

A Mathematical Programming Formulation for Optimal Load Shifting of Electricity Demand for the Smart Grid

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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 on the smart grid 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.

Index Terms—Optimal scheduling, energy management, home automation, smart grid, smart devices

I. INTRODUCTION

THE smart grid is a cyber-physical system for which there is an enormous opportunity to improve energy efficiency and reliability through big-data.

In the field of energy management, the current trend of increasing integration of Information and Communication Technology has enabled market actors to develop technologies that has engendered the electric grid as a cyberphysical system — the smart grid. This enables the development and use of applications such as the smart meter, bidirectional communication, advanced metering infrastructure (AMI), home automation, and home area networks [1]. Measurement and recording of electricity consumption and two-way communication between the meter and the utility's system can help adjust energy consumption patterns, and thereby achieve economic benefits.

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This process requires large volumes of data. Innovations in "Internet of Things" (IoT) devices have further led to connected power meters, lights, occupancy sensors, electric vehicles, appliances, and household electric battery storage that are capable of data collection and communication. The realization of monetary and energy benefits also necessitates the efficient performance of algorithms on these large data sets with numerous decision variables. This is of particular importance in order to scale from electric grid technologies from one user, such as a residential energy customer, to multiple customers, commercial customers, communities, and beyond.

The electric grid as a cyber-physical system results in the creation of large data sets, including for example, electric meter readings, electricity end-use consumption, electricity price signals, consumer preferences, and device control signals, among others. Using this data, big data methods such as mathematical programming can manage electricity demand more efficiently and assess the likely sources of value to be derived from smart grid technologies under electricity programs such as demand response.

To meet energy needs on the grid, 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. This data includes electricity prices, electric meters, electricity end-use power consumption, consumer preferences, and control signals, among others. A valuable resource to meet energy needs is demand response.

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 [2]. 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 [3], which represents an increase of 5.9% since 2009 [2]. 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" [4]. Demand response technologies

can be and are considered as components within a broad range of energy supply scenarios [2]. Correspondingly, there are significant policy implications associated with the development of demand response technologies (DR technologies).

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 [2]. 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 purpose of the OLS model is to obtain greater efficiency and savings, both in terms of economics and energy usage. Specifically, the model achieves 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 demand response and other smart grid technologies. Chen, Wei, and Hu create an energy efficient scheduling algorithm that takes into account uncertainties in household appliance operation time and intermittent renewable generation, variable frequency drives, and capacity-limited energy storage, which may decrease monetary costs by up to 45% [5]. Mohsenian-Rad, Wong, and Jatskevich applied game theory to demand-side energy management between a utility company and its customers, showing a potential reduction in peak-to-average ratio of the total energy demand, total energy costs, and individual users' daily electricity charges [6]. In one case study, Malik and Bouzguenda [7] 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, 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 [8].

This paper addresses several principles 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, load shifting for EVs has become increasingly popular to respond to the significant energy demand created when multiple EVs charge 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 [9], [10], [11]. 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 [12] 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 [13] 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 [14], [15]. 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. 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?

Results show that appliances can save between 36-69% of the energy cost compared to a non-energy scheduled appliance. Also, payback periods for smart energy appliances can range from 2 years to 60 years depending on the appliance.

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 linked by the need to minimize the total cost and to manage total household electricity use. The modules represent energy end-uses in terms of physical behavior, end-user preferences, and automated controls. The automated controls minimize costs of energy consumption, while obeying physical characteristics of the end-uses, 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). Additionally, potential additional terms in the objective could reflect: 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 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 modules are mathematical programming optimization problems. The Load Shifting module is a linear program (LP), while the other modules are mixed 0-1 linear programs. The theoretical computational complexity of solving a continuous LP is polynomial, and LP algorithms are fully implemented into mature commercial software, e.g., Cplex, GUROBI, MOSEK, etc.. Today, a practical linear program with millions of decision variables and constraints can be solved in minutes with a PC. Many open source codes are available with slightly worse performance. The mixed 0-1 LP is theoretically proven to be NP-hard in the worst-case, but in practice many of them can be solved efficiently. For example, the 0-1 linear programs described in our paper with thousands variables and constraints were all solved on a single machine in less than a second. Typically, the mixed 0-1 LP solvers (also developed in Cplex, GUROBI, MOSEK, etc.) use LP solvers as subroutines, and intelligently solve a sequence of LPs to lead to an optimal solution.

