An Optimal and Learning-Based Demand Response and Home Energy Management System

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***Abstract*—This paper focuses on developing an interdisciplinary mechanism that combines machine learning, optimization, and data structure design to build a demand response and home energy management system that can meet the needs of real-life conditions. The loads of major home appliances are divided into three categories: 1) containing fixed loads; 2) regulate-able loads; and 3) deferrable loads, based on which a decoupled demand response mechanism is proposed for optimal energy management of the three categories of loads. A learning-based demand response strategy is developed for regulateable loads with a special focus on home heating, ventilation, and air conditioning (HVACs). This paper presents how a learning system should be designed to learn the energy consumption model of HVACs, how to integrate the learning mechanism with optimization techniques to generate optimal demand response policies, and how a data structure should be designed to store and capture current home appliance behaviors properly. This paper investigates how the integrative and learning-based home energy management system behaves in a demand response framework. Case studies are conducted through an integrative simulation approach that combines a home energy simulator and MATLAB together for demand response evaluation.**

***Index Terms*—Smart grid, demand response, home energy management, neural network, regression, optimization, dynamic electricity price, building energy consumption.**

I. Introduction

ENERGY generation, consumption and conservation are at the root of many of the most pressing issues facing today's power and energy industry. Demand continues to rise while the ability to generate and deliver energy is increasing at a much slower rate. Hence, making more efficient management and use of the electric energy produced is essential to the continued collective prosperity and quality of life. This involves reducing electricity use through activities or programs that promote 1) electric energy efficiency/conservation and 2) more efficient management of electric loads. In terms of energy efficiency, research activities include development of more efficient buildings and building materials [1], more energy-efficient ENERGY STAR home appliances [2], etc. In terms of load management, the focus of this paper, electricity consumption in residential markets is undergoing fundamental changes due to the emergence of smart appliances and Home Energy Management (HEM) automation.

A key requirement for the smart appliances within the smart grid framework is the demand response (DR). Overall, current DR approaches are of the following two types [3]: Direct Load Control (DLC) and Price-Based Control (PBC). DLC-based DR involves a power company turning off selected appliances during peak hours and is normally used to handle short-term urgent situations such as a high frequency deviation in power systems [4]–[6]. However, DLC generally leads to some loss of comfort and inconvenience on energy consumers. As a result, consumers often find this risky since their particular needs might not be addressed and participation appears low (in anecdotal terms) [8]. With increased loads and renewable energy penetration, DLC appears to be a passive approach in handling the demand response.

PBC on the other hand involves a power company incentivizing a consumer to be actively participate in a DR program and schedule the usage of home appliances based on a dynamic price tariff [9]–[15]. Electric utility companies typically use hourly real-time price (RTP) or day-ahead price (DAP) tariff in their dynamic pricing programs. The day-ahead market produces financially binding schedules for the production and consumption of electricity one day before the operating day. The real-time market reconciles any differences between the amounts of energy scheduled day-ahead and the real-time load, market participant re-offers, hourly self-schedules, self-curtailments and any changes in general, real-time system conditions. Currently, PCB techniques reported in the literature can be classified into RTP-based DR and DAP-based DR. For instance, authors in [14] proposed a RTP-based DR strategy by changing the set-point temperature to control HVAC loads depending on electricity retail price published every 15 minutes; authors in [15] proposed a real-time price-based DR management model for optimal operation of residential appliances within 5-minute time slots.

However, for efficient and long-term energy management and scheduling, healthy growth of electricity market, efficient load forecast, and minimization of power system uncertainties,

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energy consumers are strongly encouraged to schedule their electric energy usage based on the DAP tariff. Specially, the power system uncertainties were talked about in several panel sessions during 2015 IEEE PES General Meeting. In panel session entitled "Impacts of Variability, Uncertainty, and Forecasting Errors on Power Operation Planning", the panelists talked about the importance of day-ahead market in minimizing the power system uncertainties.

A large number of DAP-based DR algorithms for optimally scheduling home energy operation have been reported in the literature, including stochastic optimization methods [16]–[19] and model-based optimization techniques [20]–[23]. The stochastic optimization methods are based on statistical results of energy consumption of home appliances but unable to guarantee the most efficient DR policy for a day. On the other hand, the model-based optimization approaches can generate an optimal DR policy if accurate energy consumption model of a house is available. But, a big challenge is how to precisely model and estimate energy consumption of the three categories of loads, particularly energy consumption of a house.

Conventionally, model-based optimal DR techniques were developed mainly based on simplified energy consumption models. In [21], the energy consumption of a house is modeled based upon simple conduction heat transfer equations. A simplified thermal system modeling approach was used in the GridLAB-D [22], a distribution system simulator, to estimate thermal loads of a residential house based on first principles. In [23], a quasi-steady-state approach was adopted to estimate hourly building electricity demand, in which the building thermal model is built based on an equivalent resistance-capacitance network [24]. In [25], Široký *et al.* proposed a model predictive control (MPC) strategy, which employs a model of the building dynamics based on the conventional simplified thermal resistance-capacitance network models for buildings. The MPC strategy was further improved in [26] and [27] by introducing some stochastic impacts to the building model to formulate a stochastic MPC method.

However, actual energy consumption of a residential house is much more complicated, which are affected by geographical location, design architectures, occupants, weather, seasons, etc, and can change over time. In [28], a regression approach was proposed to model daily energy consumption of a house based on the assumption that data can be obtained repetitively for each trial of a 24-hour thermostat setting during a day until the regressed model matches perfectly with simulated energy consumption for that day. Clearly, this assumption is impossible for a practical house. As a result, developing a learning mechanism that can identify energy consumption model from history data and update the model daily in real-time is critical for the model-based optimal DR methods.

Various learning mechanisms have been developed for prediction and forecast of weather, power generation and loads. For example, the authors in [29] used a neural network to predict household heat demand in order to find a better matching between demand and supply. However, the learning purpose proposed in this paper is completely different.

The main objective of this paper is to develop an integrative and adaptive demand response and HEM system considering variable and real-life conditions. The paper proposes a decoupled DR strategy and an interdisciplinary mechanism that integrates machine learning in artificial intelligence, optimization in mathematics, and data structure design in computer science to develop DR and HEM systems. Because of this, the proposed DR and HEM technique can be adaptive to real-life weather, seasonal, and house condition changes. This learning based and decoupled DR concept, system and mechanism are novel and have not been reported in literature.

In the sections that follow, the paper first presents an integrative and decoupled optimal DR strategy in Section II. Section III shows a learning-based DR and HEM for HVAC. A co-simulation system, suitable for evaluation of the proposed DR and HEM mechanism, is built in Section IV. Then, Section V studies and compares the proposed and conventional DR methods through simulation. We used hourly models in our study throughout the paper since both the real-life electricity price and weather forecast used in this paper were recorded hourly. Finally, the paper concludes with a summary of the main points.

