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A Multiagent Energy Management Control System for Commercial & Industrial Applications

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A MULTIAGENT ENERGY MANAGEMENT CONTROL SYSTEM FOR COMMERCIAL AND INDUSTRIAL APPLICATIONS

by

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Dedication

This work is dedicated to God, my loving wife, Jessica, and to my family who have supported me throughout my academic career.

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ABSTRACT

Commercial and industrial customers have increasingly adopted fully-automated demand response (auto-DR) as part of their energy management control strategy to mitigate the effects of rising electricity costs. Some of these customers have also contracted with their power provider to permit voluntary curtailment of power consumption to be negotiated by a human operator. Even still, at the customer-side there are needs to maximize cost savings and automate decision making, and at the provider-side there are needs to reduce peaking demand and demand volatility. This thesis describes a centralized multiagent approach that automatically negotiates demand curtailment with a power provider while making the best use of available distributed energy resources. Weather-dependent load and source forecasting methods are implemented to improve decision-making of the agents. Power forecast uncertainty is measured in terms of confidence levels. The effectiveness of the approach was evaluated by simulating the system performance of an actual nursing home that was notionally-augmented with a photovoltaic (PV) power source and battery energy storage system. Actual power consumption data for two representative four-day periods during spring and summer of 2012 were used, together with the simulated performance of the PV and battery systems working together with the agent-based controller. The multiagent system with peak-time load curtailment was able to reduce total electric usage costs by 24%.

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List of Abbreviations

AR .... Autoregressive

Auto-DR .... Automated Demand Response

C&I .... Commercial and Industrial

CCM .... Contracted Curtailment Mode

DER .... Distributed Energy Resources

DOD .... Depth of Discharge

DWM .... Dynamic Weighted Mean

EMCS .... Energy Management Control System

GPN .... Green Power Node

HVAC .... Heating, Ventilation, and Air Conditioning

MAS .... Multiagent System

R-GPN .... Residential Green Power Node

RTP .... Real Time Pricing

TOU .... Time of Use

VPP .... Virtual Power Plant

CHAPTER 1

INTRODUCTION

To counter rising electricity costs and volatility, customers and power providers are looking more into the use of customer-side DERs (distributed energy resources), demand response, and curtailment programs. Some providers are now offering auto-DR (automated demand response) contracts and incentives for customers with EMCSs (energy management control systems).

Future smart grids will be more intelligent, more autonomous, better integrate demand-side DERs, and provide for seamless user input. They will employ the use of two-way communications between customers and their power provider for quick transfer of energy use data [1]. The EMCS proposed in this paper is designed to act in such a system where automatic negotiation between the customer and the power provider may be provided as an additional service.

The Commercial and Industrial Green Power Node Multiagent System (C&I GPN MAS) is designed for connection, coordination, and automatic negotiation and bidding with a power provider, utility, or Independent System Operator (ISO). This work is an extension of the Residential Green Power Node (R-GPN) project laid out in [2]. The R-GPN focuses on designing an all-in-one package of power electronics and communications for smart residential demand-side management. The C&I GPN also focuses on smart demand-side management but for C&I customers who have more cost savings options available to them through their power provider or ISO. Unlike the R-

GPN, the C&I GPN focuses on a MAS design, negotiation and bidding design for curtailment and generation requests, and forecasting design. The R-GPN also laid out some interfacing between high level and low level controls for a solo, centralized converter. The C&I GPN maintains a major focus on high-level algorithms due to the range of power electronic implementations available.

Work has been done in [3] on a multiagent-based energy management system for a hybrid generation system/plant with a goal of optimizing DERs to constantly meet the load demand (load matching). The hybrid system MAS is largely designed for a microgrid-type arrangement but presents how a MAS can help coordinate multiple sources with rule-based logic and optimization. In [4] a simple multiagent energy management system is proposed that contains a centralized controller but allows for DER agents to communicate with each other by passing "tokens" for supplying different load amounts. The MAS system in this paper differs from previous work by solely focusing on a C&I application to the energy management MAS. In addition this work applies and creates forecasting methods and accounts for the forecast uncertainty in decision making. The C&I GPN MAS also provides a framework for automated two-way communication, negotiation, and bidding which is not a focus in previous work.

The use of a multiagent system for energy management control can provide more effective and organized control mechanisms. The use of utility functions to model cost savings for each load and DER provide a simple, yet effective method to monitor real time cost savings.

Accurate forecasting can play a major part in energy management decision making. Incorporating forecast uncertainty can be vital when scheduling demand response tasks.

Developing a measure and confidence of this uncertainty may increase customer and power provider confidence. Forecasting accuracy not only increases the effectiveness of customer decision making but can also assist the power provider in their total load forecasts in an effort to reduce grid demand volatility.

If the C&I customer is large enough, direct bidding into energy markets may be allowed by regional or local regulations [5]. If this option is not available to a C&I customer, the system is designed for coordination with an aggregator (3rd party) company or with a virtual power plant (VPP). Benefits to the power provider include:

1. Increase in reserve capacity through customer curtailment and dispatchable load management (DLM) programs
    a. Decrease in peaking plant dispatching (these plants usually have the highest overhead)
2. Demand metering with secure, two-way communication implemented to monitor customer usage in real-time
3. Purchasing power from customer-installed renewable generation to satisfy mandated renewable portfolio standards (RPS)
    a. RPS mandates increase purchased power costs for the provider and are usually built into the customer charge [6].
4. Receiving a local customer demand forecast with 95% confidence

There is a wide variety of commercial and industrial customers ranging from small restaurants or nursing homes to expansive military bases or manufacturing facilities. In general the MAS is assumed to have a distributed converter layout. An

example layout is shown in Fig. 1 where the customer owns photovoltaics (PV), battery storage, and diesel generation. In this example, the PV and battery storage are in close proximity and share a bidirectional inverter that allows for charging from the Grid. In Fig. 1 the loads are lumped together, but there are many C&I customers with critical or emergency loads; these are not shown to reduce visual complexity. The system is designed for islanding where the system control will operate the islanding switch. In contrast to the distributed converter layout, small customers may elect to install a centralized converter layout similar to the R-GPN which is composed of only one bidirectional converter with inputs/outputs that include PV, battery storage, and a Grid-tied AC bus. The R-GPN's centralized, bidirectional converter layout is shown in Fig. 2 along with the associated data communications used for system control.

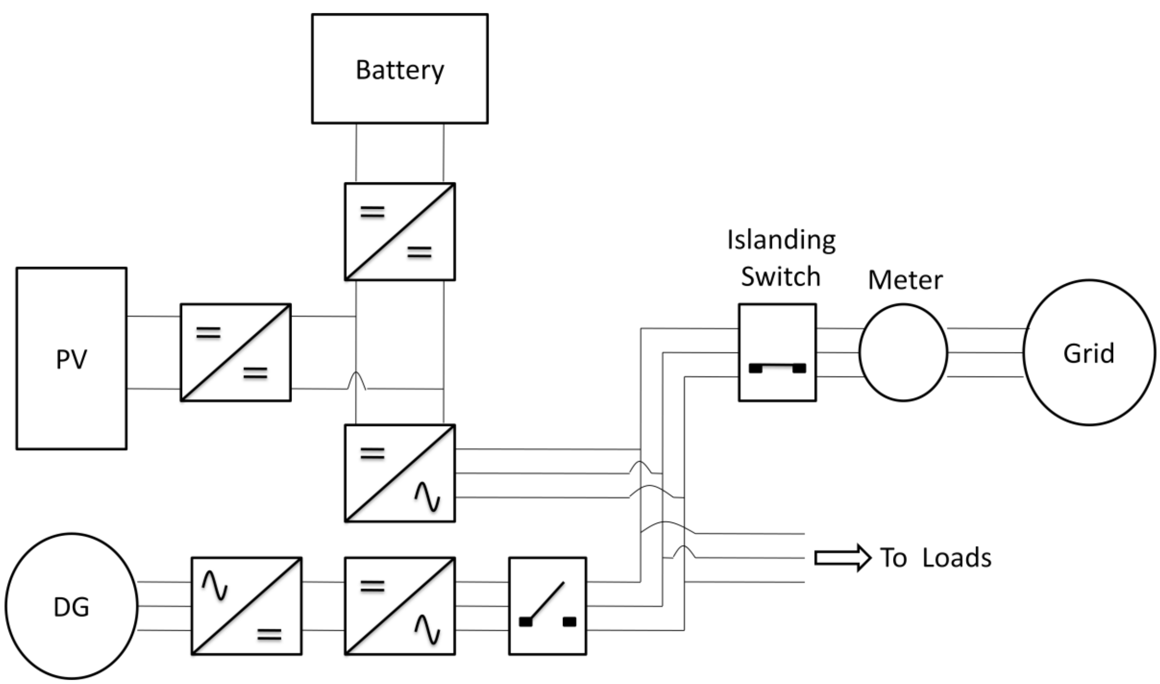

Figure 1. Converter And DER Example Layout

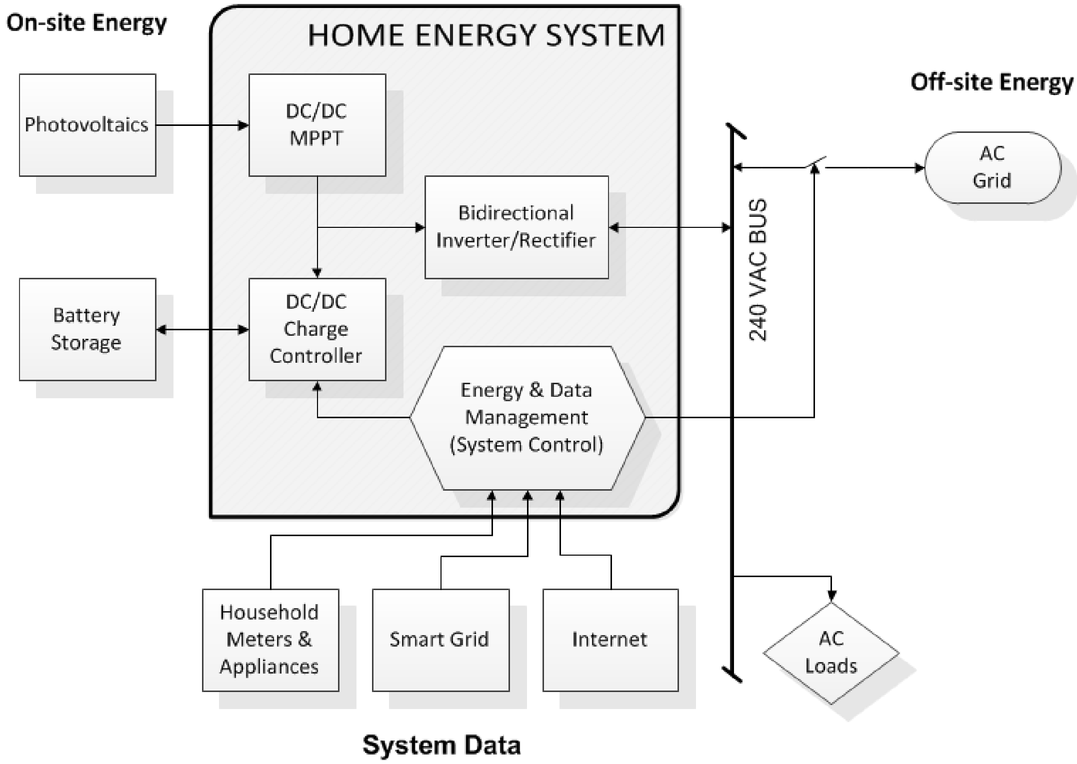

Figure 2. Residential GPN Centralized Converter & Communications Design [2]

CHAPTER 2

BACKGROUND

2.1 DEREGULATED MARKET

The U.S. deregulated market established in the 90's split up ownership of generation, transmission, and distribution and allowed customers more options on deciding how and from whom they bought power. Deregulation also helped create numerous power markets and Independent System Operators/Regional Transmission Operators (ISO/RTOs) to facilitate transmission. The deregulated structure is shown in Fig. 3. With the current deregulated system, grid reliability has become a major issue. Power transmission over long distances to profit-hungry purchasers (see *wheeling)* increases the vulnerability of the transmission lines [6]**.** Customer-owned generation has played an increasing role in the following ways:

- Can provide additional reserve capacity for a provider
- Can provide back-up/islanding during grid outages
- DG can adversely affect power quality
- Islanding presents safety concerns for line workers

FERC has mandated that ISO/RTOs allow demand-side resources participation in the ancillary services market which can increase reserves for a provider or ISO/RTO region. The best way for a C&I customer to keep ahead of deregulation and smart grid integration is to develop an energy management plan and system [6].

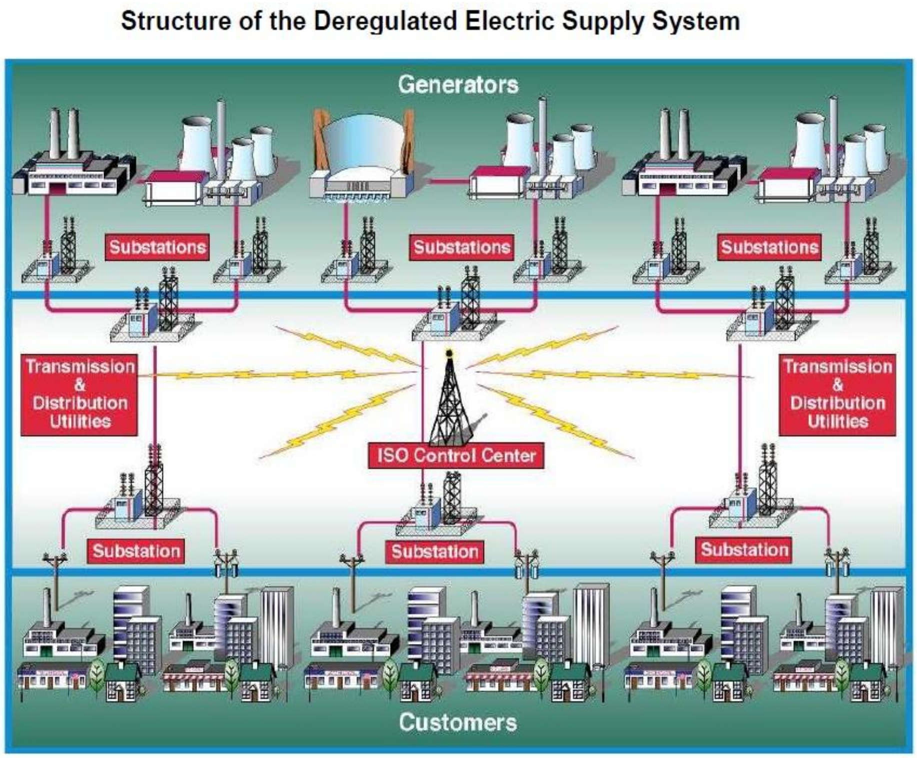

Figure 3. The Deregulated Market [6]

2.2 ELECTRIC RATES & PRICING

Electric rates are designed to recover fixed & variable costs. Customers can usually only affect actions associated with some fixed costs. Fixed costs can include:

1. Customer charge (usually a flat rate)
2. Usage or kWh charge (flat, declining block, or inverted rate; Time-Of-Use (TOU) or RTP/dynamic pricing)
3. Demand charge which is based off peak demand over a short interval (mainly non-residential) [6]

Time-Of-Use (TOU) pricing defines a flat rate for usage charges for different periods of the day. For example, an off-peak period may be defined as between 12 AM - 12 PM and 7 PM - 12 AM at $0.08/kWh and an on-peak period would be defined as between 12 PM - 7PM at $0.18/kWh. TOU rates are used for experimentation in this work. Another emerging usage pricing is the dynamic or real-time pricing (RTP). RTP pricing changes dynamically through the day usually largely dependent on the current market clearing price (MCP) for power [6].

Demand charges (for generation and/or delivery) can be reduced by reduction of C&I customers' peak power and load leveling. Generation demand charges are often eliminated after deregulation and replaced with real-time prices from a competitive power exchange. Customers with demand charges or TOU rates will have the highest bills when they have the lowest load factor (quantifies variability of energy use). "Real-time metering" or dynamic pricing usually requires the use of two-way communication system that allows the provider to read usage in real time. Customers who install these real-time meters can take advantage of the competitive power market. Some utilities will even provide customers pricing forecasts [6].

Ways to reduce customer costs include:

1. Reduce usage charges utilizing
    a. Peak shaving
    b. Load curtailment (extra incentive during peaking event) or load shifting
2. Reduce demand charges through peak shaving (load leveling)
3. Participate in contracted curtailment and standby generation programs
4. Sell renewable energy power to provider with a profitable feed-in tariff

5. Take advantage of real-time metering services for dynamic pricing
6. Enroll in a market power pool if customer qualifies or form a Virtual Power Plant (VPP) with other customers/facilities; a VPP is a commercial-sized aggregation of DERs which are controlled like a single power plant [7]

2.3 POWER EXCHANGE MARKETS

CA's and NE's ISOs allow consumers or demand response aggregators (e.g. EnerNOC) who can curtail 100 kW or more, participation into the day-ahead and real-time energy markets [C]**.** These markets mainly use either an English or Dutch Auction to reward bidders with a single bid or as-bid option. With single bid, the winning bid sets the price for all sellers. With the as-bid option, sellers are paid their bid price regardless of the winning bid. A Dutch Auction that is used in California's ISO markets is shown in Fig. 3 [6].

