A NEW APPROACH FOR ENERY SAVING TO HOUSEHOLD CUSTOMERS BASED SMARTGRID TECHNOLOGIES

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ABSTRACT

This paper addresses the energy efficiency problem of household customers by observing and responding accordingly to the condition of the upstream grid; the key condition is the market price which is passed to the end-use customers though a new market entity, namely load aggregators. A framework based on Smargrid technologies, *e.g.*, Advanced Metering Infrastructure (AMI) for monitoring home energy consumptions is proposed. The problem is to schedule and control the home electrical appliances in response to the market price to minimize the energy cost over a day. The problem is formulated using Dynamic Programming (DP) and solved by DP backward algorithm. Using stochastic optimization techniques, the proposed framework is capable of addressing the uncertainties related to the appliance performance: outside temperature and/or users' habits, etc.

Keywords: *Demand response, Home energy efficiency, Heat ventilation and air conditioning, Dynamic programming, Smartgrid.*

INTRODUCTION

This paper discusses a new approach to energy efficiency in the residential sector by watching the household consumption from the system perspective: it is more economical and efficient not only for household customers but the system-wide if the appliances and lighting are turned on in low price times and off in the high time. This can be referred to as Demand Response (DR) program and/or Home Energy Management System (HEMS). Herein, we propose a DR framework for a household that consists of two functions: (1) Off-line scheduling according to the prediction and (2) On-line control based on both the previous scheduling and real-time load measurements. The framework is based on advanced communication and automation technologies applied to the power grid, *i.e.*, Smartgrid with the key component is Advanced Metering Infrastructure (AMI). The problem is finding out the optimal consumption each time slot (stage) of the day to minimize the overall energy cost, subject to the constraint of the physical system and the users' preference of comfort.

THE PROPOSED DEMAND RESPONSE FRAMEWORK

The proposed DR framework for household customers is sketched in Fig. 1. As aforementioned, under market environments electric customers are offered choices to pay their usage corresponding to the condition of the wholesale market, *i.e.*, real-time price. The matter of fact is that it is not suitable for human to analyze and respond to the frequent change over time of the real-time price (*e.g.*, every 5 min.). Therefore, advanced communication and automations, also known as Smartgrid technologies are essentially needed here. The proposed scheme consists of two different functions: (1) Off-line scheduling according to the anticipated price and load models and (2) On-line control combining both the scheduling ahead and the real-time measurements.

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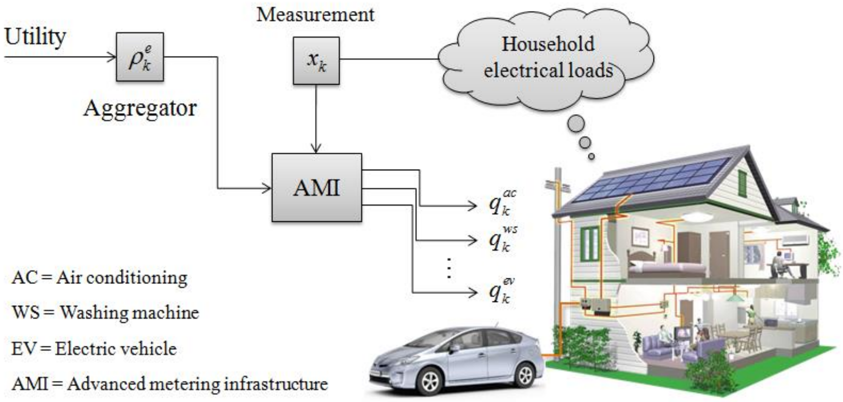

Figure 1. *The DR framework based on AMI for household customers*

Day-ahead Scheduling

The problem of day-ahead scheduling is to find out the so-called "control policy" that minimizes the expected energy cost over a day with respect to the uncertainties of the forecasting. The solution is subject the constraints associated the physical system capacity and/or the users' preference of comfort, etc. It is worth noting that the decision is made in accordance with the time basis of the electricity market, which is 5 min. in this paper. The problem can be formulated as follows [7].