II. An Integrative, Decoupled and Optimal Demand Response Strategy

A. *Typical Home Appliances*

For a typical home in the United States, home appliances are responsible for an important part of the energy bills [30]. These appliances include water heaters, clothes washers and dryers, dishwashers, refrigerators and freezers, electric stoves, lights, and HVACs. Key factors affecting the energy consumption of each appliance include: 1) appliance load level, 2) when and how long an appliance is used, and 3) how much unwanted heat is generated when using an appliance. For a flat electricity price tariff, a customer would use an appliance whenever it is needed. However, for a dynamic electricity price structure, a customer is encouraged to optimize energy consumption of DR capable appliances.

B. *Classification of Home Appliances*

The development of a DR strategy should be based on the energy usage natures of home appliances, which are divided into three categories in this paper: 1) fixed loads, 2) regulateable loads, and 3) deferrable loads. The first category may include stoves, lights, and home computers, which must be used when needed. The second may include HVAC and water heater, which can be regulated but cannot be delayed. The third may contain dishwasher and dryers which can be delayed but cannot be regulated. Among the three different types of loads, the most challenging one is a DR policy for HVAC. Traditionally, the thermostat of a HVAC unit is set at 71° or 72° for a typical house in the United States.

C. *Optimal HVAC Demand Response Mechanism*

Let's first consider HVAC only for a residential house. The objective should be minimizing customer electricity bill but not affecting customer's comfort of living [21], [22], [31].

The optimization problem is typically formulated as

$$\begin{aligned}&\text{Minimize: } C=\sum_{i=1}^{24} p_i\cdot Q_i\\&\text{Subject to: } 0\le Q_i\le Q_{\max}, T_i^{\min}\le T_i\le T_i^{\max},\\&\qquad i=1,\ldots,24\end{aligned}\tag{1}$$

where i stands for a time slot in one hour, T_i^I is the room temperature in hour i, C is the electricity cost during a day, p_i stands for the electricity price in hour i, Q_i signifies the energy consumed by the HVAC unit in hour i, and Q_{max} denotes the maximum energy that can be consumed by the HVAC unit in one hour. T_i^{min} and T_i^{max} are the minimum and maximum acceptable temperature settings at the ith hour of a day and should be determined according to occupants' thermal comfort. Traditionally, thermal comfort driven HVAC operations often use the PMV (predicted mean vote) model which has been adopted by several standards such as the ASHRAE 55 [32]. However, the PMV model has a number of drawbacks, including its inability to consider behavioral variations and the ability of humans to adapt to thermal environments [33]. To address these challenges, researchers have recently proposed personalized comfort profiles or sensing approaches in order to enable personalized comfort driven HVAC operations [34]–[38]. In a DR framework, this represents an occupant-driven temperature settings of T_i^{min} and T_i^{max} during 24 hours of a day. Regarding the model of the residential HVAC system, the equivalent thermal parameters (ETP) model has been used extensively [39]–[41]. According to the ETP model in [19], [21], [39], and [42], the room temperature evolves as

$$T_{i+1}^I=\varepsilon\cdot T_i^I+(1-\varepsilon)\left(T_i^O-\eta\cdot Q_i/A\right)\tag{2}$$

where T_{i+1}^I represents the room temperature in hour $i+1$, T_i^O stands for the outdoor temperature in hour i, η is the efficiency of the HVAC unit, ε is the system inertia, and A is the thermal conductivity. The optimization problem is to solve a 24-hour thermostat setting (T_{i+1}^I) that will minimize the electricity cost given 24-hour electricity price (p_i), 24-hour outdoor temperature (T_i^O), and initial room temperature (T_0^I). The 24-hour HVAC energy consumption (Q_i) can also be obtained through Eq. (2). Nevertheless, in reality, the relationship between indoor and outdoor temperatures and energy consumed by a HVAC is much more complicated so that actual energy consumption of a HVAC could deviate from results generated by using Eq. (2), which affects the DR efficiency. In Section III, a novel learning-based DR strategy for HVACs is proposed to overcome the challenge.

D. Optimal Demand Response of HVAC Plus Fixed Loads

When fixed loads are considered, the optimization problem shown in Section II-C needs to be modified as shown below

$$\begin{aligned}&\text{Minimize: } C=\sum_i p_i\cdot\left(Q_i^{HVAC}+Q_i^{fixed}\right)\\&\text{Subject to: } 0\le Q_i^{HVAC}\le Q^{\max}, T_i^{\min}\le T_i\le T_i^{\max}\end{aligned}\tag{3}$$

where Q_i^{fixed} represents the fixed load, i.e., it must be used when needed. For example, when it is dark, one must turn on a light; when back to home from the work, one needs to cook although it may be the peak load period. Although it is hard to estimate how much electric energy one will use in the next day, the usage of these appliances does not depend on the electricity price. Therefore, those loads are considered as future constant loads in this paper and removing the fixed loads from Eq. (3) does not affect the optimal solution so that an equivalent optimization formulation can be obtained as

$$\begin{aligned}&\text{Minimize:} &&\text{Minimize:}\\&C=\sum_i p_i\cdot\left(Q_i^{HVAC}+Q_i^{fixed}\right)\rightleftarrows &&C=\sum_i p_i\cdot Q_i^{HVAC}\end{aligned}\tag{4}$$

which indicates that the combined DR optimization for HVAC and fixed loads is equivalent to the DR optimization for HVAC load only.

E. Optimal Demand Response Involving HVAC, Fixed Loads and Deferrable Loads

When all the three types of loads are considered, we have an integrative optimization problem as shown by

$$\begin{aligned}&\text{Minimize: } C=\sum_i p_i\cdot\left(Q_i^{HVAC}+Q_i^{fixed}+Q_i^{deferrable}\right)\\&\text{Subject to: } 0\le Q_i^{HVAC}\le Q^{\max}, T_i^{\min}\le T_i\le T_i^{\max}\end{aligned}\tag{5}$$

According to Section II-D, this can be simplified as

$$\begin{aligned}&\text{Minimize: } C=\sum_i p_i\cdot\left(Q_i^{HVAC}+Q_i^{deferrable}\right)\\&\text{Subject to: } 0\le Q_i^{HVAC}\le Q^{\max}, T_i^{\min}\le T_i\le T_i^{\max}\end{aligned}\tag{6}$$

