From Passive Demand Response to Proactive Demand Participation

Nanpeng Yu, *Member, IEEE*, Tianshu Wei, *Student Member, IEEE*, and Qi Zhu, *Member, IEEE*

Department of Electrical and Computer Engineering
University of California, Riverside
Riverside, CA 92521 USA

***Abstract*—Limited progress has been made in the past few years in increasing demand response participation rate in the United States. The structural rigidity of existing price-based and incentive-based demand response programs results in inadequate and inefficient utilization of demand flexibility in electricity market operations. In this paper, an innovative proactive demand participation scheme is developed. This new scheme enables customers to actively express and communicate their consumption preferences to market operators rather than passively receive and react to time varying electricity prices and demand reduction signals. A novel framework for integrated wholesale and retail market operations with proactive demand participation and customer aggregation is proposed. The proactive demand response scheme is implemented in a simulation environment. The simulation results show that the proactive demand participation scheme is superior to the passive demand response approach. The proactive demand participation approach not only increases overall market efficiency but also reduces price volatility.**

***Index Terms*--Building Aggregation, Demand Response, Integrated Market, Model Predictive Control, Proactive Demand Participation.**

I. INTRODUCTION

Demand response (DR) enables electricity consumers to adjust their electricity usage in response to time-varying electricity price signals, incentive payments and/or direct dispatch instructions. DR resources have demonstrated their potential in improving electricity market efficiency and enhancing power system reliability. However, at 6% penetration level in the U.S. [1], their usefulness in electricity market operations is greatly limited by the structural rigidity of price-based demand response and incentive-based DR programs which are prevalent in current practice. Almost all DR customers still passively respond to time varying prices and load reduction instructions sent from utilities [2]. The low customer engagement and DR market integration hurdles could be partially explained by this passive customer participation scheme, which ultimately results in low market efficiency and high real-time price volatility.

As estimated in the Federal Energy Regulatory Commission (FERC) demand response report [3], with full participation from customers, total peak demand in the U.S. can be reduced by 150 GW compared with business-as-usual DR scenario. To unlock the full potential of demand flexibility and demand-side participation, it is necessary to fundamentally transform the way retail customers interact with wholesale power markets. In this paper, an innovative customer interaction scheme called *proactive demand participation* is developed. Under the traditional price-based and incentive-based DR approaches, customers passively receive and react to time-varying electricity rates and demand reduction signals. Under the proactive demand participation framework, an intelligent energy scheduling agent takes the initiative to convert control models for flexible loads and customer preferences into price sensitive demand bids. This new scheme allows customers to actively express and communicate their electricity consumption preferences to the distribution system/market operators and participate in the wholesale market dispatch and price formation process.

To facilitate the proactive demand participation scheme, three critical research questions need to be addressed. First, how to convert customer objectives, preferences and physical control models of flexible loads into market compatible bidding information at the individual customer level? Second, how to accurately aggregate thousands of customers' demand and bidding information while considering distribution network losses? Third, how to design an integrated transmission and distribution market framework from both engineering and economics perspectives? This paper aims at moving proactive demand participation from concepts to reality by addressing these important research questions.

We briefly discuss literatures related to the proposed work and highlight what sets our approach apart from the existing research. In the realm of demand response, many papers in the literature focus on the design of price-based demand response models and control strategies [4] such as real-time pricing (RTP) [5], critical peak pricing [6], time-of-use [7] and transaction-based control [8]. Among the existing price-based DR frameworks, iterative real-time pricing mechanism [9] and transaction-based control are two promising distributed demand management approaches. However, in practice, both approaches are time consuming and too slow for real-time operations. The iterative real-time pricing approach requires a high number of iteration for the process to converge. In addition, the convergence could not be guaranteed with a lossy

