A Collaborative Design of Aggregated Residential Appliances and Renewable Energy for Demand Response Participation

Meng Liu, *Student Member, IEEE*, Franklin L. Quilumba, *Member, IEEE*, and Wei-Jen Lee, *Fellow, IEEE*

***Abstract*—Although the locational marginal price may change dramatically within a single day in competitive wholesale electricity markets, most end users are charged monthly electricity bills over flat rates. Without financial incentives, the customers are lacking of motivation to respond to the price signals, which may result in inefficient energy consumption. In Texas, Senate Bill 1125 encourages qualified residential and commercial customer classes to participate in demand response (DR) programs. This paper proposes an idea to aggregate a number of residential customers to participate in residential DR program by employing smart appliances and a home area network to shift the coincidental peak load to off-peak hours to reap financial benefits. The operation strategies for the most representative residential load types are discussed. To further reduce electricity purchase and cut electricity bills, a solar farm with energy storage system is proposed, and the control algorithm is designed accordingly. The operation strategies are simulated for a whole year, and the annual costs are calculated and compared in this paper. The results show that, by doing load control and utilizing renewable resources, the total operation cost can be reduced significantly.**

***Index Terms*—Demand response (DR), deregulated electricity market, residential appliances management.**

I. Introduction

DEREGULATED power market has been developed to maximize social benefits for both power generation entities and load customers. In Texas, the Electricity Reliability Council of Texas (ERCOT) launched a comprehensive nodal market to improve market and operation efficiency through more rapid and granular pricing and scheduling of energy services on December 1, 2010 [1]. To provide demand resources with the opportunities to provide services, different inclusive demand response (DR) programs are designed to sustain the reliability and improve the operation efficiency of the grid [2], [3]. The U.S. Department of Energy defines DR as “Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.” [4]. While the locational marginal price (LMP) focuses on the supply side in the wholesale market that contains the cost of generation, transmission congestion, and losses, the ability to redispatch the load resources may provide efficient alternatives during peak hours, where 20% of power generation capacity is only used to maintain peak demand, which happens only 5% of the time [5], [6].

Although the LMP in the wholesale market can change from one moment to another, for most residential customers, electricity bills are still charged monthly over a flat rate, where the price does not reflect the actual electricity cost during usage [7]. Without market incentives, residential customers do not have any motivations to curtail their consumption to lower the peak demand or relief the supply shortage. The deficiency with flat rate, on one hand, forces utilities to take the risks associated with price fluctuations for keeping electricity rate constant [8], whereas, on the other hand, residential customers do not have opportunities to adjust their consumption patterns according to LMP variations to reduce electricity bills.

In 2011, Texas Legislature approved Senate Bill (SB) 1125, an act focusing on energy efficiency goals and programs, public information regarding energy efficiency programs, and the participation of loads in certain energy markets [9]. One purpose of SB 1125 is to stimulate the participation of residential and commercial customer classes in DR programs while reliability standards are maintained. At the same time, large numbers of smart meters, smart sensors, and automatic control devices are installed on residential and commercial sides via two-way communication networks, making it possible to control the smart appliances and monitor the status of home energy management systems [10]. With the vision that DR may be expanded to residential customers, this paper presents approaches to aggregate a number of residential customers to shift the coincidental peak load by adopting different operation strategies for the most representative residential load types, including heating, ventilation, and air conditioning; clothes dryers; and refrigerators, for possible system reliability improvement and financial benefits for all participating customers.

In addition, the growth of electricity demand and environmental concerns drive people to seek solutions from renewable

Manuscript received June 25, 2014; revised November 17, 2014 and February 3, 2015; accepted April 16, 2015. Date of publication April 28, 2015; date of current version September 16, 2015. Paper 2014-ESC-0253.R2, presented at the 2014 IEEE Industry Applications Society Annual Meeting, Vancouver, BC, Canada, October 5–9, and approved for publication in the IEEE Transactions on Industry Applications by the Energy Systems Committee of the IEEE Industry Applications Society.

M. Liu and W.-J. Lee are with the Energy Systems Research Center, The University of Texas at Arlington, Arlington, TX 76019 USA (e-mail: meng.liu@mavs.uta.edu; wlee@uta.edu).

F. L. Quilumba is with the Department of Electrical Energy, National Polytechnic School, Quito 170517, Ecuador (e-mail: quigufrale@ieee.org).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TIA.2015.2427286

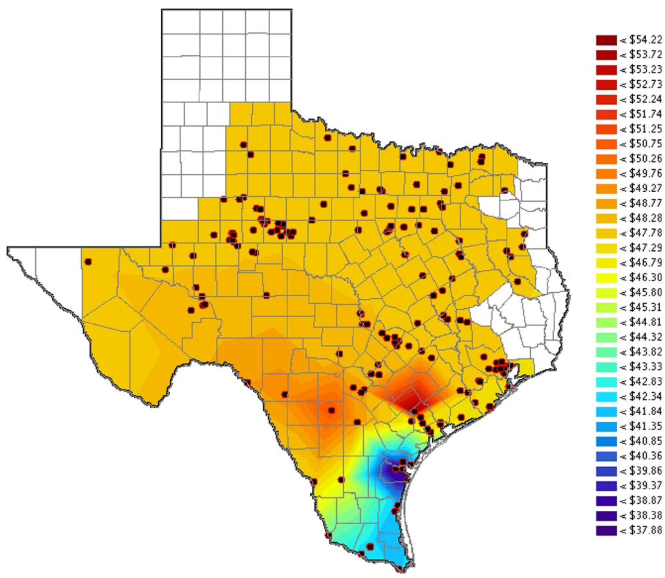

Fig. 1. LMP of ERCOT region at 14:15, June 18, 2014.

