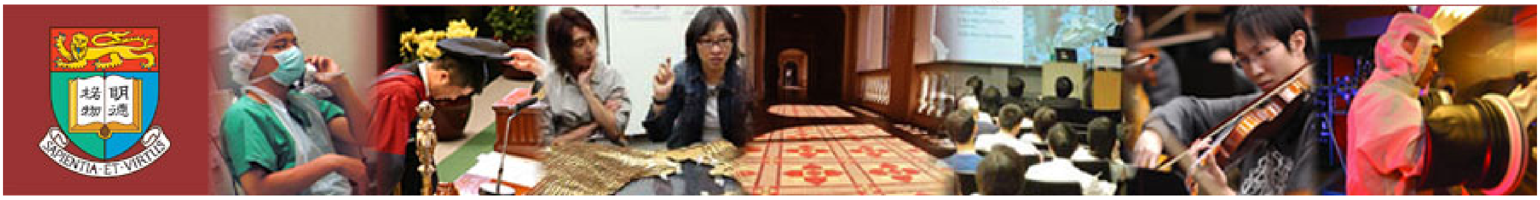

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Scenario-Based Real-Time Demand Response Considering Wind Power and Price Uncertainty

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Abstract—**Real-time pricing can potentially lead to economic advantages for consumers in the environment of smart grid. Compared with flat rates, dynamic pricing allows consumers more engagement through measures of demand response (DR). This paper investigated the optimal hourly electricity consumption scheduling problem of a given consumer responding real-time price. The objective of the proposed model is to maximize the surplus of a consumer that is equipped with wind power and storage devices. Hourly utility curve is considered as a function of power consumption. Bidirectional communication between the consumer and the supplier allows for interval price updates, so the consumer can flexibly adjust hourly demand. Key sources influencing final performance are price uncertainty and renewable power generation uncertainty. Uncertainties are modelled via scenario-based stochastic optimization, where its feasibility is illustrated in numerical simulations.**

Index Terms—**Consumer utility, demand response, real-time pricing, stochastic optimization, wind power.**

I. Introduction

In restructured electric power systems, various time-differentiated pricing programs have been proposed [1]. In comparison to conventional flat retail rates, dynamic pricing not only performs better in reflecting the actual wholesale market price, but also involves consumers in electricity markets through demand response (DR). There have been many scholastic literatures showing high anticipation that real-time pricing (RTP) can perform economically in future power markets [2], [3]. Meanwhile, the advent of advanced information and communication technologies (ICTs) in smart metering and bidirectional communication flow removes the technical barrier in implementation of a time-varying pricing program and DR.

According to agreements between the power supplier and consumers, the supplier updates the latest RTP information and broadcasts to the consumer through ICTs periodically [4]. As a profit-seeking participant, the customer can voluntarily schedule power consumptions [5]. In [6], the temperature-based thermal load control and residential micro-grid scheduling is studied. In [7], an energy management model is designed to optimize home electricity service for households with renewable energy facilities. Since different appliances own different characteristics, [8] formulates a convex problem of overall DR optimization. In [6]-[8], schedulers focus on determining hourly power consumption under the assumption that they have perfect forecast information for the whole scheduling horizon and related demand control models are solved as deterministic problems.

In real operation, there exist some uncertain elements during the scheduling horizon, such as RTP and wind power output. Researchers have conducted many studies involving issues of optimal demand scheduling with RTP. In [9], in order to deal with uncertain prices, stochastic optimization and robust optimization are adopted to manage various residential appliances. Besides price uncertainties, environmental uncertainties are considered in the household equipped with solar-assisted thermal load and the problem is solved by a rolling stochastic model [2]. In [10], three subsequent phases are proposed to study load control, namely real-time monitoring, stochastic scheduling, and real-time control. As stated in [2], [9], [10], some consumers are most concerned with minimizing their total cost, but for some profit-seeking consumers, besides bill payment, the utility obtained from consuming power is another welcome focus.

This paper proposes a scenario-based real-time demand management model. The objective of the proposed model is to maximize the consumer's surplus, which is the consumer utility minus corresponding power consumption over the scheduling horizon. Onsite wind power output and price uncertainty are modelled via a scenario-based stochastic optimization. In addition, the storage device is considered in the proposed model. Similar to [11], [12], the proposed model adopts the hourly utility curve to quantize how a specific power consumption at hour t can benefit the consumer. Parameters of hourly utility curves and other personal requirements can easily be set by the consumer through a user-friendly DR management system.