$$\min_{\substack{u_k \\ k=0,1\ldots N-1}} \underset{\substack{w_k \\ k=0,1\ldots N-1}}{E} \left\{ g_N\left(x_N\right) + \sum_{k=0}^{N-1} g_k\left(x_k, u_k, w_k\right) \right\} \quad (1)$$

Subject to

$$x_{k+1} = f_k\left(x_k, u_k, w_k\right),\ k = 0,1\ldots N-1 \quad (2)$$

$$u^{\min} \le u_k \le u^{\max},\ k = 0,1\ldots N-1 \quad (3)$$

$$x^{\min} \le x_k \le x^{\max},\ k = 1,2\ldots N \quad (4)$$

$$h_i\left(x_k, u_k, w_k\right)_{k=1,2\ldots N} \le 0,\ i = 1,2\ldots n \quad (5)$$

where x_k the state variable at the beginning of stage k; u_k the control variable during stage k; w_k the uncertainty during stage k; N is the number of stages over the scheduling period; $g_N(x_N)$ is the terminal cost, *i.e.*, the cost associated with the final state; $g_k(x_k,u_k,w_k)$ is the cost in stage k; $f_k(x_k,u_k,w_k)$ is the state transition function; u_{min}, u_{max} are the capacity limits; x_{min}, x_{max} are the physical limits of the system; and $h_i(x_1,x_2\ldots x_N)$ refers to the customers' preference, *e.g.*, human would feel comfortable if the temperature is kept within 22–26^{0}C with HVAC; batteries must be full of charge by 7:00 AM (*i.e.*, the time to go working) with EVs.

In this formulation, equation (1) is the objective function, *i.e.*, minimizing the energy costs over a day subject to the uncertainties. Equation (2) shows the modeling of loads which represents the dynamics (state transition) of the load performance. Equations (3) and (4) are the physical constraint of the loads. Finally, equation (5) represents the conditions to be comfortable setup by customers and n is the number of functions needed.

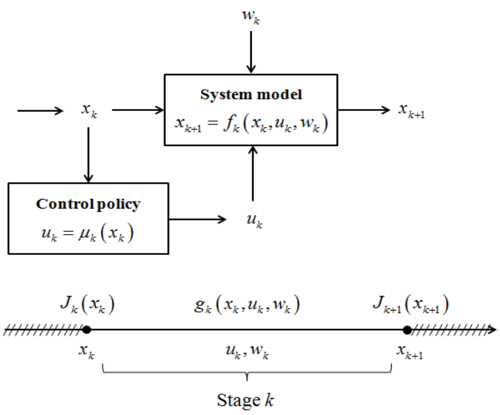

Figure 2. *The proposed DR framework and its variables defined in stage k*

The control policy resulted from the day-ahead scheduling is a set of functions of the system state, denotes $\mu_k(x_k)$, k = 0, 1…N-1, that will point out the optimal control of the system provided the measurement of the current state (*i.e.*, the scenario is cleared).

Real-time Controller

The fact is that the scenario probably differs from the anticipation due to many uncertain factors, *e.g.*, weather, temperature and users' demands, etc. Therefore, the real-time control should not only follow the previous schedule but also depend on the real-time measurement of the system. With the control policy determined ahead of time, the decision in real-time operation can be made as simply as:

$$u_k^* = \mu_k\left(x_k\right) \quad (6)$$

where x_k is measures of the state variable. The block diagram of the proposed DR and its variables defined in stage k are expressed in Fig. 2.

