gateway implementation. First, we integrated multiple bundles to the Gateway, e.g. Raritan Driver from the UCB team so that we can control task lights. Second, we proposed and implemented a new Gateway control logic in which each appliance has a priority and Gateway controls them according to the priority. Figure 1 shows the hardware relationship.
Michael Sankur of UC Berkeley worked on the Gateway bundles for the Raritan Power Distribution Units—a plugstrip that can measure power consumption and has individually controlled outlets; this entailed cleaning up the software code and synchronization issues. He encountered some problems with communication from the Gateway to the Raritan, and developed a work-around. Michael also continued work on the bundle for the ACme’s—UC Berkeley developed power sensing and controllable outlets. He developed new appliance and laptop simulations, based on Dan Arnold’s simulation for the related residential gateway project, but with ability for the Gateway and a user to control it (for this purpose he developed User interfaces for both simulations). In addition, he developed a Wattstopper bundle for the Gateway demonstration.

On April 27, the Siemens team demonstrated using the Gateway to control two different lamps given a demand response signal, and occupancy and light level from a SCR designed desktop sensor box. UC Berkeley demonstrated the Gateway’s ability to turn on and off various appliances (e.g., lamp, fan, laptop, simulated appliances), according to their assigned priorities during a demand response event in order to achieve a determine peak load shed. The final report on Task 3 titled Development of a Service Oriented Architecture (Gateway) was completed and is available at under the report section at http://i4energy.org/diadr-project-sutardja-dai-hall-0. The Gateway will continue to be developed in Task 6.
6.2 Task 5.0—Developing Demand Response Algorithms

While the demand response algorithms were demonstrated internally last quarter, these were demonstrated to DOE and the public on April 27. Part of the demonstration was the discussion of simulation results from the central load algorithms and part was a simulation of distributed load algorithms, such as the strategies for laptop power management. Jay Taneja and Nathan Murthy demonstrated the algorithms for use in a DR setting that select and charge laptops according to need while minimizing peak power consumption. The simulation included 50 laptops. The slide decks for the presentation portion of the demonstration may be found at http://i4energy.org/diadr-project-sutardja-dai-hall-0.

The final subtask of Task 5 was to document the central and distributed Demand Response algorithms. The Task 5 report begins with a discussion of establishing an energy baseline, with which to compare any energy savings. Next is the description of the algorithms that manage central loads, such as Heating, Ventilation, and Air Conditioning (HVAC) systems as well as lighting systems. Many factors, such as weather and occupancy patterns and a model of the building enter into the algorithms; the architecture is multi-agent and distributed rather than central and top-down, requiring a negotiation protocol. Then the distributed load algorithms are outlined. This process started with an innovative plugload audit of the building to automate the process of logging and accessing information about each appliance in the building. Fundamental to the distributed load management was the development of a commercial gateway. Multiple gateways can be distributed throughout the building, each controlling a number of plugload devices typical of an office, such as computers, printers, task lamps, portable heaters or fans, and refrigerators. A user interface was instrumental to the gateway to engage occupants and provide choice of appliance curtailment during DR events. Laptop/computer power management and printer management are outlined in detail. The control architecture is discussed, including discussion of agent-based control. Finally, an Energy-Plus model was developed for the algorithm simulation; the details are in the Appendix of the report. This report is titled Demand Response Algorithm Development and may be found at http://i4energy.org/diadr-project-sutardja-dai-hall-0.

6.3 Task 6.0—DIADR local control (Tier3) testing in a lab environment

The first subtask of Task 6 was integrating local DIADR control in the test office (Room 464) of Sutardja Dai Hall. This subtask included continued development of the Gateway, development of a visualization tool and simulation of the plugloads in the building, and continued development of the Gateway user interface.

6.3.1 Continued Gateway development

Michael Sankur of UC Berkeley continued work on bundle development, focusing on sMAP service bundles that take data from the Raritan PDUs and ACme’s and post it to specific SMAP urls. He started to work on time synchronization of the multiple Gateway simulation, exploring two methods. In addition to appliance simulations, Michael started work on people simulations, which will include different schedules, appliances, and priorities for those appliances. Finally, he outlined major components that are needed for the test.

Meanwhile Siyuan Zhou of Siemens Corporate Research continued work on the Gateway implementation. First, she integrated the multiple bundles to the Gateway, e.g. Raritan Driver from UCB team, laptop power control, and printer driver so that they could control a printer, the power supply of
a laptop in addition to the task lights. Second, she proposed and implemented a new Gateway control logic in which each appliance has a priority and Gateway will control them according to the priority.

6.3.1.1 Improved Gateway Software

The Gateway was improved in the past quarter with the integration of new bundles, the Raritan Driver from the UCB team, laptop power control, and printer driver. Figure 2 gives the software architecture of the Gateway.

![Gateway Software Architecture](image_url)

Figure 2: Gateway Software Architecture.

6.3.1.2 New Control Strategy

SCR is considering the scenario with four plug-in loads: two task lights with different bulbs, one printer and one laptop. The AC power supply of task lights and laptop will be controlled by the Raritan PDU, while the printer will be controlled through an Ethernet connection. Each of the appliances has a priority, and is adjustable during runtime. The default priorities are in Table 1 below:

Table 1: Default priorities.

<table>
<thead>
<tr>
<th>Appliance</th>
<th>Default Priority</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task Light (Energy Efficient Bulb)</td>
<td>0</td>
</tr>
<tr>
<td>Task Light (Normal Bulb)</td>
<td>1</td>
</tr>
<tr>
<td>Printer</td>
<td>2</td>
</tr>
<tr>
<td>Laptop</td>
<td>3</td>
</tr>
</tbody>
</table>
The smaller the number, the lower the priority. An appliance could also be set to Critical, in which case it cannot be controlled during a DR Event, and the priority is set to 100. The conditions for the appliances to be Critical are in Table 2. Whenever the critical condition is satisfied for the appliance, the priority of corresponding appliance is set to be 100, and its status will not be changed during the DR event. If the critical condition is not satisfied, the priority of the appliance returns to the default value.

**Table 2: Critical Conditions**

<table>
<thead>
<tr>
<th>Appliance</th>
<th>Critical Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task Light (Energy Efficient Bulb)</td>
<td>Occupancy == True, Light &lt; Strong</td>
</tr>
<tr>
<td>Task Light (Normal Bulb)</td>
<td>Occupancy == True, Light &lt; Strong</td>
</tr>
<tr>
<td>Printer</td>
<td>User defined</td>
</tr>
<tr>
<td>Laptop</td>
<td>Battery &lt; 40%</td>
</tr>
</tbody>
</table>

We are using an Iterative Priority Adjustable Control Strategy, where the Gateway is updating the priority of the appliances according to the Critical Conditions as well as Gateway is turning off the appliance with the lowest priority to achieve the power shedding goal. Until the goal is achieved, or no more appliances can be turned off, the Gateway Agent will return the result to SEB Agent. The flow chart is shown in Figure 3.

![Figure 3: Strategy Flow Chart](image-url)
The next steps for the Gateway development are to:
1. Integrate and modify the Smart Appliance Simulation to simulate more complicated appliance behavior, like a Refrigerator.
2. Implement the multi-agent scenario using market-based scheme.
3. Support UCB team on developing the new Web User Interface.

6.3.2 Plug load visualization and simulation

Since the last report, Jason Trager has made significant progress on the structure of the auditing data for plug loads in SDH. Not only are there sizable peak load shaving potentials embedded in the manual control of pluggable computer monitors, but also devices such as water heaters, coffee pots, and other resistive loads have been identified as prime contributors to high peak load behavior. In addition to this sizable manual load identification from the data, an automatic system is in place to display how large plug load usage is during a demand response event in office SDH 464, and can be displayed on any computer that has MATLAB software. This live auditing display is shown in the figure below.

![Figure 4: Power data visualization on floor plan of test office.](image)

This system is being prepared for deployment across the fourth floor of Sutardja Dai Hall, and is driven by pulling data from StreamFS, a streaming content management system for building sensors, and resources.

The input from the live auditing system will drive a simulation currently under development, whereby the majority of the devices in the building are simulated so that their live behavior can be understood. The device simulation will work in conjunction with the simulation of multiple gateways; the objective is to effectively inform the building manager about plugload draw throughout the building. This is the next step to achieving a sizable peak reduction during a demand response event, and will draw from the potential unattended plugload reduction in the building. In this quarter the structure of the simulation of plugloads and multiple Gateways was developed.
6.3.3 Gateway user interface

The Drupal / PHP container for the gateway web user interface proved to be problematic with our OSGi framework. We used HTTP sockets in our software toolkit to establish a steady information stream between the gateway and the web user interface; however, ensuring communication reliability over PHP and Java sockets was difficult since some information would get lost. One example occurred when changing the priority setting of a device. The user would select from a dropdown menu a list of available priority settings; a new desired device priority before a demand response event would tell the gateway how it should handle that particular device when the demand response event begins. Information about each device is sent over a persistent socket connection from the gateway to the user interface where the user can view all this information in an easy-to-understand format. After submitting a device priority change request, a script writes the new priority to an XML file that is read by the gateway. However, passing this information to the particular instance of the Appliance object to which we are making this change cannot be successfully achieved without designing another bundle that handles passing HTTP requests to Appliance objects at runtime.

Figure 5: Version 1.0 of the original gateway web user interface architecture employed XML over Java and PHP sockets. The user interface was handled by Drupal CMS.
Rather than writing an extension to the current version of the WebUI bundle, we are writing a web application on top of a lightweight Java Web Server so that we can make use of Java Servlets and Java Server Pages (JSP) to handle web requests. We can avoid implementing a request handler and instead just directly invoke methods called by a servlet that will edit an appliance object parameter, such as changing a priority setting. There are a variety of different Java Web Servers that are compatible with the OSGi Equinox platform with which we are experimenting in order to achieve the best performance: Apache Tomcat, Mortbay Jetty, or Eclipse Virgo.

Ultimately, we will replace the current XAMPP stack with a more robust Java web service stack that will be seamlessly integrated with our OSGi bundles.

6.4 Task 8.0—DIADR Building Integration

While Task 8 officially begins next quarter, work continued on the collecting, trending and analyzing of HVAC data in order to understand its behavior. SCR has been working with UCB and SBT to resolve issues with BACnet communication for trending the data. Many attributes of HVAC system (such as Flow, water flow, Water temperature, Air Temperature, VFD Speed etc.) have been trended by using a trend logger application developed for this project. In addition work began on HVAC and lighting integration.

6.4.1 HVAC integration

Discussions with the building manager and an initial data analysis identified the building as overcooled. Therefore, we are currently exploring adding Variable Frequency Drives (VFDs) to the chilled water
pumps (CHP-1 and CHP-2) and the condenser pumps (CWP-1, CWP-2, CWP-3, CWP-4). This would allow the pumps to work at less than full capacity. In addition, Jay Taneja has mapped out the relevant control loops in the building infrastructure to manage distributed temperatures; he is currently attempting to model the energy and climate effects of mitigating overheating.

