A Mathematical Formulation for Optimal Load Shifting of Electricity Demand

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***Abstract*—We describe the background and an analytical framework for a mathematical optimization model for home energy management systems (HEMS) to manage electricity demand by efficiently shifting electricity loads of households from peak times to off-peak times. We illustrate the flexibility of the model by modularizing various available technologies such as plug-in electric vehicles, battery storage, and automatic windows. First, the analysis shows that the end-user can accrue economic benefits by shifting consumer loads away from higher-priced periods. Specifically, we assessed the most likely sources of value to be derived from demand response technologies. Therefore, wide adoption of such modeling could create significant cost savings for consumers. Second, the findings are promising for the further development of more intelligent HEMS in the residential sector. Third, we formulated a smart grid valuation framework that is helpful for interpreting the model's results concerning the efficiency of current smart appliances and their respective prices. Finally, we explain the model's benefits, the major concerns when the model is applied in the real world, and the possible future areas that can be explored.**

I. Introduction

To meet energy needs, demand response is a valuable resource because it can help reduce the volatility of electricity prices, mitigate market power of generators, and enhance grid reliability. Demand response achieves these objectives by lowering the peak demand for energy, which reduces the need to construct new and expensive generation units, and by providing ancillary grid services such as regulation and reserves to reliably integrate variable resources such as renewable generation [1]. In 2013, the potential contribution of demand response resources in the United States was 28,798 MW in Regional Transmission Organization (RTO), Independent System Operator (ISO), and Electric Reliability Council of Texas (ERCOT) markets [2], which represents an increase of 5.9% since 2009 when the total was 27,189 MW [1]. Note that these values have fluctuated recently, due to economic impacts on electricity consumption.

Demand response can be defined as "changes in electric use by demand side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [3]. Demand response technologies can be and are considered as components within a broad range of energy supply scenarios [1]. Correspondingly, there are significant policy implications associated with the development of demand response technologies (DR technologies).

To enhance the effectiveness of DR, the current trend of increasing integration of Information and Communication Technology (ICT) has enabled market actors to develop technologies in various fields. For example, in the field of energy management, ICT has engendered the smart grid, which enables the development and use of applications such as the smart meter, bidirectional communication, advanced metering infrastructure (AMI), home automation, and home area networks [4]. Furthermore, an AMI, particularly the smart meter, serves the purpose of measuring and recording electrical energy consumption in time intervals that can range from five minutes to an hour. It allows for two-way communication, either in real-time or near real-time, between the meter and the utility's system. The availability of such information can be received by utilities in order to help adjust energy consumption patterns in households, and thereby achieve economic benefits.

While DR technologies are already prevalent in the commercial and industrial sectors of the U.S. economy, the market for DR technologies in the residential sector is currently in a nascent stage [1]. Accordingly, this paper examines the potential economic benefits associated with the application of DR technologies in the residential sector. Specifically, this paper offers (1) an optimal load shifting (OLS) model that can manage electricity demand more effectively; and (2) an assessment of the most likely sources of value to be derived from DR technologies.

The OLS model is formulated to be utilized by a Home Energy Management System (HEMS), which operates as a central command system for electricity usage inside a home, for components such as household appliances and air conditioning systems. The proposed model was designed for the purpose of obtaining greater efficiency and savings, both in terms of economics and energy usage. Specifically, the model achieves such savings by shifting electric loads to flatten the electricity load shapes of a particular household. Therefore, the adoption of such a model by multiple households can improve the efficiency of managing energy demand that may result in significant cost savings for consumers.

Our approach has been guided by recent academic literature, which found substantial economic benefits derived from the

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use of demand response and other smart grid technologies. In one case study, Malik and Bouzguenda [5] conducted a cost-benefit analysis and concluded that the long-term load management benefits of the smart grid outweighs the upgrade costs needed to create a more intelligent grid. Additionally, one study by Faruqui, Harris, and Hledik wrote that the maximization of economic savings requires the use of both smart meters and dynamic pricing. They estimated that the present value of savings in peaking infrastructure can be as high as 67 billion [6].

This paper addresses several principles that arise from the development of the model and from observations of current trends in the sector. First, we propose an intelligent algorithm that can effectively optimize energy consumption. In addition to reducing peak energy usage, we identified an economic interest that is advanced by implementing DR programs: the utility may be able to manage an electricity supply shortage in a more expeditious manner, with lower costs and less delay time.

Looking forward, the current business landscape indicates that HEMS technologies are set to expand with the prospect of both mature and start-up companies poised to enter the market. Importantly, it is predicted that the electric vehicle (EV) industry may play a critical role in expanding the HEMS market in the future. Recently, the concept of load shifting for EVs has become increasingly popular. Load shifting is the mechanism by which utilities can respond to the significant energy demand that is created when multiple EVs undergo charging during peak times. Through the use of an optimal decentralized protocol for EV charging, utilities can alleviate the heavy burden on the grid during peak hours by shifting the EV charging loads [7], [8], [9]. Similarly, the model aims to demonstrate the benefits of such load shifting with respect to a smart grid and the use of appliances inside the home.

Although the wide adoption of HEMS technologies is promising, the current academic literature has investigated the benefits of HEMS technologies as it is now, and the results are not entirely positive. For instance, Dam, Bakker, and Buiter [10] performed an overall life cycle impact on three HEMS that shows net energy savings over five years, but a negative return on investment in terms of monetary cost. However, their study was based on existing HEMS that did not use optimization processes and are less intelligent. Further, Hargreaves, Nye, and Burgess [11] reported on a year-long, in-home smart energy monitor trial, where results leave a homeowner more knowledgeable about reducing consumption, but not necessarily more motivated to do so. Given these results, the creation of a more intelligent HEMS helps address the negative findings of these works [12], [13]. Our model leverages algorithms that support optimization, which can result in a positive return on investment in terms of monetary cost. In addition, the intelligent HEMS could run automatically, without any reliance on the personal motivation of homeowners to reduce consumption.

Essentially, this paper offers three main contributions. First, the implementation of the model shows that the consumer can accrue economic benefits by shifting consumption away from higher-priced periods. In the results section, the precise savings are shown in addition to graphs of the shifted load. Importantly, the model has a modular design that is flexible and can be configured to accommodate added capabilities. The model consists of the following four modules: load shifting, thermal control, battery electricity storage system, and automated windows. It is concluded that potential economic savings exist; however, further research is needed to apply the model to additional data sets that represent greater diversity in terms of pricing schemes, climate conditions, and consumer preferences.

Second, the findings are promising for the continued development of more intelligent electricity management in the residential sector. For example, the model is capable of performing quickly, which can be a highly preferred attribute of any algorithm that is designed to be implemented by a HEMS for real-time dynamic management. Specifically, the flexibility of the model is demonstrated in the results section.

Third, we develop a smart grid valuation framework that can be used to interpret the results produced by the model with respect to the efficiency of smart appliances and their respective prices. The framework is centered on four key questions: (1) which smart appliance provides the greatest overall savings?; (2) which smart appliance provides the greatest incremental savings?; (3) which smart appliance has the highest benefit/cost ratio?; (4) what incentives do smart appliances provide for behavioral changes?

Finally, this paper concludes with a discussion about the model's benefits, the major concerns associated with its use in the real world, and possible future areas of investigation.

II. Optimal Load Shifting Model Formulation

This section describes the Optimal Load Shifting (OLS) model, which is a conglomeration of modules that are linked by the need to minimize the total cost and to manage the total household electricity use. The modules represent various appliances in terms of their physical behavior, end-user preferences, and automated controls. The automated controls are optimized to minimize costs of energy consumption, while obeying the physical characteristics of the appliances, the end-user preferences, and a limit on the total household electrical load.

The OLS model minimizes electricity consumption costs with perfect foresight over a limited time horizon (e.g. one week). While the nominal objective function is to minimize the total cost of electricity, potential additional terms in the objective could reflect end-user convenience in the following ways:

- coordination of stakeholder benefits (e.g. with the electric utility)
- aspects of an aggregator providing services (if present), and
- a time-sensitive mix of preferences for multiple household residents.

Because of its modular formulation, an agent can chose which modules to include or dismiss when running the OLS model. The five modules of the OLS model are:

- LS – Load Shifting

- TC – Thermal Control
- BESS – Battery Electricity Storage System
- AW – Automated Windows
- NS – Non-Shiftable

The above acronyms will be used in the following as a short form to refer to individual modules.

The following sections describe each module's control/decision variables, fixed data parameters, constraints, objective function, and its mathematical optimization formulation.

A. Indices

The OLS model has indices for end-uses and time. The end-use loads are categorized according to the way they can be shifted or not. The shiftable end-use load categories are *work storage* and *energy storage*. The end-uses for work storage and energy storage have decision variables for shifting load. Non-shiftable loads are aggregated and do not require an index.

The notation in Table I describes the general OLS model indices for shiftable loads and time. It gives the index name, the valid range of values, and a short description. These indices are utilized in all of the modules.

TABLE I
DESCRIPTIONS OF OLS MODEL INDICES

Index	Range	Description
i	$1 \leq i \leq m$	m end-uses indexed by i that are work storage, e.g. clothes washer, dishwasher, and clothes dryer.
j	$1 \leq j \leq n$	n end-uses indexed by j that are energy storage, e.g. heating, AC, refrigerator, and freezer.
t	$1 \leq t \leq h$	h intervals indexed by t, e.g. hours, 5 minutes, minutes.

B. Load Shifting Module

The load shifting (LS) module shifts the loads of work storage end-use units. Work storage end-use units have a preferred duration and time window for energy use as determined by user preferences, thereby allowing the optimization to advance or delay the work. Examples of work storage end-uses are clothes washers and dishwashers.