Unlike an HVAC load, a deferrable load has a fixed energy consumption pattern. But, this fixed load pattern can be applied to different time windows during a day. The fixed load pattern may require more than one hour of energy consumption. For simplicity, assume that the fixed load pattern is $Q^{deferrable}$ within a one-hour time frame. It is necessary to point out that the following proving process is suitable no matter the fixed load lasts more than one hour or not. Then, the above optimization problem can be expressed as

$$\begin{aligned}&\text{Minimize: } C=\sum_i p_i\cdot\left(Q_i^{HVAC}+\theta_i\cdot Q^{deferrable}\right)\\&\text{Subject to: } 0\le Q_i^{HVAC}\le Q^{\max}, T_i^{\min}\le T_i\le T_i^{\max}\end{aligned}\tag{7}$$

where θ_i is a binary integer array to indicate the status of the deferrable load with "1" meaning that the load is on, and "0" meaning that the load is off. For example, if the deferrable load is operated at ith hour of a day for one hour, then,

$$\theta_i=\left(0\ \ldots\ 0\ \underbrace{1}_{ith\ \text{hour}}\ 0\ \ldots\ 0\right)^T\tag{8}$$

Thus, the above optimization problem is equivalent to solving 24 repeating optimization problems with the deferrable load allocated to 1st, 2nd,..., and 24th hour, respectively. The final optimal solution is one that has the smallest value among all the 24 optimization problems as shown below

$$\begin{cases} \text{Minimize:} & C = \sum_i p_i \cdot \left(Q_i^{HVAC} + (1\ 0\ 0\ \cdots\ 0)^T \cdot Q^{deferrable}\right) \\ \text{Subject to:} & 0 \le Q_i^{HVAC} \le Q^{\max}, T_i^{\min} \le T_i \le T_i^{\max} \end{cases}$$
$$\cdots\cdots\cdots$$
$$\begin{cases} \text{Minimize:} & C = \sum_i p_i \cdot \left(Q_i^{HVAC} + \cdot(0\ 0\ \cdots\ 0\ 1)^T Q^{deferrable}\right) \\ \text{Subject to:} & 0 \le Q_i^{HVAC} \le Q^{\max}, T_i^{\min} \le T_i \le T_i^{\max} \end{cases}$$

Since a deferrable load has a fixed load pattern, the 24 optimization equations are equivalent to two independent optimization problems as shown

$$\begin{cases} \text{Minimize:} & C_{HVAC} = \sum_i p_i \cdot Q_i^{HVAC} \\ \text{Subject to:} & 0 \le Q_i^{HVAC} \le Q^{\max}, T_i^{\min} \le T_i \le T_i^{\max} \end{cases}$$
$$+$$
$$\begin{cases} \text{Minimize:} & C_{deferrable} = \sum_i p_i \cdot \theta_i \cdot Q^{deferrable} \end{cases} \tag{9}$$

in which the first (HVAC) is solved by using linear or nonlinear programming method while the second (deferrable load) is solved by using the binary integer programming technique [43]. In other words, the optimization problem for HVAC and deferrable loads can be solved separately and then combined together to achieve the final optimal solution. Similarly, customer driven comfort profiles for deferrable loads are typically specified in terms of preferable time windows in solving the binary integer programming problems to operate the deferrable loads.

III. Learning-Based Demand Response and HVAC Energy Management System

Fig. 1 shows the concept view of the proposed learning-based DR and energy management system for a HVAC. It includes a wireless home-area network with an intelligent Home Automation System (HAS) and multiple distributed wireless receivers [44], [45]. In a DAP tariff framework, the HAS has two functional blocks: a control block and a next-day DR block. The control block provides control commands to a local receiver at the present day based on a DR policy generated one day ahead while the local receiver regulates the operation of the HVAC, depending on the commands received from the control block. The next-day DR block receives information from the local receiver about energy usage of the HVAC at the present day as well as predicted weather and electricity price information one day ahead, and determines a DR policy for operation of the HVAC in the next day. The DR policy determined by the next-day DR block should implement the demand response of the HVAC for the maximum benefit of a residential consumer at any weather conditions. For this purpose, a learning based DR mechanism is developed. Details of the learning based DR for HVACs are presented in the following sections, which include data structure design, machine learning, and optimization formulation.

A. Data Structure Design

A special data structure design is needed to store data for the proposed learning-based DR and HVAC energy management system. The data stored should be able to capture current HVAC behavior correctly. A suitable data structure fitting this requirement is queues. For an HVAC as illustrated by Fig. 1, there are four queues and data saved in the four queues are HVAC energy consumption (Q_i), outside temperature (T_i^O), room temperature (T_i^I), and thermostat temperature settings (T_{i+1}^I). Each queue has a FIFO (first-in, first out) structure [46] and can only hold data for n days. In other words, when new data is collected each day and added to the end of the queues, the oldest data in the front of the queues will be removed. Hence, the data saved in the queue just represent the HVAC energy consumption corresponding to the most recent household and weather conditions. Assume data are collected hourly. Then, the length of each queue is $n\times 24$.

B. Learning HVAC Energy Consumption Model

There are a large number of different learning mechanisms [47]. In this section, two learning strategies are investigated.

1) Neural Network Based Learning: A multilayer perceptron [48] is used to learn the HVAC energy consumption model. Different from general prediction or forecast applications, the purpose of the neural network here is for function approximation. A neural network is proposed in [29] to predict heat profile of each individual household one day ahead. However, the neural network of this paper is not for a prediction purpose. Instead, it is used to learn the energy consumption model of an HVAC. The learned model is then used with the optimization routine to determine the next-day thermostat setting strategy for the HVAC (Section III-C).

For the learning purpose of the HVAC energy consumption model, the network has three input nodes, one hidden layer which consists of eight nodes, and one output node (Fig. 2). We also tried neural network architectures with more hidden layers and more nodes in the hidden layers. But, the difference is trivial. The three inputs of the network include: 1) outside temperature T_i^O in hour i, 2) room temperature T_i^I in hour i, and 3) room temperature T_{i+1}^I in hour $i+1$ (also represents the thermostat setting temperature in hour i). The network output is Q_i, signifying the energy consumed by the HVAC in hour i.