6.4.2 Lighting integration

The overhead office lighting system was also identified as key to load reduction. Floors 4, 5, 6 and 7 all have open plan office areas that are not zoned; hence the lights are at full power for the whole area, for much of the day. In addition, all floors have individual offices with individual occupancy sensors. Most overhead office lights have three lamps/two ballasts that allows stepped dimming (low (one ballast-one lamp), medium (one ballast, two lamps), and high (both ballasts, all three lamps)).

As a separate project from the DIADR project, UC Berkeley graduate student Andrew Krioukov designed a web-based lighting control using the BACnet points that allow the users to select their lighting zone, the desired lighting level, and to set a timer. This project was implemented on the fourth floor and tested during this quarter. The screenshots of the interface appear in the figure below.

![Web-based lighting control for open office plan spaces.](image)

We are exploring using this web-based user interface in conjunction with DR control. Regarding the individual offices, options include installing additional central controls for the individual offices or using encouraging occupant participation in dimming these lights for DR events.

6.5 Task 9.0—Enhanced Scale Testing

In preparation for Task 9 testing of the DR control strategies, we continue to try to understand the electrical loads of Sutardja Dai Hall and prepare a test plan. Since the project will not include curtailing load in the nano fabrication lab within the building, we must separate the energy loads of the office portion of the building from the total building load. This quarter we began discussions on the equipment needed to isolate the part of the building under study. In addition, in order to refine the demand response algorithms, the EnergyPlus model required refinement. Moreover, as we continue to develop
the demand response scenarios, it is clear that the building must first operate as efficiently as possible. This in turn makes developing a baseline more difficult (e.g., is the baseline the building’s electrical energy profile at the beginning of the project or after implementing energy efficiency measures?).

6.5.1 Load isolation
Starting in May, LBNL worked on the analysis of potential demand reduction in CITRIS and worked with the research team to isolate the power usage of the office portion from the whole building. Based on the current sub-metering map, LBNL helped develop the following sub-metering map for all the end-use components; marking them as belonging to office, fabrication lab, shared or other to assist in isolating the office portion from the whole CITRIS building.

![Sub-metering Map]

LBNL continued to work with UC Berkeley and SCR to establish the base load of the office portion.

**Preliminary Analysis:** From 4/4/2011 to 4/11/2011, the peak load of the office portion was calculated to be around 436 kW. This preliminary analysis included the shared power used by the fabrication lab of the cooling plants, such as the absorption chiller, cooling towers, chilled water pumps, condenser water pumps and other shared components. A target of 30% reduction from this calculated peak yields 130 kW demand reduction.
Figure 9: Electrical demand of the office portion of Sutardja Dai Hall.

**Estimation of the Office Portion’s Power Usage:** The simulation results from CITRIS E+ model indicated that the cooling loads of the office portion accounted for half of the total building load. Based on the simulation results from E+ model and mapping points shown in the submetering diagram, the estimated peak load of the office portion is around 320kW. This suggests that we need to reduce it by 96kW to achieve 30% target of demand reduction.

Figure 10: Simulated power usage of the office portion of Sutardja Dai Hall.

LBNL proposed several demand response strategies for achieving the 30% target of demand reduction in office portion and analyzed potential demand reduction by simulating several scenarios. The simulation results from E+ model indicate that the fan power usage of the AHU2A&2B system can be reduced by 39kW by resetting the zone temperature +5F, at the same time, the absorption chiller could achieve 15% steam reduction by implementing this DR control strategy.
With the help of the building manager, components such as exhaust fans, CACs, and the Chiller Multistack were turned off to better estimate the demand of the office portion. In addition, by measuring voltage, current and power factor to calculate the real power, we calculated the electricity used by certain equipment and compared it with the measured data. For those systems without sub-metering, current was recorded by sensors and power was calculated by assuming a fixed voltage of 480V and power factor of 0.98.

By running the absorption chiller only, the estimated power usage of the office portion in June was around 302kW, which included the total power usage of the pumps CHP2, CHP3, CWP-3, CWP-4, CP-2 and CH1. The total shared power usage is around 57.3kW, the simulation results indicated that the chilled water usage in office portion accounts for 50% of the whole building water usage. In this case, the power usage of the office portion would be 274.1kW under the current weather conditions.

To confirm the cooling load of the office portion of Sutardja Dai Hall compared to the whole building, the team is currently evaluating the installation of inline flow meters to measure the flow of chilled water to the office compared to that going to the nanofab lab. In addition, to separate the office loads, we have decided to have submeters installed on panels ESCD4RA and EOMD42A.

6.5.2 Refining the EnergyPlus model
LBNL continued to provide technical support to SCR for the building systems modeling and energy simulation with the calibrated Sutardja Dai Hall EnergyPlus (E+) model. With feedback from SCR, LBNL made several minor revisions to the calibrated E+ model. The summary of the revisions is as follows:
- **Missing Thermostat Control Points for L4_458 Conference Room:** SCR found the missing thermostat control points for L4_458 conference room when plotting zone temperature control schedules for each control zone. LBNL then added the thermostat control schedule to L4_458 and refined the E+ model.

- **Clarification of Output Meters for E+ Model:** LBNL added one more meter in the E+ model to sum all the electricity usage of the HVAC systems based on Siemens’s request for clarification of simulation results of the whole building electricity usage.

- **Internal Thermal Mass:** LBNL added an Internal Thermal Mass section onto the new E+ model to consider the effect of the internal thermal mass such as furniture and internal walls.

- **Refine the performance curves of supply fans and return fans:** Based on the measured power usage and air flow rate for supply fans and return fans, all the relevant performance curves were fitted into the E+ fan model for better prediction of the fan power usage.

- **Add air-side economizers:** LBNL worked with SCR to implement the air-side economizer and corresponding control sequences into the E+ model. The air-side economizer is controlled based on the outside air temperature. The outdoor air damper will be set to fully open when the outside air temperature is within 45°F-70°F. When the outside air temperature is out of this range, the outdoor air damper will be set to supply minimum fresh air to maintain indoor air quality.

- **Minimum Air Flow Rate for Each VAV Box:** SCR provided LBNL the measured minimum supply air flow rates for each VAV terminal boxes. LBNL updated the minimum air fraction to the measured minimum air flow rate for each VAV system module in the E+ model.

The cooling system for Sutardja Dai Hall switched from the compressor chiller to the absorption chiller on April 1st to provide chilled water to the whole building HVAC system. To respond to this change of operation, LBNL developed a separate E+ model running the absorption chiller only and recalibrated the E+ model by comparing the simulation results to the measured data from April 1st through April 11th.
Figure 12: Percent difference between measured and simulated electric power for various submetering points.

Figure 13: Comparison between measured and simulated whole building electricity usage over five weekdays.
On April 27th, 2011, LBNL presented the development of the EnergyPlus model. During the demo, LBNL presented the comparison between the simulation results and the measured data. For the new model with the absorption chiller only, from April 4th to April 9th, all simulation data points match the measured data within 12%.

6.5.2.1 Adjustment to the Minimum Air Flow Rate

Given by the ASHRAE standard 62.1-2010 (Ventilation for Acceptable Indoor Air Quality), all ventilation zone parameters were calculated in accordance with the ventilation requirement for each HVAC zone served by the HVAC system.

\[
V_{pz} = R_p \cdot P_z + R_u \cdot A_z
\]

(6-1)

where

- \(A_z\) = zone floor area: the net occupiable floor area of the ventilation zone \(\text{ft}^2 \) \((\text{m}^2)\)
- \(P_z\) = zone population: the number of people in the ventilation zone during typical usage.
- \(R_p\) = outdoor airflow rate required per person as determined from Table 6-1
- \(R_u\) = outdoor airflow rate required per unit area as determined from Table 6-1

Note: These values are based on adapted occupants.

There are two scenarios with a minimum ventilation requirement: one is the Required Zone Outdoor Air Flow defined in ASHRAE 62.1, as shown above, the other one is the Requirement of the Air Change per Hour (ACH), which is calculated based on the minimum air flow design factor (0.5 cfm/ft²) and is about 2.5 air changes per hour. Therefore, LBNL suggested a two-stage minimum ventilation should be considered. The first one is based on the ACH calculation, and the second stage is based on the ASHRAE standard for acceptable indoor air quality.

6.5.3 Method of developing baseload based on measured data

During this reporting period, the method for calculating a central load baseline was revised implementing a Modified Learning from Experience (MLFE) algorithm with a Recursive Least Squares (RLS) best fit algorithm for increased accuracy of load prediction. The method was compared to the previous method developed for the project and achieved better results for a given test set of days available in the sMAP database. The purpose for this improvement was the minimization of plant uncertainty for the building control system. It is crucial that there is not a significant amount of plant mismatch in proper control of the building power, thus increasing stability of the control system for the given demand response time period.

6.5.3.1 Theory

The algorithm uses inputs for a given day and produces a single output value for a baseline prediction at each time step, using what is known as Fuzzy Set Theory. Fuzzy set theory is based on the fact that uncertainty is nearly always present in real life systems. Since its introduction by Lotfi Zadeh in 1965, it has brought about a shift from the logic of probability theory, which is based on classical binary (two-
valued) logic to continuous-valued logic. Fuzzy logic involves a mapping between elements of two or more domains. Just as an algebraic function maps an input variable to an output variable, a fuzzy system maps an input group to an output group.

Uncertainty has been viewed over the centuries as incompleteness, imprecision, and complex. Uncertainty can be manifested in many forms: it can be fuzzy (not sharp, unclear, imprecise, approximate), it can be vague (not specific, amorphous), it can be ambiguous (too many choices, contradictory), it can be of the form of ignorance (dissonant, not knowing something), or it can be a form due to natural variability (conflicting, random, chaotic, unpredictable).

Fuzzy logic can be used extensively in many applications related to commercial building management systems and the grid. Fuzzy logic has the ability to predict system behavior not requiring complete accuracy but a relatively high degree of accuracy, usually set by the user with the advantage of significantly shorter calculation time. It also is very useful in predicting, within a reasonable tolerance, the behavior of systems with highly nonlinear characteristics. Systems using fuzzy logic also have a high potential to understand complex systems, devoid of analytic formulations or systems in which the causes and effects are not generally understood but can be observed.

### 6.5.3.2 Calculations

The new method requires a set of training data to generate membership functions that require a set of input that have been “fuzzified” and return a single delta output, in our case real power for the entire building. Data for the hottest ten days over the past year was gathered and used to train the algorithm. A set of input test data for three days were plugged in and tested for accuracy. The algorithm is run for each individual time step, in the preliminary testing phase, every hour, but eventually can be implemented for every 15 minute interval.

