Residential Appliances Direct Load Control in Real-Time Using Cooperative Game

Qiang Cui, Xiuli Wang, *Senior Member, IEEE*, Xifan Wang, *Fellow, IEEE*, and Yue Zhang

***Abstract*—The relatively fixed residential day-ahead real-time electricity price reflects insufficient information of the market, so the response of residential energy management system (EMS) to the real-time pricing (RTP) is not complete and therefore retailers are exposed to the risk of price fluctuation in balance market. Direct load control (DLC) in cooperative game is proposed in this paper. A cooperative game union comprised of some users and a retailer is established to minimize the union costs. The union provides an opportunity to access the balance market indirectly for residents and to reduce risks and costs for the retailer. In addition, Shapley value which embodies the fairness is used in union profits allocation. The method that avoids bidding for residential users simplifies the thresholds of residents to participate in market. Furthermore, the DLC union contributes to imbalance self-management for the retailer, which helps him avoid paying for the regulation cost involved in the deviation between the total quantity bought at markets and the actual consumption. The achievement of union's goal respects the constraints set by users. The method that alleviates the disturbance of DLC to residents meets the dual goals of being both fully responsive and non-disruptive.**

***Index Terms*—Cooperative game, direct load control, power market, smart grid.**

I. Introduction

THE recent evolution of the power systems towards a deregulated market environment together with a smart grid integrated of advanced metering infrastructure (AMI) and communication technologies is offering residential customers a way to access markets. With AMI and other emerging grid "cyber-infrastructure" developments, it is becoming increasingly feasible to provide the system services and to integrate retail demand-side capabilities into wholesale energy markets by control loads [1], [2]. The participation of residential users in demand response programs, such as direct load control, will play an important role in providing ancillary services and promoting the prosperity of power market.

Conventionally, the controlled objects of DLC are large business users equipped with high-power electrical appliances, such as heating ventilation air conditioning (HVAC), etc. DLC of ordinary residents are ignored because of the difficulties and the high cost of control. Power markets are often inefficient and not fully competitive, in part because retail-customer loads do not participate in the markets. Electricity costs vary substantially from hour to hour, often by a factor of ten within a single day. As most customers buy electricity as they always have—under time-invariant prices that are set days or months even years ahead of actual use, consumers are fully insulated from the volatility of wholesale electricity markets [3]. The relatively fixed price makes the retailer exposed to the risk in power market. The impressive strides made in metering and load control technologies enable the utility or load serving entity to maintain a continuous two-way communication with its customers' appliances, in real time. Therefore, more recently, utility as well as independent system operator (ISO) has focused their interest on the potential of demand response in the residential and small commercial sectors [4]. Thermostatically controlled loads (TCL), such as refrigerators, air conditioners(ACs), and electric water heaters, etc., and plug-in hybrid electric vehicles (PHVEs) are popular controlled objects and excellent candidates to DLC implemented in residential sector [5]–[9]. Recently, as a new building material, phase change energy storage material (PCM), has raised concern in the field of demand response [10].

DLC is a common load management program to shape the load curve to increase the system reliability and reduce the system operating cost. The coordination between DLC dispatch and unit commitment was discussed and a method for DLC dispatch with the objective of minimizing system operational costs was present in [11]. Reducing system peak and the peak-to-average ratio (PAR) in load demand were the main DLC objectives to improve system operating efficiency [12], [13]. Normally, economy and comfort are contradictory. The disturbance of the DLC to users was taken into consideration, and a multi-objective method was used to trade-off the contradiction between the economy and comfort in [14] and [15]. A DLC scheduling algorithm was discussed and a modified genetic algorithm (GA) called iterative deepening GA (IDGA) was proposed in [16]. However, centralized DLC leads to high operating costs and has been a factor in recent reductions in the amount of emergency demand responses available to regional transmission system operators [17].

Electricity demands, with the advantages of fast reaction, smooth activation, low expected costs, and well-dispersed in the distribution grid, are potential candidates to provide auxiliary service, such as frequency regulation [18]–[21]. Most researches concerned on control strategy research after load

Manuscript received May 27, 2014; revised October 05, 2014 and December 18, 2014; accepted January 03, 2015. Date of publication February 12, 2015; date of current version December 18, 2015. This work was supported by the State Grid Corporation Technology Program (No. DZN17201300045). Paper no. TPWRS-00717-2014.

The authors are with the School of Electrical Engineering, Xi'an Jiaotong University, Xi'an, China (e-mail: cui-qiang@hotmail.com; xiuliw@mail.xjtu.edu.cn).

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/TPWRS.2015.2391774

imbalance or the high price incident. In fact, the main reason of the imbalance is the fluctuations of demands. Therefore, it is very important to balance the market clearing quantity and the actual consumption at the retailing side in new markets. The offering-generation and bidding-consumption imbalance management implemented on both generation and demand sides of the market can reduce the system's imbalanced power.

The development of communication technology makes the information interaction more convenient. Based on the two-way communication technology platform, a real-time optimization approach for two-way direct load control of central air-conditioning chillers was proposed in [22]. Furthermore, automatic power control (APC) is expected to be accomplished in the household equipped with intelligent electrical appliances and EMS. According to the real-time electricity price information, EMS supervises energy consumption scheduling under the constraints set by users. Reducing household electricity bill was a common management objective of APC [23], [24]; an autonomous and distributed demand-side energy management system among users that used game theory was present in [25]. However, the incentive to cooperate with users was a simple pricing mechanism that lacked of consideration about new market environment.