1) Decision Variables: The control/decision variable x_i is the time indicator of the operating schedule for appliance i. It is a vector of dimension h where its tth entry equals 0 when the appliance does not operate at time interval t and 1 when the appliance operates; it is described in Table II. It is assumed that the appliance will finish its task without interruption[1].

TABLE II
DESCRIPTIONS OF LS MODULE VARIABLES

Control Variable	Units	Description
$x_{i,t}$	*none*	Schedule for work storage end-use i for interval t

[1]An explanation of enforcing running without interruption is located in the appendix.

2) Data Parameters: The LS module parameters appear in the major categories of user preferences, environment data, and end-use characteristics. Raw data sources must be processed into the formats of these parameters for proper use in the OLS model. Table III provides the specific details.

TABLE III
DESCRIPTIONS OF LS MODULE PARAMETERS

User Preference	Units	Description
$D_{i,t}$	{0, 1}	Indicates allowed operation of end-use i in interval t
Environment Data	**Units**	**Description**
P_t	\$/kWh	Electricity price in interval t
L_t	kWh	Fixed load in interval t
A_t	kWh	Energy Cap for interval t
End-Use Characteristic	**Units**	**Description**
Z_i	*none*	Number of intervals of consumption for end-use i
l_i	kWh	Average energy use for end-use i, when active

To aid in the understanding of this module's formulation, a work storage end-use units is introduced: a clothes washer. The washer is defined as end-use $i = 1$. Let the interval t be hours with $h = 24$ hours. Throughout this section, assumptions will be added to this example to explain the corresponding parts of the module.

3) Work Storage End-Use Illustrations: Assume that the washer consumes 0.3 kWh. Then, the average electricity use, l_i, is defined as a scalar for the energy consumption for end-use i if it were to run for an interval[2]. Therefore, $l_1 = 0.3$.

The indicator of allowable operation, D_i, is set by the homeowner. Assume the washer is allowed to operate during the time period between 12 a.m. to 8 a.m., and the model's first interval begins at 12 a.m., then the vector of dimension-24 for allowable operations is defined as

$$D_1 = [1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ \ldots\ 0].$$

The control/decision variable x_i, for end-use unit i, is a decision vector for the model. If the optimal time for the washer to run is to start at 3:00 a.m. and finish before 4:00 a.m., given $Z_1 = 1$, and the model starts at 12 a.m., then the entries of the vector will take values:

$$x_1 = [0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ \ldots\ 0],$$

where the location of the value '1' corresponds to interval 3:00 a.m to 4:00 a.m. and all other hourly values have zero value.

4) Work storage job completion: Below the constraint for job completion in the module is explained. Assume the washer runs for a full hour. If the washer (end-use unit $i = 1$) must operate one time from 12 a.m. to 8 a.m., then a condition is imposed that the sum of all hourly products of schedule

[2]It is assumed that all appliances, i, have constant energy use, in order to simplify the exposition.

operations and allowable operations equals Z_1, as a linear equation

$$(x_1 \cdot D_1) = Z_1, \text{ that is, } \sum_{t=1}^{h} D_{1,t} x_{1,t} = Z_1.$$

The right-hand side corresponds to the required number of operating intervals (hours) over all of the allowable intervals specified by user preference.

5) LS Module Formulation: The cost of electricity for end-use unit i can be expressed as

$$l_i(P \cdot x_i) = l_i \left(\sum_{t=1}^{h} P_t x_{i,t} \right),$$

where the dot operation $(\cdot)$ represents the inner product of two vectors.

Combining the above constraints and cost, the LS module takes the form:

$$\min_{x_i} \quad \sum_i l_i(P \cdot x_i) \tag{1}$$

$$x_i \cdot D_i = Z_i \ \forall i, \tag{2}$$

$$\sum_i l_i x_{i,t} + \Omega_t \leq A_t \ \forall t,$$

$$x_{i,t} \in \{0, 1\} \ \forall (i,t),$$

where Ω_t will represents other module loads in interval t.

C. Thermal Control Module

The Thermal Control (TC) module acts as a type of energy storage that can consume energy earlier or later, thereby allowing for the consumption of energy at less-costly times. Examples of thermal energy storage end-uses are heaters, air conditioners, combined heater and air conditioners (HVAC), and refrigerators. These appliances must maintain internal temperatures within user-specified ranges.

Typically, the control/decision variable for an energy storage appliance is the energy consumption per time period over the optimization horizon, and it affects how much heating or cooling is supplied by the appliance. At the same time, some tasks can be interrupted and then continued with little impact. This latter source of flexibility is not currently present in the OLS model but could be added at a later time.

1) Decision Variables: An HVAC is used to illustrate the TC module formulation. The control/decision variable is the energy $q_{j,t}$ supplied to the HVAC unit j in interval t, and the state variable is the indoor temperature $T^{in}_{j,t}$. They are summarized in Table IV.

2) Data Parameters: The TC module parameters appear in the major categories of user preferences, environment data, end-use characteristics, and appliance limitations. Raw data sources must be processed into the formats of these parameters for proper use in the OLS model. Table V provides the details.

TABLE IV
DESCRIPTIONS OF TC MODULE VARIABLES

Control Variable	Units	Description
$q_{j,t}$	kWh	Energy consumption of the thermal control end-use unit j for interval t
State Variable		
$T^{in}_{j,t}$	° F	Inside temperature of the space that is heated or cooled by end-use j for interval t

TABLE V
DESCRIPTIONS OF TC MODULE PARAMETERS

User Preference	Units	Description
$T^{min}_{j,t}$	° F	Minimum temperature for end-use j in interval t
$T^{max}_{j,t}$	° F	Maximum temperature for end-use j in interval t
Environment Data	**Units**	**Description**
P_t	$/kWh	Electricity price in interval t
$T^{ext}_{j,t}$	° F	External temperature for end-use j in interval t
A_t	kWh	Energy Cap for interval t (restated)
End-Use Characteristic	**Units**	**Description**
$q_{j,t}$	kWh	Electricity consumption for end-use j and interval t
C_j	kWh/° F	Heat capacity for end-use j
K_j	kWh/° F	Thermal conductivity for end-use j
e_j	*none*	Energy conversion efficiency for end-use j. For thermodynamic direction of heat flow, this value is positive for heating and negative for cooling.
Appliance Limitations	**Units**	**Description**
$q^{max}_{j,t}$	kWh	Energy consumption limit for end-use j for interval t

Note that because of the treatment of the efficiency e_j being positive or negative for heating and cooling, respectively, an HVAC requires two end-use indices to discern this difference and that optimality conditions ensure that only one use is active in each period, t.

3) Indoor temperature range and thermal energy control limit: It is assumed that the electric heating end-use j, must maintain temperatures between a maximum and minimum. One can think of this as a resident's preferred comfort zone.

$$T^{min}_{j,t} \leq T^{in}_{j,t} \leq T^{max}_{j,t}, \ \forall (j,t)$$

Assume t represents hours, and that the indoor temperature $T^{in}_{j,t}$ is dependent upon the energy control variable $(q_{j,t})$ for the HVAC, which is defined as end-use unit $j = 1$, and this energy quantity must be less than a maximum value, $q^{max}_{j,t}$, for each end-use unit j for all intervals t. Then, the following relation is obtained for limiting the range of the thermal energy control:

$$0 \leq q_{j,t} \leq q^{max}_{j,t}, \ \forall (j,t).$$

4) Thermal storage state equation: The actual heating (or cooling) supplied by the HVAC is typically less than $q_{j,t}$ due to losses, and it would be $e_j q_{j,t}$ for all t, where efficiency parameter e_j always has a value between -1 and 1.

Further, the thermal equilibrium is also influenced by heat flow from the surroundings, $q^{sur}_{j,t}$, through a thermal insulation model for unit j. Its relation with the given exterior temperature, $T^{ext}_{j,t}$, and state decision variable, $T^{in}_{j,1}$, is given as

$$q^{sur}_{j,t} = K_j(T^{ext}_{j,t} - T^{in}_{j,t}),\ \forall t \neq h,$$

where K_j is the thermal conductivity coefficient of unit j.

Thus, by conservation of energy and thermodynamics, the temperature difference from one interval to the next must be proportional to the energy exchanged with the HVAC and the surroundings, that is,

$$\begin{aligned} C_j(T^{in}_{j,t} - T^{in}_{j,t-1}) &= e_j q_{j,t-1} + q^{sur}_{j,t-1} \\ &= e_j q_{j,t-1} + K_j(T^{ext}_{j,t-1} - T^{in}_{j,t-1}),\ \forall (j,t) \end{aligned}$$

where C_j is the thermal heat capacity coefficient of unit j, and $T^{in}_{j,0}$, together with exogenous data parameter $T^{ext}_{j,0}$, are part of given data parameters.

5) TC Module Formulation: The corresponding cost of energy for the HVAC, defined as end-use unit j, is

$$P \cdot q_j = \sum_{t=1}^{h} P_t q_{j,t}.$$

Combining the above constraints and cost, the TC optimization module takes the form:

$$\min_{(T^{in}_j,\ q_j)} \quad \sum_j (P \cdot q_j) \tag{3}$$

$$C_j(T^{in}_{j,t} - T^{in}_{j,t-1}) = e_j q_{j,t-1} \tag{4}$$

$$+K_j(T^{ext}_{j,t-1} - T^{in}_{j,t-1})\ \forall (j,t), \tag{5}$$

$$T^{min}_j \leq T^{in}_j \leq T^{max}_j\ \forall j,$$

$$0 \leq q_j \leq q^{max}_j\ \forall j,$$

$$\sum_j q_{j,t} + Omega_t \leq A_t\ \forall t.$$

where T^{min}_j and T^{max}_j are given, and Ω_t will represents other module loads in interval t.