The neural network learning is based on the data saved in four queues (Fig. 1) and trained by using the "train" function in MATLAB, which requires multiple iterations until a stop criterion is reached. Thus, it is more computational expensive. For data of n days, the inputs to the "train" function include a $3\times n\times 24$ matrix representing network inputs of all recorded temperatures $(T_{i+1}^I, T_i^I, T_i^O)$ $(i = 1, \ldots, n \times 24)$ saved in the three temperature queues and an $1\times n\times 24$ network target vector of all recorded energy consumption Q_i $(i = 1, \ldots, n \times 24)$ saved in the corresponding energy queue. After the training, the HVAC energy consumption can be expressed by a neural network approximated function as shown below,

$$Q_i = q_{nn}\left(T_{i+1}^I, T_i^I, T_i^O, \vec{w}\right) \tag{10}$$

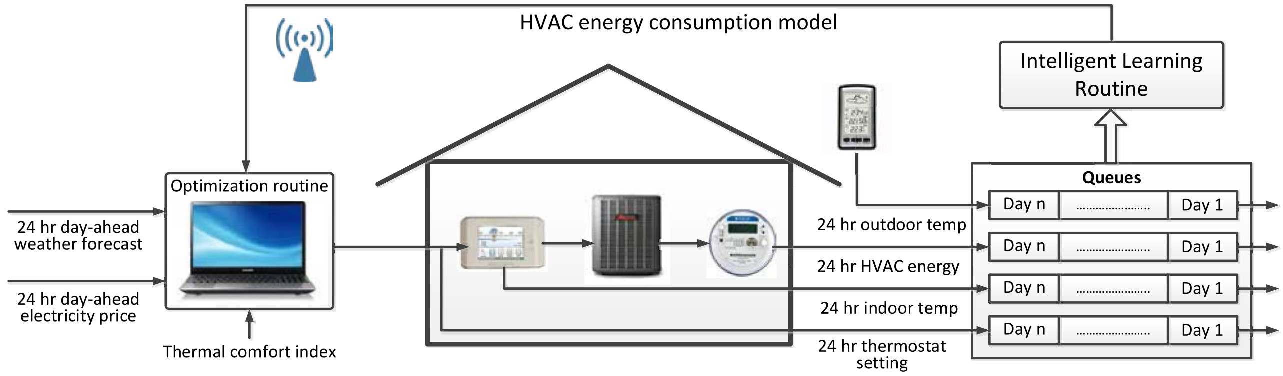


Fig. 1. Illustration of the proposed learning-based DR and HVAC energy management system. The **Intelligent Learning** routine calibrates HVAC energy consumption model Eq. (10) or Eq. (11) based on the data collected and saved in the four queues according to the neural network or regression learning approach presented in Section III-B1 and Section III-B2. The learned HVAC model is then sent to the Optimization routine. The **Optimization** routine determines 24-hour next-day thermostat temperature settings based on the HVAC model received from the Intelligent Learning routine as well as 24-hour day-ahead weather forecast and electricity price information according to the mechanism described in Section III-C. The temperature settings generated by the Optimization routine are then sent to the actual thermostat. In home, the **Thermostat** controls the operation of the HVAC at the present day based on the temperature settings generated by the Optimization routine one day ahead.

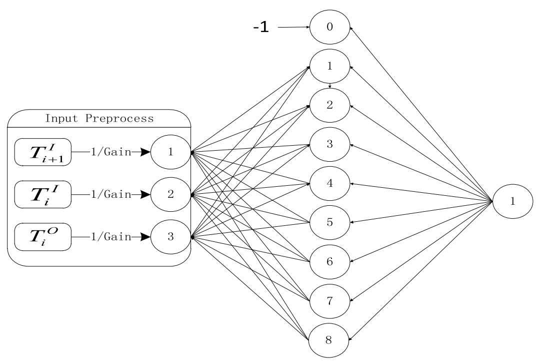


Fig. 2. A neural network architecture for learning HVAC energy consumption model.

where $\vec{w}$ is the network weight vector and is fixed after the training. Using the neural network approximated function, one can calculate how much energy Q_i within hour i is needed to regulate the room temperature from T_i^I to T_{i+1}^I when the external temperature is T_i^O. The HVAC energy consumption model learned by the neural network is updated daily based on up-to-date energy consumption data saved in the queues. As a result, the neural network approximated model can more accurately reflect the thermal behavior of a house at the present seasonal, user, and weather conditions.

2) Regression-Based Learning: Regression approach for function approximation is very effective if one knows the general format of a function that the observations would follow [49]. Based on the theoretical study about typical heat transfer modes and building heat loads [50], a 3rd order polynomial linear regression function is used to approximate HVAC energy consumption model as described mathematically by

$$Q_i = q_{reg}\left(T_{i+1}^I, T_i^I, T_i^O, \vec{\beta}\right) \quad i = 1, \ldots.., n \times 24 \tag{11}$$

where $q_{reg}(\bullet)$ is a 3rd order polynomial function of $(T_{i+1}^I, T_i^I, T_i^O)$, $n \times 24$ represents the total number of the observations saved in each of the queues (Fig. 1), Q_i is the ith HVAC energy consumption observation, $(T_{i+1}^I, T_i^I, T_i^O)$ represent thermostat settings and indoor and outdoor temperatures related to observation Q_i, and $\vec{\beta} = (\beta_1, \beta_2, \ldots, \beta_p)$ is the parameter vector that needs to be determined [49]. The polynomial function used in this paper consists of cube, square and linear terms of T_{i+1}^I, T_i^I, and T_i^O as well as a coefficient, which forms the predictor vector of the regression model. The parameter vector$\vec{\beta}$ can be solved conveniently by using the "regress" function in MATLAB. The inputs to the "regress" function include an observation vector formed by all the energy consumption observations Q_i, $(i = 1, \ldots, n \times 24)$ saved in the corresponding energy queue and a matrix formulated based on all $(T_{i+1}^I, T_i^I, T_i^O)$ saved in the three temperature queues. Similar to the artificial neural network, the regression model is updated daily after new data is saved in the queues each day. Thus, compared to the ETP model Eq. (2), the regression model can also provide more accurate estimation of HVAC energy consumption. In addition, parameters of the regression model can be calculated directly in a closed form [49], [51]. Thus, the regression-based learning is much faster than that of the neural network.

C. Optimization Routine

The optimization routine is similar to that described in Section II-C. Detailed HVAC optimization formulation for 24 hours of a day is shown by

$$\begin{aligned}
\text{Minimize:}\quad & C = \sum_{i=1}^{24} p_i \cdot Q_i \\
\text{Subject to:}\quad & 0 \le Q_i \le Q_{\max} \quad i = 1, \ldots, 24 \\
& T_i^{\min} \le T_i \le T_i^{\max} \quad i = 1, \ldots, 24 \\
& \begin{cases} Q_i = q_{nn}\left(T_{i+1}^I, T_i^I, T_i^O, \vec{w}\right) & i = 1, \ldots, 24 \text{ or} \\ Q_i = q_{reg}\left(T_{i+1}^I, T_i^I, T_i^O, \vec{\beta}\right) & i = 1, \ldots, 24 \end{cases}
\end{aligned} \tag{12}$$

where instead of using the ETP model for HVAC (Eq. (2)), a model learned by using either the neural-network (Eq. (10))

or regression (Eq. (11)) approach is employed. The predicted 24-hour outside temperature T_i^O and the 24-hour day-ahead electricity price p_i are known constants to the optimization problem. The solution of the optimization problem is the 24-hour thermostat settings for the next day. Since the model is updated daily, the DR policy solved using the learning-based model would result in more efficient operation of an HVAC at present seasonal, user, and weather conditions.