It is important to design the compensation scheme in the new operating environment [26]. Demand side bidding is a common compensation mode used in large consumers [27]. Usually, regional transmission organization (RTO) dispatches the load of which the bidding is the lowest and gives corresponding compensation. However, working out an optimal bidding strategy is difficult for generators and large consumers, let alone residents. The implementation of demand side bidding by residents causes inconvenience to RTO as well as residents.

Aiming at issues mentioned above, this paper presents a DLC model in cooperative game between residents and a retailer. The model proposes an agent mechanism that residential appliances would be controlled by the retailer. It is feasible way that collaborating with retailer to comprise larger entity to access the market for residents. Distributing residential load control to retailers reduces DLC scale in residents. In order to simplify the thresholds for residents to participate in DLC program in competitive market, the compensation method that union profit allocation based on cooperative game was proposed. Demand side resources involvement will make the market more competitive and efficient.

The motivation of this paper is to provide indirect opportunities to access balance market for residential users, and to reduce risks for the retailer and costs for all the members in the union. In addition, building this union can achieve power balance between the electricity purchasing and consumption at the retail side, and eliminate the inconvenience caused by the implementation of demand biding to residents.

II. Direct Load Control in Cooperative Game

We take NordPool as an example. Bids for each of the 24 contract periods must be submitted to NordPool before noon, as presented in the timeline in Fig. 1. Then, household EMS calculates the optimal power schedule to minimize the electricity bill within constrains set by the user after reception of

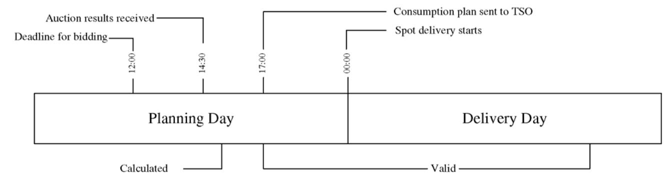


Fig. 1. NordPool's spot market timeline.

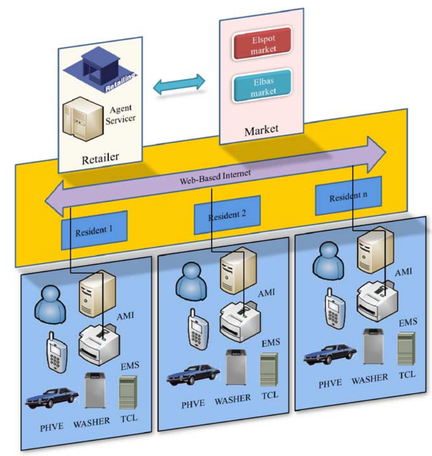


Fig. 2. DLC framework.

the price information. The household controlled objects include TCL, PHVE, washer, etc.

Day ahead RTP, which is hypothetical tariff to residents by default and is adjusted once a day, reflects Elspot market (day-ahead spot market) state. The household EMS only respond to day-ahead market. As Elbas market (hour-ahead balance market) price information isn't available for residents, the demand response in residents cannot fully reflect the costs of production. Therefore, the retailer bears the risk of price fluctuation completely in Elbas market and markets operate inefficiently.

As an agent of the union, retailer controls union load directly. On one hand, users can access the balance market indirectly and benefit from the market. On the other hand, the retailer can reduce the market costs and risks effectively. The union DLC framework is shown in Fig. 2. Residents in the union will sent control constrains to the retailer's agent servicer, such as the indoor temperature at sample point, PHVE during charging time, charging and washing time interval, etc. The control constrains set by customers can alleviate the DLC disturbance to them. The Retailer, with the target to minimize cost, plans the power scheduling and coordinates controlled appliances in the union, according to Elbas forecast price information. As the price in balance market is adjusted hourly and the bilateral deal is allowed, the union load scheduling can be adjusted more in real-time according to the latest price information. In this way, the demand responses in residents can respond not only to Elspot market price but also to the Elbas'. As loads can be adjusted according to the price fluctuation, the profit will be increased and the risk will be reduced.

The union profits are allocated daily. In cooperation game, Shapley value method is widely used in profits allocation.

Shapley value emphasizing fairness allocates profits to the union members as the marginal contribution to the union profits [28]. The union profits allocation that removes the process of direct market bidding of residents is more likely to implement in residents.

III. Model

Many existing peak demand management programs that utilize direct load control are disruptive and can have significant impacts on the end user. Load control schemes must meet the dual goals of being both fully responsive and non-disruptive [1]. In the cooperative game, let $\boldsymbol{N}$ denote union, $\boldsymbol{S}$ denote any coalition in the union, where $\boldsymbol{S} \subseteq \boldsymbol{N}$, and i denote any member in the union. In control model, the constraint conditions are set by users in person, So that the control objective is achieved non-disruptively.

A. Household Appliances Model

Household appliances are controllable load including TCL, PHVE, washer and dryer, dishwasher, etc. They become an important kind of object of DLC because of their ability to store and shift energy.

1) Individual TCL Model: We model the temperature state evolution of an individual TCL with a discrete time difference equation used in [5] and [8]:

$$\theta_i(t+1) = a_i\theta_i(t) + (1-a_i)\left(\theta_{a,i}(t) - x_{i,c}(t)\theta_{g,i}\right) + \varepsilon_i(t) \quad (1)$$

where $\theta_i(t)$ is the indoor temperature at time step t, θ_a is the ambient temperature, and ε is a noise process. The dimensionless TCL parameter a_i equals $e^{-h/(C_iR_i)}$, where C is a TCL's thermal capacitance, R is its thermal resistance, and h is the simulation time step. $\theta_{g,i}$, the temperature gain when a TCL is ON, equals $R_iP_{trans,i}$, where P_{trans} is a TCL's energy transfer rate, which is positive for cooling TCLs and negative for heating TCLs according to our conventions. The power consumed by TCL when it is on, P_i, is equal to $|P_{trans,i}|/COP_i$, where COP is its coefficient of performance (COP). The control variable $x_{i,c}$ is a dimensionless discrete variable equal to 1 when the TCL is ON and 0 when the TCL is OFF.