The given set of inputs used for the training MLFE algorithm includes previous day power data for the building, morning-of power data for the building, and current real-time weather data. The inputs used for the prediction algorithm are the following:

**Previous days power data:**

- $X_1$: 3 hottest days of previous 10 days average power data for each time step, $PL(d,h)$

**Morning-of data:**

- $X_2$: Actual load at 10 AM day-of, $AL(d,10)$
- $X_3$: Actual load at 11 AM day-of, $AL(d,11)$

**Real-time weather data:**

- $X_4$: Relative humidity at each time step, $RH(d,h)$
- $X_5$: Outside air temperature at each time step, $OAT(d,h)$

**Output:**

- $Y$: Power at each time step, $AL(d,h)$

The data above is first normalized using the maximum values for each category seen in the entire data set. Once normalized, Gaussian membership functions have been used for input output functions, although any membership function could have been used. The output membership function is a delta function, an impulse function of no width, that occurs at a value $b_1$ with full membership.
Rules are developed by the algorithm in the following manner for our system of multiple inputs and a single output:

\[
\text{IF } X_1 \text{ and } X_2 \text{ and } X_3 \text{ and } X_4 \text{ and } X_5 \text{ THEN } Y
\]

Gaussian Membership functions take the form of Equation (1).

\[
\mu = \exp \left[ -\frac{1}{2} \left( \frac{x_i - c_i}{\sigma_i} \right)^2 \right] \tag{1}
\]

- $x_i$: $i$th input variable
- $c_i$: $i$th center of the membership function (where membership achieves maximum value)
- $\sigma_i$: spread of $i$th membership function (constant)

First, a Modified Learning from Experience (MLFE) algorithm must be used to generate a rule-base, since we have no knowledge of the characteristic behavior from the data sets. The rule-base consists of the number of rules and the rule parameters.

The process is initiated by setting the number of rules, $R = 1$, and for $x_1$, $c_1$, $c_2$, $c_3$, $c_4$, $c_5$ we use the first day training data-tuple in $Z$. $X_1$ is set to be $c_1$, $X_2$ is set to be $c_2$, and so on, and $x_4$ is set to $y^1$. In the algorithm, $b_i$ is the point in the output space at which the output membership function for the $i$th rule is
a delta function, and \( c^j_i \) is the point in the jth input universe of discourse where the membership function for the ith rule achieves a maximum. The relative width, \( \sigma^j_i \), of the jth input membership function for the ith rule is always greater than zero. It is important to note that the spreads can never be set to zero, to avoid a division by zero error later in the algorithm. The spread will be assumed to be equal to 0.065.

For this example we would like the fuzzy system to approximate the output to within a tolerance of 0.05, thus we set \( \epsilon_f = 0.05 \). We also introduce a weighting factor, \( \omega \), which is used to calculate the spreads for the membership functions, as given later in Equation (3). The weighting factor is used to determine the amount of overlap between the membership function of the new rule and that of its nearest neighbor. For this project, the value of the initial weighting factor, \( \omega \) is set to 0.08.

The output of the training data set is then compared to the real power data from the training sets to see how well the fuzzy system is mapping the information. The required stopping condition for the algorithm is shown below. The difference must be smaller than the user set tolerance in order for no additional rules to be added.

\[
|f(x^i|\theta) - y^i| < \epsilon_f \quad (2)
\]

If the tolerance is exceeded, a rule is added to the rule-base to represent \((x_2,y_2)\) by modifying the current parameters \( \theta \). \( R \) is set to 2, \( b_2 = y_2 \), and \( c^2_j = x^2_j \).

If an additional rule is needed, the centers for the new rule are set to the next training data inputs, \( x^i_j \), and the relative widths are determined by the MLFE algorithm based on achieving an appropriate overlap between membership functions. This overlap is set by a user defined weighting factor (\( \omega \)).

\[
\sigma^i_j = \frac{1}{\omega} \left| c^i_j - c^\text{min}_j \right| \quad (3)
\]

where:

\( c^i_j \): the current input training data set, \( x^i_j \)

\( c^\text{min}_j \): the nearest membership function centers to the new membership function centers \( c^i_j \)

\( \omega \): the user defined Gaussian membership function width weighting factor

This process of adding additional rules using the next training data set repeats until Equation (2) is satisfied.

**6.5.3.3 Recursive least squares**

After the rule-base has been generated with the MLFE algorithm, the RLS algorithm calculates \( \hat{\theta}(k) \) at each time step \( k \) from the past estimate \( \hat{\theta}(k-1) \) and the latest data pair that is received, \( x^k \& y^k \).

Recall that \( b_i \) is the point in the output space at which the output membership function for the ith rule is a delta function, and \( c^i_j \) is the point in the jth input universe of discourse where the membership
function for the $i^{th}$ rule achieves a maximum. The relative width, $\sigma_j$, of the $j^{th}$ input membership function for the $i^{th}$ rule is always greater than zero.

Now we calculate the regression vector, $\xi$, based on the training data using Eq. (4)

$$
\xi(x) = \frac{\mu_i(x) \prod_{j=1}^{n} \exp \left( -\frac{1}{2} \left( \frac{x_j - c_i^j}{\sigma_j^i} \right)^2 \right)}{\sum_{i=1}^{R} \prod_{j=1}^{n} \exp \left( -\frac{1}{2} \left( \frac{x_j - c_i^j}{\sigma_j^i} \right)^2 \right)} \tag{4}
$$

Recall that in the least squares algorithm the training data $x_i$ are mapped into $\xi(x_i)$ which is then used to develop an output $f(x_i)$ for the model.

A covariance matrix is used to determine the least squares estimate vector of the training set, $\hat{\theta}$, which is calculated using the regression vector and a previous covariant using Equation (6). To do this, an initial covariance matrix, $P_0$, must first be calculated using a parameter, $\alpha$, and the identity matrix, $I$. $P_0$ is used to update the covariance matrix, $P$, in the next time step. A recursive relation is established to calculate the values of the $P$ matrix for each time step using Equation (5). The value of the parameter $\alpha$ should be greater than 0. Here a value of 100 is used for $\alpha$. $I$ is an $R \times R$ identity matrix.

$$
P(0) = \alpha I
$$

$$
P(k) = \frac{1}{\alpha} \left[ I - P(k-1) \xi(x^k) \left[ \lambda I + \left( \xi(x^k) \right)^T P(k-1) \xi(x^k) \right]^{-1} \left( \xi(x^k) \right)^T P(k-1) \right] \tag{5}
$$

$$
\hat{\theta}(k) = \hat{\theta}(k-1) + P(k) \xi(x^k) [y^k - (\xi(x^k))^T \hat{\theta}(k-1)] \tag{6}
$$

$$
f(x|\theta) = \hat{\theta}^T \xi(x)
$$

6.5.3.4 Results

Using the MLFE/RLS algorithm, predictions were made for the afternoon hours from 1 PM to 5 PM in 1 hour intervals. The predicted values were compared against the previous load baseline prediction algorithm. The error was measured in percentage error with the true power values from the three test days chosen.

Parameters

| Tolerance: 0.05 |
| Weighting Factor: 0.08 |
| Initial Spread: 0.065 |

Error Results (in Percentage)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1:00 PM</td>
<td>2.5</td>
<td>3.25</td>
<td>8.0</td>
<td>-7.5</td>
</tr>
</tbody>
</table>
Table 3: Error results.

<table>
<thead>
<tr>
<th>Time</th>
<th>0.43</th>
<th>7.46</th>
<th>4.2</th>
<th>0.23</th>
<th>41.4</th>
<th>13.5</th>
<th>24.0</th>
<th>8.91</th>
</tr>
</thead>
<tbody>
<tr>
<td>2:00 PM</td>
<td>2.67</td>
<td>16.9</td>
<td>6.75</td>
<td>3.4</td>
<td>30.7</td>
<td>18.0</td>
<td>18.21</td>
<td>14.4</td>
</tr>
<tr>
<td>3:00 PM</td>
<td>0.26</td>
<td>0.75</td>
<td>5.13</td>
<td>7.2</td>
<td>37.9</td>
<td>9.0</td>
<td>17.06</td>
<td>6.67</td>
</tr>
<tr>
<td>4:00 PM</td>
<td>-1.3</td>
<td>-1.3</td>
<td>1.8</td>
<td>1.3</td>
<td>37.9</td>
<td>8.2</td>
<td>21.92</td>
<td>4.85</td>
</tr>
<tr>
<td>5:00 PM</td>
<td>-1.3</td>
<td>-1.3</td>
<td>1.8</td>
<td>1.3</td>
<td>37.9</td>
<td>8.2</td>
<td>21.92</td>
<td>4.85</td>
</tr>
</tbody>
</table>

The MLFE/RLS algorithm seems to offer robustness from unusual phenomenon. After further examination of the third test day, October 28, it was found that the building had unusual power behavior on the morning of the test day. Power use at the 10 AM and 11 AM hours was seen as not typical for a non-holiday weekday. It can be seen that the MLFE/RLS algorithm provides a little more robustness to unexpected occurrences in input behavior or disturbances. The other two test days, show relatively no significant difference in the outcomes. In some cases the MLFE/RLS algorithm does better and in other cases the Old Method does better. If more test data were available, a further examination would have been done on accuracy of the two methods.

6.5.4 Demand Response scenario development

The Demand Response scenarios are expected to include curtailment to the overhead lighting, plugloads, and the HVAC system during peak times to achieve the goal of 30% reduction. The team has focused on the HVAC system scenarios, which include reducing load on the Air Handling Units for the office (AHU2A and AHU2B), using global room temperature reset, supply air temperature reset, and static pressure reduction.

6.5.4.1 Understanding HVAC control sequence modeling

6.5.4.1.1 Basic AHU control

In this project, the AHU2A/2B system that provides conditioned air to office spaces in Sutardja Dai Hall is the key to demand reduction. Figures 16 and 17 shows two snapshots from the on-site facility management system, which provides a big picture of AHU2 system implemented, including supply air subsystem (12a) and return air subsystem (12b).
The AHU control sequence includes:

1. Supply/Return Air Fan Control
   a. Two supply fans work in parallel, and the VFD speed of the two supply fans are modulated to maintain the supply duct static pressure set-point of 1.35 in.w.c
b. Two return fans also work in parallel, and the VFD speed are modulated to maintain the total air flow at a level so that the difference between total supply air flow rate and total return air flow rate is constant (21000 cfm).

A MATLAB model was created for the AHU control as seen in Figure 18 below.

![Figure 18: Matlab Simulink Model of AHU control](image)

6.5.4.1.2 Cooling Coil/Economizer Control

a. A temperature sensor senses the supply air temperature, and provides signal to a PID controller, whose output is acting on cooling coil valves, maximum outdoor air dampers, return air dampers and exhaust air dampers, so that the supply air temperature is tracking its set-point, which is 56°F.

b. Minimum outdoor air dampers should be fully open when the AHU2 system is operating.

c. When the outdoor air temperature rises above 70°F, the economizer closes the maximum outdoor air damper and exhaust air damper, and fully opens the return air damper.

d. When the outdoor air temperature drops below 45°F, the cooling coil valve is closed.