The following sections describe the mathematical formulation of each module.

A. Indices

The OLS model has indices for end-uses and time. End-uses are categorized as either shiftable or non-shiftable. The

shiftable end-use loads are further categorized as *work storage* or *energy storage*, with associated decision variables for shifting load. Non-shiftable loads are aggregated and do not require an index. The notation utilized in all the modules are detailed in Table I.

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. These 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 operating schedule for work-storage end-use i . It is a vector of dimension h where its t th entry equals 0 when the appliance does not operate at time interval t and 1 when the appliance operates. The appliance is assumed to finish its task without interruption¹.

2) *Data Parameters*: The LS module parameters appear in the major categories of user preferences, environment data, and end-use characteristics, as detailed in Table II.

TABLE II
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, defined as end-use $i = 1$. Let the interval t be hours with $h = 24$ hours.

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

3) *Work Storage End-Use Illustrations:* Assume the washer consumes 0.3 kWh and takes one hour to run. Then, the average electricity use, l_1 , would be $l_1 = 0.3^2$.

Assume the homeowner wants the washer to operate between 12 a.m. to 8 a.m., and the model's first interval is 12 a.m., then the vector of allowable operation, D_1 , has dimension-24 and is equal to:

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

If the optimal time for the washer to run is between 3:00 a.m. and 4:00 a.m., given $Z_1 = 1$, then the corresponding entries of x_1 , the control/decision variable, are:

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

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:* A constraint for job completion is imposed. Assume the washer must operate once between 12 a.m. to 8 a.m. and takes one hour to run. Then a condition is imposed that the sum of all hourly products of schedule operations and allowable operations equals Z_1 :

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

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:

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

$$\begin{aligned} x_i \cdot D_i &= Z_i \ \forall i, \\ \sum_i l_i x_{i,t} + \Omega_t &\leq A_t \ \forall t, \\ x_{i,t} &\in \{0, 1\} \ \forall (i, t), \end{aligned} \quad (2)$$

where Ω_t will represents other module loads in interval t .

C. Thermal Control Module

The Thermal Control (TC) module controls thermal energy storage end-uses, for example: heaters, air conditioners, and refrigerators.

Typically, the control/decision variable for an energy storage appliance is the energy consumption per time period over the optimization horizon, which affects how much heating or cooling is supplied by the appliance. These appliances must maintain internal temperatures within user-specified ranges.

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

1) *Decision Variables:* The control/decision variable is the energy consumption $q_{j,t}$ of the thermal control end-use unit j for interval t , and the state variable is the indoor temperature $T_{j,t}^{in}$ of the space that is heated or cooled by end-use j for interval t

2) *Data Parameters:* The TC module parameters appear in the major categories of user preferences, environment data, end-use characteristics, and appliance limitations, as detailed in Table III.

TABLE III
DESCRIPTIONS OF TC MODULE PARAMETERS

User Preference	Units	Description
$T_{j,t}^{min}$	° F	Minimum temperature for end-use j in interval t
$T_{j,t}^{max}$	° F	Maximum temperature for end-use j in interval t
Environment Data	Units	Description
P_t	\$/kWh	Electricity price in interval t
$T_{j,t}^{ext}$	° 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
$q_{j,t}^{max}$	kWh	Energy consumption limit for end-use j for interval t

To illustrate the TC module formulation, a heating, ventilation, and cooling (HVAC) system is used, defined as end-use unit $j = 1$. 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:* A thermal storage end-use j , must maintain temperatures between a maximum and minimum, such as a resident's preferred comfort zone.