For each user $i \in S$ at time $t \in (\alpha_{i,c}, \beta_{i,c})$, the sample temperature is within the tolerance of set temperature deviation. Let $\theta_{set,i}$ denote the temperature set point, and δ_i denote the dead-band width:

$$\theta_{set,i} - \delta_i/2 \leq \theta_{i,t} \leq \theta_{set,i} + \delta_i/2 \, \forall i \in \boldsymbol{S}, t \in (\alpha_{i,c}, \beta_{i,c}). \quad (2)$$

2) PHVE Model: For each user i, the predetermined total daily energy consumption is E_i. For example, A PHEV needs 16 kWh to cover a distance of 40 miles daily [2]. The user needs to select the beginning $\alpha_{i,v} \in T$ and the end $\beta_{i,v} \in T$ of a time interval that PHVE can be scheduled. Clearly, $\alpha_{i,v} < \beta_{i,v}$. For example, a user may select 8:00 PM and 7:00 AM for its PHEV to have it ready before going to work, out of this interval, PHVE is in work state and charging is prohibited. We assume that the charging power is constant during the charging period. The charged capacity of a PHVE needs to meet its required predetermined daily consumption. Therefore, we have the following equation:

$$P_{Rv} \sum_{t=\alpha_{i,v}}^{\beta_{i,v}} x_{i,v}^t = E_i - SoC_i \, \forall i \in \boldsymbol{S} \quad (3)$$

and

$$x_{i,v}^t = 0, \quad \forall i \in \boldsymbol{S}, \forall t \in T \backslash T_{i,v} \quad (4)$$

where P_{Rv} denotes charging power, SoC denote state of charge, T denote load control horizon, and $T_{i,v} \triangleq \{\alpha_{i,v}, \cdots, \beta_{i,v}\}$ denote the enabled charging time. The control variable $x_{i,v}$ is a dimensionless discrete variable equal to 1 when charging and 0 when waiting.

The duration of charging denoted by VT_i is set up to prolong the service life of batteries:

$$\sum_{k=t}^{t+VT_i-1} x_{i,v}^k \geq VT_i\left(x_{i,v}^t - x_{i,v}^{t-1}\right) \quad \forall i \in \boldsymbol{S}, t \in T. \quad (5)$$

3) Washer Model: The user needs to select the beginning $\alpha_{i,w} \in T$ and the end $\beta_{i,w} \in T$ of a time interval that WASHER can be scheduled. The washing process usually needs to be finished in the duration WT_i without interruption, that is

$$\sum_{t=\alpha_{i,w}}^{\beta_{i,w}} x_{i,w}^t = WT_i \quad \forall i \in \boldsymbol{S} \quad (6)$$

and

$$\sum_{k=t}^{t+WT_i-1} x_{i,w}^k \geq WT_i\left(x_{i,w}^t - x_{i,w}^{t-1}\right) \quad \forall i \in \boldsymbol{S}, t \in T \quad (7)$$

$$x_{i,w}^t = 0, \quad \forall i \in \boldsymbol{S}, \forall t \in T \backslash T_{i,w} \quad (8)$$

where the control variable $x_{i,w}$ is a dimensionless discrete variable equal to 1 when washing otherwise 0. $T_{i,w} \triangleq \{\alpha_{i,w}, \cdots, \beta_{i,w}\}$ denote the enabled washing time.

B. Retailer's Settlement Model

Normally, the generating process is relatively stable and the unit can follow the automatic generation control (AGC) instruction to produce. Unit failure rate is very low. Even outage appears, the load can be balanced by other units and the regulation cost is easy to calculate. However, load fluctuation in consumption is relatively frequent, and the regulation cost is not easy to calculate. Most regulation cost is caused by load fluctuation, so the retailer should pay for the additional cost involved in the deviation between market clearing quantity and the actual consumption.

Functioning as a balancing market to the Elspot day-ahead market, Elbas offers opportunities to reduce risk and increase profit. Elbas plays an important complementary role in creating an efficient power market. It offers an alternative to the balancing market for all or some of the imbalances a member may have after the day-ahead trades are final.

The income of producer was defined in [29]. Here, the cost of retailer is comprised of Elspot cost, Elbas cost, and regulation cost:

$$C_t = S_t^P S_t^D + E_{t-1}^{P,B} E_{t-1}^{Q,B} + R\left\{S_t^D - S_{t'}^Q - E_t^{ND}\right\} \quad (9)$$

where $E_{t-1}^{P,B}$ denote the price of energy bought at Elbas in hour $t-1$ and $E_{t-1}^{Q,B}$ denote the quantity bought at Elbas in hour $t-1$; S_t^P denote the Spot market price when energy is delivered, S_t^D denote energy delivered from the spot market and $S_{t'}^Q$ denote the quantity bid in the Spot market at time t'; E_t^{ND} denote energy not delivered from the Elbas market and $R\{e\}$ denote the regulation cost.