D. Battery Electricity Storage System Module

The Battery Electricity Storage System (BESS) module represents how a battery can store energy during intervals when electricity prices are low and provide electricity for household appliances when electricity prices are high. This may be beneficial for those non-shiftable loads that occur in peak hours.

1) Decision Variables: The decision variables for the module are b_t, the charging rate at interval t, and b^{dis}_t, the discharging rate at interval t. The variables indicate the amount of that energy the battery consumes during charging and the amount of energy the battery supplies during discharging. The state variable, s_t, is the amount of energy stored in the battery at the end of interval t. They are summarized in Table VI.

TABLE VI
DESCRIPTIONS OF BESS MODULE VARIABLES

Control Variable	Units	Description
b_t	kWh	energy consumption for the battery for interval t
b^{dis}_t	kWh	energy provided from battery for interval t
State Variable		
s_t	kWh	amount of energy stored in battery for interval t

2) Data Parameters: The BESS Module parameters appear in the major categories of end-use characteristics and appliance limitations. Raw data sources must be processed into the formats of these parameters for proper use in the OLS model. Table VII provides additional details.

TABLE VII
DESCRIPTIONS OF BESS MODULE PARAMETERS

Environment Data	Units	Description
A_t	kWh	Energy Cap for interval t (restated)
End-Use Characteristic	**Units**	**Description**
b^{eff}	*none*	battery efficiency between 0 and 1
Appliance Limitations	**Units**	**Description**
b^{lim}	kWh	maximum storage capacity of the battery
b_{max}	kWh	maximum charge rate of the battery
b^{dis}_{max}	kWh	maximum discharge rate of the battery

Typically, the physical battery that the homeowner purchases will provide the battery size, maximum charge rate, and discharge rate.

3) Battery Storage: The amount of energy stored in the battery for interval t is defined by the amount of energy from the previous interval plus or minus the amount of energy it consumes during charging or provides during discharging, between the previous interval and the current one. Due to inefficiencies, the actual energy consumed or provided by the battery is less than the amount of energy that the battery consumes or provides. This inefficiency is represented by the state equation constraint:

$$s_t = s_{t-1} + b^{eff} b_t - \frac{1}{b^{eff}} b^{dis}_t\ \forall t.$$

Furthermore, s_0 is a given parameter, representing the starting state of charge.

4) BESS Module Formulation: Note that the corresponding *net* cost of electricity for the battery is

$$P \cdot (b - b^{dis}) = \sum_{t=1}^{h} P_t(b_t - b^{dis}_t).$$

Combining the above constraints and cost, the BESS Module takes the form:

$$\min_{(s,b,b^{dis})} \quad P \cdot (b - b^{dis}) \tag{6}$$
$$\begin{aligned}
s_t = s_{t-1} + b^{eff} b_t - \tfrac{1}{b^{eff}} b_t^{dis} \ \forall t, \\
0 \leq s_t \leq b^{lim} \ \forall t, \\
0 \leq b_t \leq b_{max} \ \forall t, \\
0 \leq b_t^{dis} \leq b_{max}^{dis} \ \forall t, \\
(b_t - b_t^{dis}) + \Omega_t \leq A_t \ \forall t,
\end{aligned}$$

where Ω_t will represents other module loads in interval t.

E. Automated Windows Module

The previous modules have unique formulations, while the Automated Windows (AW) Module breaks that trend, because it is a variation of the TC Module. This section describes the treatment of automated windows that can be opened and closed in order to supplement the HVAC system with fresh air, especially when the external temperature is within the comfort range. The model treats the difference between opened and closed windows simply as a change in the thermal conductivity K_j defined earlier.

1) Modifying Thermal Control Module: The easiest extension to the TC Module formulation (3) would be making K_j into a decision variable where it could take on continuous values between a lower bound (closed window value) and upper bound (open window value). Although this modification is logically straightforward, it creates a difficulty for the integer progamming solver by making constraint (5), reproduced below, quadratic:

$$C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) = e_j q_{j,t-1} + K_j(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \ \forall (j,t),$$

since both K_j and $T_{j,t-1}^{in}$ are now decision variables.

2) Linear Relaxation: In order to alleviate this unwanted quadratic formulation, two modifications are made. The first is to assume that the window can only be completely opened or completely closed. Therefore, this allows data parameter K_j to be either K_j^{cw}, representing the thermal conductivity when windows are closed, or K_j^{ow}, representing the thermal conductivity when windows are fully open. Note that if end-use j has no controllable windows, then $K_j^{cw} = K_j^{ow}$.

The second modification is to perform a linear relaxation on the quadratic formulation with the aid of the first modification. This is realized by creating a new binary variable w_t, which acts as an indicator of whether the windows are open or not, during interval t.

The first step in the relaxation is turning the equality constraint (5) into an equivalent set of two linear inequality constraints.

$$C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \leq e_j q_{j,t-1} + K_j(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \ \forall (j,t),$$
$$C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \geq e_j q_{j,t-1} + K_j(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \ \forall (j,t).$$

Then create a duplicate set of the two inequality constraints, and replace k_j in the first set with K_j^{cw} and in the second set with K_j^{ow}.

$$C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \leq e_j q_{j,t-1} + K_j^{cw}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \ \forall (j,t),$$
$$C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \geq e_j q_{j,t-1} + K_j^{cw}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \ \forall (j,t);$$

and

$$C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \leq e_j q_{j,t-1} + K_j^{ow}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \ \forall (j,t),$$
$$C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \geq e_j q_{j,t-1} + K_j^{ow}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \ \forall (j,t).$$

Only one set of the two inequality constraints should hold during each interval t. To ensure this, the model introduces the binary variable w_t along with a large scalar value S to the four inequalities above in a way that will tighten one set of inequalities (indicating that the corresponding thermal conductivity is being used) and relax the other set (indicating that the other thermal conductivity is inactive).

$$\begin{aligned}
C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \quad &\leq e_j q_{j,t-1} + K_j^{cw}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \\
&\qquad + S w_{t-1} \ \forall (j,t), \\
C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \quad &\geq e_j q_{j,t-1} + K_j^{cw}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \\
&\qquad - S w_{t-1} \ \forall (j,t);
\end{aligned}$$

and

$$\begin{aligned}
C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \quad &\leq e_j q_{j,t-1} + K_j^{ow}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \\
&\qquad + S(1 - w_{t-1}) \ \forall (j,t), \\
C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \quad &\geq e_j q_{j,t-1} + K_j^{ow}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \\
&\qquad - S(1 - w_{t-1}) \ \forall (j,t).
\end{aligned}$$

(The run times for scenarios of this formulation are described later.)

3) TC/AW Module Formulation: Thus, the combined TC and AW module formulation takes the form:

$$\min_{(T_j^{in},\ q_j,\ w)} \quad \textstyle\sum_j (P \cdot q_j) \tag{7}$$
$$\begin{aligned}
C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \quad &\leq e_j q_{j,t-1} \\
&\quad + K_j^{cw}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \\
&\quad + S w_{t-1} \ \forall (j,t), \\
C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \quad &\geq e_j q_{j,t-1} \\
&\quad + K_j^{cw}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \\
&\quad - S w_{t-1} \ \forall (j,t), \\
C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \quad &\leq e_j q_{j,t-1} \\
&\quad + K_j^{ow}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \\
&\quad + S(1 - w_{t-1}) \ \forall (j,t), \\
C_j(T_{j,t}^{in} - T_{j,t-1}^{in}) \quad &\geq e_j q_{j,t-1} \\
&\quad + K_j^{ow}(T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \\
&\quad - S(1 - w_{t-1}) \ \forall (j,t), \\
T_j^{min} \quad &\leq T_j^{in} \leq T_j^{max} \ \forall j, \\
0 \leq q_j \quad &\leq q_j^{max} \ \forall j, \\
w_t \quad &\in \{0, 1\} \ \forall t, \\
\textstyle\sum_j q_{j,t} + \Omega_t \quad &\leq A_t \ \forall t.
\end{aligned}$$

where again $T_{j,0}^{in}$, together with exogenous data parameter $T_{j,t}^{ext}$, are given parameters, and where Ω_t will represents other module loads in interval t.

F. Non-Shiftable Loads Module

The Non-Shiftable Loads (NS) Module implements the system's power constraint on the household appliances that are fixed and can not be shifted. It also reports the fixed cost of the non-shiftable loads. The module has no decision variables, and its purpose is strictly for accounting.

These fixed loads can be denoted by L_t, a fixed load in interval t. Thus, the (fixed) electricity cost from the NS load would be

$$P \cdot L = \sum_{t=1}^{h} P_t L_t.$$

The impact on other module formulations is that A_t, the energy cap for interval t, is simply replaced by $(A_t - L_t)$. It is assumed that the non-shiftable load does not exceed the energy cap, or that an internal energy source can keep this constraint feasible.

III. Results

This section exercises the OLS model for five cases that vary by modules, end-use data sourcing, and form of electricity prices. Table VIII highlights the salient aspects of the data for each case [3].

The five cases vary across three locations. The Modules column indicates which modules of the OLS model are utilized in each case. The acronyms are defined in Table A of the Appendix. The Data column indicates whether the data is Real, from actual measurements, or Simulated, based on assumed appliance loads and end-use timings. The outside temperature and electricity prices are actual data. The column for Electricity Pricing indicates the type of prices used for that location. Time of Use (TOU) can have two or three pricing periods per day. Day Ahead prices are specified hourly on the day before use takes place.