ILLUSTRATIVE EXAMPLE

This section provides an illustrative example where the proposed framework is tested in the DR problem of HVAC loads in a real-time electricity market. The idea of HVAC is taking advantages of the slow dynamics of the heating/cooling process compared to the changing rate of the price signal (*i.e.*, 5 min.) to manage the HVAC operation with the target of minimizing the total energy cost in a day while maintain comfort levels to the users. The framework specified for HVAC is as follows.

$$\min_{\substack{q_k^{ac} \\ k=0,1...N-1}} \; \mathop{E}_{\substack{T_k \\ k=0,1...N-1}} \left\{ \sum_{k=0}^{N-1} \rho_k q_k^{ac} \right\} \quad (7)$$

Subject to

$$t_{k+1} = t_k + \alpha q_k^{ac} + \beta\left(T_k - t_k\right)$$

or (8)

$$t_{k+1} = \left(1-\beta\right) t_k + \alpha q_k^{ac} + \beta T_k, \; k = 0,1...N-1$$

$$q_{\min}^{ac} \le q_k^{ac} \le q_{\max}^{ac}, \; k = 0,1...N-1 \quad (9)$$

$$t_{\min} \le t_k \le t_{\max}, \; k = 1,2...N \quad (10)$$

where q_k^{ac} is the energy consumption of HVAC during state k, [kWh]; t_k is the indoor temperature at the beginning of stage k, [^{0}C]; T_k is the outside average temperature during stage k, [^{0}C]; N is the number of stages; α is the equivalent thermal resistance of HVAC, [^{0}C/kWh]; β is the coefficient of the heat transfer between the indoor and outdoor space, [p.u.]; $q_{\min}^{ac}, q_{\max}^{ac}$ are the capacity limits of HVAC, [kWh]; and $t_{\min}$, $t_{\max}$ are the lower and upper temperature of human comforts, [^{0}C], *e.g.* human feels comfortable with the temperature between 22–26^{0}C. It is worth noting that with time basis of electricity market is 5 min., resulting in the number of stages is 24×12 = 288 in a day.

The control policy constructed through the above scheduling problem combined with the real-time measurements (of the actual indoor temperature) will be used to determine the optimal decision as follows.

$$q_k^* = \mu_k\left(t_k\right) \quad (11)$$

The proposed HVAC scheme will be compared with the traditional scheme that HVAC is controlled by a thermostat. With the upper/lower set-points, HVAC will be switched on/off when the indoor temperature reaches the lower or upper bound of the customers' preference, respectively. This can be described mathematically in the following.

$$q_{k+1}^{ac} = \begin{cases} q_{\max}^{ac} & \text{if} \quad t_k \le t_{\min} \\ q_k^{ac} & \text{if} \quad t_{\min} < t_k < t_{\max} \\ 0 & \text{if} \quad t_k \ge t_{\max} \end{cases} \quad (12)$$

The price data used in this study is obtained by modifying the hourly electricity price of PJM market from March 24th to 30th 2014 (Monday to Sunday of a whole week) [8]. It is noted that the hourly price is determined through day-ahead bidding in electricity markets. The real-time imbalance caused by load deviations from the anticipation will be handled by calling upon the up/down regulation services; this action results in the real-time price differed from the hourly price [9]. The temperature in this study is referred from National Climate Data Center at New York, USA in the same period as the PJM price [10]. The price and temperature data are displayed in Fig. 3.

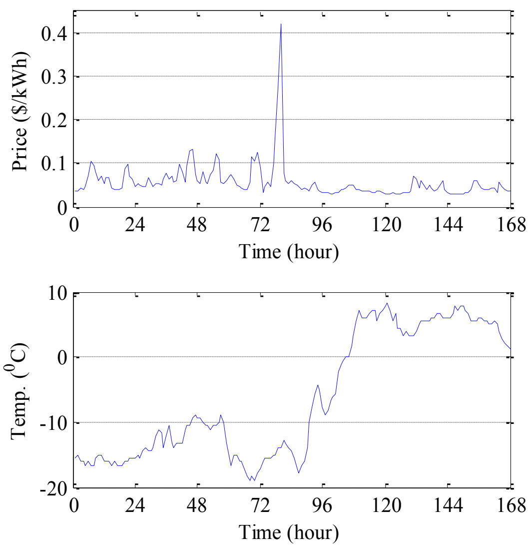

Figure 3. *The PJM hourly price and temperature in New York, USA from March 24th to 30th 2014*