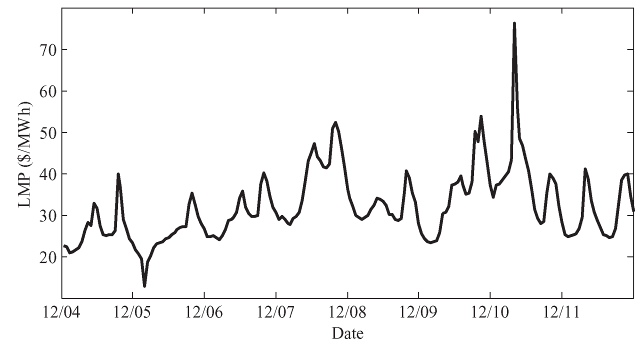

Fig. 2. LMP of a node in north Texas in December 2013.

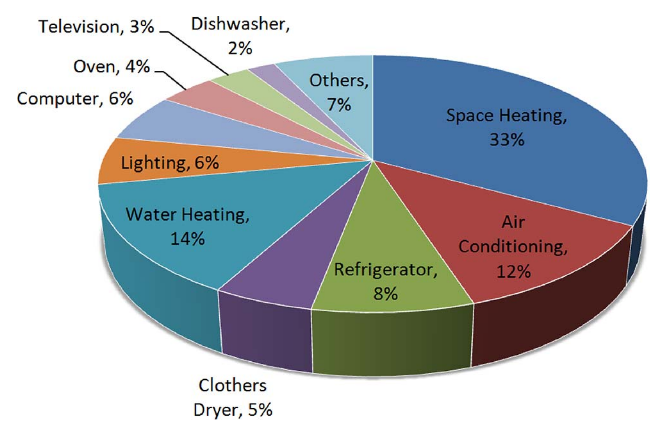

Fig. 3. Residential appliances electricity consumption percentage.

energy. The installation capacity of renewable energy has been growing in recent years and will continue increasing in the years to come. This growth is mainly dominated by wind and solar energy [11]. In addition to wind, Texas has abundant solar resources that can be exploited to produce electricity. Therefore, this paper also proposes an idea to install a solar farm coupled with energy storage devices to supply the aggregated demand to further increase the financial benefits for all participants.

The remainder of this paper is organized as follows. Section II introduces LMP in ERCOT nodal market. Section III describes the classification of residential appliances. Section IV discusses the operation strategies for different load types in the collaborative system. Section V designs the operation strategies for storage devices according to the availability of solar power. Simulation results for different load operation strategies are presented in Section VI. Section VII draws the conclusions.

II. LMP in ERCOT Nodal Market

LMP is the "marginal cost of supplying, at least cost, the next increment of electric demand at a specific location (node) on the electric power network, taking into account both supply bids and demand offers and the physical aspects of the transmission system including transmission and other operational constraints" [12]. LMP includes marginal cost of generation, marginal cost of losses, and marginal cost of transmission congestion [5]. In real-time nodal market, ERCOT provides the LMP for the next 5 min on its website. The LMP at different nodes can vary significantly across the ERCOT region, as depicted in Fig. 1, at 14:15 on June 18, 2014. In addition, the LMP of a single node can substantially change along the day, for instance, Fig. 2 shows the LMP of one week in December 2013 at a node located in north Texas. To design the operation strategies for a group of appliances according to LMP variations, it is assumed that the aggregated loads are billed for the energy charges according to LMPs.

III. Residential Appliances Classification

In recent years, the wide spread of smart meters, smart sensors, and automatic control devices in distribution and residential levels has created a platform to control the operation of residential appliances in an intelligent way considering both household economic benefits and grid operational constraints [10]. An optimal operation schedule is able to make decisions for the appliances for switching on/off, cycling, and shifting working time while compromising the comfort and convenience of customers within a predefined tolerable range. The smart appliances can be classified into different categories according to appliance characteristics and consumption patterns.

The most common appliances account for different shares of residential electricity consumption [13], as shown in Fig. 3, where air conditioning (AC) and space heating account for nearly half of the consumption. Water heating, refrigerators, lighting, and clothes dryers also occupy significant parts of the electricity bills. Residential appliances can be classified according to their properties and criticality to daily life, making it possible to design operation strategies accordingly. The appliances are generally classified into noncontrollable and controllable appliances, where controllable appliances are further classified into thermostatically and nonthermostatically controlled appliances; the classifications of major residential appliances are shown in Table I [10]. The noncontrollable appliances are the critical loads, which are not suitable for rescheduling in DR programs. For controllable appliances, the thermostatic ones have thermal inertia, which means the

TABLE I
MAJOR RESIDENTIAL APPLIANCES CATEGORY

Non-controllable Appliances	Controllable Appliances	
	Thermostatically Controlled	Nonthermostatically Controlled
Lightning	Air Conditioner	Clothes Washer
Refrigerator	Space Heater	Clothes Dryer
Television	Water Heater	Dish Washer

load consumption of the current moment is influenced by the consumption of the previous moment and will affect the next moment. For nonthermostatical load, there are flexibilities on their service time and can be deferred as needed. Being the most representative appliances in each category, AC/heater, clothes dryer, and refrigerator are chosen in this study to discuss the operation strategies for each type of appliances. By aggregating a number of appliances and shifting the coincidental peak load by certain amount of time, financial benefits can be achieved.

IV. AGGREGATED APPLIANCES OPERATION STRATEGY

A. AC/Heater Load Control: Steps of Temperature

It is common practice for most residential consumers to set the thermostat of AC/heater at a constant temperature set point. This practice is inefficient and costly in a real-time electricity pricing environment since the AC/heater still operates at the same set point even if the LMP is high. On the other hand, when the price is low, this practice does not take advantage of that low price to operate AC/heater at the coldest/hottest allowable temperature to reserve the thermal energy for the subsequent periods.

The thermodynamics of AC/heater systems located at the end user is modeled as in [14]. It is assumed that the system is equipped with smart controls that manage the power consumption during the day in response to price signals, while at the same time maintaining the inside temperature within preset comfort limits. The following equation is used to simulate the indoor temperature of the next time frame [15]:

$$T^{\mathrm{in}}(K+1) = \epsilon T^{\mathrm{in}}(k) + (1+\epsilon)\left(T^{\mathrm{out}}(k) \pm \eta_{\mathrm{COP}}\frac{P(k)}{A}\right)$$
$$(+ : \text{heating}, - : \text{cooling}) \quad (1)$$

where

$T^{\mathrm{in}}(k)$	inside temperature in period k;
$T^{\mathrm{out}}(k)$	outside temperature in period k;
$P(k)$	power consumption in period k;
η_{COP}	coefficient of performance;
ϵ	factor of inertia (0.96).
A	overall thermal conductivity (0.14 kW/°F).