The rest of the paper is organized as follows. Section II models the consumer's surplus maximization problem via scenario-based stochastic optimization. Section III shows the

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rolling implementation procedure. Section IV presents numerical hourly demand scheduling followed by conclusions in Section II.

II. Model Description

A. Objective of Stochastic Optimization

The proposed scenario-based real-time stochastic optimization incorporates uncertainties of real-time electricity price and wind power output pertaining to *24–t* hours following the current hour *t*. For a consumer owning wind power facilities, he/she is assumed as knowing the wind power production data and electricity prices for the initial *t–1* hours, i.e. $\pi_{1,2,\ldots,t}$ and $W_{1,2,\ldots,t}$. Meanwhile electricity price of the current hour *t*, π_t, is assumed to be broadcasted 15 minutes prior to current hour *t*, wind power production forecasting error for the current hour is ignored, and at the end of hour *t*–1 battery state of charge SOC_{t-1} is assumed known. The consumer should schedule the power consumption for the periods from the current hour *t* to the end of the day, i.e. hour 24. Because decisions are made in the environment of uncertainties, in order to tackle those uncertainties, stochastic optimization is adopted. Using historical data and known data of current day, ARMA-based time series model and Monte Carlo simulation generate multiple scenarios spanning from hour *t+1* to hour *24*. Each scenario *s*, as represented in (1), includes the uncertain elements for the remaining 24–hours, i.e. real-time electricity price $\pi^s_{t+1,t+2,\ldots,24}$ and wind power production $W^s_{t+1,t+2,\ldots,24}$.

$$\text{scenario } s \ = \left\{\pi^s_{t+1,\mathrm{t}+2,\ldots,24}, W^s_{t+1,t+2,\ldots,24}\right\} \qquad (1)$$

The occurrence probability of each scenario is ρ^s. For a set with *NS* scenarios, $\sum_{s=1}^{NS}\rho^s = 1$ [13].

The objective (2) is to maximize the expected consumer surplus from current hour *t* to the end of the scheduling horizon, which is the consumer's utility minus electricity bill of corresponding power consumption.

$$\max\ u_t(d_t) - \pi_t p_t + \sum_{s=1}^{NS}\rho^s\sum_{l=1}^{24-t}\left[u^s_{t+l}(d^s_{t+l}) - \pi^s_{t+l}p^s_{t+l}\right] \quad (2)$$

The decision variables of the objective (2) include load levels d_t and battery charge/discharge rate r_t for the current hour *t*, load levels (d^s_{t+1}, $l = 1,2,\ldots,24-t$), and battery charge/discharge rate (r^s_{t+1}, $l = 1,2,\ldots,24-t$) for the remaining 24–*t* hours in scenario s. In (2), d_t represents load level at hour *t*, $u_t(d_t)$ is the function of power consumption, π_t is the electricity price of the current hour *t*, and p_t is the power drawn from grid. While in scenario *s*, d^s_{t+l} represents the scheduled load level at hour *t*+*l*, π^s_{t+l} represents electricity price at hour *t*+*l*, and p^s_{t+l} represents the power drawn from grid at hour *t*+*l*.

The objective function (2) is subject to various constraints as shown below.

B. System Constraints

Hourly load level d_{t+l} is obtained from the sum of battery discharge r_{t+l}, wind power generation w_{t+l}, and power bought from grid p_{t+l}.

$$d_t + r_t \le w_t + p_t \qquad (3)$$

$$d^s_{t+l} + r^s_{t+l} \le w^s_{t+l} + p^s_{t+l} \quad \forall l = 1,2,\ldots,24-t \qquad (4)$$

$$p_t \ge 0 \qquad (5)$$

$$p^s_{t+l} \ge 0 \qquad \forall\, l = 1,2\ldots,24-t \qquad (6)$$

Constraints (3) and (4) are on power balance. The proposed model assumes electricity is not sold back to grid and constraints (5) and (6) ensure the power drawn from grid is not negative. The positive and negative value of variables r_t and r^s_{t+l} represent when the battery is charging, and discharging respectively.