IV. Developing Simulation Scheme for Optimal and Learning-Based Demand Response Evaluation

For performance evaluation, a co-simulation system is developed, which consists of 1) a house energy consumption simulator, 2) a mechanism for the decoupled and learning-based DR simulation, and 3) DR evaluation.

A. Home Energy Consumption Simulation

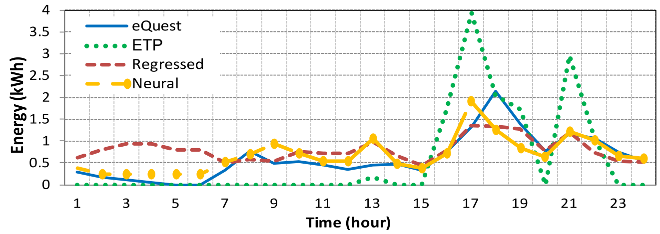
We used building simulation software eQUEST as a virtual test bed to simulate home energy consumption [52]. Using eQUEST, one can 'build' a simulated house that is similar to a practical one. The simulator uses standard commercial building materials defined in the software library and real-life weather and solar data available at [53].

For energy consumption simulation of a residential house, an architectural simulation model of the house was created based on the blueprint and construction materials used to build an actual house. For the study in this paper, a generic floor plan for a two story, 2,500 square foot house was used. The location for the model is Springfield, IL. Details about how to build a simulated house can be found in [28] and [52].

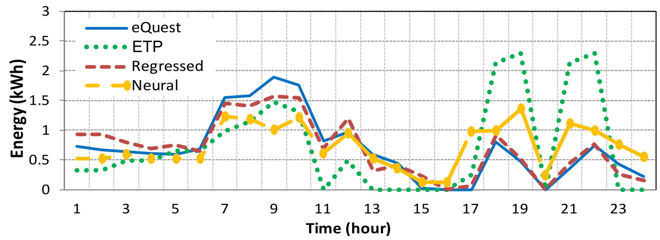
B. Learning HVAC Energy Consumption Model

With the home energy simulation system, we can evaluate the learning mechanisms presented in Section III-B. We used actual weather data in Springfield, IL [53] and DAP tariffs from Ameren Focused Energy [54]. The evaluation is conducted in the following ways. 1) The thermostat settings are generated daily by using a heuristic algorithm, which is basically a dynamic look-up table approach, to determine the thermostat settings based on DAP and lower and upper boundaries acceptable for the thermostat settings [55], [56]. 2) The generated thermostat settings, together with the corresponding weather information for that day, are loaded into the home energy simulation system. 3) The results generated are saved into queues (Fig. 1). 4) HVAC energy consumption model of the home is learned based on the data saved in the queues by using neural network and regression approaches.

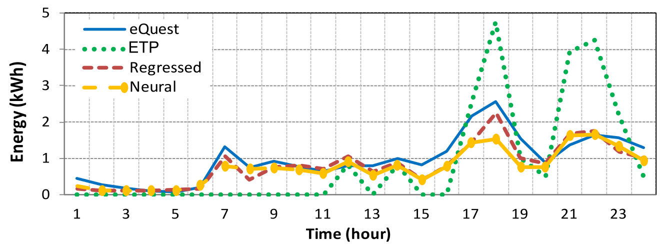
Figure 3 compares HVAC energy consumption obtained through eQUEST simulation and by using ETP, neural network and regression models. For the neural network and regression approaches, the model was acquired based on the data saved in the queues, updated each time when new data was added into the queues, and then used to estimate HVAC energy consumption for the next day. For example, if the model is updated on Tuesday, it will be used to estimate energy consumption on Wednesday. Therefore, the test data is always different from the historical data saved in the queues. As shown by the figure,



a) Day 3 (Day 1&2 data are used to generate NN and regression models)



b) Day 5 (Day 1-4 data are used to generate NN and regression models)



c) Day 7 (Day 1-6 data are used to generate NN and regression models)

Fig. 3. Illustration of learning HVAC energy consumption model as the data saved in the queues increases.

TABLE I
Error Analysis of Learned HVAC Energy Consumption Model

Day	Measured (kWh)	Estimated (kWh)		Error (kWh)		Error (%)	
		Reg	ANN	Reg	ANN	Reg	ANN
1	22.8	26.1	27.2	7.6	10.4	33.38	45.53
2	19.5	13.1	12.2	6.4	7.5	32.53	38.58
3	14.7	19.3	19.7	4.2	4.6	28.73	31.14
4	14.6	18.8	19.7	4.1	4.2	27.46	28.94
5	16.6	18.7	17.5	3.2	3.2	19.05	18.94
6	14.7	13.2	13.2	2.8	2.8	18.93	19.10
7	23.2	21.5	22.1	3.5	3.3	15.02	14.40

results generated by using the ETP model are quite different from "actual" simulated energy consumption. However, for neural network and regression approaches, the estimation becomes more and more reliable and accurate as more data are available in the queues, demonstrating that it is effective and possible to use the learning-based approach to estimate HVAC energy consumption model.

Table I presents a corresponding error analysis [57] for estimation of HVAC energy consumption from Day 1 to Day 7 using regression and neural network models. Note: similar to [57], the kWh error is the sum of the absolute error for 24 hours of a day while the % error is the kWh error over the measured kWh consumption. The table demonstrates that as more data is collected and saved in the queues, the estimation error reduces.