Furthermore, it is assumed that the smart control maintains the inside temperature within certain limits, which is around the user-defined temperature set point. Thus,

$$T^{\min} \le T^{\mathrm{in}} \le T^{\max} \qquad \forall k \qquad (2)$$

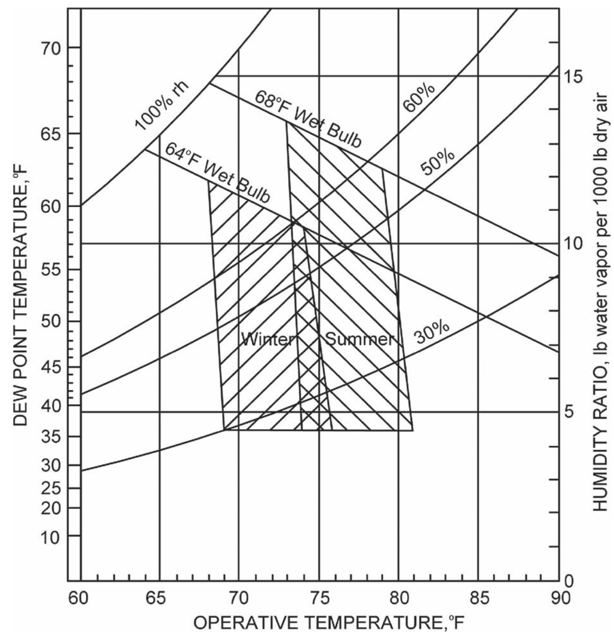

Fig. 4. ASHRAE summer and winter comfort zones [16].

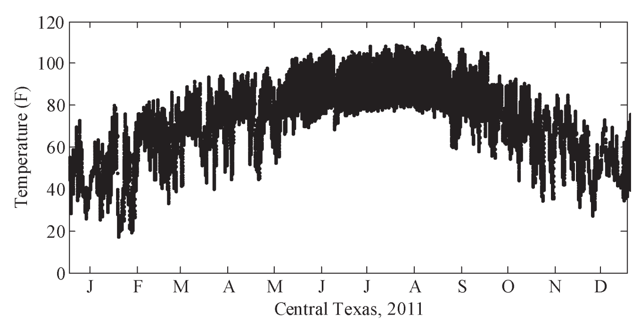

Fig. 5. Annual temperature of a node in central Texas in 2011 (°F).

where

T^{set}	user-defined temperature set point;
ΔT	maximum deviation from set point (2°F);
$T^{\min}$	minimum inside temperature ($T^{\mathrm{set}} - \Delta T$);
$T^{\max}$	maximum inside temperature ($T^{\mathrm{set}} - \Delta T$).

For the operation strategy, it is considered that the AC/heater operates within the ASHRAE comfort zones [16]. Comfort zones are seasonal: the summer zone is separated from the winter zone. As shown in Fig. 4, both zones cover approximately 6°F.

Outdoor temperature data of the year 2011 are obtained from [17] for a node in central Texas for simulation purposes. Fig. 5 shows the temperature data of the entire year. Fig 6 shows the outdoor temperature data on a hot summer day, whereas Fig. 7 shows outdoor temperature data on a cold winter day for illustration purposes. These data are used for AC/heater load control simulations together with the LMP of the same year at the same node.

Five LMP breaking points are chosen as demonstrations for establishing the Steps-of-Temperature-based load control. The first point is \$0/MWh, and the rest points are selected as the percentiles of 2.5th, 25th, 50th, and 75th of the annual LMP data, which are 14, 23, 26, and \$35/MWh, respectively. The

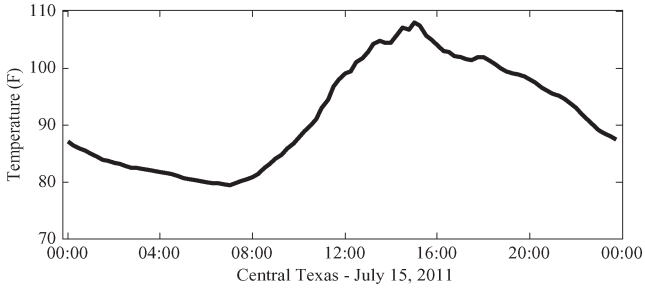

Fig. 6. Temperature at a node in central Texas on a summer day (°F).

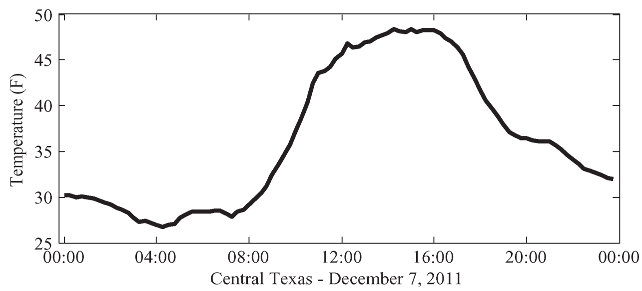

Fig. 7. Temperature at a node in central Texas on a winter day (°F).

AC is operated the coolest possible (near the lower boundary of the ASHRAE summer comfort zone, e.g., 75° F) when the LMP is lower than the predefined value (e.g., $14/MWh). On the other hand, the AC load is operated the hottest (near the upper boundary of the ASHRAE summer comfort zone, e.g., 79° F) when the LMP is higher than the predefined value (e.g., $35/MWh). The AC is operated between these two boundaries depending on the real-time electricity prices. This strategy is called the "Steps of Temperature Preferences" or the "Steps of Temperatures" [18]. Consumers can easily adjust and balance the price and temperature settings according to their preferences while still maintaining their comfort from the saving.