C. Demand Response Constraints

A consumer's demand consists of two parts, i.e. baseload and flexible load. Baseload is fixed while flexible load is price-responsive. Figure 1 illustrates the stepwise utility curve in which OA is the baseload ($d_{t+l}, \forall l = 0,1,\ldots,24-t$) whose utility can be regarded as infinite and is ignored in this model, AB, BC and CD represent the power range of the *k*[th] segment of utility step. $\overline{d_{k\cdot t}}$ indicates the maximum demand in the *k*[th] segment. For the sake of simplicity, we assume there are three segments in total. Based on characteristics and application of loads, parameters of utility curves can be pre-programmed by the consumer.

$$d_t = d_{b\cdot t} + \sum_{k=1}^{3} d_{k\cdot} \qquad (7)$$

$$d^s_{t+l} = d_{b\cdot t+l} + \sum_{k=1}^{3} d^s_{k\cdot t+l} \quad l = 1,2,\ldots,24-t \qquad (8)$$

$$0 < d_{k\cdot t} \le \overline{d_{k\cdot t}} \qquad (9)$$

$$0 < d_{k\cdot t+l} \le \overline{d_{k\cdot t+l}} \qquad l = 1,2,\ldots,24-t \qquad (10)$$

$$u_t(d_t) = \sum_{k=1}^{3} C_{k\cdot t}d_{k\cdot t} \qquad (11)$$

$$u^s_{t+l}(d^s_{t+l}) = \sum_{k=1}^{3} C_{k\cdot t+l}d^s_{k\cdot t+l} \quad l = 1,2,\ldots,24-t \qquad (12)$$

$$\mathrm{RD} \ge d_t - d^s_{t+1} \qquad (13)$$

$$\mathrm{RD} \ge d^s_{t+l+1} - d^s_{t+1} \quad l = 1,2,\ldots,24-t \qquad (14)$$

$$d^s_{t+1} - d_t \le \mathrm{RU} \qquad l = 0,1,\ldots,24-t \qquad (15)$$

$$d_{t+l+1} - d_{t+l} \le \mathrm{RU}, \qquad l = 1,2,\ldots,24-t \qquad (16)$$

$$\mathrm{E}_{day} \le \sum_{t=1}^{24} d_t. \qquad (17)$$

Constraints (7) and (8) illustrate the consumer's utility. (9) and (10) show the demand range of each segment. Parameter $C_{k\cdot t}$ indicates the utility obtained per unit power consumption at segment k. Constraints (11) and (12) give the correlation between segment demand and total demand. (13)-(16) limit the maximum ramping down and ramping up values happening between two successive hours. Also, in (17), a preset minimum daily energy consumption E_{day} should be guaranteed.

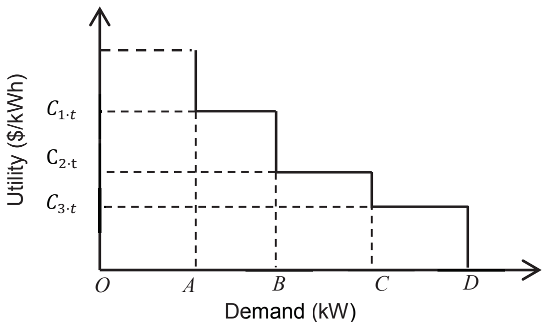

Figure 1. Stepwise demand utility curve.

D. Battery Constraints

A simple battery model is considered. In (18), battery charge rate and discharge rate are limited between a threshold, where the positive r_{t+l} means charge, and the negative means discharge. *Cap* represents the battery capacity. Constraints (19) shows that present state of charge equals that of the previous hour plus charge/discharge status of present hour. The constraint (20) assures that the battery works between a safety range, which can extend battery life. Constraint (21) requires that a minimum threshold of energy will be stored in the battery in the end of the day.

$$-R_{min} \le r_{t+l} \le R_{max} \qquad l = 0,1,\dots,24-t \quad (18)$$

$$SOC_{t+l} = SOC_{t+l-1} + r_{t+l}/Cap \qquad l = 0,1,\dots,24-t \quad (19)$$

$$\underline{SOC} \le SOC_{t+l} \le \overline{SOC} \qquad l = 0,1,\dots,24-t \quad (20)$$

$$\underline{SOC_{24}} \le SOC_{24} \quad (21)$$

III. ROLLING MODEL IMPLEMENTATION

Similar to [4], with the help of an advanced energy management system, the consumer updates hourly demand scheduling on an hourly basis. For the sake of simplicity, we take hour t as an example to describe the implementation procedure, which means there are $24-t$ hours remained to schedule power consumption in the operation day. In fact, however, only the demand schedule related to the hour t will be really implemented and the solution in scenario part (i.e. demand schedule from hour $t+1$ to hour 24) is only auxiliary. The objective (2) is implemented in following steps:

1) Information update: The power supplier broadcasts the price for hour t several minutes prior to t. (e.g., 15 minutes). Meanwhile wind power production forecast is updated by the local advanced energy management system.