A. Case 1: Boston Load Shift

Although the data is based on actual measures of end-use, it lacks a substantial amount of information and points of interest that are desirable for testing the OLS model. The following list highlights its major limitations:

- It does not have the end-user's temperature preference.
- It does not indicate whether the house has an electric, gas, or hybrid HVAC system.
- Outside temperatures are close to the typical comfort range.
- It is not clear whether the available data indicates the home's entire electric usage.
- The Boston area implements only a peak and off-peak time-of-use pricing scheme.

Given these limitations, this data is used merely to test the model's ability to shift loads. The shiftable loads are HVAC, clothes washer/dryer, and dishwasher. In order to test the full model, assumptions are needed for the HVAC data, which are explained shortly. Nevertheless, the results are still promising.

[3]The appendix contains a section called "Data" that explains fully the data used to create each case.

The model is run once a day starting at 12 a.m., for seven days, without lookahead, which is unnecessary. Both the start time and the duration used in the OLS model are generally configurable and can be changed to meet user preferences. During the week tested, the OLS model shifted loads on four out of the seven days. The daily Original and Shifted electricity costs are listed in Table IX, with the total savings from load shifting being 4.63%, which appears in the second row of the last column.

Comparing results between the Original row and the Shifted row, observe that no shifting takes place on days 3, 5, and 7. The remaining load shifting occurred as follows:

- washer, dryer, and dishwasher on days 1 & 6,
- dishwasher on days 2 & 4.

In the TOU pricing scheme, savings are limited. Loads are shifted from afternoon and evening times (peak hours) to early morning times (off peak hours). Because some appliances were already running in off-peak hours, savings are limited. In this data set, there is no indication of an HVAC system, which could be a major controllable load affecting energy costs and benefits. To overcome this, the other cases include HVAC use with thermal control.

To make up for the limitations of the Boston dataset, the OLS model is run on the fuller, simulated data for Springfield. Case 2 has only the load shifting and thermal controls; Case 3 adds a battery to the home; and Case 4 adds automated windows.

Solution times for the Boston Load Shift case are very fast. Because the OLS model is so simple, all CPU times are less than one second.

B. Case 2: Springfield without Battery

For the Springfield cases, the OLS model is run every two days, starting at 3 p.m., for a total of six days (three runs). Each run has no lookahead, because the storage is so small that it cycles each day.. Further, the end-user's preferred comfort range for the thermal controls is between 60 °F and 70 °F.

The shiftable loads in Cases 2, 3, and 4 are: HVAC, dishwasher, clothes washer/dryer, and PEV charger.

Figures 1 to 3 depict a time series for the original and shifted loads in kW for 5 minute intervals. The 0 interval is 3:00 p.m.

In Day 1 (8/11), the washer, dryer, dishwasher, and plug-in electric vehicle loads shift to the cheapest electricity price intervals, which is in the early morning. (The PEV was only driven a short distance on this Sunday, therefore the load for the PEV is very low compared to a weekday). In Day 2 (8/12), only the dishwasher and PEV loads shift. The PEV has a smaller preference window than the dishwasher; both items are shifted to the cheapest electricity price intervals for their respective preference windows.

In Day 3 (8/13), the washer, dryer, dishwasher, and plug-in electric vehicle loads shift to the cheapest electricity price interval in the early morning. In Day 4 (8/14), only the dishwasher and PEV loads shift. They are shifted to the cheapest electricity price intervals for their preference window.

In Day 5 (8/15), the washer, dryer, dishwasher, and plug-in electric vehicle loads shift to the cheapest electricity price

TABLE VIII
DESCRIPTIONS OF CASES

Case	Location	Modules	End-Use Data	Electricity Pricing	Time Step
1	Boston, MA	LS, NS	Real	Time of Use	60 min.
2	Springfield, IL	LS, TC, NS	Simulated	Day Ahead	5 min.
3	Springfield, IL	LS, TC, BESS, NS	Simulated	Day Ahead	5 min.
4	Springfield, IL	LS, TC, AW, NS	Simulated	Day Ahead	5 min.
5	Austin, TX	TC, NS	Simulated	Time of Use	5 min.

TABLE IX
CASE 1: BOSTON LOAD SHIFT. DAILY ELECTRICITY COSTS FOR 5/15/11-5/21/11

	Day 1	Day 2	Day 3	Day	Day 5	Day 6	Day 7	Total	**Savings**
Original	\$1.41	\$1.56	\$1.10	\$0.83	\$0.83	\$1.20	\$0.84	\$7.78	–
Shifted	\$1.31	\$1.47	\$1.10	\$0.77	\$0.83	\$1.10	\$0.84	\$7.41	4.63%

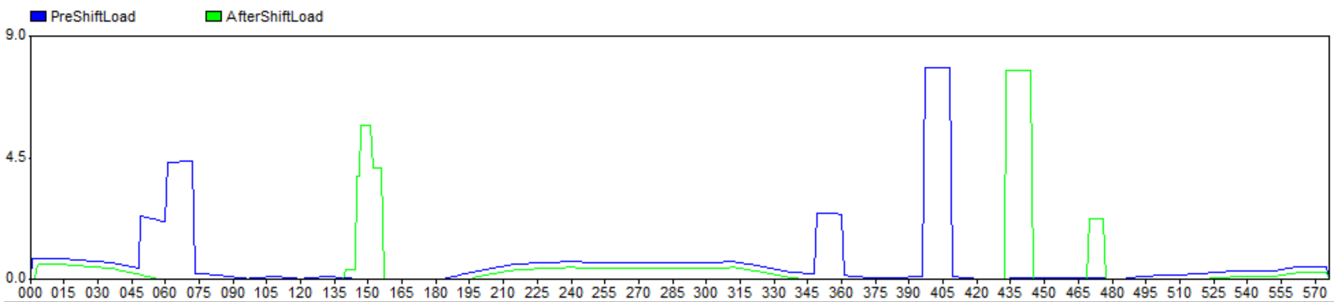

Fig. 1. Case 2: Springfield without Battery. Original and shifted loads for 8/11 - 8/12/13

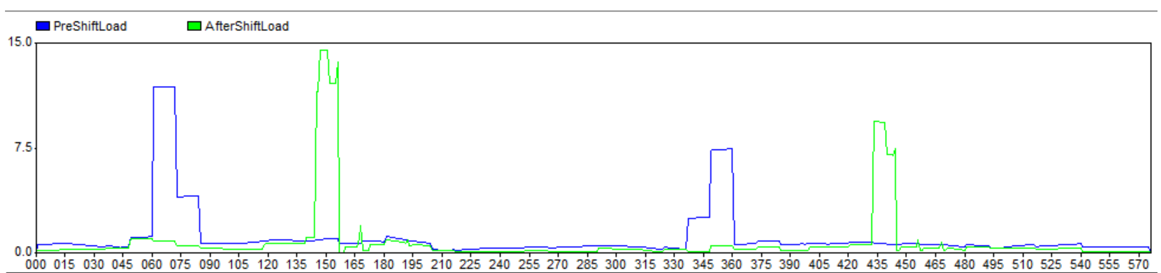

Fig. 2. Case 2: Springfield without battery. Original and shifted loads for 8/13 - 8/14/13

TABLE X
CASE 2: SPRINGFIELD WITHOUT BATTERY. SAVINGS FOR 8/11/13 – 8/16/13

Days	Days 1 & 2	Days 3 & 4	Total 5 & 6	Savings	
Original	\$0.95	\$1.39	\$1.21	\$3.55	
Shifted	\$0.55	\$0.80	\$0.80	\$2.15	39.44%

TABLE XI
CASE 2: SPRINGFIELD WITHOUT BATTERY. SOLUTION TIMES IN CPU SECONDS.

	Days 1 & 2	Days 3 & 4	Days 5 & 6
Solution Time (sec.)	0.80 s	1.00 s	0.97 s
Total time (sec.)	1.11 s	1.41 s	1.06 s

time in the early morning. In Day 6 (8/16), only the PEV load shifts to the cheapest electricity price intervals for its preference window.

Note that end-uses are shifted to early morning hours, which is when electricity prices are lowest. Also, the persistent, small gap between the original and shifted loads stems from the energy saved due to the flexibility in the end-user's comfort range as opposed to having a single temperature setting.

Over the 6-day period, this simulated end-user realizes almost 40% savings by utilizing load shifting and smart thermal controls, as summarized in Table X.

Computation times for each 2-day sequence are listed in Table XI. The solution time is that spent on solving the optimization problem, while the total time includes setup and reporting.

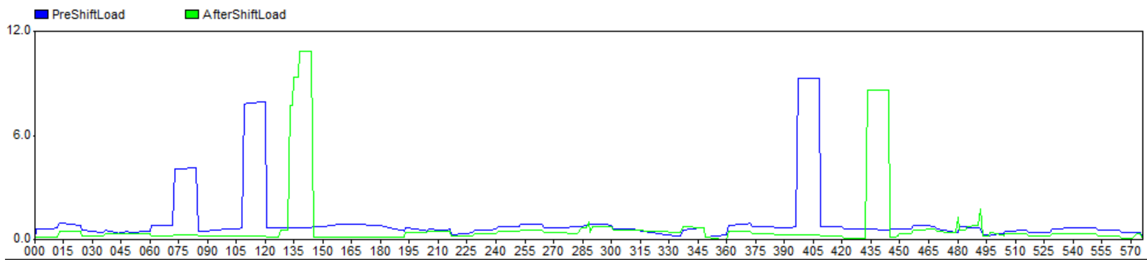

Fig. 3. Case 2: Springfield without battery. Original and shifted loads for 8/15 - 8/16/13

C. Case 3: Springfield with Battery

The Springfield results can be further improved by adding battery storage. A battery has the flexibility to charge when electricity prices are low and to let the end-user use the stored energy during high price periods. This effectively allows an end-user to shift their non-shiftable loads.