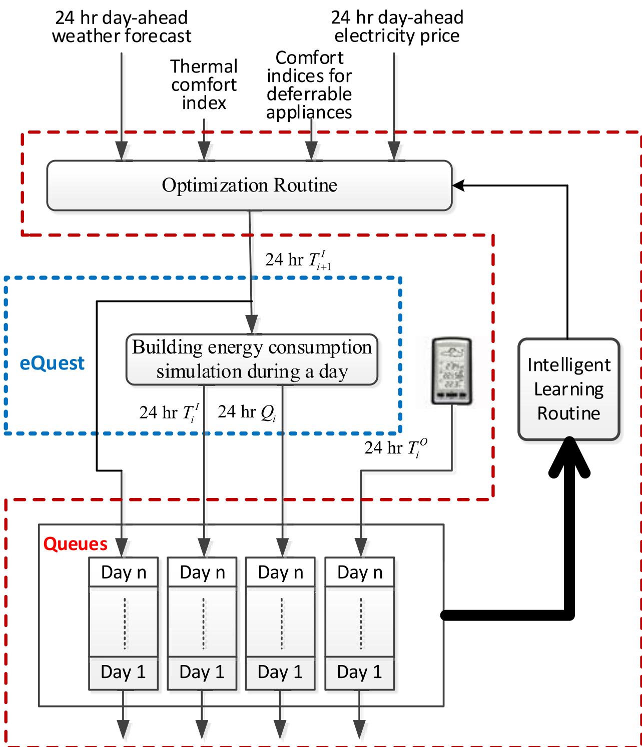


Fig. 4. Learning-based DR simulation system. The function of each block is similar to the corresponding block shown in Fig. 1 except that the actual house and HVAC is simulated by using eQuest.

It is necessary to point out that unlike time-series based prediction which normally requires history time-series data, the estimation generated by using neural network or regression model in this paper represents a mapping from $(T^I_{i+1}, T^I_i, T^O_i)$ to corresponding HVAC energy consumption Q_i. Hence, the estimation or the mapping is almost not affected by a sharp outdoor temperature change. Additionally, if there is a discrepancy in the learned energy consumption model, only the efficiency of the next-day DR policy generated from the optimization routine is affected but not the physical system behavior such as the HVAC.

In terms of computational speed, the ETP model is fixed and does not need to be updated each day; the neural network can learn the HVAC model in several minutes for typical three-week data stored in the queues by using MATLAB over a 2.6GHz PC; the regression approach can get the HVAC model in seconds because the computation of the parameters for the regression model only involves matrix multiplications and a small matrix inversion as explained in [49] and [51].

C. Integrative Simulation System

The integrative simulation system is similar to Fig. 1 and contains two settlement parts, with one for execution of the home energy management at the present day and the other for computation of the DR policy for the next day. For the present day, the simulation starts with a specification on how to operate home appliances based on a DR policy determined one day ahead, which includes thermostat setting of HVACs and when to use dryer, dishwasher, electric stove, etc. Then, energy consumption of a residential house is simulated by using eQUEST for a practical weather pattern of the day, including temperature, humidity, solar radiation, etc., at a location. The results generated by the home energy simulator are loaded into a MATLAB-based energy cost computation subsystem for DR evaluation. At the same time, an optimal DR policy is generated for the next day based on weather prediction, updated HVAC energy consumption model, day-ahead electricity price, customer's thermal comfort index, and comfort indices for deferrable appliances. The two settlement processes continue day after day. Figure 4 shows the flowchart of the integrative simulation system, in which how to develop a learning-based DR policy is presented in Section III and the following section too.

V. Simulation Study and Results

This section presents a study of the proposed decoupled and learning-based DR by using the integrative simulation system developed in Section IV, which requires forecasted weather and electricity price data in 24-hour ahead. The weather forecast is available from National Weather Service and the 24-hour electricity price can be provided by an electric utility one day ahead. For example, Ameren Focused Energy, serving about 2.4 million electric customers in Illinois and Missouri, has very detailed RTP and DAP tariffs posted on their website since June 1, 2008 [54].

A. Optimal and Learning-Based HVAC Demand Response

We used the regression approach to update HVAC energy consumption model and the optimization routine presented in Section III-C to obtain an optimal DR policy. Since an optimal DR policy is determined one day ahead, there is enough time to complete the model update and calculate the thermostat settings for the next 24 hours.

However, for a new home or HVAC unit, the data queues are empty at the beginning. Thus, initial DR policies need to be generated by using a conventional mechanism, such as the heuristic algorithm or the optimization algorithm based on ETP model. Algorithm 1 presents the pseudocode that illustrates how HVAC energy consumption model is learned and how an optimal DR policy is generated and updated. Initially, home appliances are managed through a heuristic DR policy for a prescribed number (numDay) of days and results about HVAC energy consumption data, 24-hour weather forecast, 24-hour DAP, and 24-hour thermostat settings are saved in queues every day until the queues are full (Lines 1 to 7). Then, a HVAC energy consumption model for the time window represented by the length of the queues is obtained through the regression approach (line 8), based on which an optimal DR policy is generated (line 10). The DR policy is loaded into the home energy simulator (line 11) to obtain HVAC energy consumption for the next day (line 12). The results obtained, together with the information of weather forecast, 24-hour thermostat settings and 24-hour indoor room temperature, are saved in the queues (line 13). At the same time, old 24-hour

Algorithm 1 Optimal and Learning-Based Demand Response

{Initial demand response using the heuristic DR policy as shown by Fig. 1}
1: **for** d=1 to numDay
2: Read in 24-hour weather forecast T_i^O; read in 24-hour day-ahead electricity price P_i (i=1,..., 24); read in next-day thermal comfort index.
3: Obtain 24-hour thermostat setting T_{i+1}^I (i=1, ..., 24) by using the algorithm shown by Fig. 1.
4: eQUEST $\Leftarrow T_i^O, T_{i+1}^I$ (i=1, ..., 24).
5: Obtain HVAC energy consumption Q_i (i=1, ..., 24) through simulation in eQUEST
6: $Q_{queue} \leftarrow Q_i, T_{room\_queue} \leftarrow T_i^I, T_{setting\_queue} \leftarrow T_{i+1}^I$, $T_{out\_queue} \leftarrow T_i^O$(i = 1, ..., 24)
7: **end for**
{Optimal and learning-based demand response for any subsequent days as shown by Fig. 5}
8: Update HVAC energy consumption model by using neural network or regression approach.
9: Read in 24-hour weather forecast T_i^O; read in 24-hour day-ahead electricity price P_i (i=1, ..., 24)); read in next-day thermal comfort index.
10: Generate 24-hour thermostat setting T_{i+1}^I (i=1, ..., 24) by using nonlinear programming or PSO method [28].
11: eQUEST $\Leftarrow T_i^O, T_{i+1}^I$($i$=1, ..., 24).
12: Obtain HVAC energy consumption Q_i (i=1, ..., 24) through simulation in eQUEST
13: Update the data queues
14: Repeat Steps 8 through 13 day after day until a stopping condition is met.

data in the front of the queues are removed. The process continues to update HVAC energy consumption model and to generate new optimal DR policy day after day.

Note that the length of the queues should be selected in such a way that any update of the HVAC energy consumption model based on the data saved in the queues should reflect recent seasonal, weather, user, house conditions, etc., within two or three weeks. For example, we do not want to learn the HVAC model based on data collected many years ago.