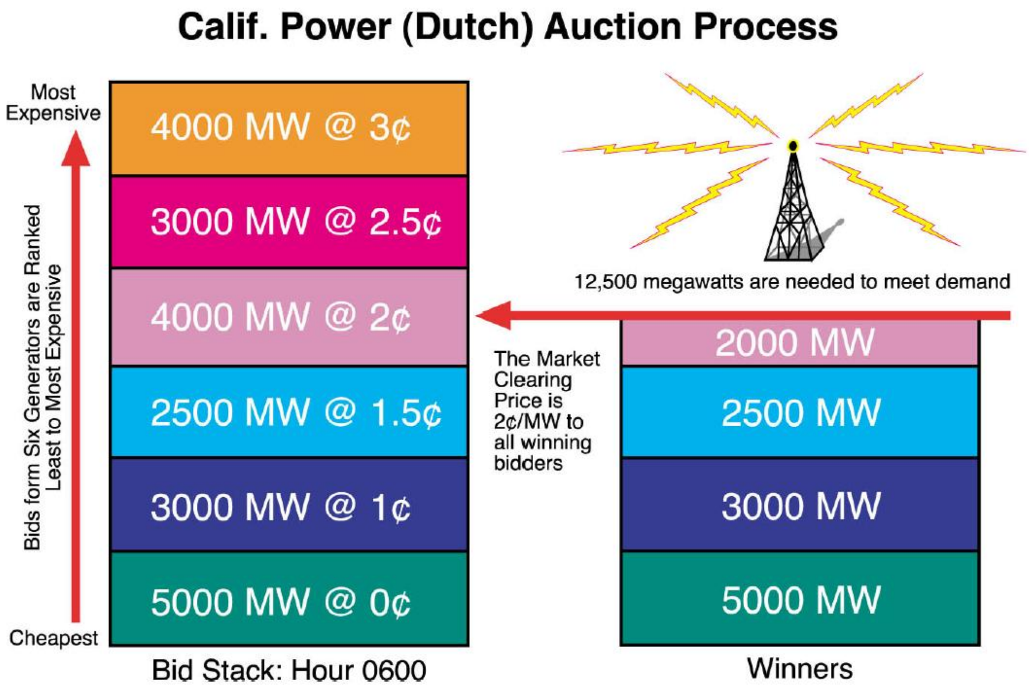

Figure 4. An Example of the Dutch Auction in California Power Exchange Markets [6]

2.4 STATE OF AUTOMATED DEMAND RESPONSE

Automated demand response (auto-DR) has been implemented increasingly at the C&I level for the last decade. One requirement usually for auto-DR is for the C&I customer to have some form of energy management control system (EMCS). Fig. 5 shows an auto-DR setup currently used at C&I facilities. An example procedure used for the setup is the following:

1. The power provider or an ISO identifies DR event and price signals that are sent to a DR automation server (DRAS)
2. DR event and price services are published on the DRAS.
3. DRAS Clients (web service software) update latest event information or price from the DRAS every minute.
4. Customer pre-programmed DR strategies determine action

5. C&I facilities' EMCSs carry out load shedding based on DR signals [8].

Fig. 6 shows types of load curtailment used for auto-DR at C&I facilities tested in [9] and the demand reduction intensity for each type. The Zone Setpoint and the Direct Fan/Chiller control constitute heating, ventilation, and air conditioning (HVAC) curtailment. It can be visually discerned from the figure that HVAC curtailment has a higher potential for demand savings.

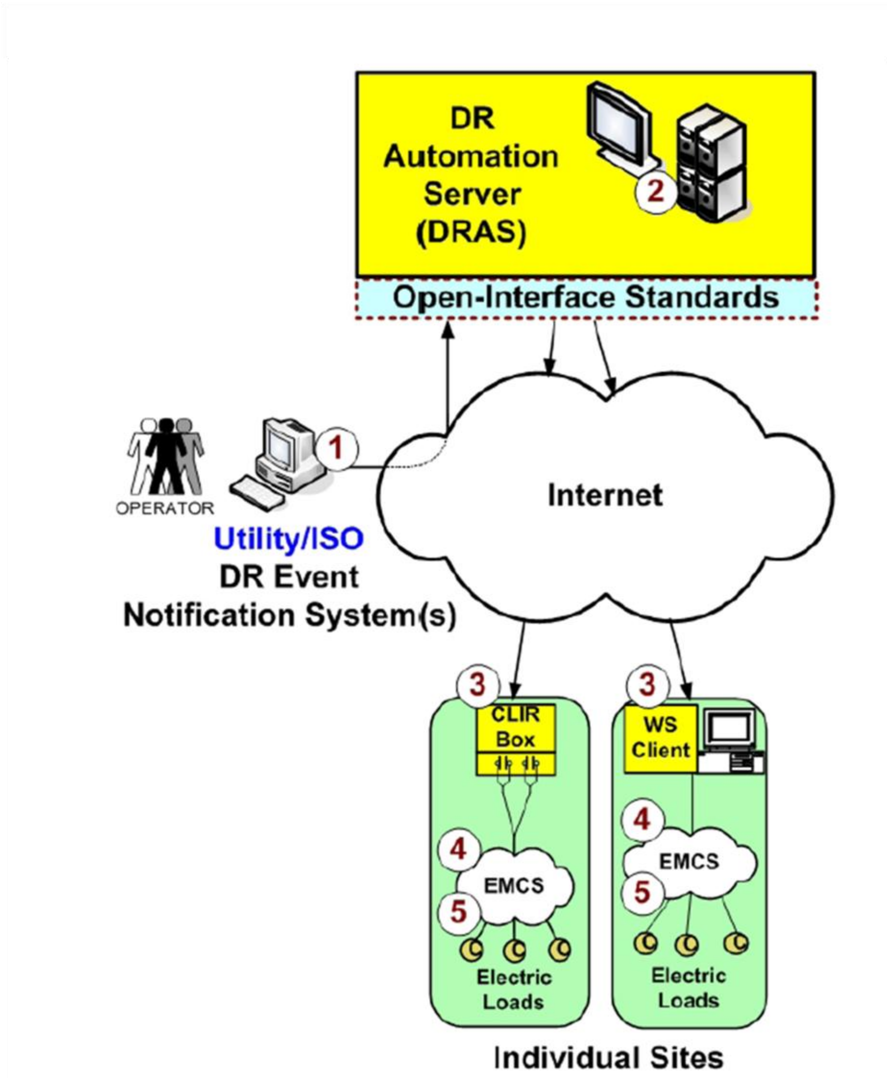

Figure 5. Auto-DR Configuration in C&I Facilities with EMCSs [8]

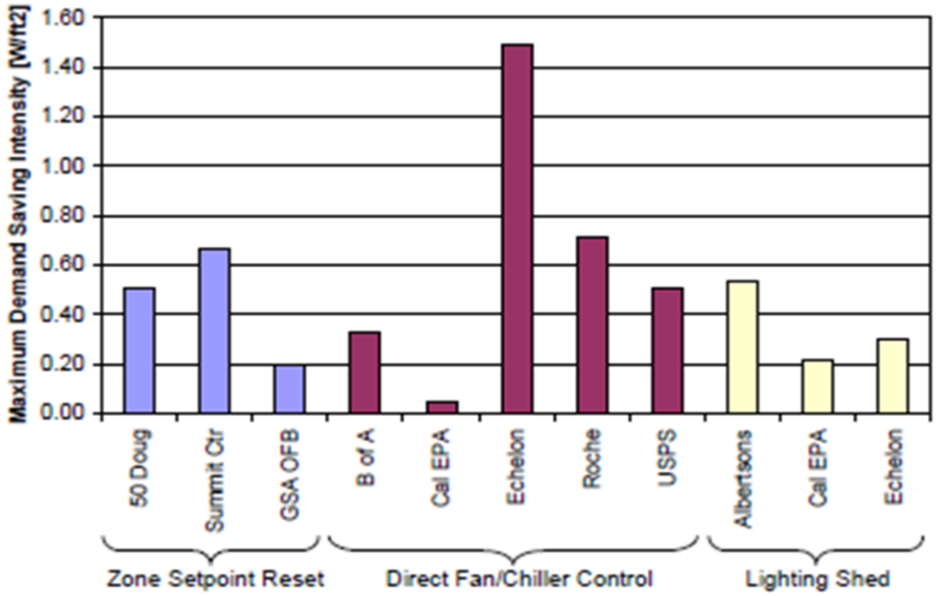

Figure 6. Demand Saving Intensity by Load Shedding/Curtailment Strategy (W/ft^2) [9]

CHAPTER 3

MAS DESIGN

A centralized MAS (multi-agent system) is implemented that includes DERs and smart loads. A multi-agent approach is chosen to provide better communications and energy management control for a system with DERs. The MAS is composed of three types of agents. *Load/source agents* provide a means to curtail or increase their power and provide energy use data to the building agents. *Building agents* aggregate the energy use data from the load/source agents and aim to maximize the social welfare (see 3.2). The *negotiation agent* uses the user-inputted strategy to make decisions on load curtailment or negotiation and communicates with a power provider or a third party.

Figure 7 shows the communication structure of the MAS. The system has a dedicated Internet connection that allows for weather and pricing data retrieval. It also could allow for the two-way communication with the power provider.

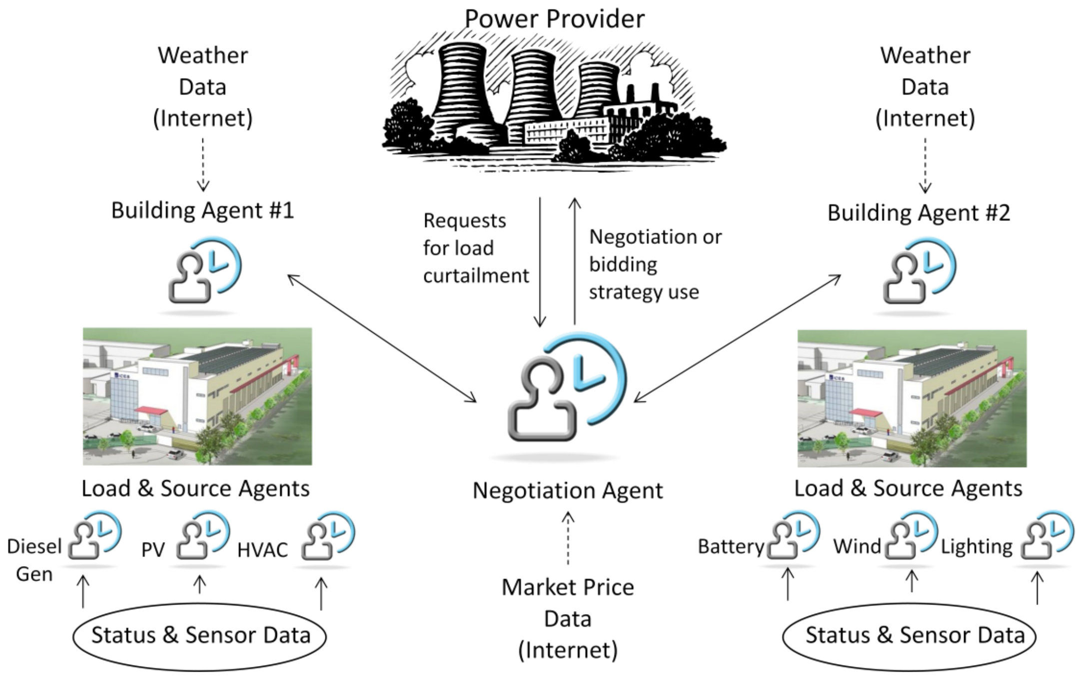

Figure 7. MAS Communication

3.1 UTILITY (COST) FUNCTION

Each of the load/source agents have a utility function which represents the amount of cost savings possible from demand reduction at an iterative 15 min. time step. Assuming a linear load, the utility function of the load agent is shown in (3.1) where **c** = (c_0, c_1,...,c_n) is a vector denoting a certain curtailment setting at time t with domains for each type of curtailment shown in Table I ($c_n \in D_n$). The building manager/user will set these curtailment settings. We define the settings as having one to three limits (c_{L0}, c_{L1}, c_{L2}) where c_{L0} is the normal or starting curtailment setting for the load, c_{L1} represents the first level user-defined limit, and c_{L2} represents an optional second level user-defined limit. The user also needs to set the *target daily savings* which is an independent variable that is used by the negotiation agent to determine if curtailment action should be taken. The *target hourly savings* is another variable calculated by dividing the target daily

savings by 24. Or create three different target hourly savings, one for each peak period (e.g. off-peak, mid-peak, on-peak) by dividing by the amount of hours in each period.

The cost of electricity in (3.1) is represented by r(t) at time t, $e(c_{L0})$ is the energy consumption at the baseline or normal operation setting for the load, and $e(c_n)$ represents the energy consumption of the load for the curtailment setting. Utility values would normally be normalized to range from 0 to 1 because functions can have multiple inputs and varying units. In this work we focus exclusively on cent/dollar savings so the utility functions are not normalized. Figure 8 shows the utility function of a linear lighting load agent (linear fluorescent dimming ballasts) located in a high-rise office building for an entire on-peak period. The x-axis is mapped for every possible curtailment setting/level (c) in kWh and ΔV on the y-axis represents the utility or cost savings in dollars for each curtailment level.

$$u_{LOAD}(n,t) = r(t)(e(c_{L0}) - e(c_n)) \tag{3.1}$$

Table I. Load Curtailment Domains

Type of Curtailment	Domain ($D_0, D_1, \ldots, D_n$)	Example c_{L0}
Lighting Dimness	$D_{Lighting}$: {0%, 10%, 20%,...,100%}	100%
HVAC Setpoint	D_{HVAC} : all integer °F	74°F

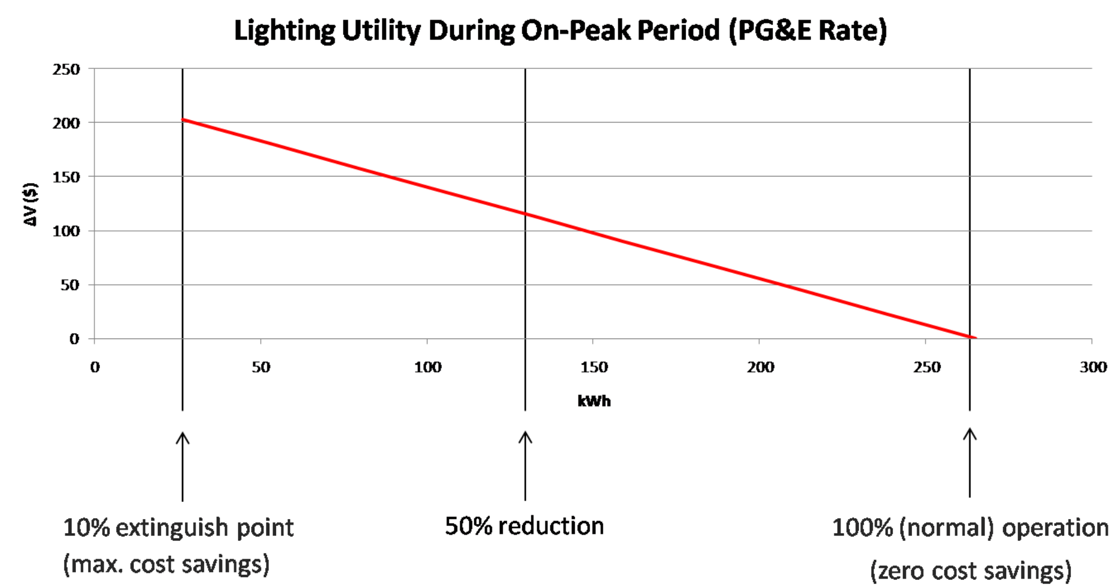

Figure 8. Utility Function of a Linear Lighting Load

Equation (3.2) shows the utility function for a DER agent which will be aggregated to compute total savings from DER use. Equation (3.3) shows the utility function for a battery agent which factors in the battery degradation cost $d_k(t)$ at the specified depth of discharge (DOD) at time t. As noted in [1] for the R-GPN, the cost per cycle can be written as (3.4). Using the cost per cycle, the battery degradation cost can be calculated in (3.5) where I_{bat} is the discharge current of the battery, the time step is 15 min (quarter of an hour), and Ah_t is the amp-hour capacity of the battery at the specified DOD at time t.

$$u_{DER}(t) = r(t)(P_{DER}) \tag{3.2}$$

$$u_{BAT}(t) = r(t)(P_{BAT} - d_k(t)) \tag{3.3}$$

$$Cost\ per\ cycle = \frac{Cost\ of\ battery\ bank}{Expected\ cycle\ life} \tag{3.4}$$

$$d_k(t) = \frac{1}{2} cost\ per\ cycle(I_{bat})\left(\frac{1}{4}\right)h(\frac{1}{Ah_t}) \tag{3.5}$$

3.1.1 COMFORT CRITERIA

The utility function described in Section 3.1 does not note the effect of load curtailment on employees or customers. There have been several papers on inclusion of comfort criteria. One uses the results of user studies/questionnaires to get the most accurate inputs for comfort to maximize productivity [10]. Our system's main human interaction was aimed at the building manager setting curtailment constraints. It would be up to the building manager in this instance to gauge comfort either by an employee/customer study or another method.

3.2 MAXIMIZING SOCIAL WELFARE

The goal of the system is to maximize the social welfare (or cost savings) by maximizing the aggregate utility of all load/source agents as described in the previous section. This strategy is shown in (3.6). As noted in Section 3.1, the utilities are constrained by user-set curtailment settings and curtailment decisions are affected by the user-set target daily savings.

$$s^* = arg \max_s \sum_i u_i(s) \tag{3.6}$$

3.3 AGENT FUNCTIONS

3.3.1 LOAD/SOURCE AGENTS

The load/source agents are initially assumed to be associated with "non-smart" loads and sources where the agents at minimum, accept and respond to control and curtailment signals from the building agents. The load/source agents also communicate relevant sensor data to the building agents for utility function calculation and updating. Alternatively smart agents can be used for loads/sources for utility function updating and other calculations that were originally tasked to the building agents.

As defined in Section 3.1, there is a user-defined normal operation point, first-level curtailment limit, and an optional second-level one. For example, the lighting and heating, ventilation, and air conditioning (HVAC) limit setpoints would be defined as [78, 76, 74]°F. Alternatively to setting limits, curtailment ranges can be set for use with smart load agents. As an example, consider an office building with smart agents for lighting and heating, ventilation, and air conditioning (HVAC) loads, the building manager will still set two levels of curtailment constraints but in this case instead of setting two setpoints, the manager will set two ranges for each load (e.g. Lighting 1st level: 80% - 90%, Lighting 2nd level 60% - 80%; HVAC 1st level: 72 deg. - 74 deg., HVAC 2nd level 74 deg. - 78 deg.). This will allow the smart agent more degrees of freedom to change curtailment based on sunlight illumination or occupancy.

3.3.2 BUILDING AGENTS

The building agents perform energy management control for a singular building or location and communicate with the load/source agents and the negotiation agent. The building agents aggregate utility functions for the load/source agents and provide this cost

saving information to the negotiation agent. The building agents also perform load and weather forecasting, task allocation for load/sources, and database management. Weather forecasts are accessed over the building agents' Internet connection for load and DER power forecasting.