The regulation cost function is defined as

$$R\{e\} = \begin{cases} R_t^U e & e \geq 0 \text{ (Up regulation)} \\ -R_t^D & e < 0 \text{ (Down regulation)} \end{cases} \quad (10)$$

where e is the deviation between market clearing quantity and the actual consumption. It is defined as

$$e = l_t - \left(E_{t-1}^{Q,B} + S_{t'}^Q\right) \quad (11)$$

where l_t is the electricity consumed by the union $\boldsymbol{N}$ at time t. Let $l_{S,t}$ denote the electricity consumed by the coalition $\boldsymbol{S}$ at time t, and $l_{C_N S,t}$ denote the electricity consumed by the set $C_N \boldsymbol{S}$ at time t, which is the complementary set of $\boldsymbol{S}$. A_i denotes the set of household appliances such as washer and dryer, refrigerator, dishwasher, AC, PHEV, etc.:

$$l_t = l_{C_N S,t} + l_{S,t} \quad (12)$$

and

$$l_{S,t} = \sum_{i \in S} \sum_{a \in A_i} x_{i,a}^t P_{R,a}. \quad (13)$$

Energy delivered from the spot market is defined to be

$$S_t^D = \begin{cases} 0 & \text{when } l_t < E_{t-1}^{Q,B} \\ l_t - E_{t-1}^{Q,B} & \text{when } l_t \geq E_{t-1}^{Q,B} \end{cases} \quad (14)$$

and energy not delivered from the Elbas market is defined to be

$$E_t^{ND} = \begin{cases} 0 & \text{when } l_t \geq E_{t-1}^{Q,B} \\ E_{t-1}^{Q,B} - l_t & \text{when } l_t < E_{t-1}^{Q,B}. \end{cases} \quad (15)$$

The additional regulation cost is based on the deviation between the total quantities bought at two markets and the actual consumption. When the actual consumption equals to the total quantities, there is no regulation cost. If the actual consumption is greater than the total quantities, units load have to be adjusted upward, and the retailer needs to pay for up regulation cost and vice versa, shown as Fig. 3.

C. Cooperative Game Model

Under RTP day-ahead, the demand response to the cost of power market is not fully responsive. Retailers undertake the entire risk in the balance market so that the market is inefficient. In

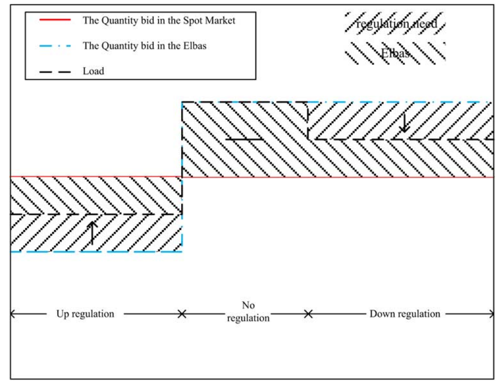


Fig. 3. Regulation problem.

the union, the retailer can schedule power consumption within the constraints set by users to reduce the union bought electricity costs. Then, union profits would be allocated for all union members.

1) Optimization Problem: Electricity payments between retailer and users are counterbalanced within the union, so the union electricity cost C_N is electricity purchasing cost of retailers in the market. We are now ready to formulate the energy consumption scheduling problem of the union as the following optimization problem:

$$\min\ C_N = \sum_{t \in T} E_{t-1}^{P,B} E_{t-1}^{Q,B} + S_t^P S_t^D + R\left\{S_t^D - S_{t'}^Q - E_t^{ND}\right\} \quad (16)$$

subject to the following constraints:

For retailer, the quantity sold at Elbas will be limited in the quantity biding in the Spot market:

$$E_{t-1}^{Q,B} \geq -S_{t'}^Q. \quad (17)$$

For each TCL, that will satisfy the temperature constraints in (2). For each PHVE, that will satisfy constraints in (3), (4), and (5). For each washer, that will satisfy constraints in (6), (7), and (8).

2) Profits Allocation: The profits of each coalition $\boldsymbol{S} \subseteq \boldsymbol{N}$ is denoted by $v(\boldsymbol{S})$, and defined as the decrement in electricity purchasing cost of the coalition denoted by $C(\boldsymbol{S})$. There are not union profits if no player accesses balance market besides the retailer. Clearly, only the coalition including the retailer can produce profits, because the retailer is the only agent in the union to access balance market. The profits of members are allocated according to Shapley value, which are formulated as the following equations:

$$v(\boldsymbol{S}) = C(\emptyset) - C(\boldsymbol{S}) \quad (18)$$

and

$$\varphi_i(v) = \sum_{\boldsymbol{S} \subseteq N \setminus i} \frac{s!(n-s-1)!}{n!} \left(v(\boldsymbol{S} \cup i) - v(S)\right) \quad (19)$$

where $\varphi_i(v)$ denote the allocated profits value of the member i, n, and s are amounts of members in the union $\boldsymbol{N}$ and in the coalition $\boldsymbol{S}$, respectively.

D. EMS Model

Household EMS plans the energy consumption scheduling of all appliances to reduce the user's total electricity payment denoted by F, within the upcoming scheduling horizon. The problem is obtained as

$$\min \quad F = \sum_{t\in T}\sum_{a\in A_i} p_t x_{t,a} P_{R,a}. \tag{20}$$

The appliances will satisfy the constraints in (3)–(8).

IV. Algorithm and Dynamic Adjustment

A static decision-making consist in scheduling switches status of appliances and developing an Elbas bidding strategy for a upcoming time, according to the electricity price forecasting. Actually, the market forecasting information change from hour to hour as the new data adds. Thanks to bilateral deal, retailer may adjust the current scheduling dynamically in advance to respond to the change of market information. During actual operation, the retailer predicts Elbas price every hour. The forecasting model used here is ARIMA electricity price forecasting model in [30]. Based on price forecasting together with the bilateral deal plan, scheduling of appliances' switch and Elbas bidding strategy of retailer for a upcoming time are formulated and adjusted constantly. In the coming hour, appliances will be controlled according to the latest scheduling. The specific process is as follows:

a) Update the forecasting data of electricity price in balance market.
b) Update parameters of the existing model, such as PHVE remaining energy, current switch state, etc.
c) Solve the decision-making model
d) Adjust the energy consumption scheduling and bidding strategy.
e) Control appliances in the union according to the latest scheduling in the coming hour.
f) Allocate the union profits after the scheduling of the whole day has been delivered.