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

Assume t represents hours, the temperature $T_{j,t}^{in}$ is dependent upon the energy control variable ($q_{j,t}$), which must be less than a maximum value, $q_{j,t}^{max}$, for all intervals t . Then, the thermal energy control is limited by:

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

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 transfer from the surroundings, $q_{j,t}^{sur}$ through:

$$q_{j,t}^{sur} = K_j (T_{j,t}^{ext} - T_{j,t}^{in}), \forall t \neq h,$$

where K_j is the thermal conductivity coefficient of unit j .

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

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

where C_j is the thermal heat capacity coefficient of unit j , and $T_{j,0}^{in}$, together with exogenous data parameter $T_{j,0}^{ext}$, 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:

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

$$C_j (T_{j,t}^{in} - T_{j,t-1}^{in}) = e_j q_{j,t-1} \quad (4)$$

$$+ K_j (T_{j,t-1}^{ext} - T_{j,t-1}^{in}) \quad \forall (j, t), \quad (5)$$

$$T_j^{min} \leq T_j^{in} \leq T_j^{max} \quad \forall j,$$

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

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

where T_j^{min} and T_j^{max} 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 a battery that can charge when electricity prices are low and supply electricity when electricity prices are high.

1) *Decision Variables*: The decision variables for the module are b_t , the energy consumption for the battery for interval t , and b_t^{dis} , the energy provided from battery for interval t . The state variable, s_t , is the amount of energy stored in the battery at the end of interval t .

2) *Data Parameters*: The BESS Module parameters appear in the major categories of end-use characteristics and appliance limitations, as detailed in Table IV. Typically, the physical battery that the homeowner purchases will provide the battery size, maximum charge rate, and discharge rate.

TABLE IV
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_{max}^{dis}	kWh	maximum discharge rate of the battery

3) *Battery Storage*: The amount of energy stored in the battery s_t for interval t is the amount of energy sotred in the previous interval plus or minus the amount of energy charged or discharged since the previous interval:

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

Where b^{eff} is due to inefficiencies and s_0 is the starting state of charge.

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

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

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

$$\min_{(s, b, b^{dis})} P \cdot (b - b^{dis}) \quad (6)$$

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

$$0 \leq s_t \leq b^{lim} \quad \forall t,$$

$$0 \leq b_t \leq b_{max} \quad \forall t,$$

$$0 \leq b_t^{dis} \leq b_{max}^{dis} \quad \forall t,$$

$$(b_t - b_t^{dis}) + \Omega_t \leq A_t \quad \forall t,$$

where Ω_t represents other module loads in interval t .

E. Automated Windows Module

The Automated Windows (AW) Module is a variation of the TC Module and represents automated windows that open and close to supplement the HVAC system when the external temperature is within the comfort range. The difference between opened and closed windows is represented 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) is to make K_j into a decision variable that can take on continuous values bounded by values that represent closed and opened windows. This creates difficulty for the integer programming solver by making constraint (5) quadratic since both K_j and $T_{j,t-1}^{in}$ are now decision variables.

2) *Linear Relaxation*: To alleviate this unwanted quadratic formulation, first, the windows are assumed to be completely opened or completely closed. This allows K_j to be either K_j^{cw} , the thermal conductivity when windows are closed, or K_j^{ow} , the thermal conductivity when windows are open. Note that if end-use j has no controllable windows, then $K_j^{cw} = K_j^{ow}$.

Second, a linear relaxation is performed on the quadratic formulation by creating a new binary variable w_t , to indicate whether the windows are open or not, during interval t .

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

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

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 end-uses that cannot be shifted or controlled. These fixed loads are 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 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. DATA

The total size of the data depends on the number of energy end-uses, the data sampling rate, and the desired time resolution of the energy consumption schedule. For all the modules, the scheduling horizon length and the period length can be

specified by two integers. The electricity price and energy capacity values are represented by two floats per time sample. The size of data for the modules is summarized in Table V. The Automated Windows module requires the Thermal Control module as well. For the Load Shifting module, the non-shiftable load may require several data series of floats. This is because the non-shiftable end-uses likely require more than one meter. As a result, the non-shiftable load likely needs to be calculated as the sum of power consumption across the non-shiftable loads, which gives one float per non-shiftable end-use per timestamp.