The strategy to control the heater follows a similar approach. The heater is operated the hottest possible (near the upper boundary of the ASHRAE summer comfort zone, i.e., 73° F) when the LMP is lower than the predefined value (e.g., $14/MWh). On the other hand, the heater load is operated the coolest (near the lower boundary of the ASHRAE summer comfort zone, i.e., 69° F) when the LMP is higher than the predefined value (e.g., $35/MWh). The heater is operated between these two boundaries depending on the real-time LMP.

B. *Clothes Dryer: Price Naming*

The control strategy of Price Naming, as presented in [19], is a suitable strategy to be exploited for nonthermostatically controlled residential appliances such as clothes dryers. This is a familiar operation mode in the online discount reservation in [20] or in the auto insurance in [21], and it is adopted as load control strategy. An operator of the aggregated load can "name" his/her own electricity purchasing price for the load controller to send the control command to operate an appliance when the LMP drops below the desired price threshold [19]. By shifting the aggregated load usage to subsequent cheaper LMP time frames, the overall consumption is not reduced, and

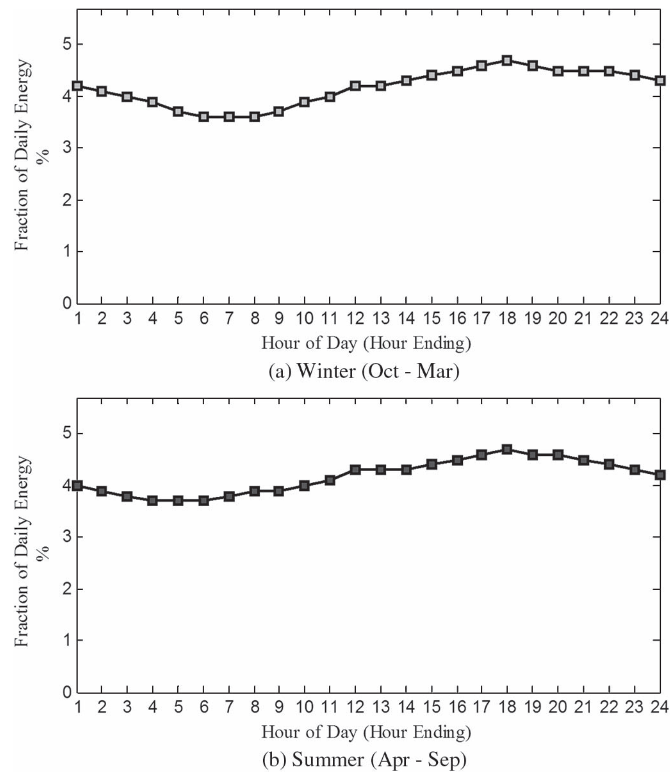

Fig. 8. ELCAP: refrigerator load shape for an average (a) winter and (b) summer day.

the desired missions are accomplished, but the benefits can be substantial.

For modeling the clothes dryer consumption, a one-year worth of statistically averaged usage pattern of this end-use appliance is utilized. For the purpose of this study, the load data obtained as part of the End-Use Load and Consumer Assessment Program (ELCAP) are used, which have been made publicly available in [22]. The average yearly consumption (kWh/year) of clothes dryers can be expressed as follows [23]:

$$538.2 + 179.4 \times N_{\mathrm{br}} \tag{3}$$

where N_{br} is the number of bedrooms ($N_{\mathrm{br}} = 3$ in this study).

C. *Refrigerator*

Similarly, a one-year worth of statistically averaged usage pattern of this end-use appliance is utilized from the ELCAP data [22]. The average annual consumption (kWh/year) of a refrigerator is 434 kWh/year. Refrigerator is classified as a noncontrollable appliance; therefore, its original consumption pattern will not be modified. The hourly electricity consumption by a refrigerator on an average winter and summer day is shown in Fig. 8(a) and (b), respectively.

V. Solar Power and Energy Storage

A. *PV and ESSs Integration*

Texas is rich in solar resource. With the advantages of emission-free, long-life-span, and low-maintenance requirement, photovoltaic (PV) is a preference for harvesting solar energy in this study. The incentives and rebates from federal, state, and local levels make the PV installation feasible.

The day–night cycling causes the output of PV to be extremely unevenly distributed. Typically, the maximum PV output in a single day appears around 2 P.M., whereas the peak hours of the demand are between 4 and 7 P.M., which is usually when LMP increases dramatically. To effectively utilize PV output, energy storage systems (ESSs) are implemented in this collaborative system to store the excess energy when the PV generation is higher than the load consumption. The stored energy is used to supply load when the PV power cannot fulfill the load, and it can be also used to mitigate possible price spikes or sags. In order to encourage the installation of PVs, federal, state, local, and private incentives and rebates offer numerous economic stimuli such as tax credits, tax deductions, property tax relief, purchase incentives (rebates), and production incentives. One example is the residential PV installation in Austin, Texas [24]. If the customers participate in the incentive program, the residential customer can take the advantage of local and federal incentives, including a solar panel rebate of $3/kW from the local utility, a rebate of $0.8/kW for participation in a demonstration project, and a 30% federal tax incentive. Assuming a lifetime of 25 years for the solar panel system, the approximate daily cost for each kilowatt installation is as low as $0.04. Another example can be found at the University of Texas at Arlington [25]: the installation of 384.93-kW solar panels atop Park North and Park Central parking garages costs the university $368 000, but Oncor (local utility) provided a $390 000 rebate. From these two examples, the cost of PV installation can be reduced to a negligible level via incentives and rebate programs. Several PV and energy storage hybrid projects are built across the world to mitigate the intermittence of the renewable energy. Meanwhile, the importance and benefits of installing ESS have been realized more and more in recent years; for example, in California, the Public Utilities Commission requires 1.325 GW of battery installation by 2020 [26]. Another example is that Oncor just announced that it is willing to invest more than $2 billion to store electricity in thousands of batteries across North and West Texas beginning of 2018 [27]. The selection and sizing of ESS are beyond the scope of this study. Due to the advance in technology, the costs of PV and ESS have dropped significantly in recent years. In addition, federal and local incentive programs make the cost estimation for the installation of PV and ESS become location dependent. Therefore, this study defines the operation strategies with the assumption that both PV and ESS are available and their installation and operation cost are excluded in the calculation. One has to consider the actual installation and operation cost and other potential opportunities when implementing this option.