Algorithm of the DLC model in cooperative game was coded with Matlab, and called for Cplex to solve the decision making process. Program flow chart is shown in Fig. 4.

V. Simulation Results

In this section, we present simulation results. In our considered benchmark, there are $n = 6$ members in the union including one retailer and five customers/users who subscribe for the DLC services. We assume that each user has 3 appliances with transferable loads, that is to say, with soft energy consumption scheduling constraints set by users. Such appliances may include ACs (rated power: 4 kW), PHVEs (rated power: 5 kW, daily usage: 15 kWh), washer (rated power: 0.6 kW), etc. In addition, we take some fixed loads into account, which are uncontrollable. It is reasonable to assume that most users have electric cars to be charged sometime from late afternoon to early morning of the next day. For simplicity, we assume that $\alpha_{i,v} = 20:00, \beta_{i,v} = 7:00$ for all PHVEs and $\alpha_{i,w} = 21:00, \beta_{i,w} = 7:00$ for all washers. The indoor temperature is set at 27°C with a tolerance of ±1°C, but there are diversities in the sample time. Of course, parameters of user's

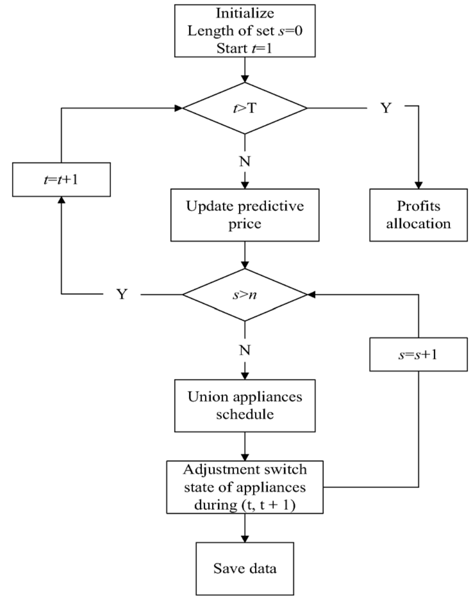


Fig. 4. Program flow chart.

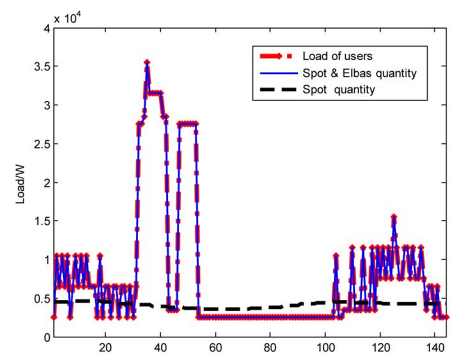


Fig. 5. Users' power scheduling and retailer's purchasing strategy in balance market when not allied.

EMS can be set according to the actual situation. The horizon of DLC is from 17:00 to 17:00 of the next day with a step of 10 min.

Fig. 5 shows the power scheduling of the 5 users when they are not in the union and corresponding strategy of retailer in the balance market. In this situation, users' load is controlled by their EMS rather than the retailer. EMS schedules consumption according to Elspot price to achieve a minimum electricity payment. So the retailer cannot change actual consumption but regulate the bidding strategy in balance market. The regulation cost is so high that the retailer has to buy or sale energy in balance market to balance the deviation between the quantities bought at Elspot market and the actual consumption. The retailer's passive strategy to follow the fluctuation of load makes him avoid paying for the regulation cost but exposed to the risk of unstable price in balance market. What is more, users can only respond to spot price to reduce electricity payment, so they can't get benefits from balance market.

The load is transferable when residents ally with retailer, as shown in Fig. 6. Without the union, most residents' loads concentrate upon the off-peak of RTP, which is the response to the

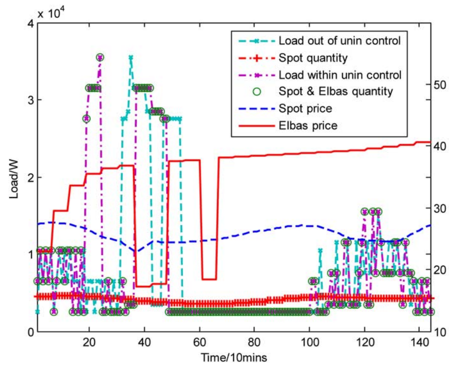


Fig. 6. Comparison between residents allied with retailer or not.

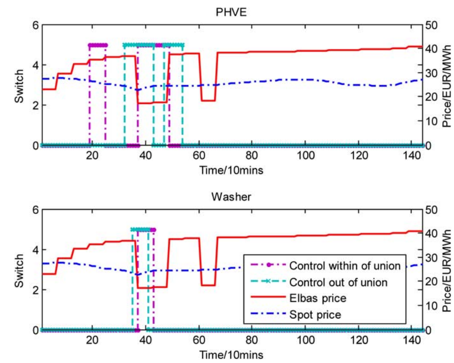


Fig. 7. Final PHVEs charging scheduling and washers control strategy scheduling.