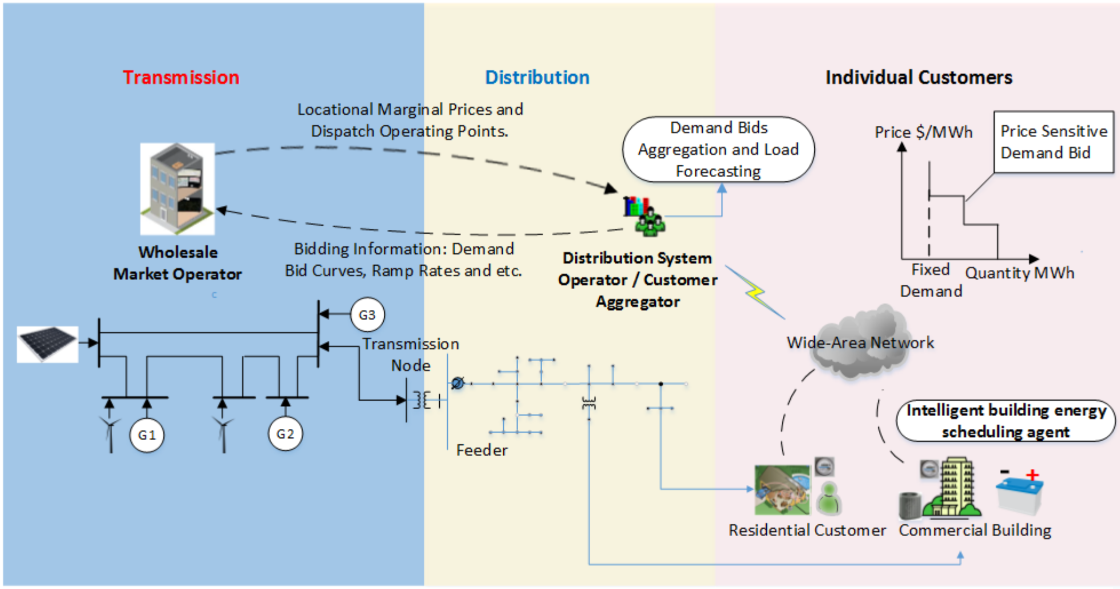

Figure 1. Integrated Market Operations Framework with Proactive Demand Participation

and delayed communication platform [10]. In our proposed proactive demand participation approach, the customers could directly send price sensitive demand bid curves to the distribution system operator. Hence, the electricity market optimization could be completed in one iteration. In the transaction-based control framework [8], each device is given the ability to negotiate deals with its peers. The bilateral negotiation process is complex and time consuming. In addition, parties in the bilateral negotiation process may fail to reach an agreement due to price forecast bias and high risk aversion factors [11]. In our proposed approach, distribution system operator aggregates demand bids and coordinates demand management among customers. This hierarchical approach makes market clearing process much more efficient.

The remainder of this paper is organized as follows. Section II proposes a comprehensive framework that empowers customers to proactively participate in wholesale electricity market and price formation process. Section III presents the intelligent building energy scheduling algorithm and the price sensitive demand bid construction methodology. The proposed algorithms and framework are implemented in a simulation testbed. The numerical study results are presented in Section IV. The conclusions are stated in Section V.

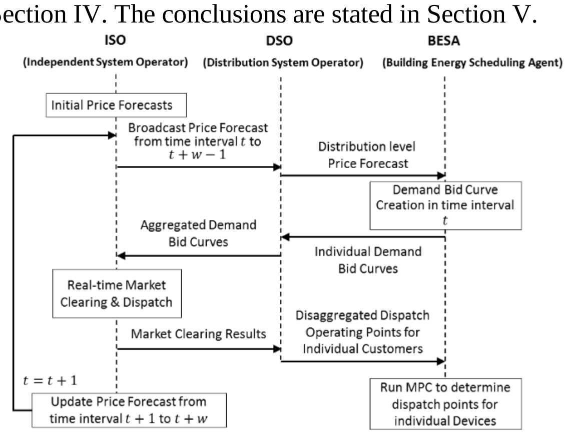

Figure 2. Proactive Demand Response Flowchart

II. Integrated Market Operations with Proactive Demand Participation

The proposed integrated electricity market operations framework is shown in Figure 1. The framework can be divided into three levels, transmission system, distribution system and individual customers. Three types of decision making entities are key to integration of flexible loads. They are intelligent building/customer energy scheduling agents, distribution system operators/customer aggregators and wholesale market operators.

A. *Wholesale Market Operator*

As shown in Figure 2, in real-time market operations, the wholesale market operator will first broadcast price forecasts for time interval t to $t+w-1$. Upon receiving aggregated price sensitive and fixed demand bids and supply offers from distribution system operators and generators, the wholesale market operator clears the real-time energy market to determine the hourly dispatch schedules and locational marginal prices (LMPs) of energy. The market clearing algorithm is formulated as following.