3.3.3 NEGOTIATION AGENT

The negotiation agent functions as the decision-making identity in the MAS. The agent acts in the user's best interest to maximize cost savings within user-defined constraints for curtailment and standby power. The agent can negotiate curtailment and standby contracts and send aggregated load/source info. to a power provider, aggregator, or virtual power plant (VPP). Pricing data and forecasts (some providers may provide RTP forecasts) can be accessed over the Internet connection. The agent also provides the structure for direct market bidding if the customer qualifies for their location (usually >100 kW of curtailable load for bidding in day-ahead capacity market or ancillary services market). Acceptance of direct market bidding by customers has just started with mainly a few Regional Transmission Operators (RTOs) accepting, but it is expected that customer participation will still remain rare in the near future given its current state. The most likely scenario for market bidding will involve indirect participation through an aggregator or a third party [11].

3.3.4 NEGOTIATION MECHANISMS

Contract Net Protocol

The contract net protocol can easily allow a power provider to secure their needed demand reduction amounts from participating C&I customers. The protocol's operation is shown in Table II. PG&E's InterAct system has a similar, basic setup for curtailment

requests where the task, award amount, and contract are all communicated in the beginning to the customers who only decide to accept or reject the request [12].

To execute the protocol you must have the following:

1. Eligibility specification
2. Reserve requirement
3. Bid specification
4. Expiration time
5. Secured communication and digital acceptance of contracts [13]

Table II. Contract Net Protocol Order of Operation

Step Number and Operation	Description
1. Future Peak Event	Power provider predicts a future peak event; sets a min. reduction amount for bids; sets a max. pay out (optional).
2. Task Announcement	Provider announces task to participating customers over secured Internet message, RF smart meter communication, or other method
3. Customers Bid	Customer's system receives announcement and automatically sends a bid back
4. Provider Awards	Provider awards bids until reduction amount is met, starting with the lowest bids
5. Contract	Customer's system receives and accepts contract with award amount; communicates back to provider

Table III. Summary of Agent Functions

Agent	Function
Negotiation Agent	• Cost analysis & decisions • Negotiation & bidding with a power provider, market, or VPP • Standby & curtailment contract negotiation
Building Agents	• Energy management control • Load & weather forecasting • Baseline database management • Load/source task allocation • Receive price/weather forecasts
Source (DER) Agents	• Respond to energy management & DR tasks & send sensor data • Grid disconnect control for islanding • Low-level charging control for battery/E.S.U.
Load Agents	• Respond to management & DR tasks & send sensor data • Programmable scheduling control (e.g. for lighting, HVAC) • Occupancy control (smart agent) • Cycle time control for HVAC (smart agent)

3.4 OFFICE BUILDING EXAMPLE

Figure 9 shows the simulated load breakdown of a high-rise office building. The building was simulated in [14] using the building energy simulation tool eQuest. As you can see, the HVAC comprises approx. 50% of total load and the lighting approx. 25%. Table IV shows the specifications for this example where a PV and battery combination is used for peak shaving. The PV is sized to 50% of the peak load, while the battery system is sized at 100% providing a ~600 kWh usable capacity at a 50% depth of discharge (DOD). The office building has a 450 kW diesel genset that was reserved only for emergency/backup use. PG&E time of use pricing is used, consisting of off peak, mid peak, and on peak period. This scenario uses the following curtailment constraints, set by the building manager: Lighting = [100, 50]% and HVAC = [78, 72]°F where the values 50% lighting and 72°F represent the first level curtailment constraints (no second level constraints specified/used). The building manager in this example only wants load curtailment initiated when he can earn at least a $.60/kW/hr curtailment credit. In later sections, first level curtailment will be used for daily on-peak demand reduction while second level curtailment is reserved for additional leverage in contract negotiations to reach a customer's target daily savings.

The results of a one day simulation are shown in Fig. 10. With normal use of the PV and battery with peak shaving, the projected payback period is approx. 13 years. The projected 2020 cost is much less at approx. 2-3 years payback. The default peak shaving strategy utilizes the battery at full potential during the on peak period to reduce grid demand. The battery is recharged during the off peak period from the grid. On this particular day, a curtailment contract is requested by the power provider and agreed upon

by the customer between 2 PM - 5 PM for a min. 100 kW reduction. The total aggregate utility (total cost savings) is also shown in Fig. 10. The total utility is calculated for each 15 min. period and the total savings for the day are $887 without load curtailment. With the acceptance of the curtailment contract, the savings almost double to $1667.

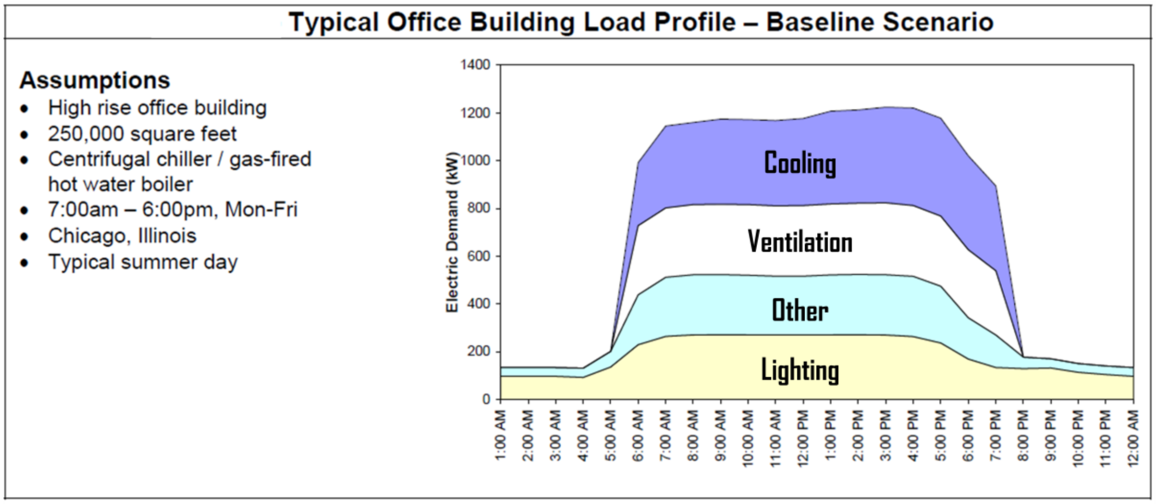

Figure 9. Office Building Load Profile [14]

Table IV. Scenario Specifications for Office Building Example

Specification	Type /Size	Cost/Payment
C&I Structure	Office Building (1200 kW peak steady state load)	
Critical/emergency load	30% of peak S.S. load (50% lighting, 100% computer equip.)	
TOU prices	California (PG&E) (>200kW/month customers)	On-peak: 14.160 cents/kWh (6 hours) Off-peak: 8.128 cents/kWh
PV size	600 kW	2011 Cost: $7.24/W (>10kW) ; 2020 Projected Cost: $1/W Total Cost: $4,344,000; $600,000
Battery size	10 X 119.5 kWh (lead-acid deep cycle) = 1195 kWh	$235,200
Diesel genset size	450 kW (125% of critical load) [not used for peak shaving in this scenario]	Pre-owned ~0.075 gallons/kWh with ~$4.40/gallon diesel gas
PV & battery payback period (rough approximate)		2011: ~13 years 2020 Projected: ~2 years
Curtailment level constraints	Lighting: [100, 50] HVAC: [78, 72]	Day-ahead event: 50/cents/kW/hr Day-of event: 60/cents/kW/hr

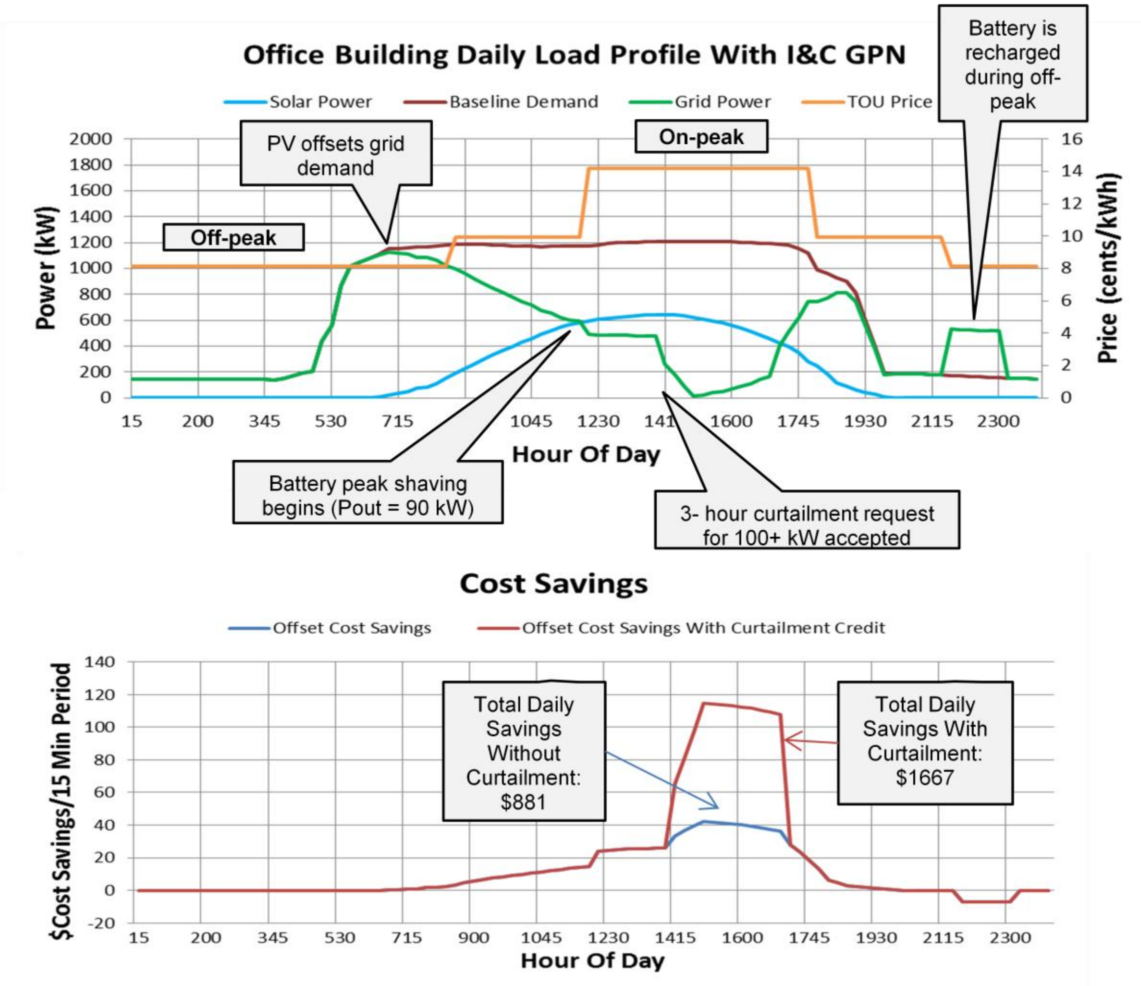

Figure 10. Office Building Load Profile & Cost Savings (Utility) Per 15 Min. Period

CHAPTER 4

NURSING HOME USE CASE SUMMARY

A nursing home with a 50 kW peak load located in the Upper Midwest is used as a use case in this paper. The actual breakdown of the load is not known but an estimated breakdown is shown in Fig. 11 based on an average nursing home [15]. The nursing home is assumed to have a 25% (of peak load) critical load need.

Choosing the optimal selection of distributed energy resources for a commercial or industrial customer is a complex problem and is investigated in depth by Lawrence Berkeley National Laboratory in [16]. Berkeley Laboratory developed a DER Customer Adoption Model (DER-CAM) that makes a first major step towards optimal selection of DERs for a microgrid and customer-owned DERs. Based off optimal DER sizing identified in [16], sizings for the case study were selected and are shown in Table V.

Diesel or traditionally-fuelled generation can provide reliable backup or peak shaving services to a C&I customer. Though new legislation limits the use of diesel generation currently installed in C&I facilities for non-backup or non-emergency situations. EPA 40 CFR Part 63 Subpart ZZZZ mandates that reciprocating internal combustion engines (RICE) used in non-emergency applications >300 hp and manufactured before June 2006 must be retrofitted to reduce and regulate emissions. Installation of the emissions control equipment must be completed by May 2013. Diesel generation used for standby/emergency generation purposes or with <300 hp are not largely affected by this legislation (except for monitoring and testing) [17].

The diesel generator used our use case is set to 16 kW (125% of critical load). The cost of running the diesel generator is 33 cents/kWh (using $4.40/gallon of fuel) compared to the cost of using the battery bank which is 8.1 cents/kWh for off-peak charging. The diesel generator used for this use case is for backup only, but it can also be used to satisfy standby generation contracts or to make up for sudden load or source changes during periods of load curtailment.

The energy storage unit is a 38.04 kWh deep-cycle lead-acid battery with a chosen max. DOD of 50%. The deep-cycle battery selected can deliver 2100 cycles at a 80% DOD or 4000 cycles at a 50% DOD. Peak shaving with the battery over a seven hour peak period with a 50% max. DOD, sets the battery power, Pbat, at 2.72 kW. The Peukert's constant for flooded deep-cycle ranges from 1.2 to 1.6. This value is used to compute the changing capacity of the battery as it degrades and takes more energy to charge, which is equated in Peukert's Law. Computing this value is necessary for accurate battery management and SOC estimation [18].

Based off actual auto-DR strategies employed by companies and discussed in [9], the following parameters for load curtailment limits are set for the nursing home use case:

1) HVAC: [74, 76, 78]
2) Lighting: [100, 80, 60]

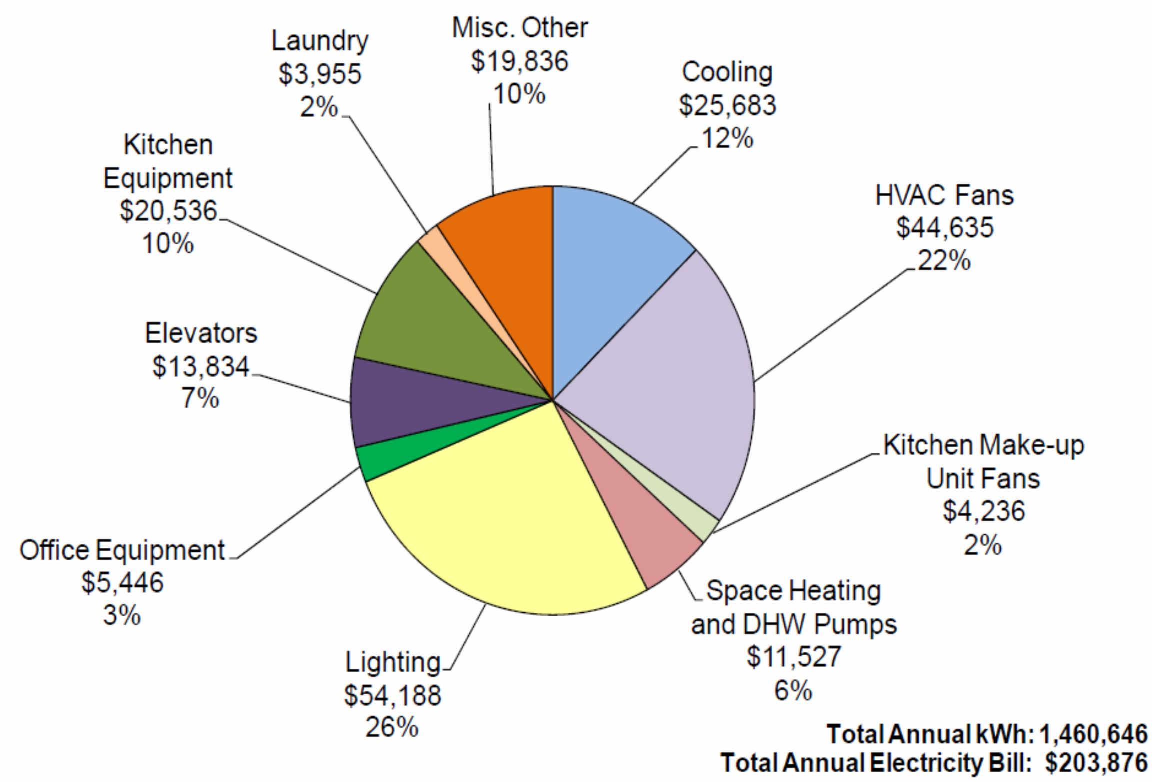

Figure 11. National Survey Of Nursing Home Electricity Consumption [15]

Table V. Nursing Home Use Case Specifications

Specification	**Type / Size**	**Cost or Savings**
Critical load	25% of peak load (50 kW) = 12.5 kW	
TOU prices	Duke Energy Pilot Program	On-peak: 18.00 cents/kWh (12pm – 7pm) Off-peak: 5.31 cents/kWh
PV size	12.5 kW (100% of critical load)	2012 Cost: $5.03 / W (5 kW – 217 kW sys.) Total = $62 875; [2020 Projected Cost: $2.29 / W]
Battery size	38 kWh, 24 V, lead-acid deep cycle (22 % of critical load) (max. DOD = 50%)	$8099.97 Lifetime = 10+ years or 4000 cycles
Diesel genset size	16 kW (125% of critical load)	Pre-owned; ~$4.40/gallon
On-peak curtailment strategy (uses 1st level, load curtailment)	30% reduction lighting load 2 degree HVAC setpoint change	Results in a 17.8% reduction from baseline
Target daily savings	25% reduction of PV/battery payback period (2nd level, load curtailment used for contract negotiation)	$6.38 / day
PV/battery payback period		PV + Battery Peak Shaving (only): ~12.5 years W/target daily savings: ~9.4 years

4.1 SIMULATION ENVIRONMENT

NetLogo is a programming language and software designed for customizable, simulated multiagent system testing**.** NetLogo has an interface that allows for parameters to be quickly tuned and for multiple results and graphs to be shown on the same screen. Figure 12 shows the NetLogo interface used for this work. This interface could be used as a model for a building manager interface or GUI. The interface allows for quick changes to the DER amount, electric rates, and the daily probability for receiving a curtailment request. The building manager/user can set two levels of constraints for curtailment. The total utility (cost savings) can be shown in real-time. Snippets of the NetLogo code are laid out in the Appendix along with detailed explanations of parameters and variables.