We have obtained two sets of trended data (June 13 and 20) for AHU economizer analysis. A simplified air mixing model has been adopted, where mixed air temperature (MAT) is a weighted average of outdoor air temperature (OAT) and return air temperature (RAT). The weightings of the two temperatures are the percentages of the two portions in the mixed air:

\[
MAT = OA\_PCT \times OAT + (1 - OA\_PCT) \times RAT
\]

And hence, we can obtain the outdoor air percentage (OA\_PCT) by

\[
OA\_PCT = \frac{MAT - RAT}{OAT - RAT}
\]

According to the AHU control sequence, the supply air temperature is maintained by a PID whose output is acting on the maximum outdoor air damper. Figure 19 shows the values of outdoor air percentage (OA\_PCT) and outdoor air damper (OAD) on the two data sets.
For BACnet trend data 06-20-2011-1206 (Figure 19), since outdoor air dampers =0 for both 2A and 2B over the recorded time, assuming outdoor air dampers were working well (i.e. both dampers for 2A and 2B were fully closed), the outdoor air percentages in Figure 19 should be all from the minimum outdoor air dampers. Therefore, during the recorded period, **minimum outdoor air dampers contributed about 33.3~40.1% (for 2A) and 33.6~43.7% (for 2B) of the mixed air.**

According to Equation (2), when outdoor air temperature and return air temperature are close to each other, and when mixed air temperature and return air temperature are close to each other, the error in outdoor air percentage calculation will be significant. Therefore, for BACnet trend data 06-13-2011-1534 (Figure 20), we only analyzed data points # 400-945. In AH2B, outdoor air dampers was always 100, implying that total outdoor air dampers (=OAD + MIN_OAD) was 100, which further implies that return air damper was fully closed and exhaust air damper was fully open. In this situation, the outdoor air percentages should be 100, as there was no return air going into mixed air. However, the measured outdoor air percentages were 81.4~98.4%, **NOT 100%**. It’s very likely that the return air damper for 2B was leaking and/or stuck. In AH2A, outdoor air damper was varying in a large range, [0, 60], however, the outdoor air percentages did not change much. In fact, the outdoor air percentage level was very close to the minimum outdoor air damper level obtained from Figure 20. More work is needed to reveal the cause of this observation. Correlation analysis also gave that the correlation coefficient between AH2A outdoor air damper and AH2A outdoor air percentage is -0.7685, implying a negative, if any,
correlation, which does not make much sense. So, in summary, AH2B return air damper might be leaking and/or stuck, and AH2A maximum outdoor air damper might be malfunctioning.

The cooling coil valve is another actuator controlled by the supply air temperature PID controller. However, it is not an easy task to model the heat transfer dynamics in a cooling coil valve. An intuitive yet rationale alternative means is to fit the output of the heat transfer to a function of the input. Since the cooling coil heat transfer is to reduce the temperature of mixed air to supply air temperature and the supply air flow rate is very stable, it is reasonable to first investigate the relation between temperature drop (mixed air temperature – supply air temperature) and the cooling coil valve process value. Figures 21 and 22 shows the analysis done on both data sets.

Figure 21: (MAT-SAT) vs CCV <BACnet Trend Data 06-20-2011-1206>

Figure 22: (MAT-SAT) vs CCV <BACnet Trend Data 06-13-2011-1534>
It seems that BACnet trend data 06-20-2011-1206 has too few data points to draw any conclusion of supply air temperature drop and cooling coil valve (Figure 21). However, trend did exist based on 06-13-2011-1534 data set (Figure 22).

Figure 22 AH2A: if we ignore the data points with cooling coil valve closed, i.e. CCV=0, we obtain
\[(MAT - SAT)_{AH2A} = 0.6744 \times AH2A_{CCV} + 6.5255 \quad (R^2 = 0.6527) \quad (3)\]

And Figure 22 AH2B:
\[(MAT - SAT)_{AH2B} = 0.7509 \times AH2B_{CCV} - 18.923 \quad (R^2 = 0.8951) \quad (4)\]

A correlation analysis suggests that the correlation coefficient between supply air temperature drop and cooling coil valve are:
- AH2A: 0.8079
- AH2B: 0.9461

Therefore we can conclude that there is strong positive correlation between supply air temperature drop and the value of cooling coil valve process variable, and a linear relation is very likely.

6.5.4.1.3 Zone Temperature Control—Reheat VAV box

In a VAV box, the cooling mode and heating mode alternate when the room temperature passes through a threshold value. In this report, only the cooling mode is considered.

In cooling mode the PID controller generates a loopout signal which is used in creating a FLOW STPT following the rule:
\[FLOW\ STPT = CLG\ LOOPOUT \times (100 - \frac{CLG\ FLOW\ MIN}{CLG\ FLOW\ MAX} \times 100) + \frac{CLG\ FLOW\ MIN}{CLG\ FLOW\ MAX} \times 100 \quad (5)\]

For the cooling mode, most zones’ minimum air fraction is set as 0.4. For Room 464, minimum air is 300cfm and maximum air is 752cfm. For heating mode, the minimum air fraction is one: the flow is fixed and set as the minimum air of the cooling mode.

According the collected data of Room 4-464 on 6-30-2011, the measured FLOW STPT and measured CLG LOOPOUT satisfy the relationship above.

Likewise, the flow Loop feedback signal FLOW is calculated by the rule:
\[FLOW = \frac{AIR\ VOLUME}{CLG\ FLOW\ MAX} \times 100 \quad (6)\]

Measured AIR VOLUME and measured FLOW validate their relationship above according to the collected data of 6-30-2011.

The MATLAB simulink model is built under the following assumptions:

1. Under the cooling mode, the thermal load of single zone Qt has a fixed value during a small period of time.

2. Cooling mode and heating mode alternate when the room temperature exceeds a threshold value, but for now only take the cooling mode into consideration.
3. All the data used in process identification is based on the experiment which the setpoint of room temperature is set to 60K at 1:00AM to 3:00AM (Data: row 1136- row 1255).

The final Simulink Model for cooling mode is shown as follows:

![Simulink Model](image)

Figure 23: VAV control Simulink Model

We assume the dynamics of the thermal process of single zone as the following:

\[ \rho C_{pa} V_r \frac{dRMT}{dt} = \rho C_{pa} (SAT - RMT) - \frac{(RMT - OAT)}{R} + Qt \]  

(7)

The Relationship between Damper Position and AIR VOLUME:

\[ AIR VOLUME = a \times DMPR POS + b \]  

(8)

By applying the system Identification method using least squares, the thermodynamics can be identified:

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Rho</th>
<th>Cpa</th>
<th>Vr</th>
<th>R</th>
<th>Qt</th>
<th>a</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>0.6594</td>
<td>0.0478</td>
<td>567.7237</td>
<td>131.7605</td>
<td>269.1131</td>
<td>0.11</td>
<td>301.69</td>
</tr>
</tbody>
</table>

Table 4: Parameters for single zone model identification.

Figure 24 is the simulation result for the least squares method:

Comparison of Measured Room Temperature (RMT) and Simulated Room Temperature (RMT_sim)

![Simulation Result](image)

Figure 24: Simulation Result Using LS Method

Figure 25 shows the simulation results using ARX model:
The results show that the simulated result of SAT is not acceptable due to the lack of parameters of thermodynamics. To address this issue, adding more parameters to the thermodynamics would be an effective solution. In addition, to adjust the dynamics of thermal process of a single zone, approximating with an ARX model is the most promising solution for this problem.

### 6.5.4.2 Individual DR Strategy Investigation

The updated AHU and Reheat VAV models were incorporated into a revised version of EnergyPlus model, which was named as “CITRIS V5-1”. This model has the air economizer mechanism implemented, and the minimum air fractions for all VAV systems are set at 0.4 (in accordance with the settings in the building). Calibration against the measured energy consumption showed about 85% accuracy of the model.

Based on E+ model delivered in May, 2011 (Version 5), we investigated individual DR strategies by applying the global room temperature reset and AHU supply air temperature reset. We found that a high minimum air fraction can prevent energy consumption reduction. We also plan to study the impact of static pressure reset. However the current E+ model doesn’t support a pressure control fan model. We have to model the fan manually and derive some theoretical results of the impact of static pressure change on demand reduction.

**Weather pattern classification**

As mentioned above, the August weather has been categorized based on historical data. A total of 19 patterns have been identified. Other than finding the optimal control strategy for each weather pattern, the difference of the energy consumption yielded by different weather patterns is also of interest. For this purpose, three typical weather patterns were chosen for our tests representing a hot (Pattern 2), mild (Pattern 4) and cool (Pattern 19) weather. The outdoor dry bulb temperature profiles are drawn in Figure 26.
6.5.4.2.1 Global Zone Temperature Reset

The optimal “Pre-Cooling and Exponential Zone Reset” strategy for each pattern was adopted in testing, which has normal temperature at 72°F, pre-cooling temperature at 70°F ($t_1$ to $t_2$), reset temperature at 78°F ($t_2$ to $t_3$), with a pre-cooling starting time 6:00am. The three key transition times for each strategy are summarized in Table 5.

![Outdoor temperature profile](image)

**Table 5: Optimal set-point strategy times tested.**

<table>
<thead>
<tr>
<th>Pattern</th>
<th>$t_1$</th>
<th>$t_2$</th>
<th>$t_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>5</td>
<td>11</td>
<td>18</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
<td>12</td>
<td>18</td>
</tr>
<tr>
<td>19</td>
<td>5</td>
<td>13</td>
<td>17</td>
</tr>
</tbody>
</table>

The total HVAC system load profiles are plotted in Figure 9. According to this data, a GTA strategy resulted in the most peak load reduction (about 40kW) in hot weather, whilst on the cool day, no significant, if any, peak load shedding would be expected.
We first studied the zone temperature profiles. Our current model defined 135 zones including offices, labs, conference rooms and others. We chose 17 of these zones to represent the temperature changes in the areas of interest. These 17 zones are listed in Table 6.

<table>
<thead>
<tr>
<th>Floor</th>
<th>Zones</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>L2_200, L2_250</td>
</tr>
<tr>
<td>3</td>
<td>L3_356, L3_310, L3_337</td>
</tr>
<tr>
<td>4</td>
<td>L4_464, L4_422, L4_421</td>
</tr>
<tr>
<td>5</td>
<td>L5_568, L5_550, L5_510</td>
</tr>
<tr>
<td>6</td>
<td>L6_621, L6_666, L6_623</td>
</tr>
<tr>
<td>7</td>
<td>L7_768, L7_738, L7_722</td>
</tr>
</tbody>
</table>

Table 6: Representative Zones

The zone temperature profiles of baseline shown in Figure 28 suggest that the temperature control for all monitored zones is functioning, and external weather does not have significant influence on zone temperature profiles.
We further investigated the energy consumption of three essential components of HVAC systems: the supply fan, return fan and the absorption chiller. The energy consumption was plotted in Figure 29(a)-(c).