Further, the end-user may sell the electricity back to the utility during high-price times if the utility permits, as is possible in this case.

Figure 4 depicts battery charging and discharging (kW) in 5-minute intervals, where interval 000 is 3:00 pm. The battery has an 8.0 kWh capacity and a maximum charge and discharge rate of 1.44 kW. When adding this battery to the Springfield case for Days 1 and 2, the savings rises to 74%, which occurs because the battery charges during the low price periods (late night) and discharges during the peak periods (late afternoon).

The original electricity cost for Days 1 and 2 is \$0.95. After load shifting without the battery, the cost reduced to \$0.55, and after load shifting with the battery, the cost is \$0.25. Thus, with the battery, the end-user realizes over 70% savings for the two-day testing period.

While this is a simple example, use of the battery becomes more important when the household may reach its total electricity limit. In which case, energy in the battery can be utilized to reduce the cost of non-shiftable loads in high-priced hours, while keeping the total household load below the household limit.

The solution times are on the order of one second for the first two-day horizon. Therefore, adding the OLS battery storage module has not added much burden to the computation.

D. Case 4: Springfield Automated Windows

Automated windows could make thermal controls even smarter, because they add an ability to open and close the windows as a supplement to the HVAC system. When utilizing the AW module, the thermal controls receive an extra operation to intelligently control the home temperature, but the Springfield case did not yield obvious economic savings. Days 1 and 2 resulted in the windows being opened for a single fifteen-minute period. This translated into a negligible increase in savings of 0.01% compared to only utilizing the LS and TC modules.

Alternative climate scenarios and locations must be tested to determine whether automated windows can make a meaningful impact on electricity costs.

Table XII compares the solution and total CPU times across cases 3, 4, and 5 for the first two days of the horizon.

TABLE XII
COMPARISON OF COMPUTATIONAL EFFORT FOR DAYS 1 AND 2 IN CPU SECONDS

Case	Solution time	Total time
2: Springfield without Battery	0.8 s	1.1 s
3: Springfield with Battery	1.0 s	1.2 s
4: Springfield Automated Windows	118.8 s	119.2 s

It is clear that adding the OLS automated windows module significantly increases the computational burden. This leads to the conclusion that there is a future avenue of investigation to explore alternate modeling and solution approaches in order to more efficiently determine how to automatically control windows.

E. Case 5: Austin Pre-Cooling

The Austin Pre-Cooling case demonstrates pre-cooling the household for a somewhat artificial case of allowing the indoor temperature range to vary more widely. It includes only the Thermal Control module of the OLS model and therefore the model minimizes only the costs related to the HVAC. The two time-series charts in Figure 5 show related temperatures and the operation of the HVAC over the model horizon (Tues - Thurs, 8/6/2013 3:00 PM to 8/8/2013 3:00 PM).

These series are shown over identical time periods, and the inside temperatures and HVAC loads are shown before (pre-shift in red) and after (post-shift blue) load shifting. The yellow temperature series is the outside temperature, which is mostly synchronous with the HVAC loads, as expected.

The pre-shift indoor temperature is maintained within a narrow band at an almost constant level. The post-shift indoor temperature is maintained over a wider band in order to better demonstrate the operation of pre-cooling the household, in anticipation of higher electricity prices. In this case, pre-cooling takes place every time the TOU scheme changes from a lower price to a higher price. Over this two-day window, pre-cooling is exercised four times. There is no pre-heating, because the outside temperature is always higher than the indoor temperature range.

The Austin HVAC system has a 2 kW capacity, and for the periods directly prior to the electricity price change, the HVAC will work at this capacity to lower the indoor temperature

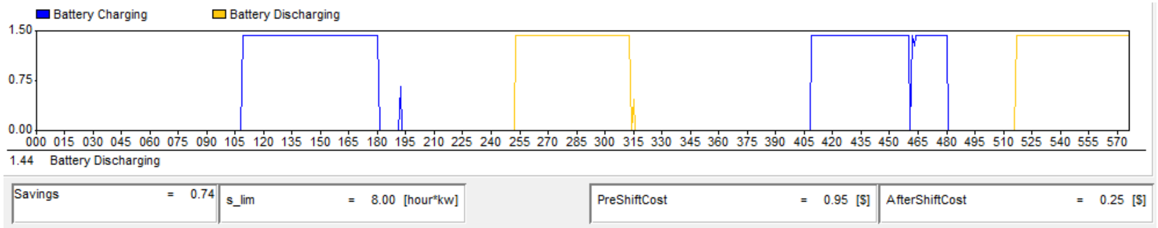

Fig. 4. Case 3: Springfield with Battery. Original and shifted loads for 8/11 - 8/12/13

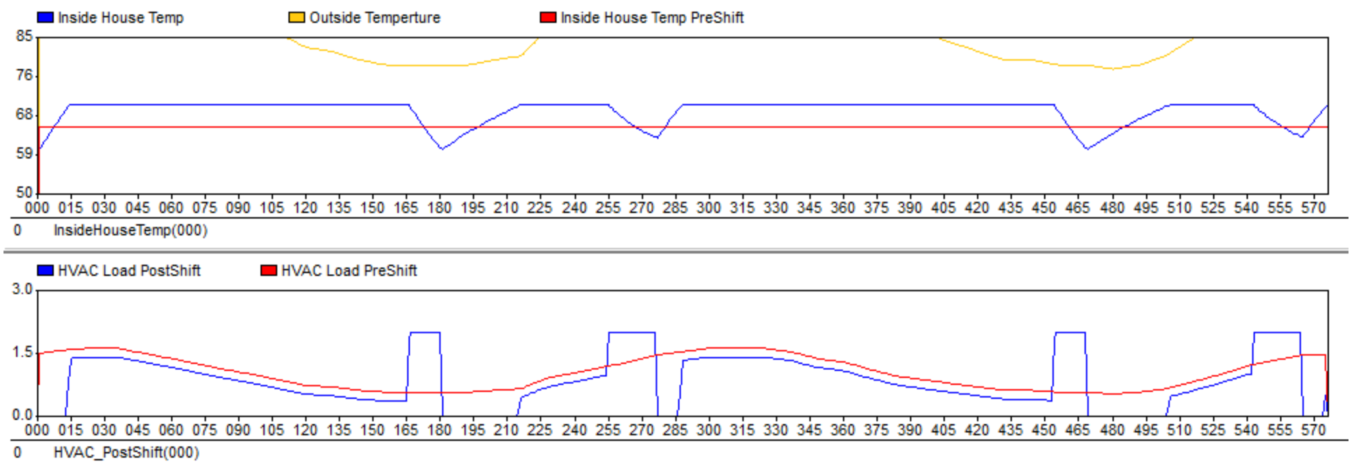

Fig. 5. Case 5: Austin Pre-Cooling. Home temperature and HVAC loads for 8/6/13 - 8/8/13

to the lower bound of the preference range. The indoor temperature change is timed to hit the lower bound just as the TOU price rises. Instead of using energy shortly after this higher-price period begins, the OLS model turns off the HVAC and lets the indoor temperature rise until it meets the upper bound on the preference range. Then, it turns on the HVAC and keeps the temperature at the upper bound, which is the most efficient level, because it has the smallest difference with the outside temperature, which governs heat transfer through the building insulation.

Allowing a wider indoor temperature range obviously decreases energy costs by itself, because the indoor temperature is allowed to be higher than the nominal level for high outside temperatures. However, further savings are realized from the pre-cooling, within the wider allowable indoor temperature range. For the two-day period, the end-user realizes a 27% savings, where the HVAC cost without use of the TC module is \$2.88 and with its use is \$2.10.

Since this version of the OLS model tests only the HVAC in order to demonstrate pre-cooling, the model formulation is a linear program, which leads to a solution time of less than one second.

IV. Smart Grid Analytical Framework

The 5 sets of case study results provide useful insights about the valid operation of the OLS model and how overall optimization of the HEMS can provide end-user savings. This section describes a framework to further aid in interpreting the OLS model results. The OLS model is a tool that provides a way to study the fundamental behaviors of a HEMS before and after adding smart modules for various types of functionality, like load shifting, thermal controls, and battery storage. This Smart Grid Analytical Framework builds on the types of observations made possible by the OLS model to allow investigators to answer questions like:

- Which smart appliance provides the greatest overall savings?
- Which smart appliance provides the greatest incremental savings?
- Which smart appliance has the highest benefit/cost ratio?
- What incentives do smart appliances provide for enabling behavioral changes?

This section describes four analytical frameworks that can help answer these questions.

- *Smart Appliance Cost Analysis* - Compares actual appliance costs with and without communication and control abilities. This is useful for understanding the cost structure of smart appliances for investment purposes.
- *Smart Appliance Benefits Analysis* - Shows how to use the OLS model and cases to investigate appliance-level benefits. This is useful for understanding individual end-user decision-making.
- *Smart Appliance Marginal Benefit Analysis* - Shows how to use the OLS model and cases to investigate the marginal benefits of individual appliances. This is useful for understanding the benefits of scale and the potential decisions of an aggregator or electric utility.

- *End-User Preference Sensitivity Analysis* - This is useful for understanding the value of various rate designs and their potential benefits to end-users and other stakeholders.

A. Smart Appliance Cost Analysis

This Smart Appliance Cost Analysis compares the costs of actual appliances for which there are comparable smart and non-smart versions. A smart appliance is one that has the ability to be remotely controlled, and companies have been introducing recently these kinds of smart household appliances. However, their offerings are still few in number. In the following, a company's smart appliance was compared in price to a company's most-similar model without the smart characteristic. Due to the current nature of the market for smart appliances, they are all higher-end models, and it was not possible to locate lower-tier models with smart characteristics at this time. Further, not all appliance providers have smart appliances in each category. For instance, there appears to be only one smart dishwasher as of April 2014.