B. ESSs Operation Strategy

The operation strategy is designed to choose the power sources for supplying customer appliances, which can be PV output, ESS, or grid. The control strategy is illustrated in Fig. 9. At each time step i, PV output P_{pv}, load consumption P_{load},

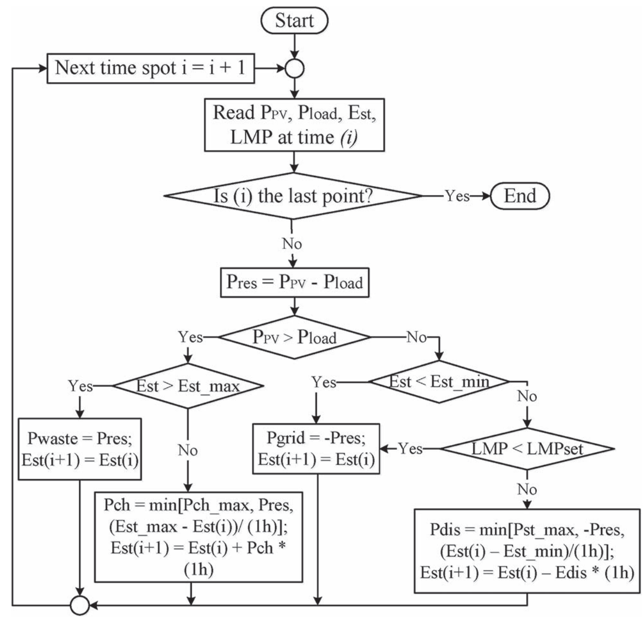

Fig. 9. Dispatch algorithm of PV power and energy storage devices.

ESS energy status E_{st}, and LMP are read. The residue power P_{res} is calculated by

$$P_{\mathrm{res}} = P_{\mathrm{pv}} - P_{\mathrm{load}}. \tag{4}$$

If $P_{\mathrm{res}} > 0$, the residue power will be either used to charge ESS when the storage is not fully charged or dumped, which remains unchanged. When $E_{\mathrm{st}} \geq E_{\mathrm{st\_max}}$, the wasted power P_{waste} and E_{st} are calculated as

$$P_{\mathrm{waste}} = P_{\mathrm{res}} \tag{5}$$

$$E_{\mathrm{st}}(i+1) = E_{\mathrm{st}}(i). \tag{6}$$

When $E_{\mathrm{st}} < E_{\mathrm{st\_max}}$, the storage devices can be charged, and the charging power P_{ch} is limited by the physical limits of the inverters $P_{\mathrm{ch\_max}}$,P_{res} and the ESS energy status. P_{ch} and E_{st} are calculated as

$$P_{\mathrm{ch}} = \min\left[P_{\mathrm{ch\_max}}, P_{\mathrm{res}}, \left(E_{\mathrm{st\_max}-E_{\mathrm{st}}}(i)\right)/(1h)\right] \tag{7}$$

$$E_{\mathrm{st}}(i+1) = E_{\mathrm{st}}(i) + P_{\mathrm{ch}} \times (1h). \tag{8}$$

If $P_{\mathrm{res}} \leq 0$, the PV output is not enough to cover the load consumption. If E_{st} is smaller than or equal to the minimum limit $E_{\mathrm{st\_min}}$,E_{st} will not be changed, and the power imported from the grid, i.e., P_{grid}, will compensate the shortage of PV power, i.e.,

$$P_{\mathrm{grid}} = -P_{\mathrm{res}} \tag{9}$$

$$E_{\mathrm{st}}(i+1) = E_{\mathrm{st}}(i). \tag{10}$$

On the other hand, if $E_{\mathrm{st}} > E_{\mathrm{st}}(i)$, a threshold price, i.e., $\mathrm{LMP}_{\mathrm{set}}$, is chosen to avoid overcycling of the ESS, but still reduce purchasing electricity from grid if the LMP is high. In this paper, $\mathrm{LMP}_{\mathrm{set}}$ is the 75th percentile of the whole-year LMP. When LMP < $\mathrm{LMP}_{\mathrm{set}}$, buying electricity from the grid

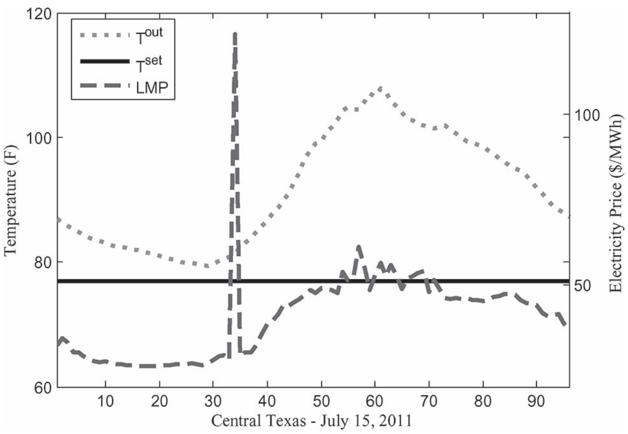

Fig. 10. Outside temperature, temperature setting, and LMP as seen from a residential customer in central Texas on July 15, 2011.