TABLE V
DATA SIZE GROWTH RATE PER MODULE

Module	Data per End-Use	Data Per End-Use Per Timestamp
Load Shifting	-	1 float, 2 binary
Thermal Control	3 float	3 float
Automated Windows	TC + 2 float	TC + 1 binary
Battery Electricity Storage	3 float, 1 int	1 float

One can see how the size of the data grows quickly when accounting for numerous end-uses across numerous houses.

IV. RESULTS

This section exercises the OLS model for five cases summarized in Table VI³. The cases vary by location, modules, end-use data sourcing, and form of electricity prices.

The Modules column indicates which modules are utilized. 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 measured data. The Electricity Pricing columns indicates the type of prices: Time of Use (TOU) can have two or three pricing periods per day, while Day Ahead prices are hourly and specified the day before electricity use.

A. Case 1: Boston Load Shift

This data is based on actual measures of end-use and is used to test the load shifting module. The shiftable loads are HVAC, clothes washer/dryer, and dishwasher. The model is run once a day starting at 12 a.m., for seven days. Both the start time and the duration used in the OLS model are configurable. During the week tested, the OLS model shifted loads on four out of the seven days: the washer, dryer, and dishwasher on days 1 & 6, and the dishwasher on days 2 & 4. The total savings from load shifting is 4.63%, with the daily Original and Shifted electricity costs listed in Table VII.

Under Boston's TOU pricing scheme, 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.

Solution times for the Boston Load Shift case are very fast with all CPU times less than one second.

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

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

	Day 1	Day 2	Day 3	Day 4	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%

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. Furthermore, the end-user's preferred comfort range for the thermal controls is 60 °F to 70 °F.

The shiftable loads in Cases 2, 3, and 4 are: HVAC, dishwasher, clothes washer/dryer, and PEV charger. Figure 1 depict a time series for the original and shifted loads in kW for 5 minute intervals. The 0 interval is 3:00 p.m.

End-uses are shifted to early morning hours, which is when electricity prices are lowest, or to the cheapest electricity price intervals for respective preference windows. 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 end-user realizes almost 40% savings by utilizing load shifting and smart thermal controls, as summarized in Table VIII. The computation time for each run is about a CPU second.

TABLE VIII
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%

C. Case 3: Springfield with Battery

The Springfield results can be further improved by adding battery storage. Figure 2 depicts battery charging and discharging (kW) in 5-minute intervals, where interval 000 is 3:00 pm. 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, which reduced to \$0.55 after load shifting, and to \$0.25 after adding the battery.

The battery becomes more important when the household approaches its total electricity limit, when the battery can 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 two-day horizon. Thus, the 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 by supplementing the HVAC system. The Springfield case did not yield obvious economic savings because the windows only opened for a single fifteen-minute period in two days, with 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 IX compares the solution and total CPU times across cases 3, 4, and 5 for the first two days of the horizon.

TABLE IX
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

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 to more efficiently determine how to automatically control windows.

E. Case 5: Austin Pre-Cooling

The Austin Pre-Cooling case demonstrates allows the indoor temperature range to vary more widely so that the house can be pre-cooled in anticipation of higher electricity prices. It includes only the TC module and therefore minimizes only the costs related to the HVAC.