Figure 29: Breakdown of HVAC power reduction with global temperature reset.
From Figure 29 (a) and (b), we find that the fan units in the AHU system consume up to 80kW electricity; although this represents less than 16% of total HVAC energy consumption, it contributes the majority of peak load reduction. This result suggests our future work needs to focus on adjusting the fan set-points, such as duct static pressure and air volumes.

The fans are currently modeled in a way that does not allow sophisticated adjustment. A new version of Energy Plus model is under development. However, the current model allows us to adjust supply air temperature and VAV minimum air fraction, which are believed to be essential for fan power consumption.

6.5.4.2.2 Supply air temperature impact on energy consumption

Without changing zone temperature, we studied how supply air temperature impacts the demand reduction. The baseline zone temperature is set as [70F, 72F] for dual-setpoint strategy. The power of return fans, supply fans, absorption chiller and total HVAC system was obtained from the EnergyPlus V5 model simulation. The temperature was monitored for the same 17 zones.

Figures 30, 31, and 32 illustrate the impacts of changing supply air temperature under hot weather condition (Pattern 2), mild weather condition (Pattern 4) and cool weather condition (Pattern 19) while Figures 33, 34, and 35 show the zone temperature profiles for these days under different supply air temperature setpoints. The base supply air temperature set-point is set as 56°F.

![Figure 30: HVAC power vs. SAT (Pattern 2 (hot), constant SP).](image-url)
Figure 31: HVAC power vs. SAT (Pattern 4 (mild), constant SP).

Figure 32: HVAC power vs. SAT (Pattern 19 (cool), constant SP).
Figure 33: Zone Temperature vs. SAT (Pattern 2, constant SP).

Figure 34: Zone Temperature vs. SAT (Pattern 4 (mild), constant SP).
Here are the conclusions from the plots:

1. Only Pattern 4 shows substantial HVAC energy consumption change with the supply air change. However, supply air temperature reset will not save energy. Instead, by increasing supply air temperature, we will have smaller temperature difference between supply air and room air, so more air flow will be required, and thus supply fan and return fan energy will be increased. However, it is possible that less chilled water is required to cool that mixed air to supply air temperature, so chiller energy will be decreased, which has to be validated by looking into absorption chiller steam usage. From the temperature profile, resetting supply air temperature leads to zone temperature increase, which would suggest overall energy consumption actually is reduced.

2. For Pattern 19, it is easy to explain the negligible impact of supply air temperature change since the cooling load itself is negligible. As fans are running at minimum level, increasing SAT results in total HVAC energy reduction is due to less use of chiller pump power.

3. For hot days (Pattern 2), it seems that E+ model has a fan max power setting we find skeptical (supply fan 42kW, return fan 36kW), which make the system saturated for all the supply temperature settings. The correct settings for max power has to identified, which uses two 75hp supply fans, corresponding to a total 100KW of rated supply fan power. Theoretically, if the fan runs at a saturated state (constant air volume), the chiller energy consumption will be dramatically reduced by raising supply air temperature. We will further investigate this.
4. Changing the supply fan will not be intuitive for demand reduction with current sizing of the Sutardja Dai Hall HVAC system. Resetting the supply air temperature will not necessarily reduce the electricity demand since the VAV boxes will work hard to request more air flow to compensate the higher supply air temperature which consequently increases fan energy consumption. Equivalent energy from steam should be considered for demand reduction. Additional constraints have to be made, e.g., limit the zone air flow to minimum while resetting the supply air temperature.

6.5.4.2.3 Minimum Air Fraction impact on energy consumption

Minimum air fractions for all zones are 0.1, 0.2, 0.3 and 0.4. Figures 36, 37, and 38 show the simulation results of minimum air fraction changes on energy consumption. It is expected that substantial reduction of base supply/return fan energy consumption will be achieved when VAV boxes are running at minimum air, e.g., under cool weather conditions.

However, according to simulation results shown in Figures 36, 37, and 38, changing the minimum air fraction does not affect HVAC energy consumption, even for Pattern 19. The E+ model should be revised before we can test the impact of minimum air fraction change.
Figure 36: HVAC power vs. Min Air Frac (Pattern 2 (hot), constant SP)
Figure 37: HVAC power vs. Min Air Frac (Pattern 4, constant SP).
6.5.4.3 Fan models

We also would like to investigate the impact of Static Pressure Reset on HVAC energy usage. However, the current E+ model doesn’t allow for such change. While LBNL is working on improving the fan model in E+, we did some investigation to identify a fan energy consumption model from theoretical analysis and real measurement data.

From Figure 38 above, we can see that, no matter how cold the outdoor weather is, the energy consumption of fan components has a lower limit due to the minimum air requirements. This limit is about 28kW for supply fans and about 26kW for return fans, according to the simulation model. We are able to verify the existence of this power consumption lower bound.

See Figure 39: three days were chosen to represent three typical days- cold day (02/18), mild day (06/01) and hot day (07/03). Fan power was calculated using the following equation:

\[ W = 0.98 \sqrt{3} \times I \times V \]  

Where, \( I \) is the VFD current trended via BACnet, and \( V \) is the voltage which is constant at 480V.
Return fan flow was monitored as the total flow of both AH2A and 2B return fans.

The result is summarized in Table 7

<table>
<thead>
<tr>
<th></th>
<th>cold</th>
<th>mild</th>
<th>hot</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>2/18</td>
<td>06/01</td>
<td>07/03</td>
</tr>
<tr>
<td>OAT(F)</td>
<td>37-45</td>
<td>53-64</td>
<td>59-87</td>
</tr>
<tr>
<td>Supply Fan</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Power (kW)</td>
<td>35-37</td>
<td>35-37</td>
<td>35-39</td>
</tr>
<tr>
<td>Flow (10000CFM)</td>
<td>3.4-3.5</td>
<td>3.3-3.6</td>
<td>3.3-3.6</td>
</tr>
<tr>
<td>Return Fan</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Power (kW)</td>
<td>14-15</td>
<td>13-15</td>
<td>14-15</td>
</tr>
<tr>
<td>Flow (10000CFM)</td>
<td>2.2-2.3</td>
<td>2.2-2.4</td>
<td>2.1-2.5</td>
</tr>
</tbody>
</table>

Table 7: Fan Power and Flow.

Figure 39: Fan Power and Flow
According to the above data, we can see that during cold, mild and most of the time on hot days, the fan flows and fan powers are at relatively the same level, whilst at very hot times, such as 14:00-18:00 on the hot day, the fan power and flows significantly increased. This implies that during cold, mild and most of the time on hot days, the fan is running at a low level determined by zone minimum air demands, and will run faster when the outdoor air temperature reaches 80°F or higher. The fan power range obtained from BACnet trend data (Table 7) are not the same with those identified from simulation, because the simulation was not calibrated against fan energy meter data.

Zone minimum air settings are defined by VAV control. According to the control sequence of each VAV box, while in the heating mode, the air volume is maintained at the minimum air flow rate; in the cooling mode, the air flow rate is controlled by the VAV air damper, whose position is controlled by the room air temperature PID controller. By implementing optimal global temperature adjustment strategies, we are basically trying to keep the air flow rate to each zone at the minimum level. But in reality, the minimum air volume to each zone is set at a point much higher than the requirement. Simple calculation would prove this.

According to ASHRAE Standard 62.1-2010 (Ventilation for Acceptable Indoor Air Quality), for office space, the occupancy density (D_o) is 5 per 1000 ft², the by-person outdoor air rate (R_p) is 5 cfm/person, and by-area outdoor air rate (R_a) is 0.06 cfm/ft².

Take zone S4-16 (office room L4-464) as an example: the area (A) is 300 ft², so the required minimum fresh air flow rate (Q_{minOA}) should be

\[ Q_{minOA} = A \times D_o \times R_p + A \times R_a = 300 \times 5 + 300 \times 0.06 = 25.5 \text{ cfm} \]  

Consider the previous finding that the outdoor air takes at least 33% of supply air, the minimum air flow rate (Q_{minSA}) for zone S4-16 is:

\[ Q_{min} = \frac{Q_{minOA}}{33\%} = \frac{25.5}{33\%} = 77.3 \text{ cfm} \]  

However, the trend data revealed that the minimum air flow rate for zone S4-16 is set at Q_{min}=300 cfm, which is nearly four times higher than required. This is the case for most, if not all, zones in Sutardja Dai Hall.

We believe that if we lower all minimum air flow rate set-points, we can lower the total fan air volume, and thus reduce the fan power consumption for peak demand response. Because, according to the first fan law, the fan air flow (Q) is proportional to fan speed (V), i.e.:

\[ Q \propto V \]  

And the second fan law says the pressure rise (DP) is proportional to the square of the fan speed:

\[ DP \propto V^2 \]  

And an ideal fan power equation is:

\[ W = DP \times Q \propto Q^3 \]  

Therefore, reducing total air volume could reduce fan power.

Putting fans into ductwork yields a slightly different situation. In this case, fan pressure rise is not proportional to the square of the fan speed. Instead, it is the summation of two portions:

\[ DP = P_s + P_v \]  

Where, \( P_s \) is the duct static pressure; and \( P_v \) is the velocity pressure, caused by the movement of the air, and is related to the air flow rate:
where $k$ is a flow-pressure constant determined by the duct geometry. And the fan power $(W)$ then has:

$$W = DP \times Q = (P_s + P_f)Q = P_sQ + kQ^3$$

In the CITRIS building, supply fans are maintaining constant supply duct static pressure. As $P_s$ is maintained constantly, reducing supply air volume $Q$ will reduce $DP$. The supply fan power $W$ will decrease in the end. Return fan control is maintaining a constant difference between return fan air volume and supply air volume. Given that supply air volume decreases due to total air demand decrease, return air volume should decrease accordingly.

A simple calculation can be done to verify Equation 17 for our work. Supply fan current and flow have been trended, and the static pressure set-point is known (1.35 inWC or 336 Pa). We can find instantaneous fan power $(W)$ from the VFD current using Equation 9.

Let $Y=W-P_sQ$, and $X=Q^3$. Trend data 07-01-2011 gives that the correlation coefficient between $X$ and $Y$ is 0.882 for supply fan A, and 0.843 for supply fan B. Strong correlation between $X$ and $Y$ proves the validity of our model. The upper two panels of Figure 40 are the Y-X scatter graphs for both fans. Note that averaging smoothing needs to be applied to the VFD current and fan flow rate data, to reduce the impact of sensor noises, otherwise the model identification will give a faulty result. From the lower two panels of Figure 40, we can see that the fan power predicted by our model matches the measured one closely. The model parameters estimated are shown on top of each plot. One issue is that the residue term $(C)$ has a value about 28,600 W, which is quite large. We suspect that the fan power calculation (Equation 9) might be questionable.