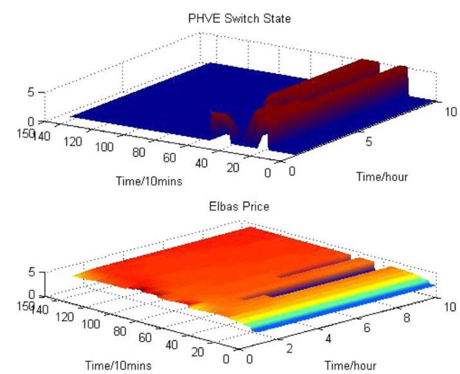


Fig. 8. Dynamic PHVEs charging scheduling.

day-ahead market. With the union, appliances can be control by the retailer within the constraints set by the user. The retailer can't only strategically buy or sale energy in balance market to avoid paying for regulation cost, but also strategically adjust consumption scheduling to increase union profits. In addition, bilateral deal, of which the agreed price is much lower at given time, was allowed in the balanced market, so surplus controllable load can be shifted to the time to reduce the union cost. Through union agent direct control load, users can not only respond to a day-ahead market but also respond to a more real-time balance market. It meets the dual goals of being both fully responsive and non-disruptive and increases the market activity. Regulation cost is avoided due to the fact that the amount of energy bought in markets equals to the actual consumption at any time. It also meets the goal to achieve self-management of the imbalance between the quantities bought at markets and the actual consumption in the union.

PHVEs may be charged from 8:00 PM to 7:00 AM of the next day, which is denoted by 19–84 (with a step of 10 min). Here, 1 indicates 17:00 (the start time for DLC). SoC is 0 initially for all PHVEs, so charging time need is 3 h. Fig. 7 compares PHVEs charging states and washers control strategy when it is controlled by agent with the union and by EMS without the union. The charging time of PHVEs controlled by EMS is on RTP off-peak while it is on off-peak of the comprehensive price of RTP and Elbas when it is controlled by the agent. The washers control strategy is similar to that of PHVEs, except that the washing time is 1 h. Fig. 8 describes the dynamic charging scheduling in the union control mode. Capture time of lowest electricity price signal is an important factor that affects PHVEs charging scheduling. At the first scheduling time (17:00), the Elbas price of 19–24 (20:00–21:00) and 43–54 (0:00–2:00) is the lowest. Therefore, the charging time is scheduled preliminarily at these three hours. At this time, the charging energy hasn't been delivered from market, so the retail can still adjust the scheduling according to subsequent price changes. After 2 hours, it is the time to make the third scheduling. As the Elbas price becomes lower on 19–36 (20:00–23:00), the charging time is rescheduled for this period and it hasn't started yet. At 20:00, we assume that retailer makes a deal with wind farm at a low price for 43–48 (0:00–1:00), and some PHVEs charging time is shifted to this time. Therefore, the latest charging scheduling is adjusted to 19–30 (20:00–22:00) and 43–48 (0:00–1:00). Due to the validation of the agreement, the charging time on 0:00-1:00 is forbidden to adjust and the charging time that can be scheduled reduces to 2 h. In addition, it is the time to implement the scheduling on 20:00-21:00, and the charging time that can be scheduled reduces to 1 hour. According to the subsequent price changes, PHVEs charging scheduling has been adjusted correspondingly. All PHVEs charging task is completed at 1:00 and the final charging time is 19–24 (20:00–21:00) and 37–48 (23:00–1:00). Although the relative low price signal on 3:00–4:00 is captured when making scheduling at 23:00, the adjustable charging time remains only 1 h. Therefore, no charging scheduling is arranged on this period.

Fig. 9 depicts the AC control strategy of a user who sets sample temperature at 27°C between 14 and 37, under two kinds of control mode. The sample temperature at timing point concentrates in the upper bound of constraint when AC is controlled by EMS. While, the temperature changes more smoothly when the AC is controlled by the agent and the temperature at the upper bound of constraint is less than that of EMS mode. It alleviates the disruption to the user in the union and acquires a higher comfort level when AC is controlled by the agent. Clearly, total energy consumption is identical, but consumptive scheduling is different. The AC is started and stopped with a delay when it is out of union control, but in advance when it is within union control. AC load is shifted forward for 30 min from 35 to 32. The reason is that AC control strategy is response to nothing but Elspot price when AC is out of union control,

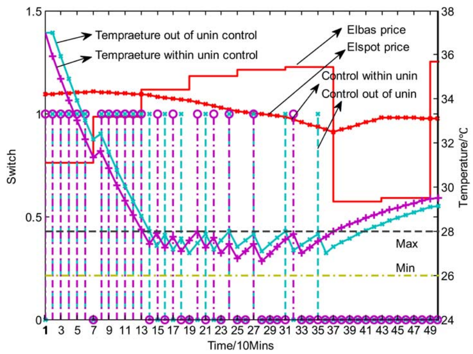


Fig. 9. Final AC control strategy scheduling.

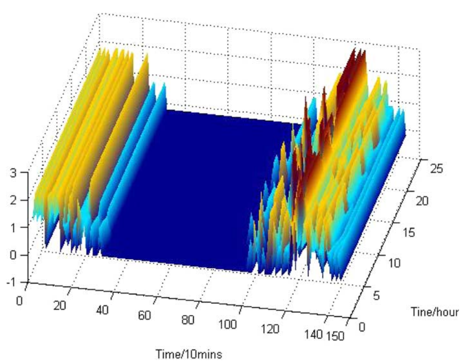


Fig. 10. Dynamic AC control state scheduling.

while it is comprehensive response to Elspot price and Elbas price within union control.