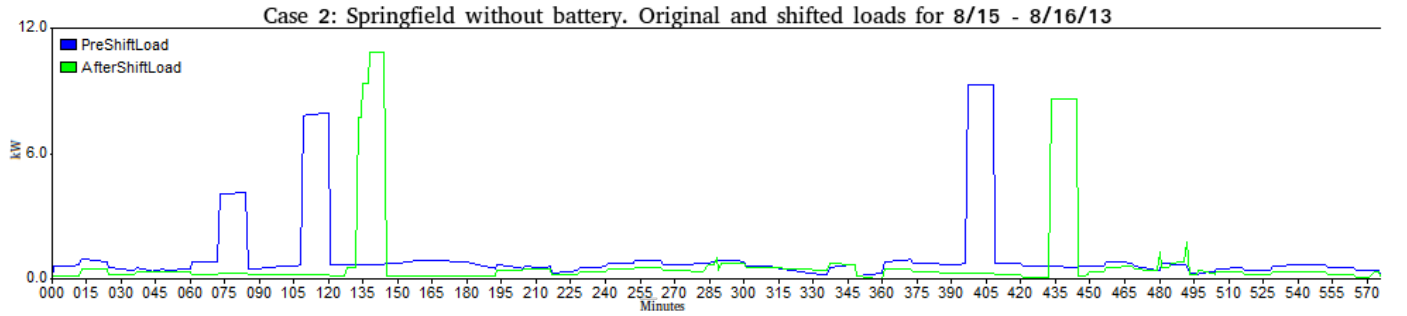


Fig. 1. Case 2: Springfield without battery. Original and shifted loads for 8/15 - 8/16/13

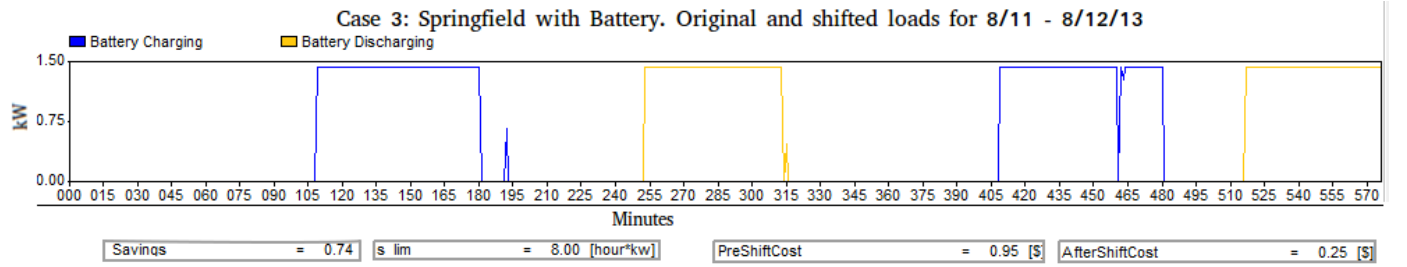


Fig. 2. Case 3: Springfield with Battery. Original and shifted loads for 8/11 - 8/12/13