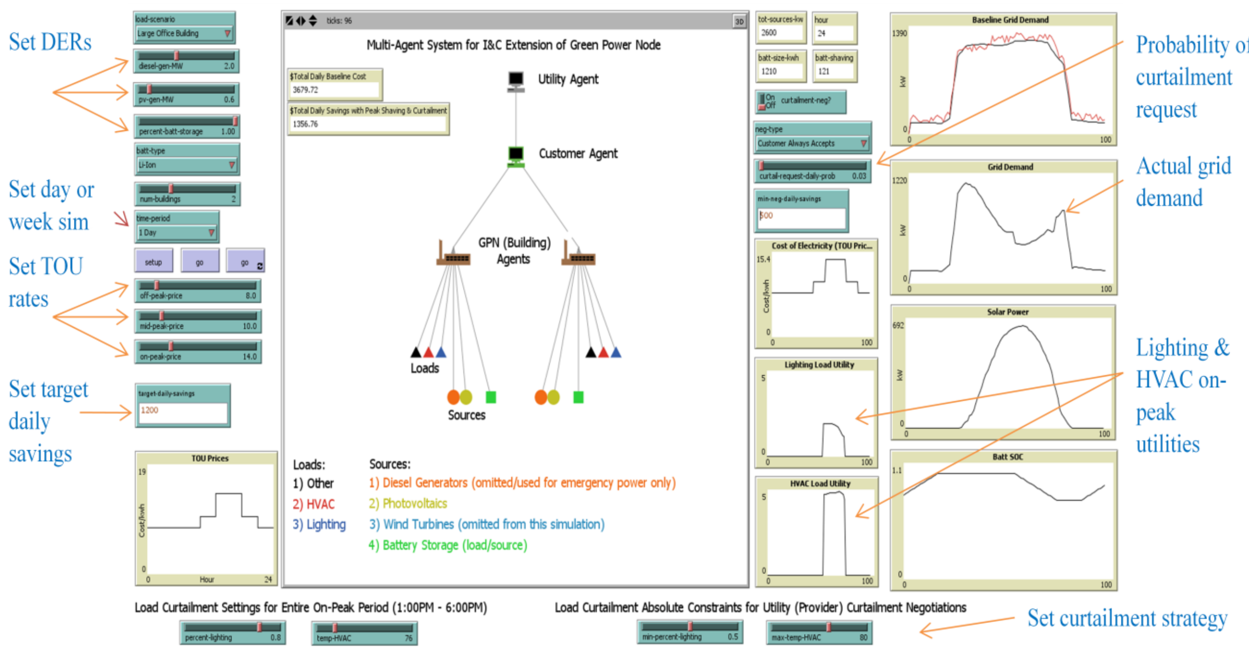

Figure 12. Simulation Environment In NetLogo

CHAPTER 5

FORECASTING

The system employs load and weather-dependent load forecasting methods for use in decision-making. To make accurate cost saving decisions for the customer, improve energy management, negotiate standby and curtailment contracts, and indirectly or directly participate in market bidding, the system needs the ability to forecast load and photovoltaic (PV) power. Accurate forecasting offers a benefit not only to the customer-side decision-making and system control but also to the power provider's demand-side management in a smart grid. Available online weather forecasts can be utilized for PV forecasting, wind generation forecasting, and lighting and heating, ventilation, and air conditioning (HVAC) load forecasting. The following sections offer an initial step in accurate forecasting for the system that could have applications in any demand-side EMCS.

Equations (5.1) and (5.2) show the day-ahead, forecast baseline updating and modification that occurs at the end of a day. There is also a long-term database baseline that stores all data collected that can be used for long-term studies. The forecast baseline is an average of the data collected over *N* days. In this work, *N* = 3 (three days) is used for all baselines. B_t represents the updated baseline value at time period t (15 min. or 1 hour time step/resolution) while $B_{old,t}$ represents the old baseline value. s_t^d represents the load data(or weather data) on the previous day d at time period t. *N* represents the number of days used to create the baseline. At midnight the building agents average the previous

day's entire actual load and weather data into their respective forecast baselines, which is shown in (5.1) for one data point. The agent must then remove the last day (now the fourth day) from the baseline s_t^{d-3}, which is shown in (5.2) for one data point. Baselines are used in all the forecasting methods in this chapter. Load baseline data is collected directly from the nursing home site. Historical weather and solar radiation data are collected from the site www.wunderground.com. Temperature and cloud cover forecasts used in this chapter are collected at 5 P.M on the previous day from weather.com for the spring data and the National Oceanic and Atmospheric Administration (NOAA) website at www.noaa.gov for the summer data. Weather.com was initially used until it was discovered that NOAA provided a useful integer percentage for cloudiness data in contrast to weather.com's non-numerical data (e.g. "Partly Cloudy").

Updating Forecast Baseline for Database:

$$B_t = \frac{N(B_{old,t}) + s_t^d}{N+1} \tag{5.1}$$

Modifying Forecast Baseline for Next Day:

$$B_t = \frac{(NB_{old,t} - s_t^{d-3}) + s_t^d}{N} \tag{5.2}$$

5.1 DAY-AHEAD LOAD FORECASTING

Day-ahead load forecasting is essential for maximizing cost savings/utility for the customer. For negotiation of curtailment contracts, it is vital to know the amount of DERs that will be available at any given time. Accurate day-ahead load forecasting can also allow for participation in a day-ahead market. Two day-ahead forecasting methods are implemented and compared in this section.

5.1.1 AUTOREGRESSIVE MODEL

The autoregressive (AR) model which is laid out in [19] and shown in (5.3) uses the last three days of the same day type (e.g. weekdays vs. weekends) where *d* stands for the referenced day and *p* stands for the time period (15 min). And *c* is a constant and φ is a scaling parameter that weighs each day's value. *q* specifies the amount of days used in the forecast. In [19] the following parameter values were arbitrarily set: q = 3, c = 0 and φ = 1 / 3 for i = 1, 2, 3 which is equivalent to taking an average of the three values. Using c = 0 and φ = 1 / 3 for i = 1, 2, 3, q values of 1, 2, 3, 4, 5 were tried for the nursing home use case before setting q = 3, which had the best performance. Using q = 3 and c = 0, φ values of {φ_1 = 2/3, φ_2 = 1/6, φ_3 = 1/6}, {φ_1 = 1/2, φ_2 = 1/4, φ_3 = 1/4}, and {φ_1 = 1/3, φ_2 = 1/3, φ_3 = 1/3} were tried with the latter performing best. Using this equation, a forecast baseline can be created for each 15 min. period (96 data points).

$$B_t^{p,d} = c + \sum_{i=1}^{q} \mathrm{\varphi_i^{p,d}\, s_{t-1}^{p,d}} \tag{5.3}$$

Several weeks of load data was analyzed for the spring and summer 2012 season for the nursing home and correlation was mathematically examined to determine any relationship between the days that could separate them into a different day type. It was determined that Sundays during the summer season were significantly different than the other days during the summer. Sundays during the spring season did not vary enough from the other days, partly due to the lower heating/cooling demand during the spring. So for Sundays during the summer season, the same method is used as in (5.3) but instead of using the past three days (only one day type), the past three Sundays from the previous three weeks are used. Results using the AR method are shown in Tables VI and VII for

four day periods in spring 2012 and summer 2012 respectively. Figures 13 and 14 show the AR forecast performance for Apr. 6, 2012 and Apr. 6 - 9, 2012 respectively.

5.1.2 EXPONENTIAL SMOOTHING

As discussed in [20] for Grid-level forecasting (in GW), this method uses load data from the past three weeks of the same day (e.g. for a Monday forecast, it uses the previous three weeks' actual Monday load data) with varying scale factors and max. load averages. The equations derived in [20] for calculating the forecast max. load, average normalized value, and the 15 min. forecast (hourly periods used in [20]) are shown below in (5.4), (5.5), and (5.6) respectively. α is the scale factor = 1 / N where N is the number of days, here again it is 3. X is the actual max. load on day, d. In (5.5) the numerator represents the 15 min. load on the same day from the previous week (repeat for the last three weeks) while the denominator represents the daily max. value for the 15 min. load from those days. Using (5.6) a forecast baseline can be created for each 15 min. period.

$$F_d = \propto X_{d-1} + \propto (1-\propto) X_{d-2} + \propto (1-\propto)^2 X_{d-3} + (1-\propto)^3 F_{d-3} \qquad (5.4)$$

$$AVG\_PU_t^{WD} = \frac{MW_t^{WD}}{MW_{max}^{WD}} \qquad (5.5)$$

$$B_t^{WD} = F_d(Avg\_PU_t^{WD}) \qquad (5.6)$$

The performance of the exponential smoothing and AR methods are compared in Tables VI and VII for four days during spring 2012 and four days during summer 2012 respectively. The forecasting performance is evaluated using the Mean Absolute Percentage Error (MAPE). This is a commonly used error for measuring the performance

of load forecasting. The day-ahead MAPE for the four days using the AR method is slightly better than the exponential smoothing method for both spring and summer. The AR method is selected and used for the rest of the analyses based off these results.

5.2 15 MINUTE LOAD FORECASTING USING DYNAMIC WEIGHTED MEAN

To increase the accuracy of forecasting during the day and for better short-term energy management, a dynamic weighted mean (DWM) is applied every time step (15 min.) using the day-ahead forecast baseline and the previous step's actual value. The method is described as "dynamic" since the singular weight value is recalculated every time step. Each time step, (5.7) calculates the error variance V_1 of the forecast baseline to the actual load value, $s_t^{p,d}$. And (5.8) calculates the error variance V_2 of the predicted value to the actual load value. These variances are used to calculate a weight value in (5.9) that changes each time step and has a value between 0 and 1 (initially at *weight* = 0.5). Equation (5.10) shows the main formula used to calculate the corrected (new) forecast for the next time step where B_{t+1} represents the next 15 min. period in the day ahead, forecast baseline. The *weight* value allows us to weigh the accuracy of the forecast baseline value vs. the accuracy of the DWM value each time step.

$$V_1 = B_t - s_t^{p,d} \tag{5.7}$$

$$V_2 = pred_{load,old} - s_t^{p,d} \tag{5.8}$$

$$weight = \frac{V_1}{V_1 + V_2} \tag{5.9}$$

$$pred_{load,new} = B_{t+1} + weight(s_t^{p,d} - B_{t+1}) \tag{5.10}$$

Results for the DWM method are shown in Tables VI - VIII. When applied to the exponential smoothing and AR day-ahead forecasts, they have nearly identical MAPEs. The exponential smoothing method performs scarcely better and this can most likely be contributed to the smoothing method's improved peak matching compared to the AR method. The smoothing method better mirrors peak behavior in the load but does not mirror the value-density as well as the AR method which can be greatly improved with the DWM. The AR method is still the chosen method for this work because the day-ahead forecast is much more valuable than the 15 min. forecast for negotiation and bidding.

An improvement on the 15 min. forecasting could be the application of a univariate (only one variable) Kalman filter. The DWM method used has a similar structure to the univariate Kalman filter where the forecast baseline represents the univariate dataset, but the DWM method lacks the use of noise or state covariance variables. [21] formulates equations for a Kalman filter to estimate noise and covariance variables for a univariate measurement dataset. These equations can be implemented and tested to possibly improve the performance of the 15 min. forecast.

5.3 WEATHER FORECASTING

Weather forecasting can be used to aid with load and HVAC forecasting, solar radiation forecasting, and wind generation forecasting. Solar radiation forecasting and the effect of outdoor temperature on the total load is explored briefly in this section. Solar

radiation forecasts will provide the PV output forecast which will be used to compute the predicted grid demand for the day.

Changes in the outdoor, ambient temperature have a delayed effect on the indoor temperature and thus the HVAC load. Correlating the load and temperature data from the nursing home with various delays produces very low correlation for the 15 min. periods during the spring season. In [22] a thermal response time constant equation is formulated for a residential home using a lumped parameter approach. This equation can be used to estimate the time it takes for the indoor temperature to rise or fall during residential HVAC curtailment. The equation only uses a single thermal time constant variable to represent a home's physical thermal qualities and HVAC system type. The average home is identified to have a thermal time constant ranging from 5 - 15 hours. A home's time constant can vary at anytime due to various factors including heating from indoor loads, solar radiation changes, and outdoor wind speed changes. For a C&I building, the effect of these factors are significantly amplified, and the simplified, residential equation may not accurately represent the thermal time response of a large C&I building. To accurately model a C&I building's thermal characteristics, a building simulation software like eQuest is used to include structure details like HVAC type, HVAC orientation/layout, building size, and total window surface area [14]. The most direct solution for the MAS is to pull data from the HVAC agent on-site, collecting data on cycle time, temperature setpoints, and total HVAC load. This data can be quickly analyzed and used to create an accurate HVAC forecast.

South Carolina Electric & Gas (SCE&G) has implemented a program (started August 2010) that applies a Weather Normalization Adjustment (WNA) to the base

electric rate for their customers. The goal of the WNA is to reduce the demand volatility on SCE&G and at the same time, reduce price volatility on the customer that is caused by extreme hot or cold weather. The end effect on customers' bills is a drop in cost per kWh consumed when peak reduction incentive should cause an increase (e.g. extremely warm summer month or extremely cold summer month compared to the last 15 years) or a rise in cost when there should be a decrease (e.g. abnormally cool summer month). The major problem with the WNA is it greatly increases customer uncertainty and direct customer involvement in demand-side peak reduction. It also does not help that this program was initiated with a base electric rate hike, thus, the WNA may have decreased customer cost, but overall customer costs were driven up [23].

An alternative for reducing demand volatility due to extreme temperatures is incorporation of the effect of local temperatures into customer load forecasting. With our system, the customers implement the forecasting themselves, thus helping the customer plan their own demand response. Forecasts can then be communicated to the power provider to increase the accuracy of their grid-level day forecasts. This way demand volatility can be better predicted for the power provider and customer cost can be more effectively handled.

5.3.1 MAXIMUM TEMPERATURE SENSITIVITIES FOR SUMMER LOAD FORECASTING

Reference [20] also presents a method for grid-level summer forecasting that utilizes the maximum predicted temperature for the forecasted day and the actual maximum temperature from the previous day. Reference [20] goes further into detail utilizing past seasonal data and constructing multiple temperature sensitivities, but only

the core equations are implemented for investigation in this work. Equations (5.11), (5.12), (5.13) are identical to the corresponding equations in [20]. In (5.11) the difference in maximum temperatures is calculated for the forecasted day, T_{max}^{WD}, and the (actual) previous day, T_{max}^{before}. Equation (5.12) does the same as (5.11) to calculate the variation in load $\Delta\lambda$ using the maximum load of the forecasted day and the previous day. Equation (5.13) calculates the temperature sensitivity ΔD using the previous calculated values. Equation (5.14) that calculates the max. load forecast value is slightly altered from the equation in [20] where $F_{d,max}$ is equivalent to F_d calculated in (5.4) and the temperature sensitivity ΔD is only calculated for one day. Equations (5.6) and (5.15) are identical except for the new max. load forecast value.

$$\Delta T = T_{max}^{WD} - T_{max}^{before} \tag{5.11}$$

$$\Delta\lambda = \lambda_{max}^{WD} - \lambda_{max}^{before} \tag{5.12}$$

$$\Delta D = \frac{\Delta\lambda}{\Delta T \times \lambda_{max}^{before}} \tag{5.13}$$

$$F_{max}^{WD} = \left| F_{d,max} + \Delta D \times \Delta T \times F_{d,max} \right| \tag{5.14}$$

$$B_t^{WD} = F_{max}^{WD} \left(Avg\_PU_t^{WD} \right) \tag{5.15}$$

The above equations were used to calculate their respected MAPEs for summer 2012, and the results showed an increase in MAPE for all days except June 28th which had a MAPE of 7.12%. April 6 had the lowest percentage error for its max. temperature

forecast attained from the NOAA website. The worst increases were for June 29th and 30th which had MAPEs of 9.16% and 12.48% respectively. These days also had the worst percentage error in their max. temperature forecasts.

To improve the performance of the temperature sensitivities, (5.15) was combined with the AR equation, (5.3), modifying the $Avg\_PU_t^{WD}$ value originally outlined in (5.5). Instead of using the previous three weeks of the same day to calculate the numerator value MW_t^{WD}, the previous three days were used as in the AR method (e.g. for a forecasted Friday, use Tues., Wed., and Thurs. of the same week). Different variations of the AR combination were explored before arriving at this variation which produced the lowest MAPEs. These MAPEs are compared to the MAPEs from solely applying the AR method in Table IX for the summer 2012 period.

5.3.2 FORECASTING WITH SMART HVAC/THERMOSTAT AGENT

To have the ability to accurately forecast the HVAC system, you must first know the HVAC power consumption or the HVAC percentage of the total load. Data analysis and prediction could be performed using the HVAC data with affecting independent variables like temperature or wind speed. Major goals of this analysis would be to first identify the building and HVAC type. Even after these identifications, accurate forecasting would be difficult without additional HVAC data like temperature setpoints and duty cycle time. To obtain this information for the C&I GPN MAS, the thermostat for the HVAC could be either a programmable thermostat with wireless communication or operate as a complete smart agent with inputs to adjust the duty cycle, occupancy, and temperature setpoint controls.

5.3.3 SOLAR RADIATION FORECASTING

Although the AR method is mainly used in load forecasting, it is also used for solar radiation forecasting in this work. Unlike the AR load forecasting used in the previous sections, the solar radiation forecasting uses the day type criteria to identify three distinct types of solar radiation days. These day types are "Sunny" "Cloudy," and "Very Cloudy" or alternatively cloud cover % ranges of 0% - 20%, 20% - 50%, and 50% - 100%. The day types are identified by the % cloud cover or cloudiness data. The forecasted day's type is identified from the downloaded weather forecast (cloud cover) from either the NOAA's website or Weather.com.

One of the most significant outputs of the forecast is the total solar radiation for the day which is used to compute the total PV output for the day. Table VIII shows the percentage error of the total solar radiation for the four days selected in the spring. The forecasting method still needs to be improved by adding more day types, e.g. "Very Sunny," "Sunny," "Partly Cloudy," "Mostly Cloudy," and "Very Cloudy." Performance may also be improved by splitting the day in half and identifying two day types for the forecasted day (e.g. one day may be mostly cloudy in the morning but very sunny in the afternoon). There is a limit on the number of day types that can be used before forecasting accuracy starts to drop. Further investigation is needed.