Fig. 10 depicts the dynamic adjustment of AC control state in the union. As shown in the figure, a small-scope fluctuation of the price in balance market causes a large-scope adjustment, which indicates that AC load is sensitive to electricity price. AC load is finally delivered to the compromised region of RTP and Elbas price in the Fig. 6. In the union, AC load can respond to two markets' price information. Clearly, the transferable ability of TCL is not as strong as that of PHVE. However, it has the potential in DLC within a tolerable temperature deviation.

VI. Union Profits Allocation

Table I lists the cost of coalitions $\boldsymbol{S}$ including retailer, in the union $\boldsymbol{N} = \{\text{Custom1, Custom2 and Custom3Custom4, Custom5, Retailer}\}$. Clearly, the cost will reduce with the enlargement of the scale of coalition, because the union can schedule more loads to the time interval of off-peak price.

Table II lists the allocated profits of members in the union. Only the coalition including retailer will have profits, because the retailer, as agent of the union, can access market directly. Therefore, the allocated profit of retailer is absolutely dominant in the union. Through allying with retailer, the user's electricity bill decreases about 4%. By cooperating with users, the retailer's absolute costs decreases 54% and it's relative costs reduces 7.56%. In the cooperative game union comprised of users and retailer, the retailer, as the agent of union, controls

TABLE I
Cost of Coalitions in the Union

Coalition	Costs (10^{-6}EUR)	Coalition	Costs (10^{-6}EUR)
{R}	5288491	{RC123}	5054388
{RC1}	5210442	{RC124}	5050851
{RC2}	5210548	{RC125}	5051501
{RC3}	5210369	{RC134}	5047517
{RC4}	5203687	{RC135}	5047005
{RC5}	5202217	{RC145}	5050663
{RC12}	5132500	{RC234}	5049941
{RC13}	5132548	{RC235}	5046381
{RC14}	5125745	{RC245}	5048086
{RC15}	5124275	{RC345}	5043065
{RC23}	5132655	{RC1234}	4969814
{RC24}	5125756	{RC1235}	4968343
{RC25}	5124285	{RC1245}	4967296
{RC34}	5125887	{RC1345}	4963560
{RC35}	5124417	{RC2345}	4962444
{RC45}	5117414	{RC12345}	4886296

TABLE II
Allocated Profits Value of Members in Union

Member		Value (10^{-6}EUR)	Payment (10^{-6}EUR)	Rate (%)
C1		38579	850836	4.5342
C2		38831	966288	4.0186
C3		40219	983075	4.0912
C4		41362	929917	4.4479
C5		42047	1054681	3.9868
Retailer	Absolute	2860375	5288491	54.0868
	Relative	201154.2	2659221	7.5644

household appliances directly. All members of the union benefit from balance market: users' electricity bills, retailers' costs and market risks are all reduced.

VII. Conclusion

In order to improve the market activity and efficiency, a DLC model in cooperative game among residential users and a retailer was proposed in this paper. A large entity composed of residential users and a retailer offers residents an opportunity to participate in market competition indirectly and benefit from it.

As agent of residents, the retailer strategically adjusts power scheduling and bidding strategy to respond to the market information dynamically. Through DLC of residential appliances in the union, the retailer balances the deviation between the quantities bought at markets and the actual consumption. In addition, disruptions of DLC to residents are alleviated because the goal is achieved completely within the boundaries of constrains set by residents. What's more, it is fair to allocate profits for members in the union according to their marginal contribution to union profits, and the method of union profits allocation based on Shapley value simplifies users' thresholds to access market. The method proposed in this paper offers the retailer an opportunity to reduce risk and increase profits.

Scheduling end-use loads lean on DLC actions alone is not adequate, some other control actions must be integrated with DLC, such as price response. Only taking multiple control actions can achieve an ideal effect to improve efficiency and decrease risk. There are many interesting and worthy future research directions to advance the residential appliances DLC approach in cooperative game. In the future, we plan to explore risk evaluation and management of DLC in cooperative game. In addition, the issue of maximizing individual profits in the union would be taken into account.

REFERENCES

[1] D. S. Callaway and I. A. Hiskens, "Achieving controllability of electric loads," *Proc. IEEE*, vol. 99, no. 1, pp. 184–199, Jan. 2011.

[2] A. Ipakchi and F. Albuyeh, "Grid of the future," *IEEE Power Energy Mag.*, vol. 7, no. 2, pp. 52–62, Mar.–Apr. 2009.

[3] E. Hirst and B. Kirby, Retail-load participation in competitive wholesale electricity markets, Edison Electric Inst. Washington, DC, USA, Jan. 2001, Tech. Rep.

[4] B. Ramanathan and V. Vittal, "A framework for evaluation of advanced direct load control with minimum disruption," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1681–1688, Nov. 2008.

[5] D. S. Callaway, "Tapping the energy storage potential in electric loads to deliver load following and regulation, with application to wind energy," *Energy Convers. Manage.*, vol. 50, no. 9, pp. 1389–1440, 2009.

[6] A. M. García, M. Kessler, J. A. Fuentes, and E. Gómez-Lázaro, "Probabilistic characterization of thermostatically controlled loads to model the impact of demand response programs," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 241–251, Feb. 2011.

[7] C. Perfumo, E. Kofman, J. H. Braslavsky, and J. k. Ward, "Load management: Model-based control of aggregate power for populations of thermostatically controlled loads," *Energy Convers. Manage.*, vol. 55, no. 3, pp. 36–48, 2012.

[8] J. L. Mathieu, S. Koch, and D. S. Callaway, "State estimation and control of electric loads to manage real-time energy imbalance," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 430–440, Feb. 2013.