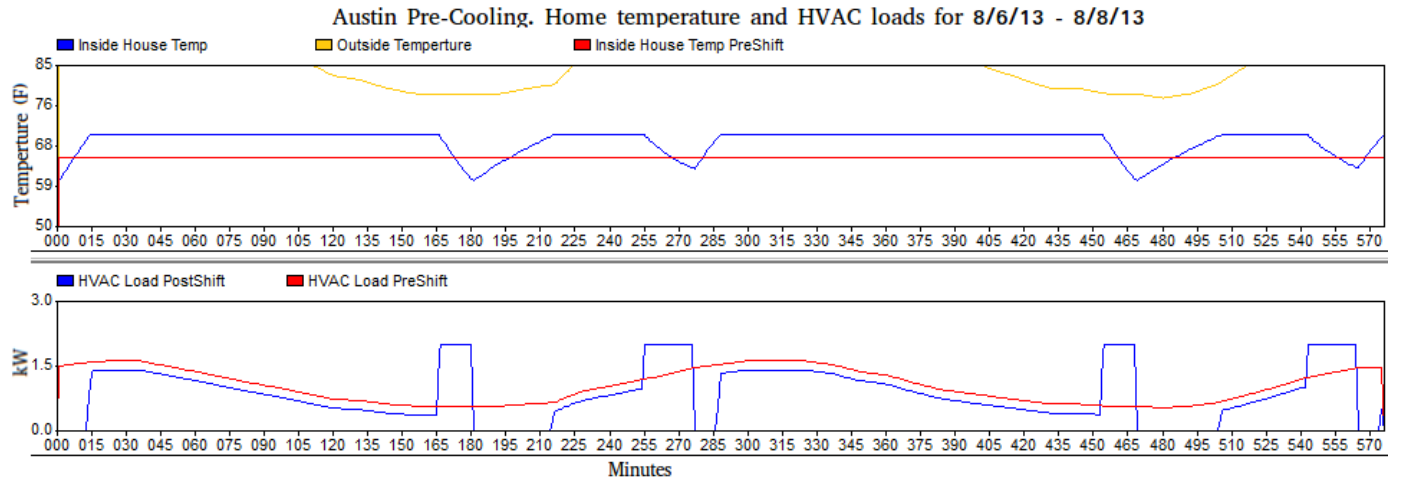


Fig. 3. Case 5: Austin Pre-Cooling. Home temperature and HVAC loads for 8/6/13 - 8/8/13

Pre-cooling occurs 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. Figure 3 shows the inside temperatures and HVAC loads 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.

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. The linear program formulation of this model leads to a solution time of less than one second.

V. SMART GRID ANALYTICAL FRAMEWORK

The 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. 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 section describes the Smart Grid Analytical Framework which interprets and builds on the OLS model's results 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 to understand the cost structure of smart appliances for investment purposes.
- *Smart Appliance Benefits Analysis* - Investigates appliance-level benefits to understand individual end-user decision-making.
- *Smart Appliance Marginal Benefit Analysis* - Investigates the marginal benefits of individual appliances to understand the benefits of scale and the potential decisions of an aggregator or electric utility.
- *End-User Preference Sensitivity Analysis* - To understand 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 a company offers 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 and are all higher-end models. Further, not all appliance providers have smart appliances in each category.

The scatter plots in Figure 4 show appliance base prices versus the absolute difference and percentage difference between the smart and non-smart versions.

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 plots indicate that smart appliances 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.

For thermostats, because almost every household already has a thermostat, an end-user may be more likely to look for the smart thermostat with the lowest cost when consideration upgrading to a smart one. As such, Table X contains the costs of the smart thermostats on the market, as of April 2014.

TABLE X
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 analysis can indicate incre-