Using this fan power predicting model, we tried to predict the amount of power reduction if zone minimum air settings are adjusted to the lowest level defined by ASHRAE standard. A previous estimation showed that current minimum air settings are about four times of the required. **If we lower all zone minimum air settings to $\frac{1}{4}$ of their current values, the total supply air flow might be reduced up to $\frac{1}{4}$ of the current rate.** The green curves in the lower two panels of Figure 40 showed the predicted supply fan power if the new settings are implemented. The peak load reduction of each supply fan could be 6~9kW, according to this prediction.
Applying the same model to return fans gave worse results (Figure 41). There are two possibilities:

a) The flow rate for each return fan is not available. Instead, the total flow rate combining both return fan A and return fan B is trended. So the Figure 41 result was achieved by assuming equal flow distribution between two return fans.

b) Return fans are maintaining constant difference between total supply air volume and total return air volume. The return duct static pressure is highly dynamic. It is possible that the flow-pressure constant $k$ in Equation 16 varies at different duct static pressure.

However, the lower two panels of Figure 41 still suggest a return fan power reduction if air requirement is decreased to $\frac{1}{4}$. It seems that about 2kW power reduction could be expected for each return fan.
When the new trend data with “VFD:POWER” is available, fan power consumption can be recorded, instead of calculated using Equation 9. “VFD:POWER” data reports the fan power percentage with respect to the fan maximum power. As of July 15, 2011, the supply fan maximum power is known to be 90 HP (~67 kW), but return fan maximum power is not clear. Applying parameter estimation to the new trend data (with “VFD:POWER”) using Equation 17 yielded a much better result (shown in Figure 42).
Considering that the residual terms in Equation 17 are significant, a new model with motor energy efficiency ($\text{eff}$) is introduced, as described in Equation 18:

$$W = \frac{1}{\text{eff}} (P_s Q + kQ^3)$$  \hspace{1cm} (18)

Equation 18 also provides a good fit of the data, and it eliminates the residual terms (shown in Figure 43).
Figure 43: Fan power model with VFD:POWER and eff (supply fan).

The models provided by Equations 17 and 18 also suggest that supply fan power reduction could be achieved by turning down the supply duct static pressure set-point. In reality, reducing duct static pressure should be done with caution, because the air handling unit requires the duct static pressure to be high enough to overcome duct flow friction, and deliver air to all zones. There must be a threshold for duct static pressure that can guarantee enough air delivery to all zones, even when the maximum air volume is demanded. As the flow dynamics in the ductwork is complicated, the static pressure threshold can hardly be described as an analytical function of zone air demands. We can only find it by either a field test or estimate it by simulation. However, we currently do not have a proper simulation model to emulate the flow dynamics in the supply ducts. Lawrence Berkeley National Lab has implemented a simple single duct dynamic model in EnergyPlus. However, that model is claimed to be acceptable to simulate "single duct" scenarios, and is definitely not appropriate to simulate the complex ductwork such as that found in Sutardja Dai Hall. So, it seems that field testing is the only way for us to find out the capacity of energy saving by adjusting static pressure set-point.

6.5.5 SEB development for central Load DR strategy Implementation

This section explains the central load DR control implementation developed within SEB, which covers controlling HVAC equipment and central lighting. HVAC control is implemented by manipulating a variety of HVAC parameters such as controlling of Zone temperature setpoints, Supply Fan speed, Supply air temperature, Alternating AHUs etc. But usage of these parameters could vary from building to building and should be discussed with the building owner in order to use them for DR control. DR strategies for central load are configured thorough the user interface.

Demand Response strategies are implemented in an incremental basis starting from fixed control strategies to a more sophisticated model predictive strategy mode. However the building should work only in one mode at a given point of time. So this mode can be decided by the building owner and changed by using the user interface. The following are the modes that can be configured:

- None
- Instant
- PeakDayPricing
The basic idea of introducing the modes is to provide implementation step-by-step and also to provide a way to adopt fixed strategies decided by the building owner that suit best his needs.

**6.5.5.1 Instant Strategy Mode**

As a first step, a set of strategies will be defined and one strategy selected manually for each kind of DR event. The user interface supports the configuring of strategies and selection of one of them by the user for each DR event category.

<table>
<thead>
<tr>
<th>DR Event Category</th>
<th>Strategy</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>DRHigh</td>
<td>Changes Temperature setpoint to 78</td>
</tr>
<tr>
<td>Medium</td>
<td>DRModerate</td>
<td>Changes Temperature setpoint to 75</td>
</tr>
</tbody>
</table>

*Table 8: DR Strategies: Instant.*

The selected strategy will be updated in the runtime data repository so that runtime components can use it to apply to the building management system for a particular DR event period. During this mode, there is no evaluation happening on the Runtime side, the selected strategy is simply applied to the building.

**6.5.5.2 PeakDayPricing Mode**

This is bit more advanced when compared to the Instant Strategy option. With this option the best strategy will be selected out of available strategies for a particular DR event category. This option also considers the forecasted outside weather conditions. The best strategy is evaluated using an energy simulation with the EnergyPlus model. During this option, notice of the DR event is provided a day before it happens, so we have sufficient time to evaluate best strategy and to apply it.

![Figure 44: Peak Day Pricing DR strategies](image)

The following table shows a sample of strategy assignment to each DR category:

<table>
<thead>
<tr>
<th>DR Event Category</th>
<th>Strategy</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>ClassifyZoneCooling</td>
<td>Uses all CITRIS office temperature setpoints</td>
</tr>
<tr>
<td></td>
<td>ExpReCooling</td>
<td>Uses all CITRIS office temperature setpoints</td>
</tr>
</tbody>
</table>
classify zone heating uses all citris office temperature setpoints

strategy cooling uses all citris office temperature setpoints

medium classify zone cooling uses all citris office temperature setpoints

exp re cooling uses all citris office temperature setpoints

classify zone heating uses all citris office temperature setpoints

strategy cooling uses all citris office temperature setpoints

<table>
<thead>
<tr>
<th>Table 9: DR Strategy example for Peak Day Pricing.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criteria</td>
</tr>
<tr>
<td>---------------------------</td>
</tr>
<tr>
<td>peak energy</td>
</tr>
<tr>
<td>peak price</td>
</tr>
<tr>
<td>total energy</td>
</tr>
<tr>
<td>total price</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 10: Strategy evaluation criteria.</th>
</tr>
</thead>
</table>

6.5.6 Distributed Load DR Algorithm

During the current reporting period, SCR created five different distributed DR control scenarios (as sent to UCB earlier). We are planning to demonstrate the first two scenarios of applying adaptive DR control. These two strategies are essentially central optimization methods. However, it is adaptive which means the DR allocation will be updated during run time, as each distributed (gateway) agent has new energy use requirements. It will either send updated load use priority to the central DR manager and let the central DR manager command distributed loads directly based on the total utility function optimization, or send a new cost profile to the central DR manager and receive a new DR assignment. Then the distributed intelligence will decide how to control the loads to meet the demand reduction locally.

6.5.6.1 Problem Formulation

Each agent used for managing load shedding contains a load set and each load is characterized by type (discrete/continuous), minimum power and maximum power and priority.

Assume that we have $N_a$ agents, and we use $r_i$ to denote the load of agent $i$ ($i=1, 2, \ldots, N_a$), and $L_{ij}$ to represent load of agent $i$, where $j=1,2,\ldots,N_{ai}$, $N_{ai}$ is the number of load of Agent $i$. $r_i$ can be expressed as Equation (19).

$$r_i = \sum_{j=1}^{N_{ai}} L_{ij}$$

The polynomial function is used to evaluate the cost function of each load, as shown in Equation (20).
\[ u(L_{ij}) = a_0^{ij} + a_1^{ij}L_{ij} + a_2^{ij}L_{ij}^2 \]  \hfill (20)

Two approaches to obtain the allocation of each load are feasible. The first one is using the cost function of each directly, and each load sends its cost function to the central DR manager, then the central DR manager uses the optimization methods to determine the optimal allocation. The second one is the control center first determines the optimal allocation for each agent, and then the agents determine the optimal allocation for each load. In this scenario, the loads do not need to send their cost functions to the control center; they send them to the corresponding agents instead. Each agent sends its cost function to the control center in order to obtain optimal allocation.

6.5.6.2 Optimization for Scenario 1

Consider a demand response control problem with participants of \( n \). The original load is \( R_0 \), the objective of shedding is \( R_p \), and, the reduction load of which is represented by \( R \), which satisfies following equation.

\[ R = R_0 - R_p \]  \hfill (21)

Use \( r_i \) (\( i=1,2,...,n \)) to denote the allocation of participant \( i \), and \( f_i(r_i) \) to represent the reduction cost function, so the problem can be described as a task allocation problem, which can be expressed as follows (in an unconstrained auction):

\[
\begin{align*}
\min & \sum_{i=1}^{n} f_i(r_i) \\
\text{st.} & \sum_{i=1}^{n} r_i = R \\
& r_i^L \leq r_i \leq r_i^U
\end{align*}
\]  \hfill (22)

Suppose that the cost function \( f_i(r_i) \) are convex and differentiable and is continuous in a surrounding of allocation, \( r_i \), so, a Lagrangian function can written as follows:

\[ \text{Min } \sum_{i=1}^{n} f_i(r_i) - \lambda (\sum_{i=1}^{n} r_i - R) \]  \hfill (23)

The optimal allocation satisfies that

\[
\begin{align*}
\frac{\partial f_i(r_i)}{\partial r_i} - \lambda &= 0 \\
\sum_{i=1}^{n} r_i - R &= 0 \\
r_i^L \leq r_i \leq r_i^U
\end{align*}
\]  \hfill (24)

According to Equation (24), if there exists a \( r_i \) in range \([0, R]\) which satisfies the first equation of Equation (22) for each \( f_i(r_i) \), we define this allocation as a unconstrained allocation. We can solve the equation (22) without considering the inequality constraints \(( r_i^L \leq r_i \leq r_i^U)\). Obviously, if an optimal allocation is achieved, the derivatives of \( f_i(r_i) \) for all the participants equal to \( \lambda \), as \( f_i(r_i) \) is defined as a cost function. Thus, we define the parameter \( \lambda \) as clearing marginal cost. The auction process can defined as follows:

1) The auctioneer initiates a \( \lambda_0 \), and sends this signal to all participants.

2) Each participant calculates its allocation \( r_i \) according to the first equation of Equation (24), and sends this allocation back to the auctioneer.

   Usually, Equation (24) is a nonlinear equation; we can use Newton-Raphson Method to solve it.

   The formulas are shown in Equation (25)
The auctioneer calculates the sum of the allocation of all participants and compares it to $R$.

If $|\sum_{i=1}^{n} \eta_i - R| \leq \varepsilon$, the auctioneer sends this cost as the final cost, else, if $\sum_{i=1}^{n} \eta_i - R > \varepsilon$, decreases the clearing cost $\lambda$, whereas if $\sum_{i=1}^{n} \eta_i - R < -\varepsilon$ increase it, where $\varepsilon$ is the arbitrary constant as for the accuracy index.