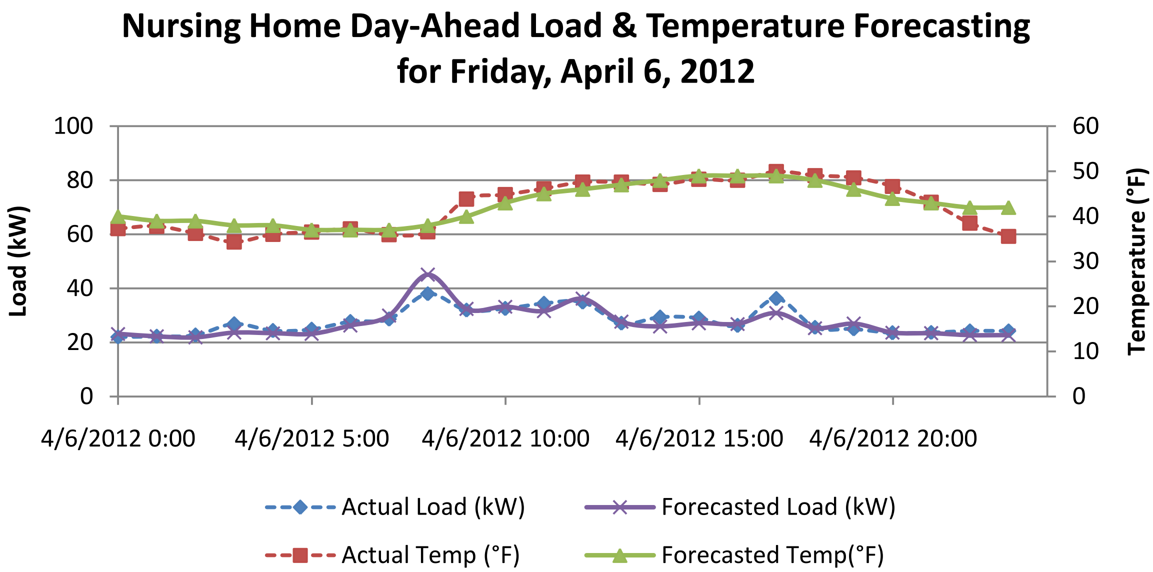

Figure 13. Day-ahead, Autoregressive Load and Temperature Forecasting (from Weather.com) Performance for Apr. 6, 2012

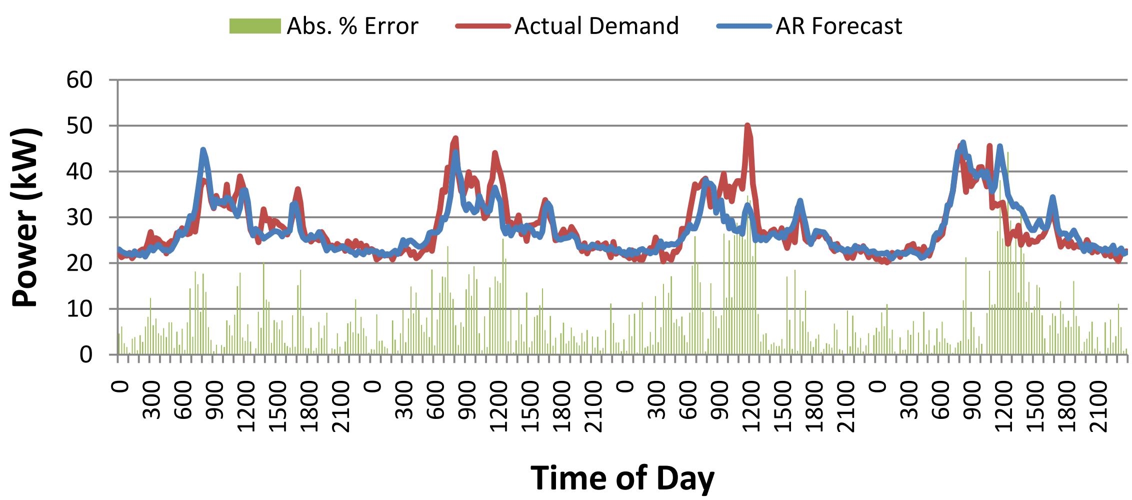

Figure 14. Day-ahead, Autoregressive Load Forecasting Performance for Apr. 6 - 9, 2012

Table VI. Comparison of Load Forecasting Methods during Spring 2012

Date (Day)	Autoregressive Day-Ahead MAPE [%]	Autoregressive MAPE [%] with 15 min. DWM	Exponential Smoothing Day-Ahead MAPE [%]	Exponential Smoothing MAPE [%] with 15 min. DWM
Apr. 6 (Fri.)	6.92	4.91	5.84	4.48
Apr. 7 (Sat.)	7.35	5.44	9.38	5.62
Apr. 8 (Sun.)	7.65	5.84	9.27	5.72
Apr. 9 (Mon.)	7.37	5.22	9.02	5.29
MAPE	**7.32**	**5.35**	**8.38**	**5.28**

Table VII. Comparison of Load Forecasting Methods during Summer 2012

Date (Day)	AR Day-Ahead MAPE [%]	AR MAPE [%] with 15 min. DWM	Exponential Smoothing Day-Ahead MAPE [%]	Exponential Smoothing MAPE [%] with 15 min. DWM
Jun. 28 (Thurs.)	7.96	5.31	7.66	4.92
Jun. 29 (Fri.)	8.72	5.36	9.22	5.80
Jun. 30 (Sat.)	8.13	5.63	9.46	5.19
Jul. 1 (Sun.)	6.36	4.73	6.20	4.72
MAPE	**7.79**	**5.26**	**8.14**	**5.16**

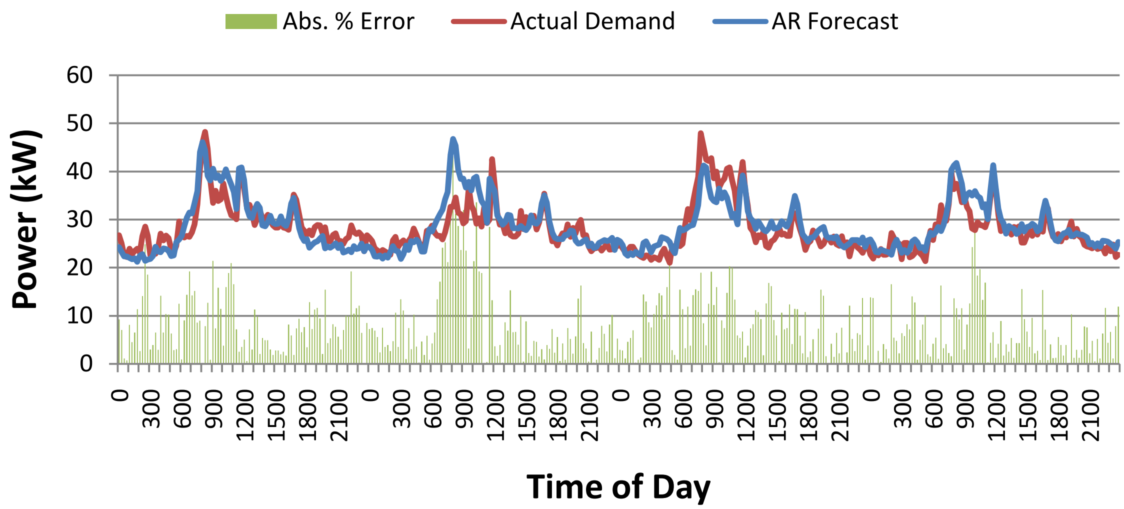

Figure 15. Day-ahead Autoregressive, Load Forecasting Performance for June 28 - July 1, 2012

Table VIII. Performance of Day-ahead, Outdoor Temperature (Weather.com Forecast) and Solar Radiation Forecasting (AR Method) during Spring 2012

Date (Day)	Temp. Day-ahead MAPE [%] (Weather.com Forecast)	Temp. MAPE [%] with 15 min. DWM	Day-ahead Error [%] of Max. Temps.	Day-ahead Abs. Error [%] of Total Solar Radiation
Apr. 6 (Fri.)	4.53	3.65	1.80	10.27
Apr. 7 (Sat.)	13.65	6.55	1.79	5.95
Apr. 8 (Sun.)	5.92	3.16	1.02	9.60
Apr. 9 (Mon.)	4.15	3.76	3.97	1.81
MAPE	**7.06**	**4.28**	**2.15**	**6.91**

Table IX. Comparison of Day-Ahead AR with and without Maximum Temperature Sensitivities during Summer 2012

Date (Day)	AR Day-Ahead MAPE [%]	AR with Max. Temp. Sensitivities Day-Ahead MAPE [%]	Change in MAPE	NOAA Predicted Max. Temp. Day-Ahead Error [%]
Jun. 28 (Thurs.)	7.96	7.78	-2.26%	0.63
Jun. 29 (Fri.)	8.72	8.53	-2.18%	3.51
Jun. 30 (Sat.)	8.13	8.13	0%	1.90
Jul. 1 (Sun.)	6.33	5.58	-11.85%	0.91
MAPE	**7.79**	**7.51**		**1.74**

5.4 INCORPORATING FORECAST UNCERTAINTY INTO DECISON MAKING

Accounting for forecast uncertainty is vital for establishing confidence in the system's decision making for both the customer and the power provider. Reference [24] details how to compute the probability density function (pdf) of a forecast knowing only the MAPE value. The author assumes a normal distribution of the absolute error where the mean is the MAPE value and the standard deviation (σ) is equal to MAPE / 3.09 where the z value for 3.09σ corresponds to the 99.9% confidence level with a minimum expected value of zero. It can also be assumed that there is a 50% probability to underestimate and a 50% probability to overestimate the actual value. With a standard

normal distribution, there is a 95.44% that a value will fall within +/- 2σ of the mean. Using an absolute value for the error facilitates two pdfs to consider for underestimation or overestimation. All values will be split evenly between the two pdfs. The resulting pdfs are shown in Fig. 16 using the summer, AR load forecasting MAPE, 7.79%.

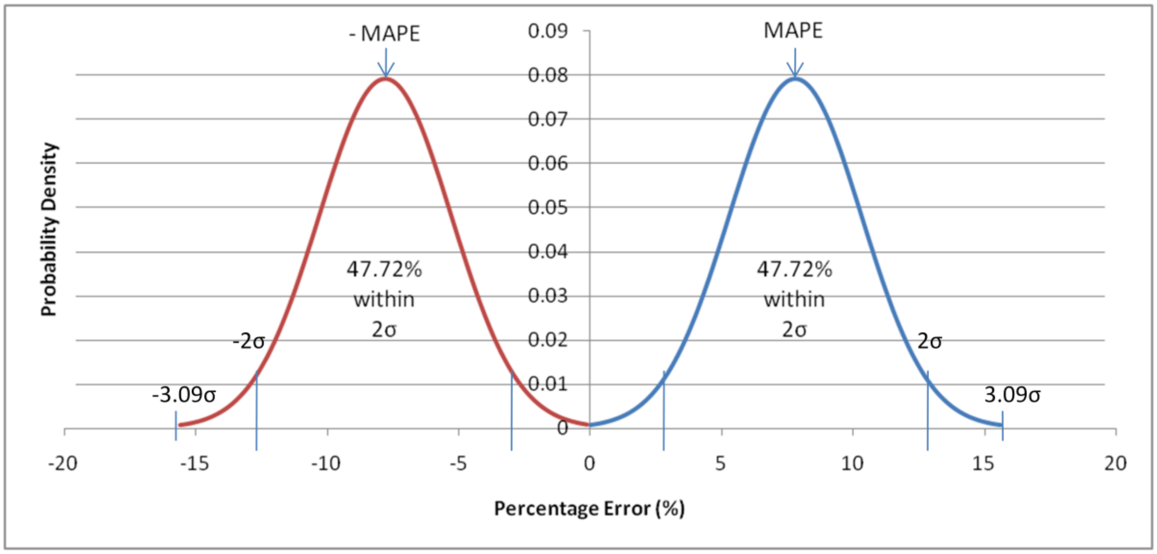

Figure 16. Probability Distribution for Load Forecasting Error using the MAPE Value only

For the nursing home use case, we decided to create a confidence interval with 95% confidence for the grid demand forecast using the load and solar radiation/PV forecasts. A 95% confidence level was selected for its common use in industry statistical analysis and forecasting. Selecting a 99.9% confidence level would produce too large of a confidence interval for the calculated MAPE values which would severely limit cost-saving decision making. In contrast a 90% confidence level would increase risk to a level most likely unacceptable for most customers and power providers. The equation for calculating the grid demand forecast(excluding load curtailment or standby generation use) is shown in (5.16) where the forecasted output of the PV along with predicted

battery/E.S.U. usage is subtracted from the total load. Having two forecasted variables with a 50/50 chance to underestimate/overestimate creates four different possibilities for the grid demand mean. We are interested in the two extreme values for our confidence interval. The lowest mean is when the load is underestimated and the PV is overestimated, shown in (5.17). The highest mean is when the load is overestimated and the PV is underestimated, shown in (5.18).

$$B_{t,grid} = B_{t,LOAD} - B_{t,PV} - P_{t,BAT} \tag{5.16}$$

$$\mu_{low} = [1 - (MAPE_{load} + 2\sigma)](S_{\text{load}}) - [1 + (MAPE_{PV} + 2\sigma)](S_{\text{PV}}) \tag{5.17}$$

$$\mu_{high} = [1 + (MAPE_{load} + 2\sigma)](S_{\text{load}}) - [1 - (MAPE_{PV} + 2\sigma)](S_{\text{PV}}) \tag{5.18}$$

5.4.1 EXAMPLE INCORPORATION OF FORECASTING UNCERTAINTY

Using the nursing home use case, assume a curtailment request is received by the negotiation agent at 7 AM on April 6, 2012 for the period 1:00 PM - 3:00 PM of the same day for 10 kW off the *baseline load*. The curtailment request is parameterized into [t0, t, Pc] representing the start and end of the period in 15 min. time steps (96 in a day) and the power reduction requested for that period. A load MAPE of 7.79%, and PV MAPE of 25% are used to calculate the forecast interval.

Using (5.16) the grid demand forecast values are calculated which include the use of static, battery peak shaving. These values are shown in Table X along with the parameters and calculations discussed in this section. Plugging into (5.17) and (5.18) we obtain the simplified equations (5.19) and (5.20) below. These equations are used to

calculate the confidence intervals (CIs) for each time step. We are interested in identifying the maximum upper CI endpoint for the requested curtailment period. This endpoint represents the max. grid demand possible (with 95% confidence) during the time period with PV and battery peak shaving. Shown in Table X, the max. grid demand for the period, 24.07 kW is at t = 55.

The max. possible load curtailment now needs to be subtracted from the max. grid demand. Curtailment constraints for the nursing home are defined as 30% reduction in lighting and a 2 degree change in HVAC setpoint. The estimated curtailment reduction is 17.8% from the baseline load. This reduces our max. peak load to 19.79 kW. Subtracting this value from the baseline load gives us a difference of 5.57 kW which is far short from the 10 kW needed. With just the decision-making discussed in this section, the curtailment request would be rejected. Changing the battery use schedule (see Section 6.3.3) is an alternative option if there is a greater cost benefit from this action.

$$\mu_{lower} = [0.872](\mathrm{S}_{\mathrm{load}}) - [1.412](\mathrm{S}_{\mathrm{PV}}) \tag{5.19}$$

$$\mu_{upper} = [1.128](\mathrm{S}_{\mathrm{load}}) - [0.588](\mathrm{S}_{\mathrm{PV}}) \tag{5.20}$$

Table X. Parameters & Calculations for Forecasting Uncertainty Example

Parameter	**Value/Calculation**
Curtailment Request	1:00 PM - 3:00 PM, 10 kW -> [52,59,10]
Baseline Load Forecast for T = [52, 59]	[27.49, 26.86, 26.30, 25.36, 25.79, 26.21, 26.61, 27.03] kW +/- 12.8%
PV Forecast for T = [52, 59]	[9.90, 10.13, 7.08, 3.09, 7.42, 8.59, 9.03, 8.81] kW +/- 41.2%
Battery Usage for T = [52, 59]	[2.72, 2.72, 2.72, 2.72, 2.72, 2.72, 2.72, 2.72] kW
Resulting Grid Demand Forecast for T = [52, 59]	[14.87, 14.01, 16.50, 19.55, 15.65, 14.90, 14.86, 15.5] kW
Grid Demand Forecast Confidence Intervals (in kW)	+/- [7.60, 7.61, 6.28, 4.52, 6.36, 6.89, 7.13, 7.09] kW
Grid Demand Forecast Upper CI Endpoint (μ_{upper})	[22.47, 21.62, 22.78, **24.07**, 22.01, 21.79, 21.99, 22.59] kW
Upper CI Endpoint With Lighting/HVAC Curtailment	[18.47, 17.77, 18.73, **19.79**, 18.09, 17.91, 18.08, 18.57] kW
Max. Allowable Demand Reduction for T = [52,59] (with 95% confidence)	25.36 kW - 19.79 kW = **5.57 kW**

Once the C&I GPN MAS is physically in place, an alternative to using the method described in this section is just using the actual grid demand collected from a sensor/s for a few days or weeks and comparing it to the calculated grid demand forecast

to produce a MAPE value. This method will not be as accurate for forecasting certain time periods during the day (larger confidence intervals) as done in this section. This is due to the difference in daily MAPE values for the different forecasts which are used as weights for averaging. There is also a need to monitor and utilize the forecasting error of the HVAC and lighting load curtailment. Adequate data was not available with this work to include load curtailment forecast analysis.

CHAPTER 6

SYSTEM CONTROL

6.1 HIGH LEVEL STATES

The system has five high level states: Automatic Response, Contracted Curtailment, Standby Generation Use, Islanding Mode, and Safe Mode. Similar to the Residential GPN, Automatic Response is the normal operating state that responds to price. Automatic Response aims to reduce usage charges (like with the Residential GPN) and/or demand charges for the C&I customer. This state includes the use of peak shaving by any distributed energy resource like PV, Wind, or battery/E.S.U. Load leveling by the battery can be done to reduce long-term demand charges. Unlike the R-GPN, load curtailment is included in this mode and is limited by user-inputted constraints. For curtailment and standby generation contracts, the system switches to the Contracted Curtailment and the Standby Generation Use state, respectively. If sudden load or source changes occur while in the Contracted Curtailment state, the system will go to the Standby Generation Use state and startup/use additional generation, if applicable, to meet the curtailment requirements. If the Grid goes offline, the system will automatically go into Islanding Mode and safely disconnect from the Grid. If the negotiation agent *and* the building agent(s) lose their Internet connection, the system automatically switches to Safe Mode. In Safe Mode, there is a priority to keep the battery/E.S.U. at 100% capacity while fulfilling all accepted contracts. Safe Mode can also be manually entered if the user knows of an impending emergency. Figure 17 shows four states of operation. Safe Mode

is not shown to maintain visual simplicity; this state would run parallel to Islanding Mode only changing "Grid online/offline" transitions to "Internet connection online/offline."