2) Scenario update: The energy management system updates and improves scenarios for operation period from hour t+1 to hour 24, where the historical series of wind power production and electricity prices up to and including hour t is used to generate scenarios via Auto-Regressive and Moving Average (ARMA) model.

3) Model solving: The objective (2) is solved. Load scheduling and battery charge/discharge rate for hour t are obtained.

4) Implementation: Based on results from step 3), the energy management system will adjust for related operation.

5) Repeat: Step 1) to step 3) will be repeated until the end of the scheduling horizon (i.e. hour 24).

IV. CASE STUDY

A. Simulation Data

A consumer equipped wind power, battery devices and advanced energy management system is considered. In following cases, we assume the consumer is self-interested and all demand changes are acceptable for the consumer as long as more benefit could be obtained. The baseload and data of utility of flexible demand are modified based on the information from [14], [15]. Figure 2 gives the actual price, which corresponds to the real-time electricity prices of the PJM markets on Friday June 28, 2013 [16].

The actual wind power production data of the same day are shown in Fig. 3, which is sampled from the area of west PJM and is minified in equal proportion [17]. Scenarios are generated using ARMA model [18] and Monte Carlo simulation.

In addition, the battery capacity is assumed to be 11.8 kWh. Other battery data used include: minimum and maximum *SOC* (0.2 and 1), initial *SOC* (0.55), maximum charge/discharge limit (3.4 kW) and the minimum state of charge requirement at the end of the day is 0.3 [6].

B. Numerical Results and Discussion

In order to study the effect of the proposed model, three cases are simulated and compared. The cases vary by the amount of the information the consumer has. The three cases are as follows:

- Case 1: Without smart grid. The hourly power consumption is scheduled in the day ahead without real-time adjustment.
- Case 2: With smart grid. With help of ICTs and an advanced energy management system, the consumer receives hourly price information and updates wind power forecasting information. The load scheduling is adjusted in a rolling window.
- Case 3: With perfect information. The consumer is assumed knowing perfect information of both prices and WP production for the whole scheduling day. Hence, the problem becomes a deterministic optimization model.

The consumer's surplus for the 3 cases are compared in Fig. 4, which illustrates that the more exact information the consumer holds, the more surplus the consumer can obtain, i.e. Case 3 > Case 2 > Case 1.

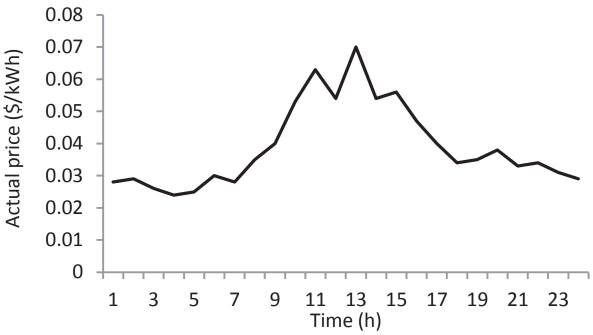

Figure 2. Actual prices.

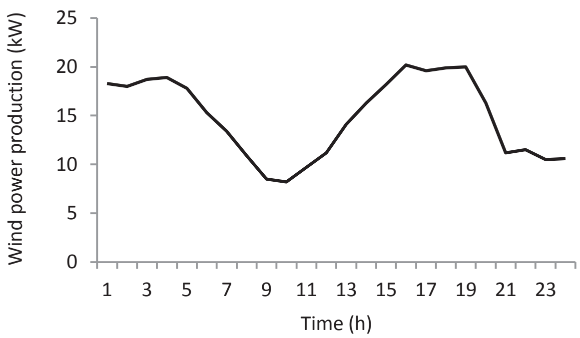

Figure 3. Actual wind power production.

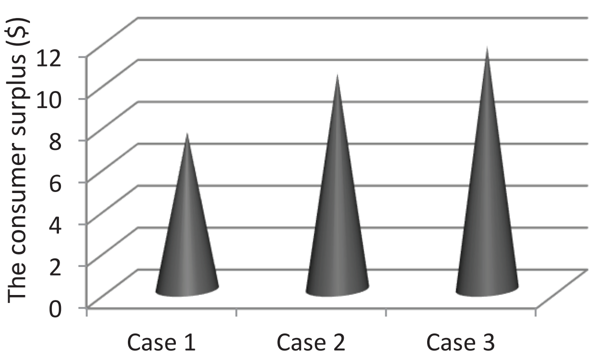

Figure 4. The consumer surplus in 3 cases.