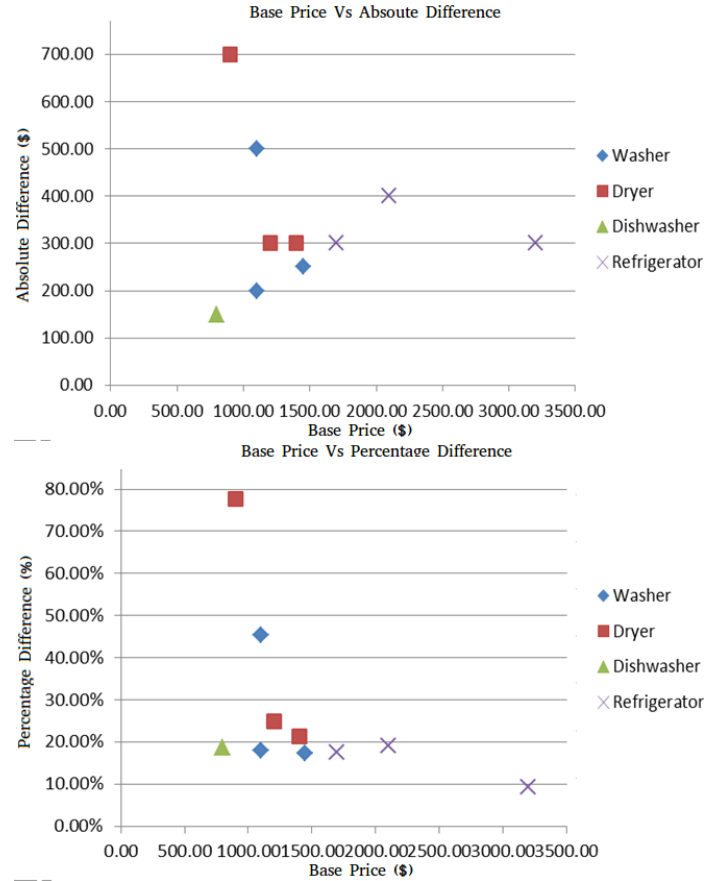


Fig. 4. Base Price v. Abs. Difference and Base Price v. Per. Difference

mental 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 XI is based on a variation of Case 2: Springfield without Battery over a 7-day horizon with a Day Ahead price range of [0.019, 0.04136] ¢/kWh. Average costs (\$/day) for each appliance are the nominal load profile in the Non-Smart column, and when its load is optimally shifted in the Smart Cost column. The Savings (\$) monetary benefit is obtained by allowing the given appliance load to shift. The Savings (%) is the percent change in Smart Cost relative to the Non-Smart Cost.

TABLE XI
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

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 [16].

TABLE XII
ANNUAL SAVINGS FOR AN APPLIANCE

Appliance	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

In Table XII, the product of the Savings (%) values and the costs for each appliance are in the Annual Savings column. 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 XII with a few assumptions about the costs of smart appliances and thermostats yields the results in the analysis in Table XIII. The following is assumed:

- A smart appliance has a markup of 20%
- Nominal costs of non-smart versions of a washer, dryer, and dishwasher are in Table XIII.
- Incremental cost of a smart charger is on the order of a smart meter, namely \$200.
- Homeowner upgrades an existing thermostat, which has no resale value, with a smart thermostat at an increment cost of about \$200
- Payback period has no discount rate and is only for ranking purposes

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. The data for a more prolonged simulation and investment study is not available, and because of this, we cannot at this time make an estimate of the opportunity for investment in energy storage.

TABLE XIII
BENEFIT-COST ANALYSIS FOR EACH APPLIANCE

Appliance	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

C. Smart Appliance Marginal Benefit Analysis

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 increases the HVAC capacity from 2 to 12 kW in the Austin Pre-Cooling case. The benefit analysis in Table XIV shows that increasing the HVAC capacity has diminishing returns.

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 5. However, 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.

VI. CONCLUSIONS

The OLS model accrued 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 continued development of smarter electricity management in the future and for continued development of big data techniques for the smart grid and other cyber-physical systems. The OLS model is capable of performing quickly. More importantly, the model has demonstrated its flexibility to configure its modules to various circumstances, such as batteries and thermal storage. 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.

The end-user can accrue economic benefits by shifting consumption loads away from higher-priced periods. In the results section, the precise savings are shown in addition to graphs of shifted loads. Smart devices and components can give extraordinary savings, but must be compared to installation and maintenance costs and a utility's willingness to buy back electricity. 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