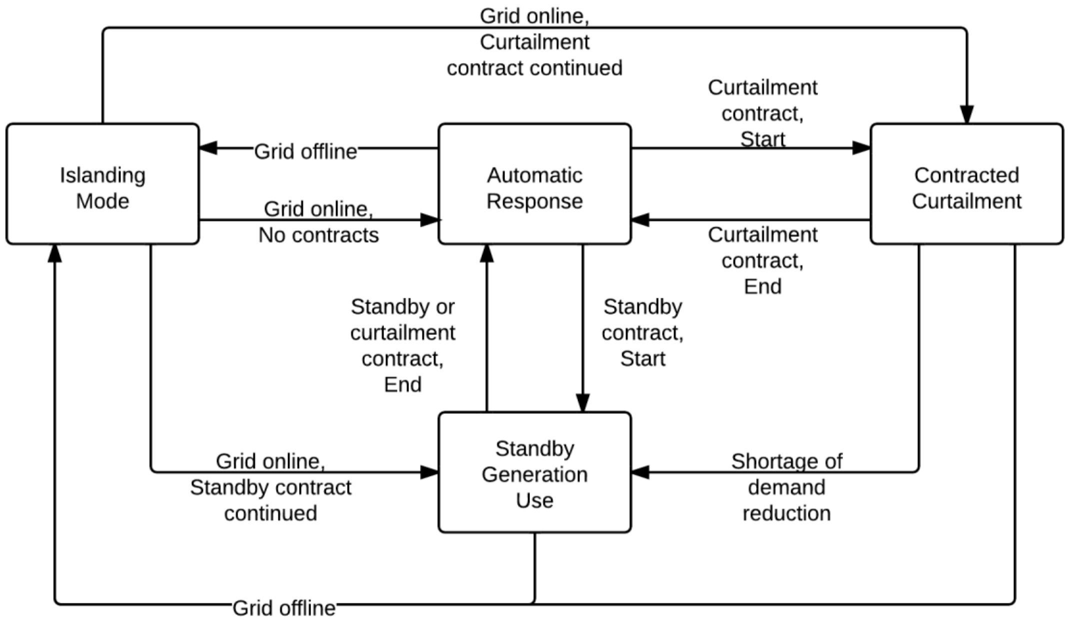

Figure 17. Four High Level States of the System (Safe Mode not shown)

6.2 AGENT CONTROL DESIGN

In this section, the high level, system control algorithms for the agents will be described. These algorithms apply to the high level decision making of the C&I MAS. The algorithms shown do not cover the interfacing to low level controls like setting current reference values for the DERs or direct interfacing with load settings for curtailment. A four day window of demand and forecasting for the nursing home use case is used to demonstrate the effect of automatic response strategies on grid demand, forecasting, and overall cost savings.

6.2.1 NEGOTIATION AGENT CONTROL

The negotiation agent's control algorithm is shown in Figure 18. Each time step, the agent first receives the aggregate utilities and grid demand forecast from the building agents. The negotiation agent also receives any relevant pricing forecast along with any curtailment and standby contract requests and any additional information made available by the power provider. This information could help describe the current status of the provider (e.g. a value that represents how significant the provider's need for demand reduction is). The negotiation agent will then update its pricing, weather, and load forecasts. The negotiation agent will combine forecasts from the building agents to produce day ahead and 15 min. DER scheduling.

After the previous actions the negotiation agent will update its target bid. This subprocess is shown in Fig. 19. The agent algorithm is set up for two rounds of bidding. For the first bid, the target daily savings and the target hourly savings are used to set the bid amount for the customer. If the target daily savings is scheduled to be met for the day, the agent will place a rational bid (see "Bidding Behavior Types") based on the target hourly savings and market clearing price. If the target daily savings is scheduled not to be met for the day and the expected savings minus the cost incurred by altering the set schedule is greater than zero, then a bid equivalent to the target hourly savings will be placed.

If the first bid is rejected and there is a second round of bidding a second bid will only be placed if the scheduled, target hourly savings will not be met for the hour. If the original bid was greater than the last successful (winning) bid, then the second bid amount will be equivalent to the last successful bid. If this is not the case, then the second

bid will be equivalent to the current total savings for the hour (total utility) plus the cost of altering the set schedule.

Once the target bid has been updated, the agent will check to see if there is a negotiable contract request. If there is, the agent will automatically send the target bid to the power provider as long as the target bid meets the minimum bid amount in the request. If the bid is rejected and the request is still open, the agent will update the target bid once more. If the bid is accepted and contracted or if the bid is rejected twice, the negotiation agent will proceed to update the operation and DR task schedules and will send these updates to the building agents. After this the negotiation agent will send the updated grid demand forecast to the power provider every specified time interval (e.g. once an hour or once a day).

Bidding Behavior Types

Three agent behavior types are described in [25], defined as rational, optimistic, and emotional. These agent types determine the agent's "decision rules" in an environment with multiple actions available each time step. The agent behavior types are based on the maximum expected utility calculated from the probabilities of success/failure for each available action.

Our negotiation agent has three types of bidding behaviors based off the types in [25]: rational, optimistic, and cautious. Agent behavior types are usually based on the maximum expected utility; in this work, we utilize the 95% confidence interval forecasts instead. The following bidding behaviors/strategies assume we do not know the winning bid/s.

The rational bidder will place a bid equivalent to the target hourly savings. If the target savings is already forecasted to be met, the rational bidder will place a bid equal to the target hourly savings + discount weight * forecasted market clearing price. The discount weight ranges from 0 to 1 and changes based on the success of previously used discount weights. The rational bidder is used in the update target bid algorithm in Fig. 10.

The optimistic bidder has the same bids as the rational bidder except it multiplies the bids by a bias value equal to 1 + (number of successful bids) / (number of unsuccessful bids). The bias value is initially equal to 1. The optimistic bidder will perform better than the rational bidder if the target hourly savings is too high.

The cautious bidder will initially place a first bid equivalent to the target hourly savings. After this the cautious bidder will place a first bid based off the last successful bid (winning contract). If this bid is successful, the bidder will slowly increase at a % rate of (last successful bid + target hourly savings) / (target hourly savings) for each new bid contract. If a first bid is unsuccessful, the cautious bidder will go back two successful bids. The goal of the cautious bidder is to secure as many contracts as possible.

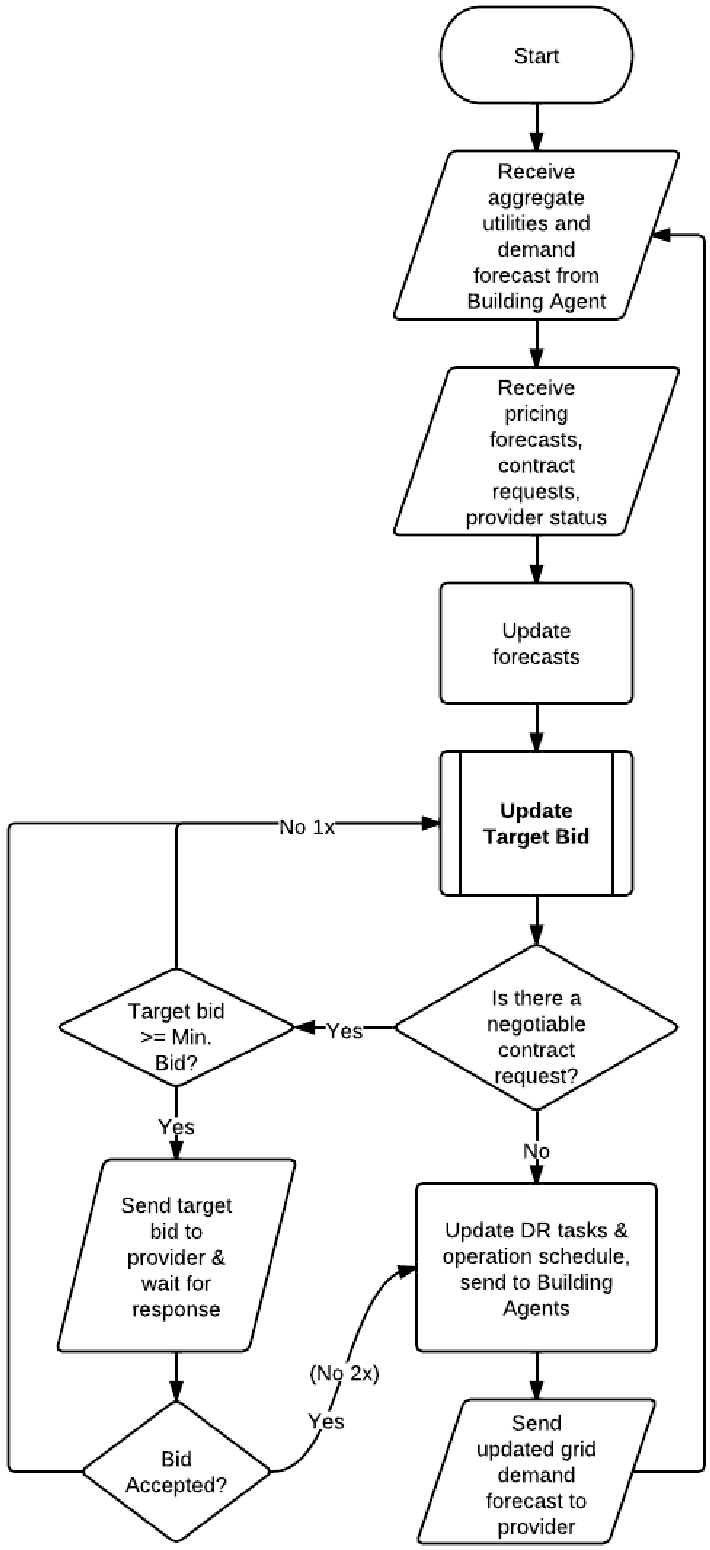

Figure 18. Negotiation Agent Algorithm

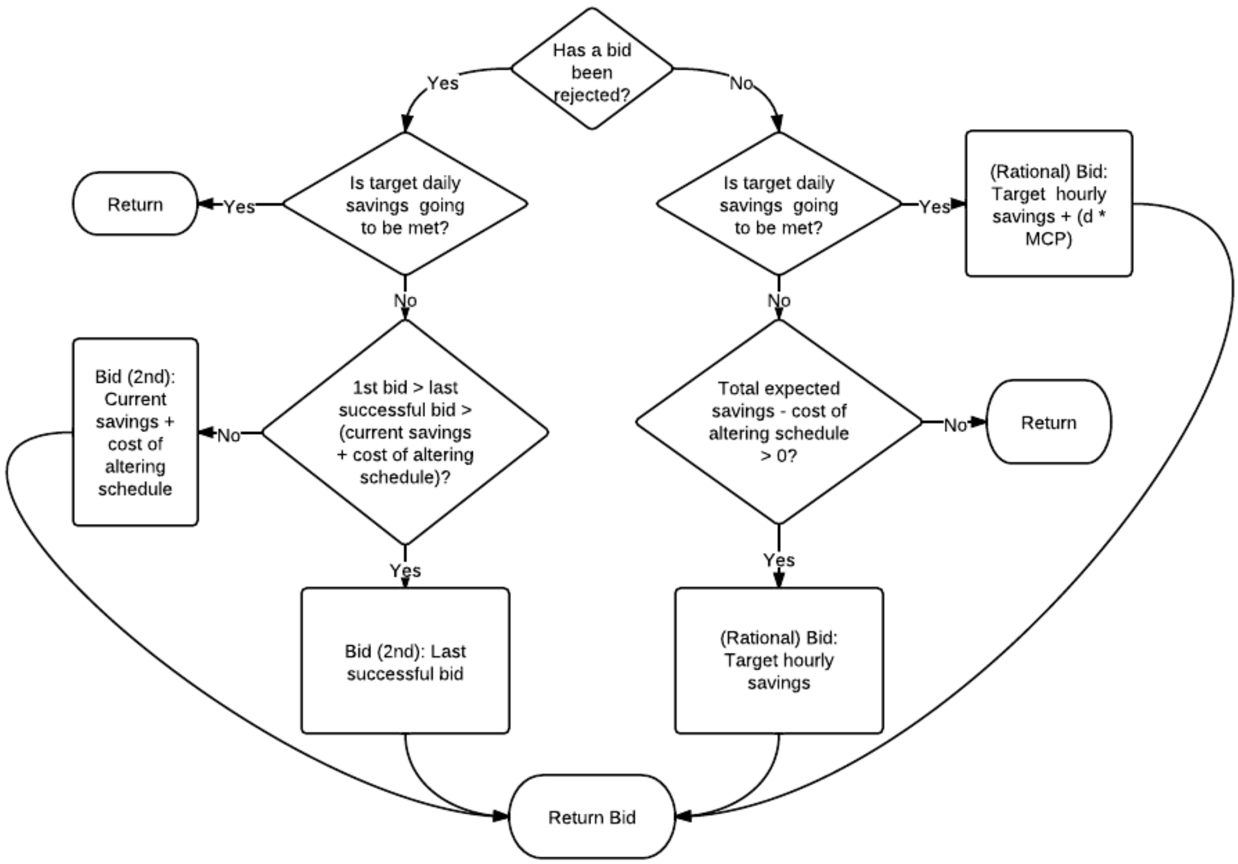

Figure 19. Update Target Bid Subprocess Algorithm

6.2.2 BUILDING AGENT CONTROL

Figure 20 shows the building agent control algorithm. The first steps in the algorithm have the agent receive the operation mode and DR task schedules from the negotiation agent and also relevant sensor data from the load/ source agents. The building agents receive weather forecast information from their Internet connection that is used for load and DER forecasting. At the beginning of the day, the building agents create the day ahead load and DER forecasts. During the day, the building agents implement the dynamic weighted mean to create the 15 min. forecasts by comparing and weighing the day ahead baseline and the actual load data.

The forecasts will be used to calculate the utilities for the load/source agents. The utilities will be aggregated by the building agents at the beginning of the day as well as every 15 min. period after. The building agents will assign and send tasks for the load source agents based off the operation mode and DR scheduling provided by the negotiation agent. This function is classified as the energy management control usually seen in C&I EMCSs. Finally, the building agents will report the aggregate utilities and confirmed load/source DR tasks.

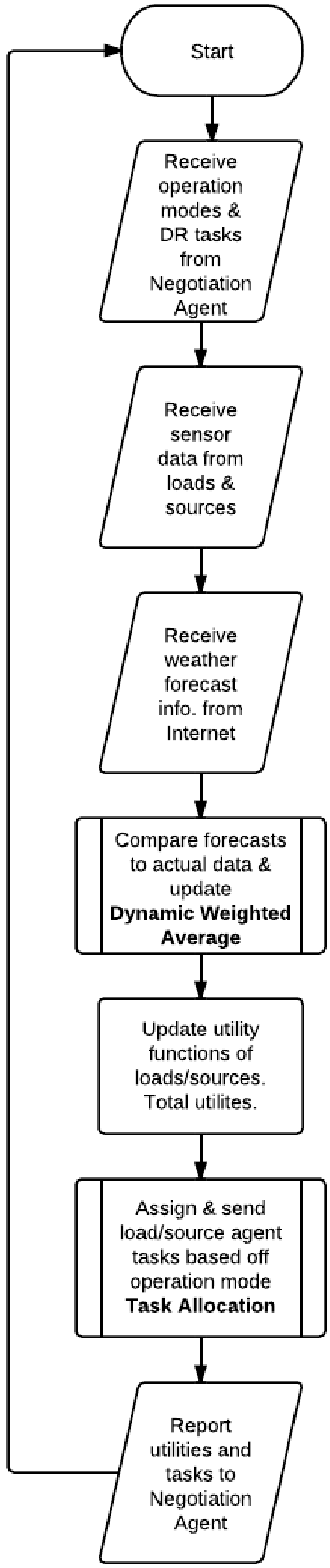

Figure 20. Building Agent Algorithm

6.2.3 LOAD/SOURCE AGENT CONTROL

The load source agents are initially defined as "dumb" agents where their main functions are accepting DR tasks and sending relevant sensing data to the building agents. DR tasks include load curtailment, increasing load, and increasing/decreasing DER output (e.g. modifying current reference value for the battery). The minimum required sensor data are relevant voltage and current values used for computing load/source power use.

A smart load/source agent implemented with the system could create their own load and DER forecast. An example of this is shown in Fig. 21 for a smart DER agent utilizing weather data and other relevant sensing data collected at the physical DER location. This data is used to update the agent's own DER 15 min. forecast based off the actual sensing data. If the forecast error is large enough, the smart DER agent will update its day ahead forecast as well. Assigning these forecast functions to a smart load/source agent will help decentralize control along with reducing computing power needed for the building agents.