Given that Case 3 is the most ideal situation and a deterministic problem, this numerical study will focus more on characteristics of Cases 1 and 2. In Case 1, the interaction between the power supplier and the consumer is not as strong as Case 2. Meanwhile the perception of outside environment in Case 2 also performs well. In Case 2, only information available to the consumer are price and wind power output prediction scenarios for the upcoming day, while in the real operation horizon, the consumer is assumed not to be updated information. Thus, the load and charge/discharge schedule have to be determined one day ahead. The rolling scheme becomes a static stochastic optimization problem.

Figure 5 depicts the scheduled hourly load level for Cases 1 and 2. In Case 2, it can be seen that from hour 1 to hour 4, due to the low-efficiency utility-load function, the consumer does not prefer to consume much power during this time period and the surplus wind power will be stored in batteries. From hour 5, the free wind power decreases, while the utility curve gradually becomes efficient and battery energy can provide free support to offset part of the influence incurred by wind power production drop. Thus, the load level begins to increase since hour 5. Originally, there would be a big load level jump in the morning. But due to the sharp decrease in wind power and increase in RTP, the demand rises more slowly in Case 2 than in Case 1. After hour 12, the utility curve presents its higher efficiency, wind power production begins to bounce back and the price drops briefly. Consequently, a power jump happens at hour 13 when the consumer could benefit more. Limited by maximum ramping rate, 72 kW at hour 13 is the maximum load level the consumer can schedule, otherwise, the load level at hour 13 would be higher. During hour 14 to hour 17, the utility curves are similar, wind power output grows and the price declines. The load level gradually rises until hour 18. The consumer assumes that power consumption cannot bring much more utility in the evening than in the midday. Although the wind power stays at a good level fluctuating between a narrow band and price keeps going down in the evening, which means the cost is not as high as that in peak time of afternoon, the load level is scheduled at a low level. In hour 21, the dramatic fall of wind power production leads to reduction in load level which lasts until the end of the day.

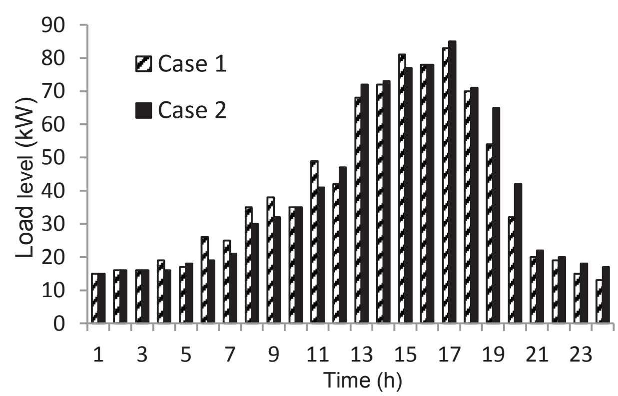

Figure 5. The scheduled hourly load level for Cases 1 and 2.

As for Case 1, all demand schedule is settled at the beginning of the day. Because forecasting results span the whole 24 hours, corresponding accuracy will be at a discount. In the beginning 3 hours, limited to maximum load level and low-efficiency utility curve, there is a little disparity between Case 1 and Case 2. But after that, power consumption scheduling presents obvious diverges.

The battery charging/discharging scheduling together with its state of charge is shown in Fig. 6 and Fig. 7. In Fig. 6, values above (below) zero mean the battery is charging (discharging). As expected, the storage device charges when there is a wind power production deficit while the electricity price is not high (hour 1 and hour 2), and discharges when wind power cannot satisfy demand while the price is high and utility function is high-efficient (hour 9, 10, 13 and 14). The reason why the battery charges at hour 24 at a low price is to meet the minimum state of charge requirement at the end of the day.

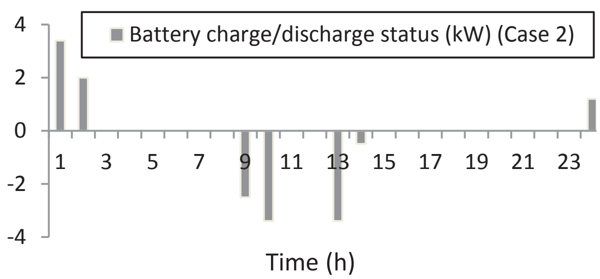

Figure 6. The battery charge/discharge status in Case 2.