TABLE XIV
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

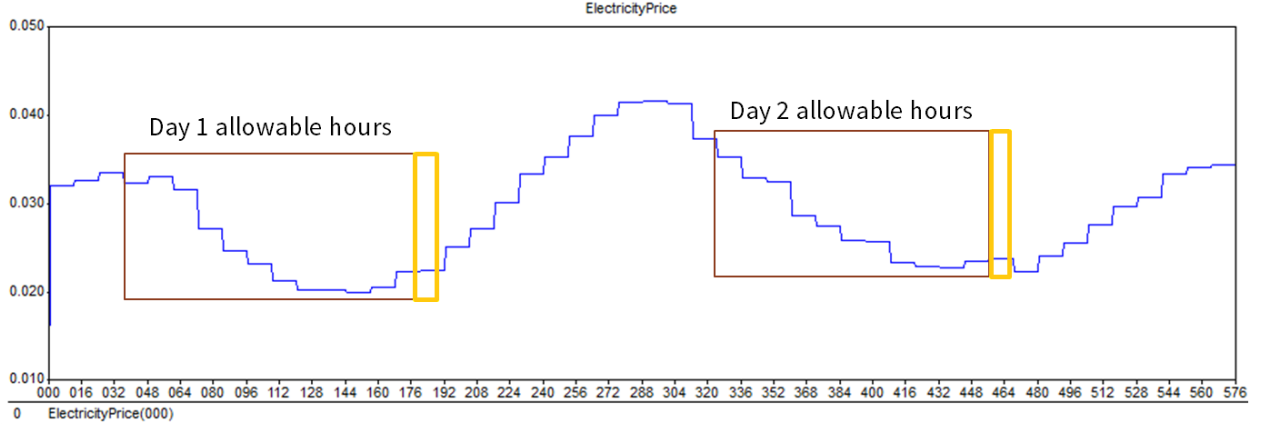


Fig. 5. Extending Resident's Allowable Hours

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

At the time of developing the algorithm, there were few load shifting algorithms. We not only show a mathematical formulation, but also demonstrate its potential economic benefit. Because of this, we chose simplifying assumptions when creating the algorithm. Future research on optimization algorithms can enable mathematical formulations of cyber-physical systems to be solved with fewer simplifying assumptions.

One simplifying assumption is for the automated windows module. We implement a linear relaxation on the quadratic constraint that is created by allowing the thermal conductivity within a range of values, when windows are opened or closed. By implementing a linear relaxation and only allowing for opened or closed windows, we are left with a much easier problem to solve. This leads to only one set of the two inequality constraints being tight and the other being slack. Further developments in optimization algorithms can solve the more difficult original problem without this relaxation.

New optimization algorithms can also be developed that more efficiently solve problems with cascading dependencies between variables and constraints to model physical phenomena in cyber-physical systems in finer detail. For example, in the thermal control module, we modeled the single residential home as one room. This assumption reduces the model complexity that would be born out of by including heat transfer between rooms and imposing individual temperature ranges for

each one. While this simplification provides a sound approach that can calculate economic benefits, future optimization algorithms can more efficiently solve more complex models. Given the trend towards smarter systems, such as homes with multiple temperature zones, such advances in algorithms may lead to additional economic benefits.

To achieve computation efficiency, special care has to be taken to formulate carefully the optimization problem. For example, one old formulation of the Automatic Windows module had a solution time in hours; but with a new formulation to deal with 0-1 variables, the solution time became seconds. Therefore, certain "know-how" in the formulation of 0-1 mixed LP achieves time efficiency that is necessary to make our models practical, and leads as well to future research for even more improvements. In general, we are confident that our OLS approaches can be fully developed into a mature and effective technology in terms of computation resources.

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 PEV, for example, for charging a fleet with overall supply capped for a limited time, or in a household, not charging a PEV concurrently with other loads during high price periods. 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. Should the technology for load shifting according to real-time rates be demonstrated to have sufficient public benefits, there is the potential for regulators to approve such rates, perhaps updating

on a 5-minute basis.

Regarding the formulation, two avenues of future investigation easily arise. First, the current formulation can be extended to multiple control zones to explore added controls and more detailed modeling of the building. For example, the behavior of the building's temperature zones can be modeled using physics-based simulation programs. Second, the automatic windows can be re-formulated to improve computation time, for example, by creating a two-level approach to address when windows should open and close. These approaches can be benchmarked with the current approach with the expectation of delivering quicker solutions to add value to consumers, utilities, and third parties.

Lastly, as an analysis tool, the OLS model can provide additional insight into residential energy consumers, demand response, and the smart grid as a cyberphysical system. 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.

The techniques and Smart Grid Analytical Framework presented here can be extended to other application domains. For example, the energy end-uses in the OLS model can be modified to handle commercial loads. The energy behaviour and physical constraints of commercial loads can be described as optimization constraints for end uses such as automated lighting systems, fleets of commercial vehicles, and commercial heating, ventilation, and cooling systems. The Smart Grid Analytical Framework can be adapted to answer questions, such as those presented in the preceding list, for commercial and industrial buildings and facilities, or networks of connected devices in the internet of things. The proposed OLS model and Smart Grid Analytical Framework represent flexible approaches with a large potential for broader applications.

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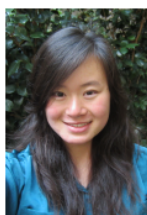
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