[9] P. S. Martín, G. Sánchez, and G. M. España, "Direct load control decision model for aggregated EV charging points," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1577–1584, Aug. 2012.

[10] A. Waqar, C. Nirmal-Kumar, and M. Mohammed, "Demand side management through efficient thermal energy storage using phase change material," in *Proc. Power Engineering Conf.*, Sydney, Australia, 2008.

[11] J. M. Chen, F. N. Lee, A. M. Breipohl, and R. Adapa, "Scheduling direct load control to minimize system operational cost," *IEEE Trans. Power Syst.*, vol. 10, no. 4, pp. 1994–2001, Nov. 1995.

[12] C. N. Kurucz, D. Brandt, and S. Sim, "A linear programming model for reducing system peak through customer load control programs," *IEEE Trans. Power Syst.*, vol. 11, no. 4, pp. 1817–1824, Nov. 1996.

[13] H. T. Yang and K. Y. Huang, "Direct load control using fuzzy dynamic programming," *IEE Proc. Gener., Transm., Distrib.*, vol. 146, no. 3, pp. 294–300, May 1996.

[14] H. Jorge, C. H. Antunes, and A. G. Martins, "A multiple objective decision support model for the selection of remote load control strategies," *IEEE Trans. Power Syst.*, vol. 15, no. 2, pp. 865–872, May 2000.

[15] A. Gomes, C. H. Antunes, and A. G. Martins, "A multiple objective approach to direct load control using an interactive evolutionary algorithm," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1004–1011, Aug. 2007.

[16] L. Yao, W. C. Chang, and R. L. Yen, "An iterative deepening genetic algorithm for scheduling of direct load control," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1414–1421, Aug. 2005.

[17] C. D. Puckett, T. P. Hennessy, G. C. Heffner, and C. A. Goldman, "Regional approaches to measurement and verification of load management programs," *IEEE Trans. Power Syst.*, vol. 23, no. 1, pp. 204–212, Feb. 2008.

[18] X. Zhao, J. Østergaard, M. Togeby, and C. Marcus-Møller, "Design and modelling of thermostatically controlled loads as frequency controlled reserve," in *Proc. IEEE PES General Meeting.*, Tampa, FL, USA, 2007.

[19] J. A. Short, D. G. Infield, and L. L. Freris, "Stabilization of grid frequency through dynamic demand control," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1284–1293, Aug. 2007.

[20] X. Zhao, J. Østergaard, and M. Togeby, "Demand as frequency controlled reserve," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1062–1071, Aug. 2011.

[21] J. Kondoh, N. Lu, and D. J. Hammerstrom, "An evaluation of the water heater load potential for providing regulation service," in *Proc. IEEE PES General Meeting.*, San Diego, CA, USA, 2011.

[22] L. Yao and H. R. Lu, "A two-way direct control of central air-conditioning load via the internet," *IEEE Trans. Power Del.*, vol. 24, no. 1, pp. 240–248, Jan. 2009.

[23] A. H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 120–133, Sep. 2010.

[24] P. W. Du and N. Lu, "Appliance commitment for household load scheduling," *IEEE Trans. Smart Grid*, vol. 2, no. 2, pp. 411–419, Jun. 2011.

[25] A. H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.

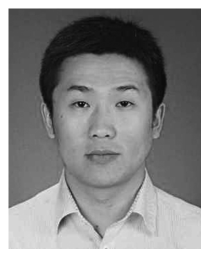
[26] Q. W. Wu, P. Wang, and L. Goel, "Direct load control (DLC) considering nodal interrupted energy assessment rate (NIEAR)in restructured power systems," *IEEE Trans. Power Syst.*, vol. 25, no. 3, pp. 1449–1455, Aug. 2010.

[27] F. S. Wen and A. K. David, "Optimal bidding strategies for competitive generators and large consumers," *Elect. Power Energy Syst.*, vol. 23, no. 1, pp. 37–43, 2001.

[28] D. Fudenberg and J. Tirole, *Game Theory*. Cambridge, MA, USA: MIT Press, 1991.

[29] U. Linnet, "Tools supporting wind energy trade in deregulated markets," Technical Univ. Denmark. Kgs. Lyngby, Denmark, 2005.

[30] J. Contreras, R. Espínola, F. J. Nogales, and A. J. Conejo, "ARIMA models to predict next-day electricity prices," *IEEE Trans. Power Syst.*, vol. 18, no. 3, pp. 1014–1020, Aug. 2003.



Qiang Cui was born in January 1985. He received the Bachelor's degree in electrical engineering from Changsha University of Science & Technology, Changsha, China, in 2008. He is currently pursuing the Ph.D. degree in electrical engineering from Xi'an Jiaotong University, Xi'an, China.

His research interests include power market and demand response.

Xiuli Wang (SM'14) was born in June 1961. She received the Master's and Ph.D. degrees from the School of Electrical Engineering, Xi'an Jiaotong University, Xi'an, China, in 1985 and 1997, respectively.

She is now a Professor at Xi'an Jiaotong University. Her research interests include power system planning, power market, and power system reliability.

Xifan Wang (F'08) was born in May 1936. He graduated from Xi'an Jiaotong University, Xi'an, China, in 1957.

He is with the School of Electrical Engineering, Xi'an Jiaotong University, where he is now a Professor. He has over 40 years of researching and teaching experience in electric power system planning and analysis. His research fields include power system analysis, generation planning and transmission system planning, reliability evaluation, and power markets.

Yue Zhang was born in March 1993. She received the Bachelor's degree in electrical engineering from Xi'an Jiaotong University, Xi'an, China, in 2014. She is currently pursuing the Master's degree in electrical engineering at Xi'an Jiaotong University.