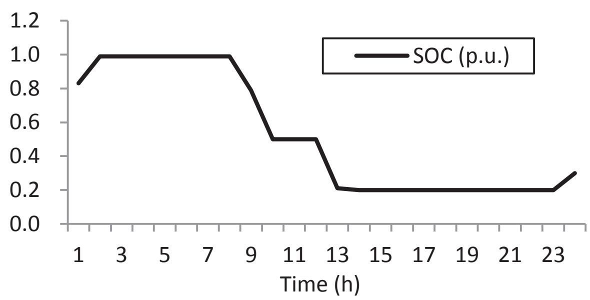

Figure 7. The battery state of charge in Case 2.

V. Conclusions

This paper proposes a real-time demand response model. Unlike the conventional deterministic model, the model not only considers both price and wind power production uncertainties, but also incorporates the utility function. In order to deal with uncertain components, a rolling scenario-based stochastic optimization is used to solve the problem. With the smart grid technologies, the power supplier can bi-directionally communicate with consumers, which will help benefit all market participants. Firstly, the real-time wholesale market situation can be converted to consumers, and resources can be consumed more efficiently and economically. Secondly, based on the proposed model, consumers can preset utility curves, schedule load level, battery status, and adjust real-time power consumption. Also the rolling implementation procedure is demonstrated in this paper. The case study shows that, under the environment of RTP and smart grid, the rolling scenario-based stochastic optimization can perform well.

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References

[1] 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.

[2] H. T. Nguyen, D. T. Nguyen, and L. B. Le, "Energy management for households with solar assisted thermal load considering renewable energy and price uncertainty," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 301-314, Jan 2015.

[3] M. K. Savolainen and R. Svento, "Real-time pricing in the Nordic power markets," *Energy Economics*, vol. 34, no. 4, pp. 1131-1142, Jul. 2012.

[4] A. J. Conejo, J. M. Morales, and L. Baringo, "Real-time demand response model," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 236-242, Dec. 2010.

[5] M. H. Albadi and E.F. El-Saadany, "A summary of demand response in electricity markets," *Electric Power Systems Research*, vol. 78, no. 11, pp. 1989-1996, Nov. 2008.

[6] M. Tasdighi, H. Ghasemi, , and A. Rahimi-Kian, , "Residential microgrid scheduling based on smart meters data and temperature dependent thermal load modeling," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 349-357, Jan 2014.

[7] M. A. A. Pedrasa, T. D. Spooner, , and I. F. MacGill, "Coordinated scheduling of residential distributed energy resources to optimize smart home energy services," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 134-143, Sep. 2010.

[8] K. M. Tsui and S. C. Chan, , "Demand response optimization for smart home scheduling under real-time pricing," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1812-1821, Dec. 2012.

[9] Z. Chen, L. Wu, and Y. Fu, "Real-rime price-based demand response management for residential appliances via stochastic optimization and robust optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1822-1831, Dec. 2012.

[10] C. Vivekananthan, Y. Mishra, and F. Li, "Real-time price based home energy management scheduler," *IEEE Trans. Power Syst.*, vol. PP, no. 99, pp. 1-11, Sep. 2014.

[11] C. L. Su and D. Kirschen, "Quantifying the effect of demand response on electricity markets," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1199-1207, Aug. 2009.

[12] H. Y. Wu, M. Shahidehpour, and M. E. Khodayar, "Hourly demand response in day-ahead scheduling considering generating unit ramping cost," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2446-2454, Aug. 2013.

[13] N. Mahmoudi, T. K. Saha, and M. Eghbal, "Modelling demand response aggregator behavior in wind power offering strategies," *Applied Energy*, vol. 133, pp. 347-355, Nov. 2014.

[14] L. Wu, "Impact of price-based demand response on market clearing and locational marginal prices," *IET Gener. Transm. Distrib.,* vol. 7, no. 10, pp 1087-1095, Oct. 2013

[15] C.L. Su, "Optimal demand-side participation in day-ahead electricity markets," Ph.D. dissertation, Univ. Manchester, Manchester, U.K., 2007.

[16] Comed-Live prices. [Online]. Available: https://rrtp.comed.com/live-prices/

[17] PJM-Operational Analysis. [Online]. Available: http://www.pjm.com/markets-and-operations/ops-analysis.aspx

[18] B. S. Chio, *ARMA Model Identification*, New York: Springer-Verlag, 1992.