Fig. 4 illustrates the control policy at some stages (stage No. 5, 6, and 100) on March 24th 2014: the optimal decision, q_k^* [kWh] as a function of the state variable, t_k [^{0}C]. Two key drivers of the control policy at each stage are: (1) the price signal and (2) the temperature of the following stages; thus, the HVAC tends to run a little at stage No. 6 (green, dashed line) since the price is quite high and expected to drop soon; in contrast, at stage No. 100 (red, broken line) HVAC is operated intensively to drive up the indoor temperature, avoiding to run with the high price in the coming stages. It is noted that the maximum capacity of 0.5kWh per stage is equivalent to a 6kW power drawn from the grid.

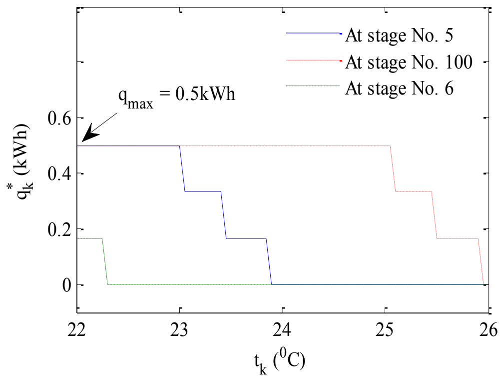

Figure 4. *The control policy on March 24th 2014 obtained from the scheduling problem*

Fig. 5 shows the indoor temperature of HVAC controlled by the proposed and traditional scheme on March 24th 2014. As aforementioned, the traditional scheme is based on a thermostat to drive the indoor temperature from the lower to upper bound (red, broken line), repetitively. On the other hand, the proposed scheme (blue, solid line) considers both the trend of electricity price and temperature in the whole period (a day); and the control policy is constructed by minimizing the total energy cost subject to the uncertainties of the prediction (*e.g.*, the outside temperature). Thus, the HVAC will run with different operating levels throughout the day, driving the indoor temperature within the comfortable range (22–26^{0}C). The economic performance of the proposed scheme in comparison with the tradition scheme is expressed in Fig. 6.

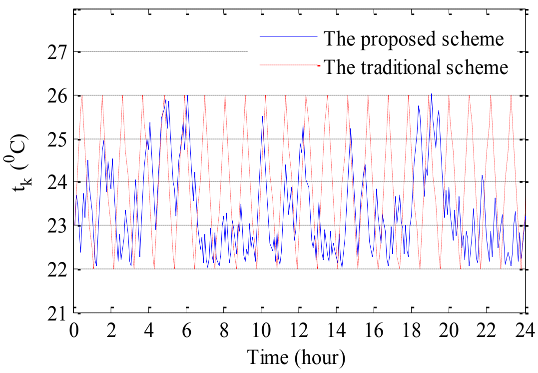

Figure 5. *The indoor temperature with the proposed and tradition operation scheme on March 24th 2014*

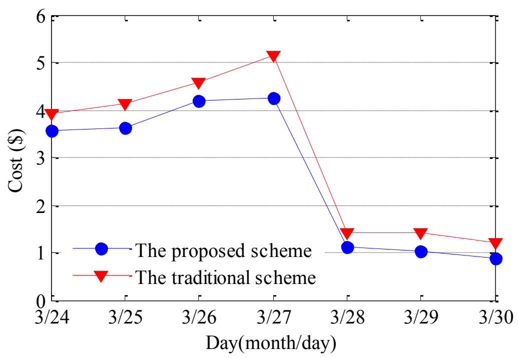

Figure 6. *The cost per simulated day (from March 24 to March 30 2014)*

Fig. 6 shows the energy cost in each day of the simulated period: from March 24th to 30th 2014. Generally, the cost is quite high from March 24th to 27th due to two reasons: first, the weather is cold with the temperature is usually lower than –10 Degree Celsius and secondly, the electricity price is relative high in weekdays (from Monday to Thursday), particularly the critical peak price occurs on Thursday March 27th. In contrast, the cost from March 28th to 30th is much slower because the temperature rises significantly (0–10 Degree Celsius) and the electricity price also decreases somehow in the weekend.