The clearing cost $\lambda$ is updated according to the following expression \[26\]:
\[
\lambda^{k+1} = \lambda^{k} + r^{k} (R - \sum_{i=1}^{n} \eta_i)
\]

Where $r^{k} > 0$ is the iteration step-size at step $k$.

4) The participants receive the clearing cost, if it is the final clearing cost, then do the load shedding according to allocation, else redo step (3).

If there does not exist such a $\eta_i$ which satisfies the first equation of Equation (24) for some of the $f_i(\eta_i)$, then we define this kind of allocation as a constrained allocation.

The process of a constrained auction is much the same as unconstrained auction, however, the step (2) is replaced by the following step.

(3)'
\[
\frac{\partial f_i(\eta_i)}{\partial \eta_i} \begin{cases} 
\leq \lambda_i, & \eta_i = \eta_i^u \\
= \lambda_i, & \eta_i^l \leq \eta_i \leq \eta_i^u \\
\geq \lambda_i, & \eta_i = \eta_i^l
\end{cases}
\]

Actually, the unconstrained auction is the special case of the constrained auction.

The reduction cost of each bidder is determined by a utility function. The higher value of the utility, the higher value the reduction cost is. For many applications, it is very normal to have a concave utility function. In this paper, we use the polynomial expression to evaluate cost function, as shown in Equation (28)
\[
u(r) = a_0 + a_1 r + a_2 r^2
\]

Where, $r$ is the reduction of load, and the coefficients $a_0, a_1, a_2$ vary according to different occupancies. For each occupancy, $r$ has a lower limit and upper limit.

**Example:**

Assume the original load is 1000W, according to a Demand Response notification, we set the objective of load shedding to 500W.

We have three occupancies, the cost functions of which corresponding reduction load are shown below.

occupancy1: $u_1(r) = 0.1 + 0.0002r + 0.0020r^2, r \in [10, 200]$,

occupancy2: $u_2(r) = 2.0 + 0.2000r + 0.0000r^2, r \in [50, 200]$,

occupancy3: $u_3(r) = 5.0 + 0.1000r + 0.0015r^2, r \in [100, 200]$.

The cost functions are also shown in Figures 45 and 46 below.
The search process of optimal load reduction using an analytical method is shown in Table 11 below:

Table 11: Discovery of optimal load reduction.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.500</td>
<td>125.0 250.0 133.3</td>
<td>508.3</td>
<td>-8.28333</td>
<td>153.35000</td>
</tr>
<tr>
<td>1</td>
<td>0.499</td>
<td>124.7 250.0 133.0</td>
<td>507.7</td>
<td>-7.70000</td>
<td>153.05862</td>
</tr>
<tr>
<td>2</td>
<td>0.498</td>
<td>124.5 250.0 132.7</td>
<td>507.1</td>
<td>-7.11667</td>
<td>152.76783</td>
</tr>
<tr>
<td>3</td>
<td>0.497</td>
<td>124.2 250.0 132.3</td>
<td>506.5</td>
<td>-6.53333</td>
<td>152.47762</td>
</tr>
<tr>
<td>4</td>
<td>0.496</td>
<td>124.0 250.0 132.0</td>
<td>505.9</td>
<td>-5.95000</td>
<td>152.18800</td>
</tr>
<tr>
<td>5</td>
<td>0.495</td>
<td>123.7 250.0 131.7</td>
<td>505.4</td>
<td>-5.36667</td>
<td>151.89895</td>
</tr>
<tr>
<td>6</td>
<td>0.494</td>
<td>123.5 250.0 131.3</td>
<td>504.8</td>
<td>-4.78333</td>
<td>151.61050</td>
</tr>
<tr>
<td>7</td>
<td>0.493</td>
<td>123.2 250.0 131.0</td>
<td>504.2</td>
<td>-4.20000</td>
<td>151.32262</td>
</tr>
</tbody>
</table>
The reduction load for occupancy 1 is 121.7W, for occupancy 2 is 250W, and occupancy 3 is 129.0W. As the maximum margin value of cost function for occupancy 1 is 0.4, which is smaller than the clearing margin cost, 0.487, so the load reduction of occupancy 2 should utilize the upper limit, i.e., 250W.
6.5.6.3 Scenario 2: Particle swarm optimization

The method described above is deterministic and it requires continuous and differentiable cost function for each participant; however, it is not practical to obtain such kind of function for every participant. This section we will discuss another optimization method for handling this issue.

For the cost function, \( f_i(r_i) \), we assume that it is discrete and follows a step change, as shown in Figure 47:

![Figure 47: Discrete cost function with step change.](image)

We use the particle swarm optimization (PSO) method to solve the load shedding problem described in the previous section. The constraints include both equalities and inequalities. Use \( x = [r_1, r_2, \ldots, r_n] \) to represent the allocated load of the participants.

The inequalities constraints can be written into following expression, where \( J \) is the number of inequalities.

\[
g_i(x) \leq 0 \quad i = 1, 2, 3, \ldots, J
\]

(29)

Since an inequality constraint of the form, \( g_i(x) \geq 0 \), can also be represented as \( -g_i(x) \leq 0 \), so the expression denotes the general form of inequalities constraints.

Rewrite the equalities constrains as follows:

\[
h_j(x) = 0 \quad j = 1, 2, 3, \ldots, K
\]

(30)

In order to implement PSO, this is transferred into the following inequality expression, where \( \epsilon \) is a infinitesimal arbitrary constant.

\[
|h_j(x)| \leq \epsilon
\]

(31)

Furthermore, it can be represented by the inequalities above.

\[
-h_j(x) - \epsilon \leq 0
\]

(32)

\[
h_j(x) - \epsilon \leq 0
\]

(33)

Thus, we convert the equalities constraints into inequalities constraints, which follow the formation of above. So the constraints, in general can written as Expression (34).

\[
g_i(x) \leq 0 \quad i = 1, 2, 3, \ldots, J + K
\]

(34)

The penalty function is introduced for handling the constraints, and is defined as follows:
\[ P(x) = y(k)H(x) \]  
\[ k \] is the algorithm’s current iteration number and \( y(k) \) is dynamically modified penalty value, usually, following formulas are used to determine this value.

\[ y(k) = \sqrt{k} \quad \text{or} \quad y(k) = k\sqrt{k} \]  
(36)

\( H(x) \) is the penalty factor, which is determined below:

\[ H(x) = \sum_{i=1}^{J+K} \theta(q_i(x))q_i(x)^{y(q_i(x))} \]  
(37)

Where, \( q_i(x) = \max(0, g_i(x)), i = 1, 2, \ldots, J + K \) is a relative violated function of constraints, \( \theta(q_i(x)) \) is a multi-stage assignment function, \( y(q_i(x)) \) is the power of the penalty function, \( g_i(x) \) is described above.

In this paper, \( \theta(q_i(x)) \) is defined as follows:

\[ \theta(q_i(x)) = \begin{cases} 1 & q_i(x) < 0.1 \\ 5 & q_i(x) < 1 \\ 10 & q_i(x) < 10 \\ 100 & q_i(x) < 20 \\ 200 & \text{otherwise} \end{cases} \]  
(38)

\( r(q_i(x)) \) is defined as:

\[ y(q_i(x)) = \begin{cases} 1 & q_i(x) < 1 \\ 2 & \text{otherwise} \end{cases} \]  
(39)

The objective of PSO is defined according to (40), where \( f(x) = \sum_{i=1}^{n} f_i(r_i) \), and the value of which can be obtain using the cost function depicted in the figure below.

\[ F(x) = f(x) + P(x) \]  
(40)

Assume that we use NP particles to implement the optimization, and for the \( n \) participants load shedding, the search space for each particle is \( n \)-dimensional, which can be represented by the vector \( x_i = (r_{i1}, r_{i2}, \ldots, r_{in}) \). The best particle of the swarm is denoted by index \( p_g = (p_{g1}, p_{g2}, \ldots, p_{gn}) \), and the best previous position of the \( i \)-th particle represented as \( p_i = (p_{i1}, p_{i2}, \ldots, p_{in}) \) and the position change (velocity) of the \( i \)-th particle is \( v_i = (v_{i1}, v_{i2}, \ldots, v_{in}) \). The process of iteration of PSO follows equations (41) and (42):

\[ v_i^{k+1} = \lambda \left( w v_i^k + c_1 r_{i1}^k (p_{g1}^k - x_i^k) + c_2 r_{i2}^k (p_{g2}^k - x_i^k) \right) \]  
(41)

\[ x_i^{k+1} = x_i^k + v_i^{k+1} \]  
(42)

Where, \( i = 1, 2, \ldots, NP \), is the size of the population of particles, \( \lambda \) is a constriction factor which is used to control velocities, \( w \) is the inertia weight, \( c_1 \) and \( c_2 \) are two positive constants, namely the cognitive and social parameters respectively, \( \eta_{i1} \) and \( \eta_{i2} \) are random numbers uniformly distributed within the range \([0,1]\). The inertia weight \( w \) is employed to control the impact of the previous history of velocities on the current velocity.

\[ w^k = w_{\text{max}} - \frac{w_{\text{max}} - w_{\text{min}}}{N_{\text{max}}} \times k \]  
(43)

Where, \( w_{\text{max}} \) and \( w_{\text{min}} \) are the maximum weight and the minimum weight respectively, in this paper we use \( w_{\text{max}} = 0.9 \) and \( w_{\text{min}} = 0.2 \), \( N_{\text{max}} \) is the maximum iteration number, \( k \) is the current iteration number.
Example

Use the same scenario described in scenario 1, in order to obtain the cost curves like figure 47, we sample the cost function in Figures 45 and 46 in scenario 1 with the increment of 10W, so we obtain the discrete cost function curves showing in Figures 48 and 49 below.

![Figure 48: Right: cost function of occupancy 1. Left: cost function of occupancy 2](image)

![Figure 49: Cost function of occupancy 3](image)

The parameters and the optimization results are shown in Table 12.

<table>
<thead>
<tr>
<th>Table 12 Parameters and optimization results using PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_1$</td>
</tr>
<tr>
<td>$c_2$</td>
</tr>
<tr>
<td>Optimization Result</td>
</tr>
<tr>
<td>Load Allocation</td>
</tr>
<tr>
<td>129.9</td>
</tr>
<tr>
<td>Cost value</td>
</tr>
<tr>
<td>Total cost</td>
</tr>
</tbody>
</table>
Compared to the analytical method, the PSO cannot achieve the global optimal allocation, however, it is very close. The total cost calculated by PSO is smaller because we adjust the cost value to the lower value for each step change.

6.5.6.4 Optimization for Scenario 2

The second approach is actually the two-layer optimization problem: the first layer is between the control center and the agents, the second layer is between the load sets and corresponding agents. If the \( r_i \) is allocated to the agent \( i \) through layer 1, for the layer 2, the optimal allocation can be obtained by utilizing the cost functions of load sets using the optimization method.