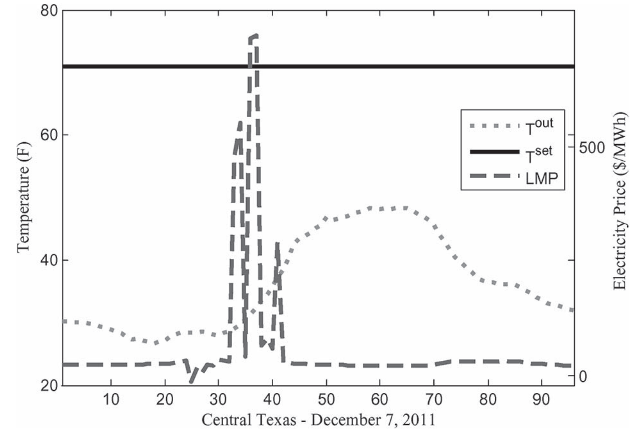

Fig. 11. Outside temperature, temperature setting, and LMP as seen from a residential customer in central Texas on December 7, 2011.

is acceptable. ESS energy status will be unchanged. $P_{\rm grid}$ and $E_{\rm st}(i+1)$ can be also calculated from (9) and (10). However, when LMP goes beyond the threshold value, the discharge power from the storage devices, i.e., $P_{\rm dis}$, will be limited by the discharging capability of the inverters, the shortage between load consumption and PV output $(-P_{\rm res})$, and the status of ESS. $P_{\rm dis}$ and $E_{\rm st}$ are respectively calculated as

$$P_{\rm dis} = \min\left[P_{\rm dis\_max}, -P_{\rm res}, (E_{\rm st}(i) - E_{\rm st\_min})/(h)\right] \tag{11}$$

$$E_{\rm st}(i+1) = E_{\rm st}(i) - P_{\rm dis} \times (1h). \tag{12}$$

VI. Simulation Results

Several conditions and assumptions are made to obtain a more realistic simulation.

1) The aggregation of 1000 households is considered. The simulation is developed for the entire year of 2011.
2) Recently, a number of major appliance companies have invested in the production of smart appliances that are capable of supporting the proposed control strategies. It is assumed that a smart appliance has the ability to automatically schedule its operation based on real-time pricing and also allows remote control by customers via smartphones or across the Internet [28].
3) The LMP at a node in central Texas is used for the aggregated load for billing purposes.
4) A distribution level solar farm with ESS is assumed to be available and supplies electricity for the 1000 customers.

Three case studies are implemented for comparison. The study results for a typical summer day (July 20, 2011) and a typical winter day (December 7, 2011) are shown as examples.

A. No Load Control

In this case, the AC/heater will always operate at the preset temperature regardless of LMP variations. As shown in Figs. 10 and 11, the AC works at 77° F, whereas the heater works at 71° F. The clothes dryer will operate without any load control either, as shown in Fig. 12.

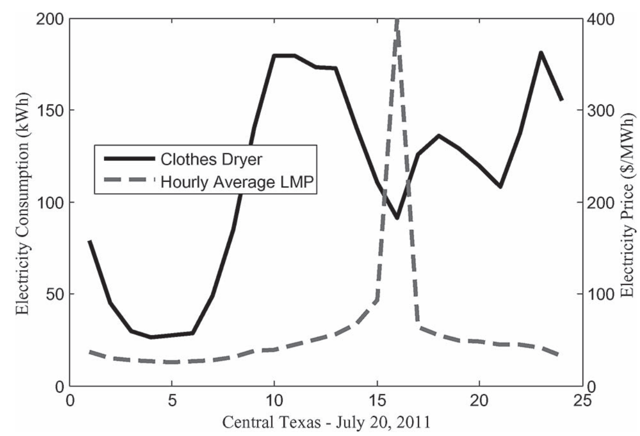

Fig. 12. Total clothes dryer electricity consumption for the 1000 customers without load control and hourly average LMP in central Texas on July 20, 2011.

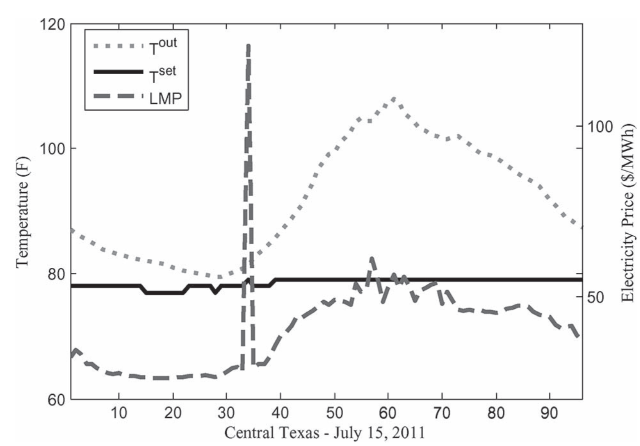

Fig. 13. Outside temperature, temperature setting, and LMP as seen from a residential customer in central Texas on July 15, 2011, under the Steps of Temperature control strategy.

B. Load Control: Steps of Temperature and Price Naming

The ACs and heaters will operate according to the Steps of Temperature control algorithm, as shown in Figs. 13 and 14,

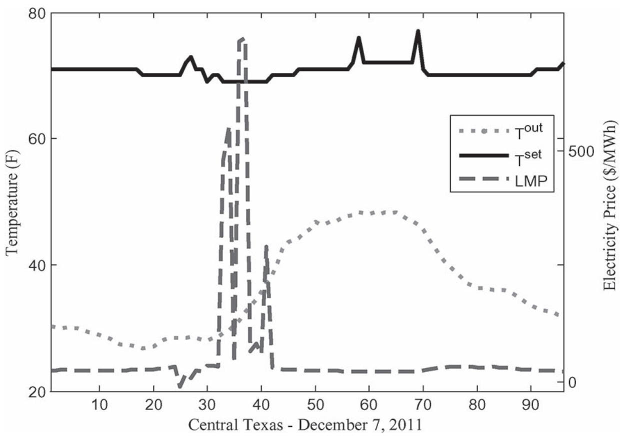

Fig. 14. Outside temperature, temperature setting, and LMP as seen from a residential customer in central Texas on December 7, 2011, under the Steps of Temperature control strategy.

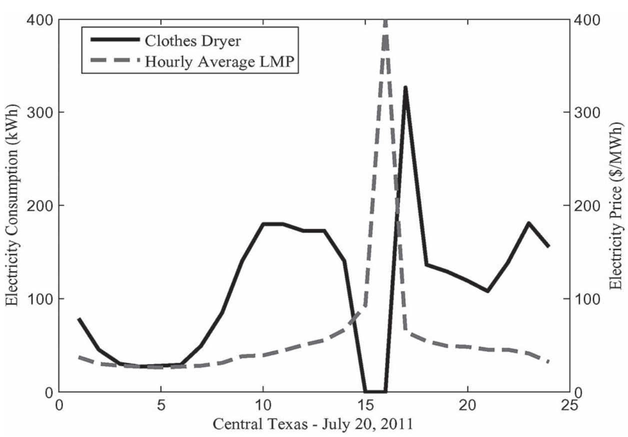

Fig. 15. Total clothes dryer electricity consumption for the 1000 customers with Price Naming load control and hourly average LMP in central Texas on July 20, 2011.

respectively. It can be noticed that the temperature setting will change depending on the real-time LMP.