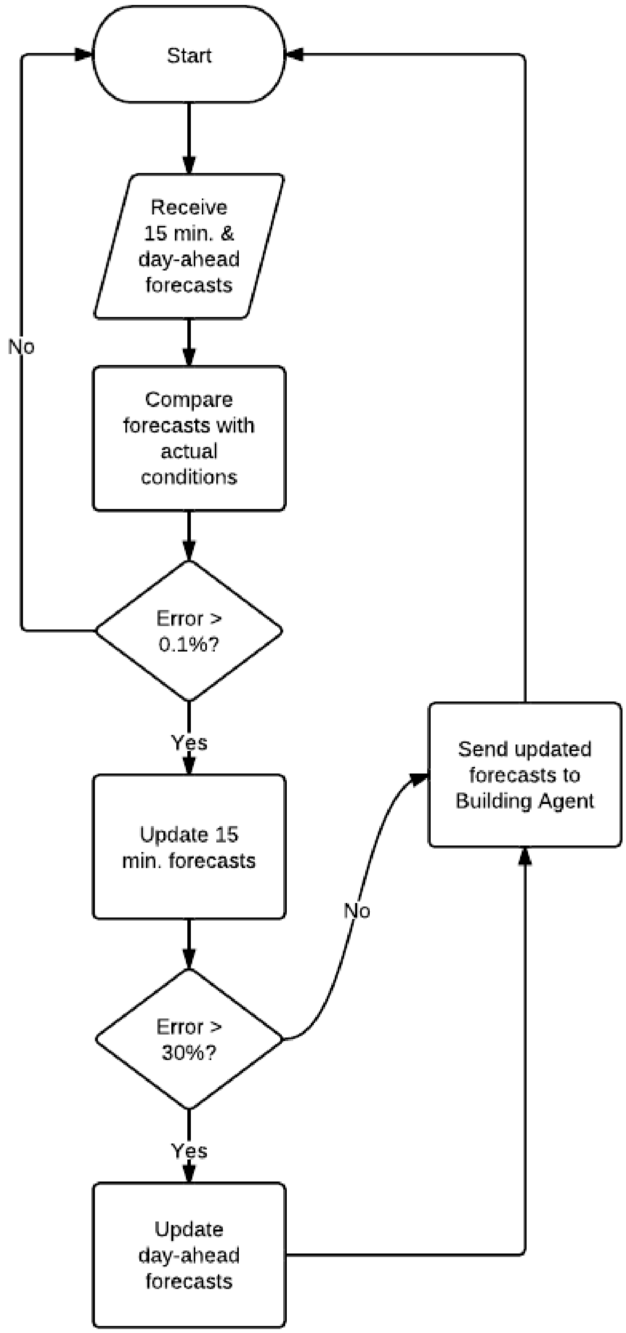

Figure 21. Example Smart DER Agent Forecasting

6.3 AUTOMATIC RESPONSE STRATEGIES

6.3.1 STATIC PEAK SHAVING

This is the default strategy for Automatic Response where the DER peak shaving resources like PV and the battery are used to their maximum during the peak period to reduce usage charges. The PV panels are connected to the local AC loads and will automatically offset their demand. Alternatively the PV can be physically connected to charge the battery or to feed-in directly to the grid. The battery's max. DOD is set and used to calculate and schedule the battery power (current reference value) over the peak period.

Figure 22 shows the result of using the static peak shaving strategy for the automatic response state for the four day period in spring 2012. The 38.04 kWh battery is discharged to 50% SOC over the seven hour on-peak period with an output battery power of 2.72 kW. This scenario also uses the first level curtailment constraints defined in Chapter 4 (2°F HVAC setpoint change and 30% lighting reduction) during the 6 hour, on-peak period. During the off-peak period, the battery is recharged to 100% SOC at the lowest possible charge rate for the eleven hour period. For this four-day window using the TOU rates defined in Chapter 4, total savings come to $74 which is a 24% reduction in total electric usage costs.

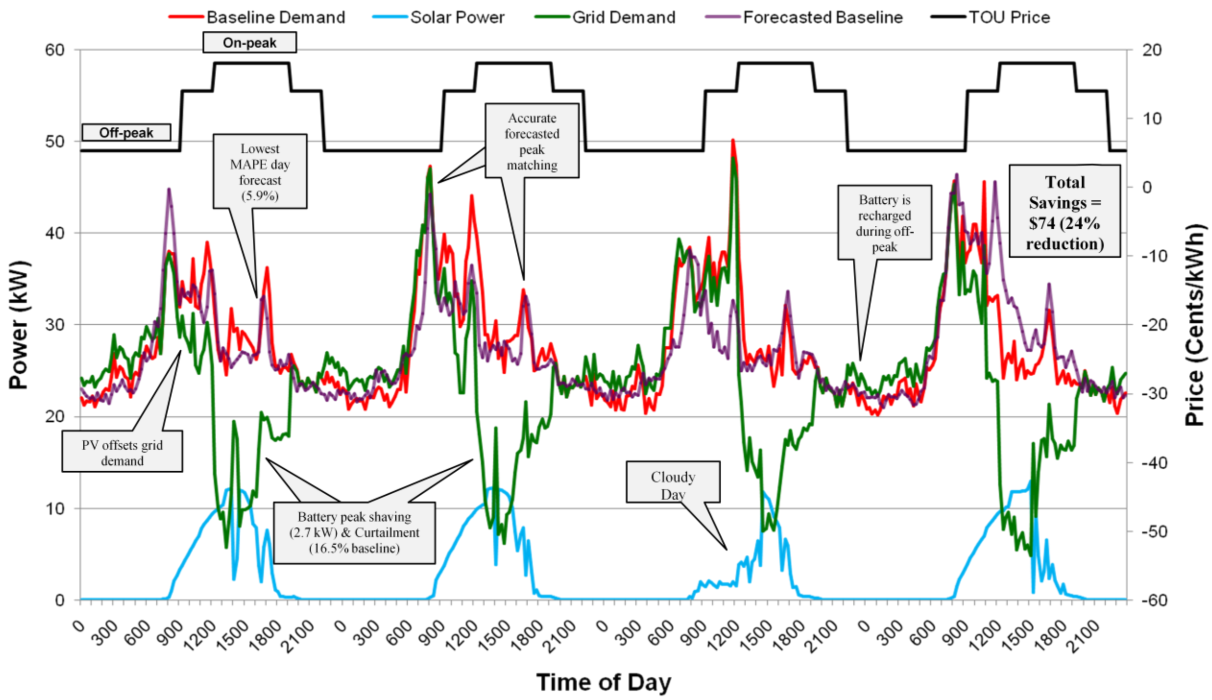

Figure 22. Nursing Home using Static Peak Shaving Strategy for Automatic Response Mode

6.3.2 LOAD LEVELING

This strategy maintains grid demand below a certain threshold. Load leveling can reduce demand charges for C&I customers. Demand charges are usually measured once a month for C&I customers at an unspecified time. The load leveling strategy uses a user-defined demand limit and keeps grid demand from passing this limit. The system defines a threshold above the user-defined limit based on the upper confidence level of the grid demand forecast similar to Section 5.4.1. This strategy schedules DER use and load curtailment at the beginning of the day by utilizing the day-ahead forecasts. The strategy schedules all available peak shaving DERs first before scheduling load curtailment. If there is insufficient load curtailment, the strategy schedules standby generation use if the user has allowed it. All additional, unscheduled DR resources use either the static or dynamic peak shaving strategy.

The system schedules and monitors the 15-min forecast during the day and by default uses additional battery power as the main load leveling source to keep the demand below the threshold. The user can also specify load curtailment as the load leveling source. By default when active, load leveling is put as the priority above other possible implemented strategies like static peak shaving. So all available resources are first applied to the top priority need. The user can change this priority if needed.

A problem with the load leveling strategy described is the scheduling error caused by the forecast error. Using the 15 min. forecast with a 95% confidence interval decreases the scheduling error but there is still opportunity for limit breeches and inefficient load leveling. Instigating effective low level controls may provide for more effective load leveling inside the 15 min. intervals. An alternative strategy for high level, load leveling scheduling is the utilization of fuzzy logic similar to the battery fuzzy logic described in [26]. The system described in [23] is also designed to coordinate with multiple battery agents. This coordination could be modified for coordination between multiple load leveling sources.

Load Leveling Example

Using the nursing home use case, we will set a limit of 30% off of the 50 kW peak load which equates to a limit of 35 kW. We will use only the battery for peak shaving and will omit PV and load curtailment for simplicity. We also incorporate forecast uncertainty for a day ahead and 15 min. battery scheduling.

The day ahead forecast has a lower CI of 30.52 kW. The 15 min. forecast has a lower CI of 31.92 kW. The load leveling strategy will first schedule the day ahead battery

use at 11:59 PM on the previous day. The day ahead MAPE used is 7.79% for day ahead and 5.35% for the 15 minute forecast.

Figure 2 shows the resulting day ahead and 15 min. load forecasting with battery scheduling. You will see that the day ahead scheduling passes the 35 kW limit on several occasions, this is where the battery drops below 20% SOC (there is insufficient capacity). Before we schedule another source to provide this disparity, we can observe what the 15 minute schedule will be during the day. Applying the 15 min. battery scheduling reduces the amount of limit breeches during the day. To make up for any lack of capacity during the day, the user can assign a second source for load leveling, which can be another DER or load curtailment.

Figure 24 shows the actual grid demand for the day when applying the 15 minute battery scheduling. You can observe another slight reduction in limit breeches of the 35 kW. If there is no other load leveling source available, the system's low level controls can possibly reduce these short duration peaks through tight low level controls.

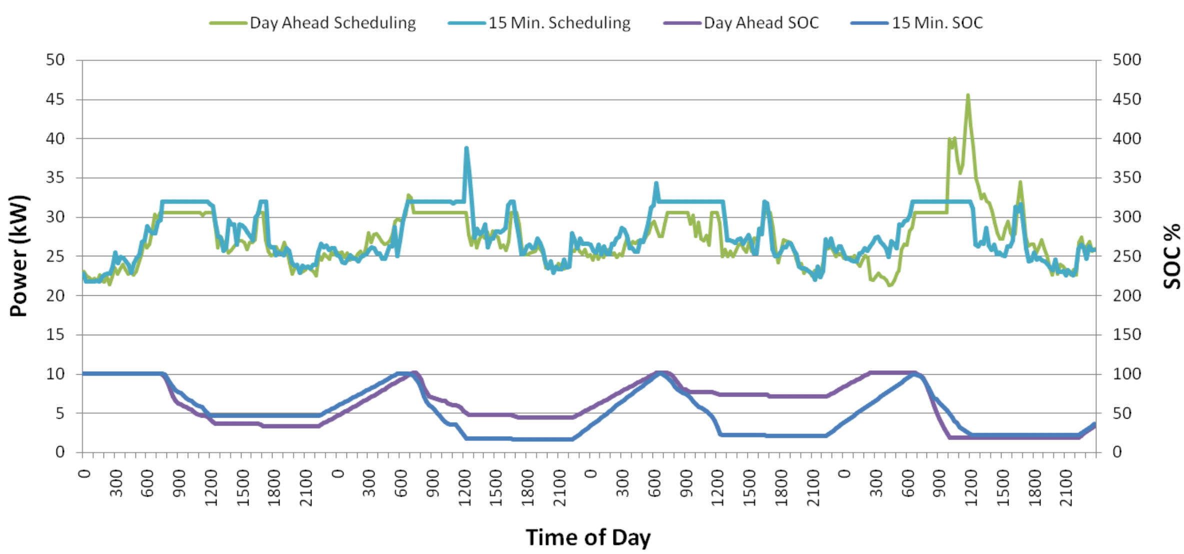

Figure 23. Day Ahead and 15 Min. Battery Scheduling for Load Leveling Example (PV & Curtailment Omitted)

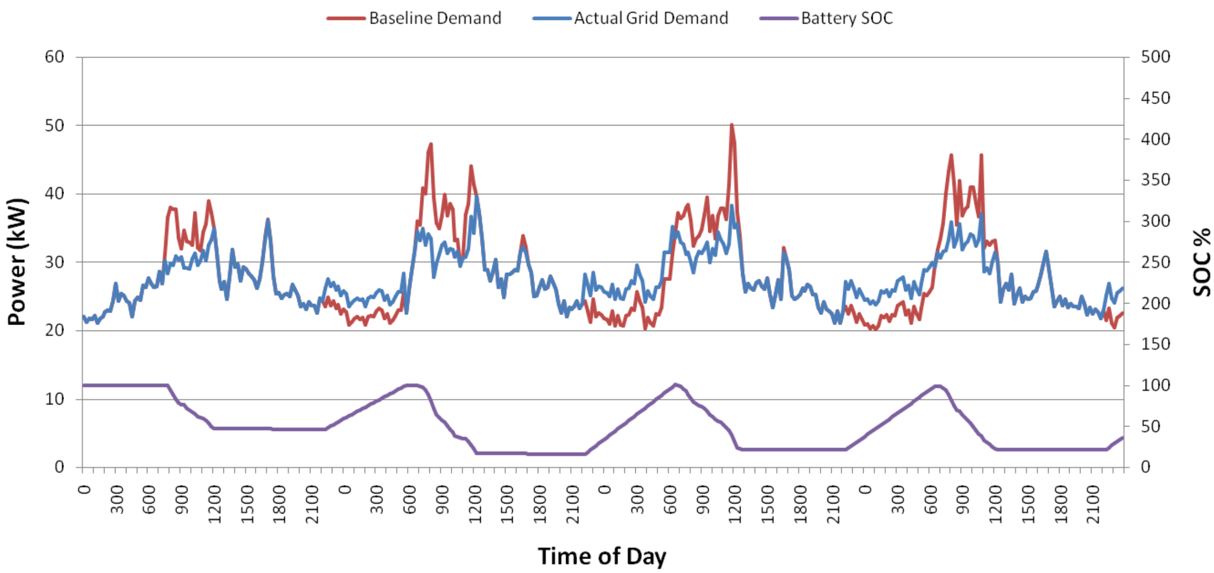

Figure 24. Actual Grid Demand & Battery SOC for Load Leveling Example

6.3.3 DYNAMIC PEAK SHAVING

This strategy can be used to alter the normal, static peak shaving schedule to save battery/E.S.U. peak shaving capacity for later curtailment potential for contracted curtailment or other cost saving opportunities (e.g. predicted spikes in kWh cost if using dynamic pricing). An example scenario is as follows:

1) The negotiation agent negotiates and accepts a curtailment contract that will need to utilize battery capacity reserved for today's on-peak period (TOU pricing). This decision is made by the negotiation agent by comparing the savings from just using static peak shaving and the savings/credit that will be received by load curtailment and battery use during the curtailment period, minus the cost of altering the peak shaving schedule.
2) The negotiation agent communicates a command to the building agents to switch to a dynamic peak shaving strategy for the Automatic Response state with inputs

defining the period and level of curtailment which will also be used to trigger an automatic switch to Contracted Curtailment at the specified time.

3) The building agents switch their strategy and immediately adjust the battery peak shaving schedule based on current conditions.

4) The building agents begin monitoring the demand forecast error and respond to any consistent error over a half-hour (2 time steps) that is outside the specified 95% confidence level (overestimate or underestimate). For example if there is a consistent underestimate for a half-hour, the building agents will respond by decreasing the time schedule for battery peak shaving by the percentage of underestimation beyond the 95% confidence level * 1σ.

6.3.4. OTHER STATIC STRATEGY CONSIDERATIONS

Pre-cooling (for the cooling season)

With an accurate HVAC forecast, a building can be pre-cooled right before a higher shift in price or on-peak period during the spring or summer season. Pre-cooling aims to achieve the assigned HVAC temp. setpoint for the higher peak period at the exact time or right before the higher peak period begins. This is achieved by using the transition function that is based on the HVAC profile/system type to accurately forecast the cooling time and further reduce on-peak demand.

Post-warming (for the cooling season)

In contrast to pre-cooling, post-warming incurs at the end of the higher peak period. Post-warming utilizes the HVAC transition function to determine the amount of time it would take for the building to warm a degree past the on-peak HVAC temp. setpoint. Knowing this delay, the HVAC can be cut off before the transition to a lower

price period while still maintaining the indoor temp. assigned throughout the on-peak period. For both pre-cooling and post-warming, we are talking about a short amount of time ranging anywhere from 5 - 30 min. only achieving a small amount of cost savings, but these savings will become significant over a month or year time frame. These strategies can be applied during the heating season also by using pre-warming and post-cooling instead.

CONCLUSION

This work presented the high-level, agent design and energy management control algorithms for the C&I GPN MAS. It was shown that these methods have the potential to reduce cost and make the use of automated demand response systems more beneficial to both the customer and power provider. Negotiation and bidding mechanisms and algorithms were presented that would give the customer potential to participate in automatic negotiations with their power provider or even to bid directly in a power market.

Forecasting methods were compared, developed, and tested for day-ahead and 15 min. weather-dependent load forecasting. The autoregressive method was most effective for day ahead forecasting for the spring, and the autoregressive with temperature sensitivities method was most effective for day ahead forecasting in the summer. The 15 min. dynamic weight mean applied to the day ahead forecasts during the day provided an approximate 30% reduction in forecasting error. Examples were given for incorporation of forecast uncertainty into the decision making algorithms. Confidence intervals for forecasts were calculated and used in decision making and automatic response strategies.

Using the static peak shaving strategy, a 24% reduction in total electric usage costs was observed for the nursing home use case utilizing PV and battery peak shaving and on-peak, load curtailment (2°F HVAC setpoint change and 30% lighting reduction). Power usage results were also shown that utilized the load leveling strategy for day-ahead and 15 min. scheduling.

WORKS CITED

[1] Mary Ann Piette, Osman Sezgen, and David S. Watson, "Development and evaluation of fully automated demand response in large facilities," Lawrence Berkeley National Laboratory, Berkeley, CA, 2004.

[2] R. Motte, "Development of a System Control Algorithm for Smart Residential Demand-side Management," unpublished M.S. thesis, University of South Carolina, Columbia, SC, 2012.

[3] Zeng Jun, Liu Junfeng, Wu Jie, and H.W. Ngan, "A multi-agent solution to energy management in hybrid renewable energy geneartion system," *Renewable Energy*, vol. 36, no. 5, pp. 1352-1363, May 2011.

[4] Jeremy Lagorse, Damien Paire, and Abdellatif Miraoui, "A multi-agent system for energy management of distributed power sources," *Renewable Energy*, vol. 35, pp. 174-182, 2010.

[5] Jeff St. John. (2010, August) Gigaom. [Online]. http://gigaom.com/cleantech/cali-opens-the-market-to-demand-response/

[6] W.M. Warwick, "A Primer on Electric Utilities, Deregulation, and Restructuring of U.S. Electricity Markets," Pacific Northwest National Laboratory, Richland, Washington, 2002.

[7] Jean Kumagai. (2012, March) IEEE Spectrum. [Online]. http://spectrum.ieee.org/energy/the-smarter-grid/virtual-power-plants-real-power

[8] Mary Ann Piette, Sila Kiliccote, and Girish Ghatikar, "Design and Implementation of an Open, Interoperable Automated Demand Response Infrastructure," Lawrence Berkeley National Laboratory, Berkeley, CA, 2008.

[9] M.A. Piette, D.S. Watson, and N. Motegi, "Findings from the 2004 Fully Automated Demand Response Tests in Large Facilities," Lawrence Berkeley National Laboratory, Berkeley, CA, 2005.

[10] Vipul Singhvi, "Machine Learning Based Building Control Strategy," Ph.D. dissertation, Carnegie Mellon University, 2006.

[11] (2011) Go Green Schenectady County. [Online]. http://www.gogreenschenectadycounty.com/demandresponse.html

[12] (2010) PG&E. "InterAct – Energy Management Tools". [Online]. http://www.pge.com/mybusiness/energysavingsrebates/demandresponse/tools/

[13] José M. Vidal, *Fundamentals of Multiagent Systems*., 2010, pp. 89-91.