The scatter plots in Figure 6 show appliance base prices versus the absolute difference (left plot) and percentage difference (right plot) between the smart and non-smart versions.

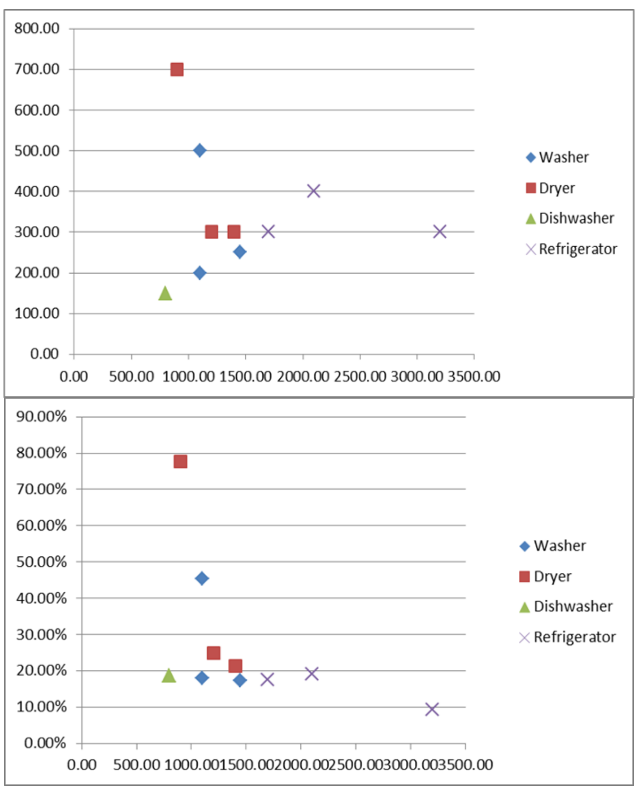

Fig. 6. Base Price v. Abs. Difference and Base Price v. Per. Difference

At this time it is difficult to form a meaningful conclusion about the cost of something being *smart*, because of the infancy of the market and the dearth of smart household appliances, infrastructure, and incentives. Yet, the right plot does indicate a trend for smart appliance prices to have about a 20% markup. One refrigerator does have a lower (10%) markup, and one washer and one dryer have much higher markups of 50% and 80%, respectively.

The above examined the incremental cost associated with adding smarts to household appliances, but the analysis did not investigate smart thermostats. It makes less sense to compare the price of a normal thermostat to a smart one, because almost every household already has a thermostat. When deciding whether to upgrade to a smart one, an end-user may be more likely to look for the one with the lowest cost. As such, Table XIII contains the costs of the smart thermostats on the market, as of April 2014.

TABLE XIII
SMART THERMOSTAT COSTS, AS OF APRIL 2014

Smart Thermostat	Cost
Nest 2nd Generation	\$250
Honeywell WiFi	\$202
ecobee Smart Si 01	\$200
Homewerks CT-30-H-K2	\$100
Allure EverSense	\$284

B. Smart Appliance Benefit Analysis

The Appliance Benefit Analysis investigates the average benefits of each appliance. This type of analysis can indicate incremental benefits by type of appliance, which can assist an end-user to understand the returns on investment from adding communication and controls to various types of appliances.

The benefit is calculated as the savings obtained from allowing each appliance's load to be shifted. Table XIV contains various measures of appliance benefits over 7 days, based on a variation of Case 2: Springfield without Battery. The prices are much lower in the off-peak period, with a Day Ahead price range of [0.019, 0.04136] ¢/kWh.

TABLE XIV
SMART AND ABSOLUTE BENEFIT OF AN APPLIANCE

Appliance	**Non-Smart Cost** (\$/day)	**Smart Cost (\$/day)**	**Savings (\$/day)**	**Savings (%)**
Washer	0.0069	0.0042	0.0026	38.35
Dryer	0.0608	0.0385	0.0223	36.67
Dishwasher	0.0347	0.0222	0.0124	35.84
PEV	0.2194	0.1263	0.0931	42.45
HVAC	0.4253	0.1383	0.2870	67.47

Average costs (\$/day) are for each appliance over the 7-day model horizon. The Non-Smart column gives the average cost for the nominal load profile of each appliance. The Smart Cost column gives the average cost of operating the given appliance when its load is optimally shifted within the limits of the end-user's preferences. The Savings (\$) benefit is the monetary value that was obtained by letting the given appliance load to shift. The Savings (%) is the percent change in Smart Cost relative to the Non-Smart Cost.

By examining these values for a given time frame, an end-user can determine whether purchasing an appliance with load shifting ability would be worthwhile.

Assuming that the Savings (%) values are typical, or that typical values can be somehow computed with the OLS model, they can be used to compute the expected annual savings attributable to each appliance, given Average Annual Costs for each appliance from energy.gov [14]. Table XV contains the elements of such a calculation.

TABLE XV
ANNUAL SAVINGS FOR AN APPLIANCE

Applinace	Savings (%)	Average Annual Cost	Annual Savings
Washer	38.35	$ 5.36	$ 2.05
Dryer	36.67	$ 71.40	$ 26.18
Dishwasher	35.84	$ 18.90	$ 6.77
PEV	42.45	$ 232.51	$ 98.69
HVAC	67.47	$ 108.00	$ 72.87

The Savings (%) values are repeated from Table XIV. The product of the Savings (%) values and the costs for each appliance are in the Annual Savings column. With this annual savings value, an end-user can compare this annual benefit with the annual amortized cost associated with adding communications and control (smarts) to the appliances and determine whether it makes economic sense to spend the extra money.

Combining the Annual Savings values in Table XV with a few assumptions about the costs of smart appliances and thermostats yields the results in the analysis in Table XVI. The following is assumed:

- The cost of making an appliance smart is an extra 20% on the purchase price.
- The nominal costs of non-smart versions of a washer, dryer, and dishwasher are given in the Table XVI.
- The incremental cost of a smart charger is on the order of a smart meter, namely $200.
- The incremental cost of a smart thermostat is about $200, assuming that a homeowner would replace a good thermostat having no resale value.
- The payback period does not include a discount rate and is only for ranking purposes.

TABLE XVI
BENEFIT-COST ANALYSIS FOR EACH APPLIANCE

Applinace	Non-Smart Cost	Incremental Cost	Annual Benefit	Payback Period
Washer	$ 600	$ 120	$ 2	60 years
Dryer	$ 300	$ 60	$ 26	2.3 years
Dishwasher	$ 300	$ 60	$ 7	8.6 years
PEV Charger	$ 2,000	$ 200	$ 99	2.0 years
HVAC	$ 200	$ 200	$ 73	2.7 years

It can be concluded from this table that adding smarts to the more energy intensive appliances, like the clothes dryer, the PEV charger and the HVAC system should provide a more robust benefit to the end user than a washer or dishwasher.

C. Smart Appliance Marginal Benefit Analysis

The following marginal benefit analysis is possible to implement for appliances that do not have defined load shapes, but are instead modeled as interactive with their environment and as having a limit on their capability. For this reason, the HVAC is used as the example appliance, and we test the sensitivity of its benefits to changing kW capacity values.

Normally an end-user decision about the appropriate size of an HVAC system is specifically based on two factors: climate and house size, but with a HEMS, one can investigate the benefits derived from the ability of a larger HVAC system to pre-cool/pre-heat faster. This analysis leverages the Austin Pre-Cooling case, which increases the HVAC capacity from 2 to 12 kW, as shown in Table XVII.

The benefit analysis in Table XVII shows that increasing the HVAC capacity has diminishing returns. Nevertheless, this framework shows how varying HVAC capacity can help to properly size the system.

D. Sensitivity on Resident's Behavior

The HEMS offers the end-user the ability to choose the allowable periods of operation to which an appliance can be shifted. One question that logically arises is, "What is the cost or benefit associated with extending or curtailing the window of allowable operation?"

Testing this condition on the Springfield cases demonstrates that no benefit is obtained from lengthening the allowable period by an hour. This is because the allowable window of operation for the set of appliances that can be shifted already encompass the lowest price period, as seen in Figure 7. But this analysis is case-specific and may show interesting results for people with particular work schedules, and alternative cases must be tested to conduct such a cost-benefit analysis.

A similar sensitivity analysis on the settings of the allowable temperature range could also be done to determine the marginal benefit of expanding the range.

V. CONCLUSIONS

It has been shown that the proposed OLS model can be used to accrue economic benefits for each of the five cases through the application of DR technologies in the residential sector. This model can effectively manage electricity demand in the residential sector and the findings are promising for the continued development of smarter electricity management in the future. For instance, the model is capable of performing quickly. More importantly, the model has demonstrated its flexibility to configure its modules to various circumstances. Therefore, existing modules can be improved as needed to represent further details of appliance use and additional modules can be added that better utilize user and electric utility preferences in order to enhance their mutually beneficial relationship.