On the other hand, the clothes dryer will operate following the Price Naming strategy. In this case, the price that lies on the 97.5th percentile of the LMP ($70/MWh) has been set as the threshold for operation, as shown in Fig. 15.

C. Load Control With PV and Energy Storage

The operation strategy introduced in Section V-B is implemented. ESS storage status and LMP are considered for the operation of PV and ESS. The hourly output curve of a Texas PV farm in the year 2011 is used for simulation. The energy capacity of the ESS is assumed as three times of the average hourly customer load consumption. The state of charge of the ESS is set between 20% and 80%.

The total load consumption and the powers supplied by the PV farm are shown in Fig. 16. The ESS energy status and LMP variation of a sample week in July is shown in Fig. 17. It is shown that the ESS is charged before high-LMP period and discharged during the peak hours.

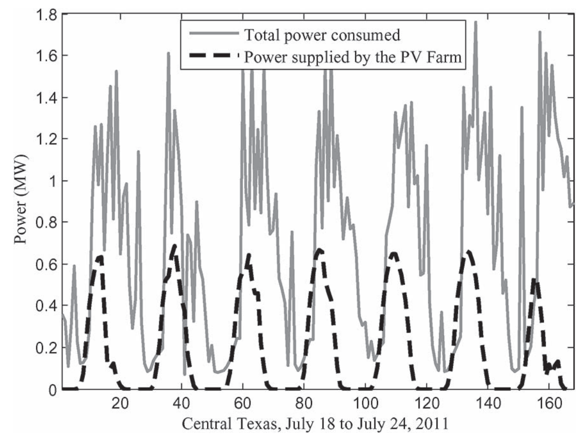

Fig. 16. Total load consumption and power supplied by the PV farm.

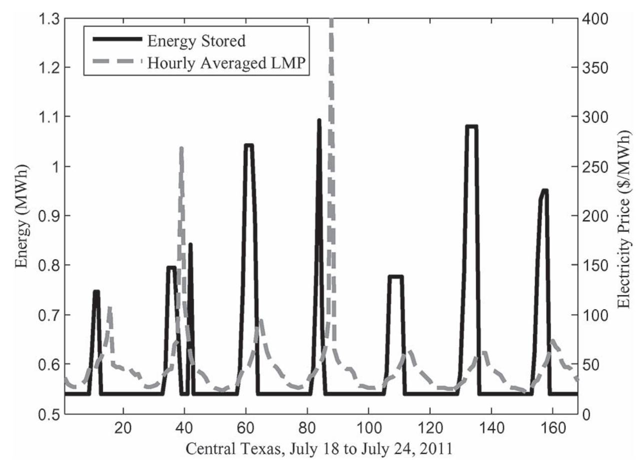

Fig. 17. Energy stored in ESS and LMP.

The operation strategy is simulated for the whole year of 2011. In summary, when no load control is performed during one-year operation, 1000 customers will consume 7183 MWh, which represents a cost of $0.42 million. After implementing the load control strategies of Steps of Temperature for the ACs/heaters and Price Naming for the clothes dryers, the annual consumption is 7067 MWh, with a cost of $0.38 million.

Finally, when the group of customers utilizes renewable resources to meet its load through the PV power and ESS coupled with the load control strategies, they will consume from the grid 4939 MWh, which, in turn, represents $0.30 million. These simulation results are summarized in Table II.

The reduction of the total cost mainly comes from two sources: the decline of electricity usage from the grid and the avoidance of consuming electricity during peak hours. The average electricity prices drawn from the grid in three different cases are calculated and compared in Table II as well, where the average electricity price is reduced by more than $6/MWh in the load control case, with PV power and energy storage available.

VII. CONCLUSION

While sustaining the reliability and maintaining the operation efficiency of the grid are the principal missions of ERCOT, DR

TABLE II
RESULTS OF THE SIMULATIONS

Strategy	Annual Electricity Consumption Drawn from the Grid (MWh)	Total Cost (Millions of $)	Average Electricity Price Drawn from Grid ($/MWh)
No Load Control	7183.3671	0.4205	58.538
Load Control: Steps of Temperature, Price Naming	7067.0862	0.3826	54.138
Load Control with PV Power and Energy Storage	5994.7382	0.3145	52.463

programs provide a new way to ensure that sufficient resources are committed in the electricity market. SB 1125 proposes the expansion of DR programs to residential and commercial customers while the reliability standards are maintained. With the vision that DR will be expanded to residential customers in the foreseeable future, an idea of aggregating a number of residences to shift the coincidental peak load by adopting different operation strategies is proposed. This study develops different operation strategies for the most representative residential load types, including ACs/heaters, clothes dryers, and refrigerators.

When real-time LMP information is taken into consideration, by grouping the residential appliances into controllable and uncontrollable loads and designing corresponding operation strategies for each load type, savings can be made for customers, and the load profiles are adjusted to facilitate system reliability.

With the utilization of solar power and ESS, PV output is used both for supplying load demand and saving energy to the ESS. The operation strategies are simulated for a whole year, and the annual costs are calculated and compared in this paper. The results show that participating in DR programs by doing load control and utilizing renewable resources, the total electricity cost can be reduced effectively, which suggests the effectiveness of the proposed approaches. Due to the available federal, state, and local incentive programs, the installation cost of PV and ESS becomes location dependent. Therefore, this paper studies the operation strategies without considering their installation and operation costs. One has to consider the actual installation and operation cost and other potential opportunities when implementing this option.

REFERENCES

[1] ERCOT History, 2005. [Online]. Available: http://www.ercot.com/about/profile/history/

[2] "Load participation in the ERCOT nodal market—Financial opportunities for reducing electricity load, demand-side working group of the ERCOT wholesale market subcommittee," Elect. Rel. Council Texas, Taylor, TX, USA, Jun. 11, 2007.