B. HVAC Demand Response Study

A comparison study was conducted as shown by Fig. 5, in which 'None' represents a constant thermostat setting at 72°, 'Heuristic' stands for the thermostat setting by using the heuristic DR policy, 'ETP' signifies the optimal thermostat setting based on the ETP model (eq. (2)), and 'Learning' represents the optimal thermostat setting by using the learning-based regression model (eq. (11)). For the heuristic algorithm, a 'nine-point' thermostat setting at 71°; 72°, 73°, 74°, 75°, 76°, 77°, 78° and 79° is used [28]. For the optimal DR algorithms, the upper and lower temperature settings are 71° and 79°, respectively. As it can be seen from the figure, the learning-based optimal DR policy is the most efficient.

However, for the DAP tariff of Ameren Focused Energy (Fig. 5a), the price difference during a day is small. Therefore, the effect of the demand response is not evident. Nevertheless, for a different location in a southern state of the United States and a DAP tariff with a large price differentiation [58], we found that the impact of the demand response is much more evident and important. Consequently, how to determine DAP tariff for energy consumers at different geographic locations is critical to achieve an effective demand response program.

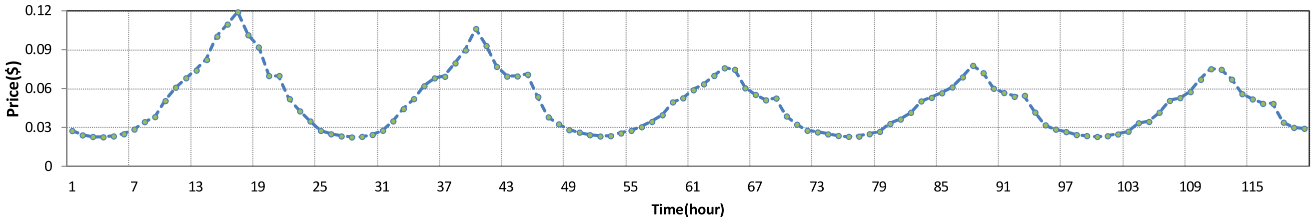
Errors in temperature forecast could be another factor affecting DR efficiency. The literature review shows that forecast errors of day-ahead temperature follow certain statistic characteristics [59], [60]. Based on the statistical distribution, "actual measured" temperature of a day was formulated by adding errors to the forecasted temperature data used in Fig. 5. We used a Gaussian deviation for errors with the mean of 0.5°F and standard deviation of 6°F [59], [60]. Then, for optimal DR policies determined using the forecasted temperature data, the effectiveness of the demand response was simulated and compared with and without the forecast errors as shown by Table II for the five days used in Fig. 5, in which the cost saving represents the saving between 'Learning' and 'None' thermostat setting approaches. As shown by Table II, the impact of the forecast errors is marginally small. This is due to the fact that errors in day-ahead temperature forecast are normally small [59], [60].

Table III compares HVAC energy consumption and cost for a hot summer day under different user's thermal comfort preferences in a scale ranging from I to IV, where I represents the highest thermal comfort preference associated with a temperature settings of 72° and 75° for T_i^{min} and T_i^{max}, and IV the lowest thermal comfort preference associated with a temperature settings of 72° and 81° for T_i^{min} and T_i^{max}. The comparison study shows that HVAC energy consumption and cost increase as the user's thermal comfort preference level increases; the difference, however, also strongly depends on outside weather or temperature of a day.

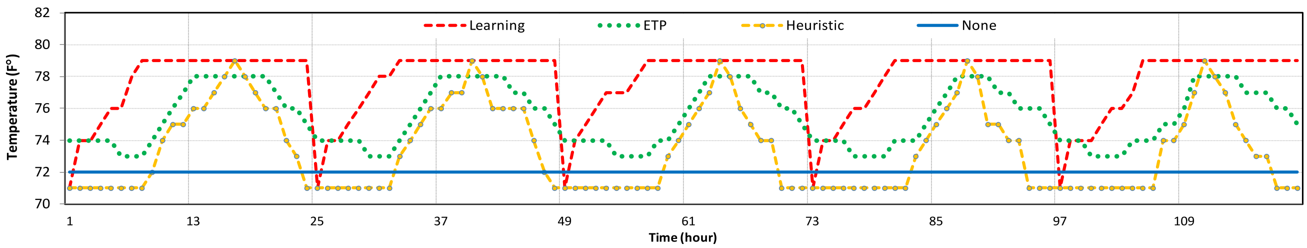
C. Integrative Demand Response

Demand responses of all the appliances within a home are managed according to the types of the appliances that are classified as fixed loads, deferrable loads, and regulate-able loads (mainly HVAC). Fixed loads does not participate in the demand response. Demand response of HVAC is presented in Section V-B. Demand response for deferrable loads is handled through the binary integer programming mechanism presented in Section II-E. Overall, an optimal DR policy for each appliance is solved individually one day ahead (Section II) and then used to control the operation of the appliance in the following day. Fig. 6 shows the simulated energy consumption of the three different types of loads based on the integrative, decoupled, and learning-based DR strategy for a day.

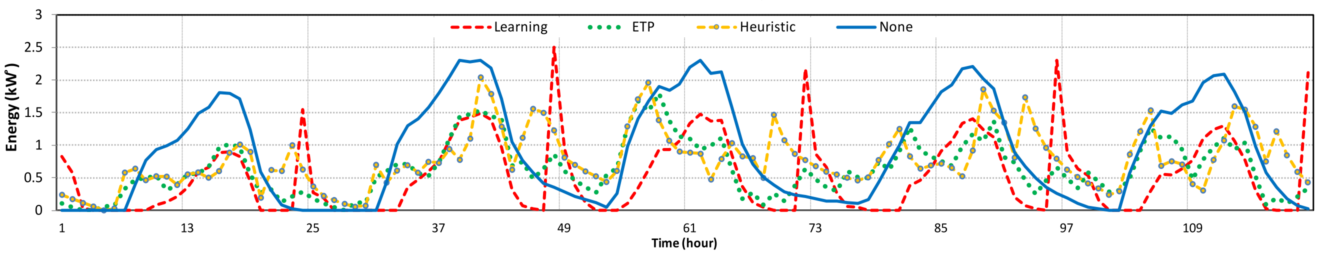
Table IV evaluates the impact of user's comfort preferences in a scale ranging from 1 to 4 for operating deferrable loads, where 1 represents the minimum annoyance (i.e., operate a deferrable load immediately) and 4 represents the maximum annoyance (i.e., postpone the operation of a deferrable load any time between 7am and 10pm). The other conditions are the same as those used in Table III except that only thermal comfort preference scale III is adopted in Table IV for HVAC operation. The study shows that energy consumption is not affected by the user's comfort demand while the overall