It has been explained that the end-user can accrue economic benefits by shifting the consumption loads away from higher-priced periods. In the results section, the precise savings are shown in addition to the graphs of shifted load. As stated above, the model has a modular design that is flexible and can be configured to accommodate added capabilities. It has been demonstrated that batteries and automated windows are examples of such added capabilities that further improve end-user benefits. The battery components can give extraordinary

TABLE XVII
CASE 5: AUSTIN PRE-COOLING. BENEFIT OF INCREASING HVAC SIZE

HVAC Capacity (kW)	**2**	**3**	**4**	**6**	**8**	**10**	**12**
Savings (%)	27.10	28.07	28.34	28.53	28.60	28.64	28.67
Savings ($)	0.78	0.81	0.82	0.82	0.82	0.82	0.83
Incremental Benefit ($)	n/a	0.0279	0.0078	0.0055	0.0020	0.0012	0.0009
Marginal Benefit ($/kW)	n/a	0.0279	0.0078	0.0028	0.0010	0.0006	0.0005

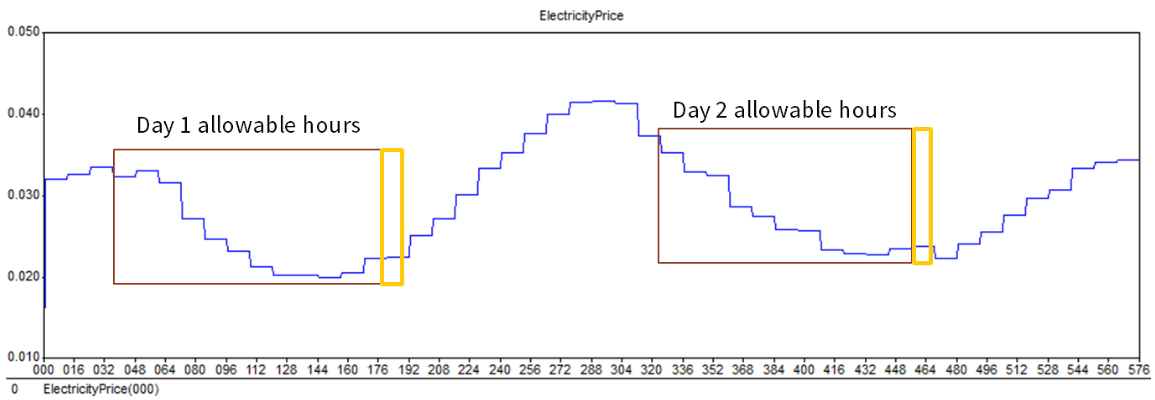

Fig. 7. Extending Resident's Allowable Hours

savings, but must be compared to installation and maintenance costs and a utility's willingness to buy back electricity. Automated windows may provide benefits, but further testing is needed to identify the optimal conditions for achieving economic savings.

In conclusion, the smart grid analysis framework provides guidance in determining whether current smart appliances are economically priced. For example, by installing a smart thermostat or dryer, the cost might be recouped within five years (based on the Springfield data set). However, a 20% markup on washers and dishwashers might not be recouped within five years, based on the simulated savings. A PEV, which is a load-intensive appliance, may see significant savings from smart charging, but it is difficult to put a cost on that ability, because of the significant variations of installations and the rapidly changing business landscape.

A. Possible Future Investigation

The OLS model's modular design provides the ability to make additional enhancements simpler to design and implement. First, it can be manipulated to handle both non-concurrent and concurrent load shifting. This idea is particularly interesting for charging PEVs. It would be possible to accrue benefits from charging a fleet with overall supply capped for a limited time. In addition, a household might mitigate costs at a time when prices are volatile by not charging concurrently.

Furthermore, the OLS model can be modified to minimize or maximize other costs and benefits regarding the operation of a household or a utility — possibly a utility's ability to weigh a demand response option versus the cost of turning on an emergency generator.

Regarding the formulation, two avenues of future investigation easily arise. The first is to extend the current formulation, which is essentially a single temperature control zone, to multiple zones. This change allows one to explore added controls and more detailed modeling of the building. For example, heat exchanges between rooms can be modeled using fluid and thermal models. Furthermore, the behavior of the building's zones can be modeled using simulation programs and languages like EnergyPlus and Modelica. By turning off or rather utilizing less energy in certain zones within a building, the model can explore possible added value to consumers, utilities, and third parties.

The second avenue of future investigation for the formulation relates to the formulation of the automatic windows. Due to the slower run time associated with the automatic windows as performed now, one could create a two-level approach to address when windows should open and close. This approach can be benchmarked with the current approach with the expectation of delivering a quicker solution.

Lastly, as an analysis tool, the OLS model can provide insight into certain aspects of residential energy consumers and demand response. A few ideas are:

- *Appliance Behavior* – Determine the most important factors affecting appliance behavior for purposes of forecasting sales and market penetration.
- *End-User Behavior* – Determine the most important factors affecting end-user behavior for purposes of characterizing how they can best benefit from the smart grid.
- *Demand-Side Pricing* – A significant application of this model is to determine prices for operating demand-side resources within a microgrid or other structure that is not large enough for wholesale pricing.
- *Demand Response Forecasting* – Calibrate a model for

controlled and voluntary demand response to various factors like weather, prices, and energy conservation announcements to be used in short-term load forecasting.
- *Long-Range Planning* – Show how aggregate load shapes change as a result of external factors like weather, prices, and incentives.
- *Energy Policy* – Determine how to represent smart grid benefits for end-users, aggregators, utilities, and the general public.

These insights may be achievable from the foundation provided by the OLS model. The OLS model represents fundamental appliance behaviors and may be scalable to larger systems to help answer key stakeholder questions.

Appendix A
List of Acronyms

AW	Automated Windows
AMI	Advanced Metering Infrastructure
BESS	Battery Electricity Storage System
BEV	Battery Electric Vehicle
DR	Demand Response
EV	Electronic Vehicle
FCEV	Fuel Cel Electric Vehicle
HEMS	Home Energy Management System
HVAC	Heating, Ventilation, & Air Conditioning
ICT	Information and Communication Technology
LS	Load Shifting
NS	Non-Shiftable
OLS	Optimal Load Shifting
PEV	Plug-In Electronic Vehicle
REDD	Reference Energy Disaggregation Data Set
TC	Thermal Control
TOU	Time of Use
UTC	Coordinated Universal Time

Appendix B
Data

This section describes the data needs for using the OLS model and data sources for these case studies. Some data pertains to appliance use, and other data is used for consumer preferences and electricity prices. These sources are combined to create cases for later analysis. The cases along with their salient characteristics are located in Table VIII, which is reproduced below. This data description is useful as a reference to publicly available data and because it demonstrates an assemblage of data needed to conduct such analysis.

A. Desired Data Properties

Optimizing electricity load shapes depends on the time-varying behavior of user preferences, end-use appliances, and electricity prices. For this reason, the model requires nominal time series load data at the appliance level. The time resolution should preferably be as fine as possible for the potential decision cycle. In the following cases, the time resolution is based on bulk electricity system (BES) [15] needs, and it ranges from seconds to minutes. Modern Advanced Meter Infrastructures make measurements on the order of 5-minute intervals, which are related to the wholesale electricity market having typically the same interval lengths for Real Time energy dispatch.

The time series data should extend from the present for about a week, and it should correspond to the end-user's flexibility to schedule their loads over the immediate future. The OLS model is a bottom-up representation of electricity use and can be concentrated on the electricity use within a single building. But it can also be used to represent coordinated behavior between multiple interconnected structures.

B. Case 1: Boston Load Shift

A highly useful initial source of end-use data is the Reference Energy Disaggregation Data Set (REDD) [16], because it is publicly available and possesses many of the desired traits described above. In addition, REDD is intended for research purposes.

The REDD data set includes energy-use data for six residential houses for about two months in 2011. However, there are long periods of sparse data, and each house has different metered components. The house known as *house_1* is described here as an example, because it had a large number of sub-meters, particularly for appliances that are candidates for load shifting. Such appliances include a dishwasher, clothes dryer, and clothes washer. The week of May 15-21, 2011 is selected for a case study, because its data is consistently available over the duration of the time period.

1) Description of house_1 Data: The *house_1* data is divided into twenty data channels and a *labels* file. The labels file contains a mapping from the numbers of each channel file to a metered circuit or appliance.

2) Pre-Processing Data: The REDD data is preprocessed to make it available in a form that fits well with the OLS model. First, the data channels are selected, and then the channel data is converted from power readings to energy use over the desired interval length. These processes are as follows.

The candidate shiftable end-uses are:
- Dishwasher
- Washer-dryer
- Heating
- Air conditioning
- Refrigerator
- Freezer
- Plug-In Electronic vehicle

All other loads in the metered circuits are treated as non-shiftable.

The data channel files have a format with two columns of data: the first column is a time stamp and the second is a power flow reading. The time stamp is in coordinated universal time (UTC) format, and these readings occur approximately every three seconds. The power flow reading is in watts. There is no header row.

To use this data stream within the OLS model, the power flow readings are first converted to units of average hourly or 5-minute energy, depending on the scenario. A MATLAB function (named `integrate_per_hour`) computes these values. To automate the process, a script (named `power2energy_per_hour`) iterates through all the data channels and converts them to streams of average hourly energy. The units of watts are thus converted to kWh.

TABLE XVIII
DESCRIPTIONS OF CASES

Case	Location	Modules	End-Use Data	Electricity Pricing
1	Boston, MA	LS, NS	Real	Time of Use
2	Springfield, IL	LS, TC, NS	Simulated	Day Ahead
3	Springfield, IL	LS, TC, BESS, NS	Simulated	Day Ahead
4	Springfield, IL	LS, TC, AW, NS	Simulated	Day Ahead
5	Austin, TX	TC, NS	Simulated	Time of Use

Since *house_1* has three data channels labeled `washer_dryer`, the energy for those three channels is aggregated (Note: that the model includes an assumption that the clothes dryer, when used, is used immediately following the clothes washer). Thus, the model assumes that the three channels represent different parts of the circuit to which a washer and a dryer are connected rather than the fact that there are three washers and dryers.