[3] J. W. Zarnikau, "Demand participation in the restructured electric reliability Council of Texas market," *Energy*, vol. 35, no. 4, pp. 1536–1543, Apr. 2010.

[4] "Benefits of demand response in electricity markets and recommendations for achieving them," U.S. Dept. Energy, Washington, DC, USA, Feb. 2006.

[5] D. Phillips, "Nodal pricing basics," Independent Elect. Market Oper., Toronto, ON, Canada, Jan. 14, 2014.

[6] H. Farhangi, "The path of the smart grid," *IEEE Power Energy Mag.*, vol. 8, no. 1, pp. 18–28, Jan./Feb. 2010.

[7] M. Ilic *et al.*, "Potential benefits of implementing load control," in *Proc. IEEE Power Eng. Soc. Winter Meet.*, 2002, vol. 1, pp. 177–182.

[8] S. Datchanamoorthy *et al.*, "Optimal time-of-use pricing for residential load control," in *Proc. IEEE Int. Conf. SmartGridComm*, 2011, pp. 375–380.

[9] Texas Legislature, May 28, 2011. [Online]. Available: http://www.capitol.state.tx.us/BillLookup/History.aspx?LegSess=82R&Bill=SB1125

[10] D. Pengwei and L. Ning, "Appliance commitment for household load scheduling," *IEEE Trans. Smart Grid*, vol. 2, no. 2, pp. 411–419, Jun. 2011.

[11] "Annual energy outlook 2012 with projections to 2035," U.S. Energy Inf. Admin., Washington, DC, USA, Jun. 2012.

[12] "Locational marginal pricing (LMP): Basics of nodal price calculation," California ISO, Folsom, CA, USA, Dec. 2005.

[13] H. Wizard, Where Your Home Energy Goes. [Online]. Available: http://www.home-wizard.com/how-to-guide/other-home-safety-savings/energy-audits/articles-videos/home-energy-use-guide.aspx

[14] P. Constantopoulos *et al.*, "ESTIA: A real-time consumer control scheme for space conditioning usage under spot electricity pricing," *Comput. Oper. Res*, vol. 18, pp. 751–765, 1991.

[15] A. A. Thatte and X. Le, "Towards a unified operational value index of energy storage in smart grid environment," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1418–1426, Sep. 2012.

[16] G. Benmouyal *et al.*, "IEEE standard inverse-time characteristic equations for overcurrent relays," *IEEE Trans. Power Del.*, vol. 14, pp. 868–872, 1999.

[17] Weather Underground. [Online]. Available: http://www.wunderground.com/

[18] S. Tiptipakorn and W.-J. Lee, "A residential consumer-centered load control strategy in real-time electricity pricing environment," in *Proc. 39th NAPS*, 2007, pp. 505–510.

[19] S. Tiptipakorn *et al.*, "Price naming on home appliance load controls in real-time pricing environment," in *Proc. IEEE Power Energy Soc. Gen. Meet.*, 2010, pp. 1–6.

[20] For Deeper Discounts—Name Your Own Price®. [Online]. Available: http://www.priceline.com/

[21] Name Your Price® Tool. [Online]. Available: http://www.progressive.com/auto/progressive-car-insurance-name-your-price/

[22] Northwest Power and Conservation Council, End Use Load and Consumer Assessment Program (ELCAP). [Online]. Available: http://rtf.nwcouncil.org/ELCAP/

[23] B. Hendron and C. Engebrecht, "Building America house simulation protocols," Nat. Renew. Energy Lab. U.S. Dept. Energy Build. Technol. Program, Golden, CO, USA, Oct. 2010.

[24] Mueller Silent Market. [Online]. Available: http://muellersilentmarket.com/2011/11/muellers-gone-solar/

[25] UT Arlington News Letter. [Online]. Available: http://www.uta.edu/news/releases/2012/08/solar-monitoring.php

[26] "Decision adopting energy storage procurement framework and design program," California Public Utilities Commission (CPUC), San Francisco, CA, USA, 2013. [Online]. Available: http://www.cpuc.ca.gov/PUC/energy/electric/storage.htm

[27] "Oncor proposes giant leap for grid, batteries," Dallas Morning News, Dallas, TX, USA, 2014.

[28] Y. Peizhong *et al.*, "Real-time opportunistic scheduling for residential demand response," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 227–234, Mar. 2013.

Meng Liu (S'12) received the B.S. degree from Shandong University, Jinan, China, in 2010, and the Ph.D. degree from The University of Texas at Arlington, Arlington, TX, USA, in 2014, both in electrical engineering.

Her areas of interest are renewable energy, energy storage, and energy storage integration to the smart grid.

Franklin L. Quilumba (S'10–M'14) received the Diploma degree in electrical engineering from the National Polytechnic School (Escuela Politecnica Nacional EPN), Quito, Ecuador, in 2008, and the M.S. and Ph.D. degrees in electrical engineering from The University of Texas at Arlington (UTA), Arlington, TX, USA, in 2014.

He was a Postdoctoral Research Associate with the Energy Systems Research Center at UTA. In 2014, he joined the faculty of the National Polytechnic School, where he currently holds the rank of Associate Professor. His areas of interest are power systems analysis, operation, stability, and control; computer simulation of electric power systems; power load modeling; generation and transmission planning; demand response; and load forecasting.

Wei-Jen Lee (S'85–M'85–SM'97–F'07) received the B.S. and M.S. degrees from National Taiwan University, Taipei, Taiwan, in 1978 and 1980, respectively, and the Ph.D. degree from The University of Texas at Arlington, Arlington, TX, USA, in 1985, all in electrical engineering.

In 1985, he joined The University of Texas at Arlington, where he is currently a Professor in the Department of Electrical Engineering and the Director of the Energy Systems Research Center. He has been involved in research on power flow, transient and dynamic stability, voltage stability, short circuits, relay coordination, power quality analysis, renewable energy, and deregulation for utility companies.

Prof. Lee is a Registered Professional Engineer in the State of Texas.