As the simulation results, it can be recognized that significant saving can be obtained by the proposed DR scheme on HVAC loads compared to the traditional operation. Particularly with the critical peak price on Thursday, the proposed scheme can manage the energy cost to be not increased that much and obtain the highest saving throughout the simulated week. In overall, the energy cost with the proposed scheme is 18.67$ while that with the traditional scheme is 21.85$; the saving in this case is about 14.55%. The HVAC modeling parameters and the customer preference is provided in Table 1.

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Table 1. *The parameters used in the simulation of the illustrative example*

System parameters		***Customer preferences***	
α (^{0}C/kWh)	2.5	t_{min} (^{0}C)	22
β (p.u.)	0.015	t_{max} (^{0}C)	26
$q_{\min}^{hvac}$ (kWh)	0		
$q_{\max}^{hvac}$ (kWh)	50		

CONCLUSION

This paper has presented a new framework for the energy efficiency of household customer based on Smartgrid technologies applied into the existing power grid. The saving can be achieved by customers actively responding to the market price which is passed to the end-users though load aggregators. The proposed framework is comprised of two main functions: (1) Off-line scheduling according to the anticipated data and (2) On-line control based on both the ahead scheduling and the real-time measurements. The problem is formulated and solved by DP backward algorithm, *i.e.*, minimizing the expected energy cost over a day subject to the uncertainty of the forecasting. The proposed framework has been specified and tested in HVAC loads under real-time electricity. The electricity price is referred from the PJM electricity market and the temperature is from National Climate Data Center in New York, USA in the same period: from March 24th to 30th 2014 (the whole week). The simulation results showed that the proposed scheme is not only capable of controlling the indoor temperature within the comfortable range (22–26^{0}C) set by customers but the energy costs can be saved remarkably. The amount of saving over the simulated period compared with the traditional operation scheme is as high as 14.55% in this study.

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TÓM TẮT

MỘT PHƯƠNG PHÁP TIẾP CẬN MỚI CHO VIỆC TIẾT KIỆM ĐIỆN NĂNG CHO CÁC HỘ TIÊU THỤ DỰA TRÊN CÔNG NGHỆ SMARTGRID

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Bài báo đề cập đến vấn đề nâng cao hiệu quả trong việc sử dụng điện năng tại các hộ tiêu thụ điện bằng cách dự báo, cập nhật và xử lý các thông tin về lưới điện; trong thị trường điện, các thông tin này được phản ánh thông qua giá điện và được truyền đến người dung điện theo thời gian thực thông qua các công ty bán điện. Trên cơ sở đó, bài báo đề xuất một mô hình quản lý và điều khiển các thiết bị điện trong hộ gia đình dựa trên những công nghệ của mạng điện thông minh (Smartgrid) với hàm mục tiêu là tối giảm hóa chi phí tiêu thụ điện năng trong ngày. Bài toán được mô hình bằng phương pháp quy hoạch động (Dynamic programming) và giải bằng thuật toán tính ngược (Backward algorithm). Ứng dụng lý thuyết sắc xuất thống kê, các đại lượng ngẫu nhiên như nhiệt độ môi trường hay nhu của cầu người sử dụng cũng sẽ được giải quyết.

Từ khóa: *Điều khiển phụ tải, hiệu suất sử dụng năng lượng, hệ thống điều hòa trung tâm, quy hoạch động, mạng điện thông minh.*

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