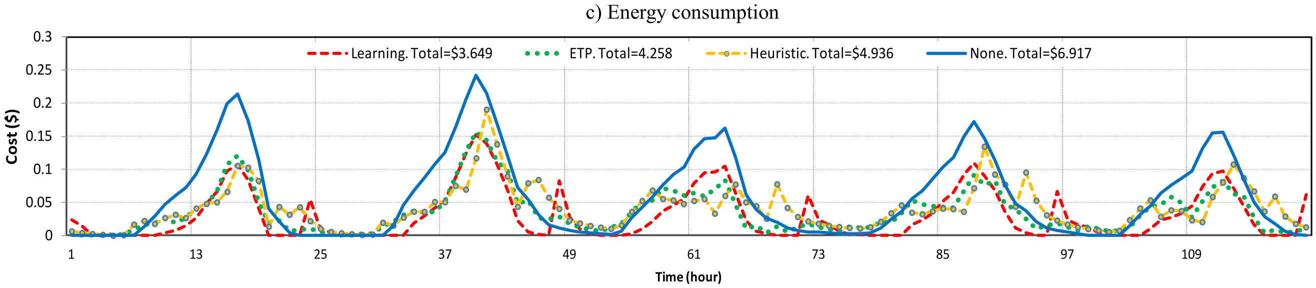
a) Day-ahead electricity price



b) Thermostat setting



c) Energy consumption



d) Hourly and total costs for five days

Fig. 5. Comparison of thermostat settings, HVAC energy consumption and cost using different DR algorithms for five continuous days.

TABLE II
COMPARISON OF HVAC ENERGY CONSUMPTION, COST AND COST SAVING WITH (W/) AND WITHOUT (W/O) ERRORS IN TEMPERATURE FORECAST

Day	Energy (kWh)		Cost ($)		Cost saving (%)	
	w/o	w/	w/o	w/	w/o	w/
1	8.081	8.089	0.5900	0.5917	56.89	56.77
2	13.325	13.338	0.9436	0.9483	46.19	45.91
3	14.535	14.550	0.7451	0.7460	42.95	42.87
4	13.673	13.680	0.7168	0.7169	45.22	45.22
5	12.904	12.910	0.6537	0.6539	44.62	44.60

TABLE III
COMPARISON OF HVAC ENERGY CONSUMPTION AND COST UNDER DIFFERENT USER'S THERMAL COMFORT PREFERENCES

Thermal comfort preference	T_i^{min}	T_i^{max}	Energy (kWh)	Cost ($)
I	72°	75°	32.806	3.129
II	72°	77°	29.787	2.733
III	72°	79°	22.302	1.936
IV	72°	81°	22.047	1.879

energy cost reduces for a more relaxing comfort preference of a user. However, the difference strongly depends on the electricity price of a day.

In future work, the proposed decoupled and learning-based optimization approach can be improved and applied to future home appliances, including roof-top solar, battery storage, and plug-in hybrid vehicles. However, since each appliance has different characteristics, a unique learning, demand response, and energy management strategy would need to be researched for each individual appliance in future work.

D. Aggregate Impact to Electricity Market

When the DAP based demand response is applied to thousands of residential houses, it would cause an aggregate impact. This aggregate effect could be affected by many factors, including 1) size and construction of the houses,

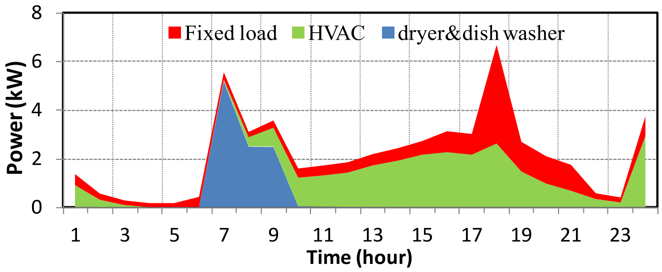


Fig. 6. Energy consumption of three types of loads during a day.

TABLE IV
COMPARISON OF OVERALL ENERGY CONSUMPTION AND COST UNDER DIFFERENT USER'S COMFORT PREFERENCES FOR DRYER AND DISHWASHER

Comfort preference	*Acceptable time window*	Energy (kWh)	Cost ($)
1	Immediately start	57.200	5.280
2	Postpone within ±3 hours and within 7am and 10pm	57.179	5.055
3	Postpone within ±5 hours and within 7am and 10pm	57.195	4.978
4	Any time between 7am and 10pm	57.167	4.793

2) comfort indices preferred by each home owner, 3) weather, and 4) electricity price, making the aggregate impact have certain stochastic characteristics. This statistical nature is vital for energy management of an electric utility.

The aggregate DR effect would also change the load pattern. In the DR framework, the load pattern will be affected not only by weather but also by the electricity price. On the other hand, the residential load is only one part of the load mix within an electric utility system. Thus, how to determine the day-ahead electricity price to make all the loads response in such a way that will benefit the energy management of the entire system presents a new challenge to electric utilities. Note that the DAP tariff should be determined based on power system economics and load forecast at a higher level and larger scale by electric utilities and load serving entities while energy consumers at the tiny house level do not participate in determining the DAP electricity price.

The above issues are not considered in this paper but are important for future research.

VI. CONCLUSION

This paper presents an interdisciplinary approach that combines machine learning, optimization and data structure design to build a demand response and home energy management system that can meet the needs for real-life implementations. Some specific features and contributions of the paper include:

- A decoupled DR mechanism by classifying home appliances into fixed, deferrable and regulate-able loads, in which DR for each appliance is solved separately and then combined together to formulate an integrative optimal DR strategy.
- A mechanism to obtain energy consumption model of a house through learning of actual measured or simulated data. The model of the house is updated daily so that it can accurately capture the thermal behavior of a house at present seasons, users, and weather conditions.
- An optimal DR technique for household HVAC unit that is obtained based on 24-hour weather prediction, day-ahead electricity price and the learning-based energy consumption model of the house.
- The DR evaluation has adopted a co-simulation strategy that combines a home energy simulator and MATLAB together for DR development and evaluation. The home energy simulation is based on eQUEST, a professional building simulation software that can provide unbiased energy consumption of a house under practical weather conditions. The DR evaluation uses MATLAB, a technical software that can accelerate the design and assessment of a DR algorithm.

The evaluation shows that the proposed learning-based DR and HEM system is the most efficient among all the DR algorithms we tested, demonstrating the effectiveness and good performance of the proposed optimal and learning-based DR and HEM method.

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