3) Data Ready for Model: The advantage of the REDD data is that it is real world data. However, it is limited in two major respects. The first limitation is the periods of missing data, which leads to questions pertaining to the use of this information as a case, particularly when coupled with the lack of specific homeowner preferences. The second limitation is the impossibility of identifying whether the given home has an electric HVAC system, because its temperate climate over the given period and/or the lack of insights about the homeowner's indoor temperature range preferences.

C. Cases 2, 3, 4: Springfield General Data

Because of the stated limitations of the REDD data, the project team prepared a separate set of simulated data for one house with the goal being to fully exercise the OLS model features. The simulated data set is based on a combination of design choices about the location, outside temperature range, and available electricity prices.

In particular, the team picked a 6-day period during August, for which weather and electricity prices could be collected directly. A Day-Ahead price scheme was chosen over a TOU scheme, because such prices have more resolution than just peak and off-peak values. Lastly, the assumed end-user has a plug-in electric vehicle, works a 9am-5pm job, and has a fairly basic set of end-use preferences.

1) Location: The location for the simulated data set was chosen to be the city of Springfield, Illinois for two main reasons. First, in the course of the chosen week (8/11/13-8/17/13), the climate requires both heating and cooling. Second, the local utility, called *Ameren*, provides its consumers with the option of day ahead pricing for electricity use. This feature is particularly attractive, because it makes the prices more varied than merely a time-of-use pricing scheme.

2) Climate: The Springfield temperatures are the actual temperatures during the modeling horizon of 8/11/13-8/17/13. They were acquired from the Weather Underground, a commercial weather service that provides real-time weather information [17]. Their site collects most of its data from the National Weather Service.

3) Electricity Price: The prices are the day ahead prices for Springfield during 8/11/13-8/17/13. They were acquired from Ameren's website [18]. It is also important to note that a person can acquire the day ahead prices one day in advance, which is a highly beneficial feature for the algorithm.

4) Simulating the Appliances:

a) Washer: The U. S. Department of Energy reports that a washer's wattage ranges from 350 to 500 watts [14]. This information was used to produce a simple algorithm to produce the kW usage for the washer when used. It is assumed the Springfield household will use its washer 4 times a week. The washer runs on Sunday, Tuesday, Thursday, and Saturday. The times were set to times of the day when the end-user would be at home: 7 pm, 8 pm, 8 pm, and 12 pm, for each day, respectively.

Next, the phantom loads for the washer, which are extremely small, were produced with a simple algorithm. The algorithm was designed by looking at the actual phantom loads from the REDD data set. From that, it appears that a washer randomly draws phantom loads at fractions of a watt throughout the day or draws no loads at all.

b) Dryer: The U. S. Department of Energy reports that an electric dryer's wattage ranges from 1800 to 5000 watts [14]. This information was used to produce a simple algorithm to produce the kW usage for the dryer when used. It is assumed that the Springfield household will use its dryer 4 times a week. It operated on Sunday, Tuesday, Thursday, and Saturday. The times were set to the times of the day when the end-user would be at home: 8 pm, 9 pm, 9 pm, and 1 pm.

Next, the phantom loads for the dryer, which are extremely small, were produced with a simple algorithm. The algorithm was designed by looking at the actual phantom loads from the REDD data set. From that, it appears that a dryer randomly draws phantom loads at fractions of a watt throughout the day or draws no loads at all.

c) Dishwasher: The U. S. Department of Energy reports that a dishwasher's wattage ranges from 200 to 2400 watts and even greater if the dishwasher's drying option is enacted [14].

This model does not use the drying option. This information was used to produce a simple algorithm to produce the kW usage for the dishwasher when used. It is assumed that the Springfield household will use its dishwasher 6 times a week. It operated on Sunday, Monday, Tuesday, Wednesday, Thursday, and Saturday. The times were set to those when the end-user would be at home: 7 pm, 8 pm, 8 pm, 7 pm, 9 pm and 6 pm, for each day, respectively.

Next, the phantom loads for the dishwasher, which are extremely small,were produced with a simple algorithm. The algorithm was designed by looking at the actual phantom loads from the REDD data set. From that, it appears that a dishwasher randomly draws phantom loads at fractions of a watt throughout the day.

d) Electric Car: The Global EV Outlook predicts 20 million electronic vehicles[4] will be used worldwide by 2020, and U.S. consumers already represent 38% of that number [19]. In addition, because a large part of an EV owner's electricity cost may be attributed to the EV, and due to the efficacy of shifting such a load, the OLS model incorporates the PEV in the Springfield simulation.

The Mini E was selected to be used for the model. The Mini E gets 0.22 kWh/mile [20]. It is assumed that the Mini E must refill after 100 miles, however, in the simulation, the automobile never reaches this level of mileage. If the Mini E's battery is completely empty and its owner seeks to recharge it fully, it would take approximately 3 hours to do so. However, in the simulation, it will never get to that point because of daily recharging and the specific homeowner's driving profile. The homeowner is assumed to be using a level 2 PEV charger [21], with maximum load of 7.68 kW [22].

e) Assumptions:

- Driver works 15 miles from his or her home.
- Driver drives 30 work miles plus a uniform random number from 0 to 10 miles on a workday
- Driver drives uniform random number from 0 to 10 miles on a weekend.
- The PEV charges every day, and the times were 4 p.m., 6 p.m., 6 p.m., 6 p.m., 6 p.m., 6 p.m., and 8 p.m. for each day, respectively.
- No phantom loads were generated for the PEV charging station.

f) Non-Shiftable Loads: Each day, a house has loads that cannot be shifted, including but not limited to televisions, stereos, laptops, lights, and tablet/phone charging. In addition, for this simulation, the refrigerator is treated as a non-shiftable load, although it could potentially be treated as an energy storage end-use. The non-shiftable load quantity was generated as a random multiple between 1.0 and 1.5 of the measured non-shiftable load from the REDD data set.

D. Case 4: Springfield Automated Windows

Mild climates can benefit from opening windows to allow temperate air to enter a building in order to maintain a preferred temperature range. This feature of the OLS model was run only on the first two days of the Springfield, IL data.

1) Time Horizon: The time period for which we test this portion is short in comparison with the one- or two-day periods we use in other cases. This is to reduce the computation time. The time period here is 4 hours of 5-minute intervals on Tuesday evening (8/13/13) from 8 pm - 12 am.

2) Location: The location is Springfield, IL.

3) Climate: The exact time horizon was chosen in order to emphasize when benefits from opening and closing windows would be apparent. The temperature begins at 60.1 degrees Fahrenheit and falls into the low 50's over the time horizon.

4) Electricity Prices: To avoid any pre-cooling or pre-heating effects, a TOU pricing scheme was chosen instead of the day ahead scheme of the other Springfield, IL cases. The modeling horizon is a peak price period, and the price is 0.12 $/kWh. [1]

E. Case 5: Austin Pre-Cooling

The Austin, Texas location was chosen in order to further emphasize the specific pre-cooling aspect of the model. Its character is that it has an external temperature range that is always above the homeowner's preferred temperature range. In this way, the model exercises only its cooling feature. For this location, only the HVAC portion of the model is tested, and according, only real data on temperature and prices are needed. The loads in this case are also synthesized for a single house.

1) Location: The city of Austin, Texas was chosen for its hot climate. The model was implemented for the period of August 6, 3:00PM to August 8, 3:00 PM (Tues-Thurs). The location provides a climate is beneficial for investigating and testing comfort preference zones, HVAC power levels, and economic impacts on locations where HVAC systems must run continuously.

2) Climate: The temperatures used are the actual temperatures in Austin, Texas during 8/6/13-8/8/13, and they range from 78.1 to 104 degrees Fahrenheit. They were acquired from Weather Underground, a commercial weather service that provides real-time weather information on the Internet [17]. The site collects most of its data from the National Weather Service.

3) Electricity Price: The prices are the TOU prices for Austin during 8/6/13-8/8/13, and they were acquired from Austin Energy's website [23]. It is also important to note that an Austin consumer can acquire TOU prices in advance, which is a highly beneficial feature for the algorithm.

Appendix C
Continuous Operation

The LS module formulation needs a few added constraints to represent the fact that some end-uses i run continuously during its duty cycle (can switch on and off at most twice). This can be achieved by adding linear constraints:

$$y_{i,t} = x_{i,t} - x_{i,t-1} \quad (8)$$

$$\sum_t |y_{i,t}| \leq 2 \quad (9)$$

$$y_{i,1} + y_{i,h} \leq 1 \quad (10)$$

The new variable y defined in (8) is introduced to indicate whether end-use i switched between on and off states in interval t. The constraint (9) guarantees that $y_{i\cdot}$ can only switch states twice over the model's horizon. With this constraint alone, there are two possibilities for $x_{i\cdot}$ to switch twice. The

[4]Electric vehicles are defined in this report as passenger car plug-in hybrid electric vehicles (PHEV), battery electric vehicles (BEV), and fuel cell electric vehicles (FCEV).

first is that end-use i will run continuously, as in the following example definitions:

$$x_i = [0\ 0\ 0\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ \dots]$$

$$y_i = [0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ \dots]$$

The second is that end-use i will run continuously at the beginning of the model for some period, stop, and then continue to run continuously at the end of the model, as in

$$x_i = [1\ 1\ 0\ 0\ \dots\ 0\ 0\ 1\ 1\ 1]$$

$$y_i = [0\ 0\ 1\ 0\ \dots\ 0\ 0\ 1\ 0\ 0]$$

To avoid the second possibility, enforce (10).

Constraints can be constructed to ensure that the washer runs prior to the dryer and that the dryer runs directly after the washer.

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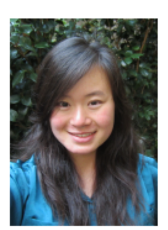

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