So the key issue is to determine \( r_i \) through layer 1 to minimize the total cost while the cost function of each agent \( f_i(r_i) \) is unknown. As discussed above, for the specified allocation of an agent, the \( f_i(r_i) \) is the optimization result of the load sets, so as the quantity of allocation vary, the cost value of which \( f_i(r_i) \) should change tracing along the minimum cost value trajectory. So, we can obtain the \( f_i(r_i) \) through a numerical way:

1. Initialize \( r_i \) with the minimum allocation \( r_i^0 \) which can be obtained using the equation above while each load set to be the minimum value, and set the iteration number \( k=0 \).
2. Solve the optimization problem described in the expression below. We gain the one optimal cost value \( f_i(r_i^k) \) with the allocation of \( r_i^k \).
   \[
   \begin{align*}
   \text{Obj.} & \quad \min \sum_{j=1}^{Na_i} u(L_{ij}) \\
   \text{Cons.} & \quad r_i^k = \sum_{j=1}^{Na_i} L_{ij}
   \end{align*}
   \]
   (44)
3. Increase \( r_i \) utilizing the equation below until it reaches the maximum value which can be also calculated using the equation above while each load set to be the maximum value.
   \[
   r_i^k = r_i^k + \Delta r_i
   \]
   (45)
4. Set \( k=k+1 \), then continue to Step 2 to calculate \( f_i(r_i^k) \), until the maximum \( r_i^k \) is achieved.

Through the abovementioned process, we actually obtain serials of values of \( f_i(r_i) \) corresponding to specified load reduction allocation \( r_i \). As the cost function of each load is polynomial function, the total cost function of an agent is also considered to be polynomial function. We use the polynomial fitting method to approximate the analytical expression of \( f_i(r_i) \), thus we can write the \( f_i(r_i) \) into the equation below:

\[
 f_i(r_i) = a_0^r + a_1^r r_i + a_2^r r_i^2
\]
(46)

Since we obtain the expressions of all the agents, we can use the optimization method to obtain the optimal allocation for layer 1.

In practice, the progress is described as follows:
1) All the load sets send their cost functions to the corresponding agents.
2) The Agents calculate their cost functions and then obtain the expressions like Equation (46).
3) The agents send their cost functions to the control center.
4) The control center determines the load reduction allocation and sends the optimal results to each agent.
5) Since each agent has received the allocation, it determines the optimal load reduction of the load sets and sends the results to them.
6) After the each load receives the load reduction command, it will do the load shedding.

Example:
In this section, we provide an example to illustrate the proposed method. This example includes four agents, nine loads in total, and each load holds cost functions with a polynomial. The detailed information is shown in Table 13 below. Two approaches for allocating are used, the first one is to use load sets directly, and the second is the two layer optimization method which is already described above. The test results are shown in Table 14 and Table 15 respectively.

Table 13: The detailed load information of the agents

<table>
<thead>
<tr>
<th>Agents</th>
<th>Load Sets</th>
<th>Coefficients of Polynomials</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$a_0$</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.2</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

Table 14: Discovery of the optimal load reduction using agent cost function

<table>
<thead>
<tr>
<th>Num</th>
<th>Clearing cost</th>
<th>Load Reduction of load sets</th>
<th>Total Reduction</th>
<th>Cost value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Agent 1</td>
<td>Agent 2</td>
<td>Agent 3</td>
</tr>
<tr>
<td>0</td>
<td>0.0000</td>
<td>23.03</td>
<td>0.00</td>
<td>10.71</td>
</tr>
<tr>
<td>1</td>
<td>0.4663</td>
<td>111.71</td>
<td>57.47</td>
<td>55.99</td>
</tr>
<tr>
<td>2</td>
<td>0.6935</td>
<td>154.93</td>
<td>94.26</td>
<td>78.06</td>
</tr>
<tr>
<td>3</td>
<td>0.7836</td>
<td>172.07</td>
<td>108.85</td>
<td>86.81</td>
</tr>
<tr>
<td>4</td>
<td>0.8193</td>
<td>178.86</td>
<td>114.63</td>
<td>90.28</td>
</tr>
<tr>
<td>5</td>
<td>0.8335</td>
<td>181.56</td>
<td>116.93</td>
<td>91.66</td>
</tr>
<tr>
<td>6</td>
<td>0.8391</td>
<td>182.63</td>
<td>117.84</td>
<td>92.20</td>
</tr>
<tr>
<td>7</td>
<td>0.8413</td>
<td>183.05</td>
<td>118.20</td>
<td>92.42</td>
</tr>
<tr>
<td>Sum</td>
<td>70.00</td>
<td>69.40</td>
<td>47.90</td>
<td>40.40</td>
</tr>
</tbody>
</table>
Table 15: Discovery of optimal load reduction using load set cost function

<table>
<thead>
<tr>
<th>Num.</th>
<th>Clearing cost</th>
<th>Agent 1</th>
<th>Agent 2</th>
<th>Agent 3</th>
<th>Agent 4</th>
<th>Total Reduction</th>
<th>Cost value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.0000</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>0.5000</td>
<td>70.0</td>
<td>25.0</td>
<td>26.6</td>
<td>18.7</td>
<td>43.0</td>
<td>24.5</td>
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<tr>
<td>2</td>
<td>0.7118</td>
<td>70.0</td>
<td>51.4</td>
<td>40.7</td>
<td>31.9</td>
<td>64.1</td>
<td>35.0</td>
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<tr>
<td>3</td>
<td>0.7920</td>
<td>70.0</td>
<td>61.5</td>
<td>46.1</td>
<td>37.0</td>
<td>72.2</td>
<td>39.1</td>
</tr>
<tr>
<td>4</td>
<td>0.8223</td>
<td>70.0</td>
<td>65.2</td>
<td>48.1</td>
<td>38.8</td>
<td>75.2</td>
<td>40.6</td>
</tr>
<tr>
<td>5</td>
<td>0.8338</td>
<td>70.0</td>
<td>66.7</td>
<td>48.9</td>
<td>39.6</td>
<td>76.3</td>
<td>41.1</td>
</tr>
<tr>
<td>6</td>
<td>0.8382</td>
<td>70.0</td>
<td>67.2</td>
<td>49.2</td>
<td>39.8</td>
<td>76.8</td>
<td>41.4</td>
</tr>
<tr>
<td>7</td>
<td>0.8398</td>
<td>70.0</td>
<td>67.4</td>
<td>49.3</td>
<td>39.9</td>
<td>76.9</td>
<td>41.4</td>
</tr>
<tr>
<td>Sum</td>
<td></td>
<td>186.8</td>
<td>116.97</td>
<td>91.48</td>
<td>104.14</td>
<td>499.38</td>
<td>234.4</td>
</tr>
</tbody>
</table>

6.5.6.5 Results and discussion:
As shown in Tables 14 and 15, the proposed 2-layer optimization method can achieve satisfactory optimal results, which are almost the same as the results obtained by using the load sets function directly. However, errors exist as we use the numerical way to obtain the cost functions of agents, and we use the polynomial fitting method to approximate the obtained cost functions, which may also amplify the error.

6.5.7 Developing a test plan
We are beginning to formulate a test plan, which includes some empirical (field) testing as well as simulations. LBNL, UCB, and SCR continue to work on the simulations of the feasible DR control strategies, including the zone temperature reset, supply air temperature reset, minimum air flow rate reset for each VAV terminal box, and implementation of the VFD pumps. Static pressure reset controls strategy cannot be simulated with the current CITRIS E+ model. Field tests should be conducted by resetting the static pressure by 30%, 50% and 70%.
7    Cost Status

The total budget for the project is listed below:

Balance as of 6/30/11: $1,255,625*

<table>
<thead>
<tr>
<th></th>
<th>DOE share</th>
<th>UCB share</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total budget</strong></td>
<td>$1,787,674</td>
<td>$375,474</td>
</tr>
<tr>
<td><strong>Budget period 1</strong></td>
<td>$898,793</td>
<td>$252,975</td>
</tr>
<tr>
<td>Salaries/Benefits</td>
<td>$190,110</td>
<td>$57,987</td>
</tr>
<tr>
<td>Supplies/expenses</td>
<td>$18,772</td>
<td>$4,514</td>
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<tr>
<td>Subcontract</td>
<td>$215,882</td>
<td>--</td>
</tr>
<tr>
<td>Overhead</td>
<td>$107,285</td>
<td>$18,431</td>
</tr>
<tr>
<td>Other costshare</td>
<td>--</td>
<td>$229,580</td>
</tr>
<tr>
<td><strong>Total costs as of 6/30/11:</strong></td>
<td>$532,049</td>
<td>$229,582</td>
</tr>
<tr>
<td><strong>Balance as of 6/30/11:</strong></td>
<td>$1,255,625</td>
<td>$145,892</td>
</tr>
</tbody>
</table>

*estimate. June figures are not available until mid-August

8    Schedule Status

This past quarter Tasks 3 (Develop a Service Oriented Architecture for DIADR) and 5 (Development of Demand Response Algorithms) were completed on schedule; the final documentation may be found at http://i4energy.org/diadr-project-sutardja-dai-hall-0. The central load algorithms will continue to be refined as the EnergyPlus model is refined. We are preparing to conduct some preliminary testing in the next quarter, which is ahead of schedule.

9    Changes

There were no changes this quarter.

10   Anticipated Problems or Delays

There were no anticipated problems or delays.
11 Absences/Changes of Key Personnel

Siemens Corporate Research had several interns join the DIADR project and contributed to the project progress, including Jianmin Zhu, Wei Zhang, Stephen Forstenlechner and Sisi Li.

12 Products of the Project

12.1 A. Publications (list journal name, volume, issue); conference papers; or other public releases of results.

None

12.2 Website with results of this project.

A temporary website for this project may be found at http://i4energy.org/diadr-project-sutardja-dai-hall-0. This site includes final reports for Tasks 2, 3, 4, and 5, all quarterly reports, and the slide decks for the April 27 demo.

12.3 Networks or collaborations fostered.

Besides the collaboration among UC Berkeley, Siemens Central Research, and Lawrence Berkeley National Laboratory, this quarter the team established communication with the Center for the Built Environment (CBE) and Berkeley Sensor and Actuator Center (BSAC) at UC Berkeley, and Adura Technologies; Raritan provided PDUs on loan for the UC Berkeley team last quarter. CBE will be conducting occupant surveys within Sutardja Dai Hall on indoor environmental quality and will also conduct surveys during demand response events to ensure occupant comfort. BSAC has developed wireless energy sensors for collecting data at building circuit breaker points; while currently there is too much interference in the data collection of adjacent circuit breakers, this technology may prove useful at a later time. Adura Technologies is providing a bid for wireless zonal control of lighting as well as central control over the individual office lighting.

12.4 Technologies/Techniques.

No new technologies were developed this quarter.

12.5 Inventions/Patent Applications

The Smart Energy Box as a potential commercial product has attracted a lot of attention from internal and external Siemens. However, there is no decision on the commercialization of SEB yet.
12.6 Other products, data or databases, physical collections, audio or video, software or netware, models, educational aid or curricula, instruments or equipment.

None

13 References