[14] National Action Plan for Energy Efficiency, "Sector Collaborative on Energy Efficiency Accomplishments and Next Steps," ICF International, 2008.

[15] Energy & Resource Solutions, "Comprehensive Energy Audit Prepared For Grafton County Complex," Haverhill, MA, 2009.

[16] Michael Stadler, Chris Marnay, and Afzal Siddiqui, "Effect of Heat and Electricity Storage and Reliability on Microgrid Viability: A Study of Commercial Buildings in California and New York States," Lawrence Berkeley National Laboratory, Berkeley, CA, 2009.

[17] Ziegler Power Systems, "Summar of NESHAP Regulations," Shakopee, MN, 2010.

[18] BD Batteries. [Online]. http://www.bdbatteries.com/peukert.php

[19] Yoseba K. Penya, Cruz E. Borges, and Denis Agote, "Short-term load forecating in air-conditioned non-residential buildings," University of Deusto, Bilbao, Basque County,.

[20] Kyung-Bin Song, Seong-Kwan Ha, Jung-Wook Park, Dong-Jin Kweon, and Kyu-Ho Kim, "Hybrid Load Forecasting Method With Analysis of Temperature Sensitivities," *IEEE Trans. on Power Systems*, vol. 21, no. 2, May 2006.

[21] Peter Ponzo. [Online]. http://www.financialwebring.org/gummy-stuff/kalman.htm

[22] John D. Kueck, Brendan J. Kirby, and Moonis R. Ally, "Using Air Conditioning Load Response for Spinning Reserve," Oak Ridge National Laboratory, Oak Ridge, TN, 2008.

[23] D. Slade. (2012, August) The Post and Courier. [Online]. http://www.postandcourier.com/apps/pbcs.dll/article?AID=%2F20120819%2FPC05%2F120819099

[24] Antonis G. Tsikalakis, Yiannis A. Katsigiannis, and Pavlos S. Georgilakis, "Determining and Exploiting the Distribution Function of Wind Power Forecasting Error for the Economic Operation of Autonomous Power Sources," National Technical University of Athens, Athens, Greece, 2010.

[25] Dylan Evans, Annerieke Heuvelink, and Nettle Daniel. "The evolution of optimism: A multi-agent based model of adaptive bias in human judgement." [Online]. http://www.dylan.org.uk/OptimismAISB.pdf.

[26] Jeremy Lagorse, Marcelo G. Simoes, and Abdellatif Miraoui, "A Multiagent Fuzzy-Logic-Based Energy Management of Hybrid Systems," *IEEE Trans. on Industry Applications*, vol. 45, no. 6, pp. 2123-2129, Nov./Dec. 2009.

Appendix A

MAS & COST ANALYSIS SIMULATION IN NETLOGO

The code described in this appendix shows the MAS and cost analysis simulation executed in the NetLogo software and programming language. In this simulation, PV generation constantly delivers power and reduces demand based on the solar radiation data. The battery by default is used for peak shaving only during the on-peak period. The battery is completely used during this period, discharging down to the minimum state of charge (SOC) value of 50%. The diesel generators are there only for emergency power and do not play a part yet in this simulation. Most diesel generation currently installed in the U.S. cannot be used for peak shaving purposes.

Auto-DR Algorithm:

1. Solar and battery sources report to GPN agents amount of energy produced. The reduced-list is formed from by subtracting this data from the old baseline load-list.
2. Loads report energy consumption data to GPN agents; this data is used to calculate the utility of the loads. For this version of the simulation, the utility just represents cost savings for the time interval.
3. The utility of the loads is aggregated into the total utility, and total cost savings can now be calculated for different curtailment amounts (in steps of 10%).
4. If the battery's SOC is not 100% and it is the off-peak period, the battery is charged from the grid.

There are two main utility lists for each load. The first predicts, at the beginning of the day, the amount of reduction from default peak shaving during the on-peak period. This list is used to compute total daily savings since there is no error in the predicted data. The second list is for the next version of the simulation where the GPN agents look ahead to the next time step and adjust for previous errors.

Tunable Interface Parameters:

1. load-scenario: allows user to choose different industrial or commercial load environments with default parameter settings [only one scenario is currently available]
2. Setting source parameters (amount of distributed generation assets)
    a. diesel-gen-MW: set rated amount of diesel generation in megawatts (MW) installed; note that this parameter does not equate to how much generation is available from the diesel gens (default available/operating power from diesel gens is set to 75% to achieve the optimal setting for cost-effectiveness and lifetime); in this simulation, the diesel genset is only there for emergency power and will/cannot operate for peak shaving
    b. pv-gen-MW : set rated amount of photovoltaic generation in megawatts (MW) installed; available power at each interval will be determined by the amount of solar radiation during the interval (interval = 15 min = 1 tick)
    c. wind-gen-MW: set rated amount of wind generation in megawatts (MW); omitted for this simulation

    d. <u>percent-batt-storage</u>: set rated amount of battery storage as a percentage of total peak load; the percentage of the rated power available will be set based on the battery type

3. <u>batt-type</u>: sets the type of battery used; will set the minimum state of charge which helps determine the battery power available
4. <u>num-buildings</u>: sets the number of buildings in an industrial/commercial complex; distributed generation assets are set to be equally dispersed between the number of buildings (e.g. for a scenario where num-buildings = 4, and pv-gen-MW = 4, it will be assumed there is a 1 MW PV installation on each building)
5. Setting Time-Of-Use (TOU) prices (time periods are set by default in code)
    a. <u>off-peak-price</u>: sets the price of electricity in cents/kWh for the off-peak period (lowest price)
    b. <u>mid-peak-price</u>: sets the price of electricity in cents/kWh for the mid-peak period
    c. <u>on-peak-price</u>: sets the price of electricity in cents/kWh for the on-peak period (highest price)
6. <u>target-daily-savings</u>: sets a target amount of daily savings that assist in adjusting auto-DR strategies within a set of constraints[not implemented yet]
7. <u>min-neg-daily-savings</u>: sets the minimum amount of cost savings needed for the customer to accept a curtailment request from the utility [not implemented yet]
8. <u>neg-type</u>: sets the type of negotiation used [not implemented yet]

9. curtail-request-daily-prob: sets the daily probability of a curtailment request being sent out by the utility agent

A.1 VARIABLE & PARAMETER SETUP

```
breed [batts batt]
breed [sources source]
breed [other-loads other-load]
breed [lighting-loads lighting-load]
breed [HVAC-loads lighting-load]
breed [GPN-agents GPN-agent]
breed [customer-negotiation-agents customer-negotiation-agent]
breed [utility-negotiation-agents utility-agent]

globals[hour price tot-sources-kw batt-size-kwh load-list actual-load-list lighting-list other-list HVAC-list solar-list tot-demand act-demand
  solar-power i peak-period ran-curtail day batt-charging? grid-demand tot-daily-base-cost tot-daily-savings
  act-load pred-load nextbaseline MAPElist errorlist weight

]
;turtles-own[power-kw]
```

```
GPN-agents-own[batt-shaving reduced-list lighting-utility-list HVAC-utility-list lighting-utility-list-on-peak HVAC-utility-list-on-peak lighting-utility HVAC-utility tot-utility-list]
batts-own[SOC]

to setup
  clear-all
  ask patches[
    set pcolor white
  ]
  setup-negotiation-agents
  setup-GPN-agents
  setup-sources
  setup-loads
  setup-batts

  set hour 0
  set i 0
  set day 0
  set grid-demand 0
  set tot-daily-base-cost 0
```

```
  set tot-daily-savings 0
  set peak-period "off-peak"
  set price off-peak-price
  set batt-charging? false

  set weight 0.55

  setup-load-list
  setup-actual-load-list
  setup-lighting-list
  setup-other-list
  setup-HVAC-list
  setup-solar-list


  set tot-sources-kw (diesel-gen-MW * 1000) + (pv-gen-MW * 1000) ;;+ (wind-gen-MW
* 1000)
  ;;set batt-kw (percent-batt-storage * tot-sources-kw)
  set batt-size-kwh (max (load-list) * percent-batt-storage)
```

```
  ;;If there are multiple buildings, they are each assumed to be the same size, have the same energy profile, and have the same amount of resources and loads (for Phase I of this simulation)
  ;;note the predicted energy profile = actual energy profile (for Phase I of this simulation)
  ask GPN-agents[
    ;;GPNs setup reduced list that subtract solar power and battery peak shaving from the predicted energy consumption list for the day
    set batt-shaving (batt-size-kwh * .5 * .2) ;batt-size-kwh using 50% (1/2) capacity over 5 hours (1/5)
    setup-reduced-list
  ]

  let l length filter [? = 0] solar-list
  let z (l / 4)
  ;set price off-peak-price

  do-TOU-plot

  reset-ticks
end
```

```
to forecast
  test-day-forecasting
end

to go

  ;at start of day, look ahead and calculate the utility (cost savings) available if the load is
curtailed during the on-peak period
  if (ticks = 0 or ticks = 96 or ticks = 192 or ticks = 288 or ticks = 384)[
    ask GPN-agents[
      calculate-lighting-utility-list-on-peak
      calculate-HVAC-utility-list-on-peak
    ]
  ]
  if (time-period = "1 Day")[
    if (ticks = 96) [stop]
    if (ticks < 96) [
      set tot-demand item ticks load-list
      set act-demand item ticks actual-load-list
      set solar-power item ticks solar-list
      set-TOU-price
```

```
      ;charging the batts at set rate during off-peak times; discharging at a set rate during on-peak times
      ;min SOC = 50%
      ask batts[
        set-batt-SOC
      ]
      set hour (i + 1) * .25
    ]
    ifelse hour = 24 [ set i 0][set i i + 1]
  ]
  if (time-period = "5 Weekdays")[
    if (ticks = 480) [stop]

    if (ticks < 480) [
      set tot-demand item ticks load-list
      set act-demand item ticks actual-load-list
      set solar-power item ticks solar-list
      set-TOU-price
      ask batts[
        set-batt-SOC
      ]
```

```
    set hour (i + 1) * .25


   ]
   ifelse hour = 24 [
     set i 0
     set day day + 1]
    [set i i + 1]
  ]
  ;;print tot-demand
  ;;print solar-power

  ask GPN-agents[
    calculate-lighting-utility-list
    calculate-HVAC-utility-list
    set-lighting-utility
    set-HVAC-utility
    calculate-grid-demand
  ]

  tick
end
```

A.2 TEST FORECASTING

```
to test-day-forecasting
 let t 0
 set MAPElist []
 set errorlist []

 while [t < 96][
  set act-load item t actual-load-list      ;;actual experimental measurements
  if (t = 95) [
   let MAPEvalue ((abs(act-load - pred-load)) / (act-load)) * 100
   set MAPElist lput MAPEvalue MAPElist

   ;calculate MAPE
   let MAPE mean(MAPElist)
   print "MAPE:"
   print MAPE
   print "---Length--"
   print length MAPElist

   set t t + 1
  ]
```

```
if (t < 95) [

  ifelse (t = 0)[
    set errorlist lput ((((item 0 load-list) - (item 0 actual-load-list)) / act-load)) errorlist
    set nextbaseline item (t + 1) load-list
    set pred-load nextbaseline
    plotxy t pred-load
  ][
    set errorlist lput ((pred-load - act-load) / (act-load)) errorlist

    ;calculate MAPE values
    let MAPEvalue ((abs(act-load - pred-load)) / (act-load)) * 100
    set MAPElist lput MAPEvalue MAPElist

    ;Calculate Weight For Dynamic Weighted Mean
    let v2 abs (pred-load - act-load)
    let v1 abs (nextbaseline - act-load)
    ifelse v1 = 0 and v2 = 0 [set weight 0.5][set weight v1 / (v1 + v2)]


    set nextbaseline item (t + 1) load-list
```

```
    ;for plotting
    ;set pred-load0 lput pred-load pred-load0
    ;plotxy t pred-load

    ;For Day-Ahead Forecast
    set pred-load nextbaseline

    ;For Dynamic Weighted Mean
    ;set pred-load (nextbaseline + (weight * (act-load - nextbaseline)))

   ]

  ]
  set t t + 1
 ]

end

to set-TOU-price
 if hour < 10[
  set peak-period "off-peak"
```

```
  set price off-peak-price
]
if hour > 9.75 and hour < 13[
  set peak-period "mid-peak"
  set price mid-peak-price

]
if hour > 12.75 and hour < 18[
  set peak-period "on-peak"
  set price on-peak-price
]
if hour > 17.75 and hour < 21[
  set peak-period "mid-peak"
  set price mid-peak-price

]
if hour > 20.75[
  set peak-period "off-peak"
  set price off-peak-price
]
```

```
end
```

A.3 CACULATING UTILITIES

```
to set-batt-SOC
  ;5% SOC discharge per hour during on-peak
  if hour > 13 and hour < 18.25[
    set SOC SOC - .0125
  ]
  ;5% charge per hour during off-peak
  if ((hour < 10.25 and SOC < 0.99) or (hour > 21 and hour < 24.25 and SOC < 0.99))[
    set SOC SOC + .0125
    set batt-charging? true
  ]
  ;print "BATT SOC"
  ;print SOC
end

to calculate-lighting-utility-list

  ;;look ahead to next time-step/tick (15 min) and update the table of utility (cost saving)
values
```

```
  ;; cost of electricity * (kW normal operation - kW curtailed operation)
   let a 0
   if ticks = 479 [stop]
   let l (item (ticks + 1) lighting-list)
   ;print "This is l"
   ;print l

   while [a < 11][
     ;;with a linear lighting load profile, the utility is:
     let u (price * 0.25 * 0.01)*(l - (a * .1 * l))  ;;cost savings = (price * 1/4 of an hour
*convert cents to dollars) - (baseline load - (% used * baseline load))

     set lighting-utility-list replace-item a lighting-utility-list u
     set a (a + 1)
   ]
   ;print "This is the LIGHTING utility-list"
   ;print lighting-utility-list
   ;set utility max utility-list
end

to calculate-HVAC-utility-list
```

;;look ahead to next time-step/tick (15 min) and update the table of utility (cost saving) values

;; cost of electricity * (kW normal operation - kW curtailed operation)

let a 0

if ticks = 479 [stop]

let l (item (ticks + 1) HVAC-list)

;print "This is l"

;print l

while [a < 11][

;;the baseline temp used in the load data is 74 deg AND 1 deg change in temp. = -10% from HVAC load baseline (approximation from power companies)...

;;...this also allows us to have the same utility function as the lighting load

;;HVAC utility-list references these temp setpoints -> [84(off) 83 82 81 80 79 78 77 76 75 74(normal)]

let u (price * 0.25 * 0.01)*(l - (a * .1 * l)) ;;cost savings = (price * 1/4 of an hour *convert cents to dollars) - (baseline load - (% used * baseline load))

set HVAC-utility-list replace-item a HVAC-utility-list u

set a (a + 1)

]

```
    ;print "This is the HVAC utility-list"
    ;print HVAC-utility-list
    ;set lighting-utility max lighting-utility-list
end

to set-lighting-utility
  if (peak-period = "off-peak" or peak-period = "mid-peak")[
    set lighting-utility min lighting-utility-list
  ]
  ;inputted, daily on-peak load curtailment strategy
  if peak-period = "on-peak"[
    set lighting-utility item (percent-lighting * 10) lighting-utility-list
    ;print "This is the LIGHTING utility-list ON-PEAK"
    ;print lighting-utility-list
    ;print "This is the lighting utility 15min ON-PEAK"
    ;print lighting-utility
  ]
end
to set-HVAC-utility
  if (peak-period = "off-peak" or peak-period = "mid-peak")[
    set HVAC-utility min HVAC-utility-list
```

```
  ]
  ;inputted, daily on-peak load curtailment strategy
  if peak-period = "on-peak"[
    set HVAC-utility item (10 - (temp-HVAC - 74)) HVAC-utility-list
    ;print "This is the HVAC utility-list ON-PEAK"
    ;print HVAC-utility-list
    ;print "This is the HVAC utility 15min ON-PEAK"
    ;print HVAC-utility
  ]

end

to calculate-grid-demand ;actual, current grid demand after all reductions and curtailments
  let g0 item (ticks) load-list
  let a item (ticks) reduced-list
  ifelse batt-charging? = true
    [set grid-demand (a - lighting-utility - HVAC-utility + (0.05 * batt-size-kwh))
      set batt-charging? false]
    [set grid-demand (a - lighting-utility - HVAC-utility)]
  set tot-daily-base-cost (tot-daily-base-cost + (price * .25 * .01 * g0))
```

```
  set tot-daily-savings (tot-daily-savings + (price * .25 * .01) * (g0 - grid-demand))
end

to calculate-lighting-utility-list-on-peak
  ;;look ahead to on-peak period and calculate utility (cost savings) for entire on-peak
period
  ;ask lighting-loads[
  ;;on-peak period 13:00 - 18:00 -> ticks/load items 51 - 71 for day one
    let a0 0
    let ltot 0
    let d0 (96 * day + 51)
    let d1 (96 * day + 71)
    while [a0 < 11][
      while [d0 < d1][
        let l0 (item d0 lighting-list)
        set ltot (ltot + l0)
        set d0 (d0 + 1)
      ]
      let u0 (on-peak-price * 0.25 * 0.01)*(ltot - (a0 * .1 * ltot))
      set lighting-utility-list-on-peak replace-item a0 lighting-utility-list-on-peak u0
      set a0 (a0 + 1)
```

```
  ]
  print "ON-PEAK LIGHTING UTILITY LIST FOR TODAY"
  print lighting-utility-list-on-peak
end

to calculate-HVAC-utility-list-on-peak
 ;;look ahead to on-peak period and calculate utility (cost savings) for entire on-peak
period
 ;;on-peak period 13:00 - 18:00 -> ticks/load items 51 - 71 for day one
 ;ask HVAC-loads[
  let a0 0
  let ltot 0
  let d0 (96 * day + 51)
  let d1 (96 * day + 71)
  while [a0 < 11][
   while [d0 < d1][
    let l0 (item d0 HVAC-list)
    set ltot (ltot + l0)
    set d0 (d0 + 1)
   ]
   let u0 (on-peak-price * 0.25 * 0.01)*(ltot - (a0 * .1 * ltot))
```

```
    set HVAC-utility-list-on-peak replace-item a0 HVAC-utility-list-on-peak u0
    set a0 (a0 + 1)
  ]
  print "ON-PEAK HVAC UTILITY LIST FOR TODAY"
  print HVAC-utility-list-on-peak
end
```