$$\max\Big[\sum_{j\in J} u_j(P_j^D) - \sum_{i\in I} C_i(P_i^G)\Big] \quad (1)$$

$$P_k - P_{gk} + P_{dk} = 0, k = 1, \dots, N_b \quad (2)$$

$$\left|\sum_{k=1}^{N_b} GSF_{b-k} \times P_k\right| \le F_{max}^b \quad (3)$$

$$P_i^{min} \le P_i^G \le P_i^{max}, i \in I \quad (4)$$

$$u_j(P_j^D) = \textstyle\sum_{l=1}^{L} w_{lj} P_{lj}^D \quad (5)$$

$$C_i(P_i^G) = \textstyle\sum_{m=1}^{M} r_{mi}\, P_{mi}^G \quad (6)$$

The objective function (1) maximizes the sum of surpluses of all proactive customers and generation power plants. The real-time market optimization problem is subject to real power balance constraints at each bus (2), thermal limit constraints for each transmission line (3), upper and lower generation capacity constraint (4). The customer utility function u_j and generation production cost function C_i are shown in equations (5) and (6). The real-time market clearing problem formulated in (1) – (6) is a linear programing problem. In the above equations, J represents aggregated demand bids set. I stands for the set of generators. P_k denotes power injection at bus k. P_{gk} represents the total generation at bus k. P_{dk} stands for total demand at bus k. GSF_{b-k} denotes generation shift factor from bus k to line b. F_{max}^{b} denotes the maximum power flow for line b. P_i^{min} and P_i^{max} represent the lower and upper limits of generator $i's$ capacity. w_{lj} denotes aggregated customer $j's$ willingness to pay for segment l of the electricity demand P_{lj}^{D}. r_{mi} denotes generator $i's$ bid cost for segment m of the generator output P_{mi}^{G}. P_j^D represents total electricity demand of jth aggregated customer. P_i^G represents total power output of ith generator.

After the real-time market is cleared, the market clearing results including LMPs and dispatch operating points for aggregated loads will be sent to the distribution system operators. At the end of process, the wholesale market operator updates price forecasts and move the optimization window one step forward.

B. *Distribution System Operator*

The distribution system operator is mainly responsible for coordinating the energy operation of millions of buildings/customers. As shown in Figure 2, after receiving the system level price forecasts, the distribution system operator will broadcast these price forecasts to individual buildings based on their network locations. For simplification purposes, it is assumed that the distribution network is perfectly balanced and lossless. Therefore, the building level price forecast is the same as the LMP forecast for the closest pricing node in the transmission system. After receiving individual buildings/customers' physical demand bid curves, the distribution system operator adds them up to an aggregated demand bid curve and submits it to the wholesale market operator. Upon receiving the dispatch operating points from wholesale market operator, the distribution system operator disaggregates the distribution system dispatch operating point into individual customers' dispatch points based on their demand bid curves.

C. *Intelligent Building Energy Scheduling Agent*

The intelligent building energy scheduling agents are designed to enable proactive demand participation. Resided in building/home energy management system, the intelligent energy scheduling agents try to minimize electricity costs and maximize occupants' comfort on behalf of residential customers and commercial buildings. The intelligent building energy scheduling agent keeps a record of the building equipment control models. The details of the control models for heating ventilation and air conditioning (HVAC) systems and energy storage systems used in this paper will be described in section III. As shown in Figure 2, the intelligent agents will first collect forecasts for key external variables such as temperature, humidity, customer usage preference and electricity prices based on information provided by distribution system operator and historical data gathered from local sensors. Next, the intelligent agents derive demand bid curves based on the customers' preference, price and temperature forecasts, and control model for flexible loads. The iterative demand bid curve generation algorithm will be discussed in section III. At last, the bidding information is sent through wide-area network to the distribution system operators. After the wholesale market operator clears day-ahead and real-time markets, the intelligent agents will receive the dispatch operating points like a regular power plant. The intelligent agents then decide how to coordinate the set points for all flexible loads within the building to follow the dispatch instructions.

III. Intelligent Building Energy Scheduling Algorithm and Demand Bid Curve Creation

At individual customer level, the peak demand and total energy cost of buildings can be greatly reduced by optimally scheduling the operations of HVAC systems. Furthermore, on the energy supply side, utilizing heterogeneous energy sources such as grid electricity, battery storage, and renewable sources provides more opportunities for reducing the peak demand and total energy cost. The demand side control (e.g., HVAC control) depends on the availability of various energy sources. The supply side energy sources scheduling (i.e., deciding which source to use and for how much at different times) requires the knowledge of demand. Therefore, it is important to co-schedule energy demands with supply sources to maximize building energy efficiency.

In our previous work [12], we developed a proof-of-concept formulation for co-scheduling HVAC control, EV charging and battery usage. The formulation is based on simplified assumptions of HVAC characteristics, building thermal model, EV charging and battery characteristics. The simulation results have shown significant energy saving potentials through co-scheduling flexible loads and energy sources.

In this work, we develop energy management algorithms based on model predictive control (MPC) to co-schedule HVAC and energy storage system operations. The co-scheduling algorithm is based on integrated formulations that accurately model the characteristics of HVAC system, its impact on the physical environment, and the characteristics of battery storage systems. The goal of the control is to reduce total energy cost of individual buildings. The formulation of MPC-based control is provided below. As stated in equation (7), the objective of the MPC-based control is to minimize building energy consumption cost and battery operating cost. $p_g(t)$ represents the real-time price forecasts for electricity. $e_H(t)$ represents HVAC energy demand which is modeled as a function of air flow volume input $u(t)$, and $e_B(t)$ denotes battery charging/discharging energy. The sum of $e_H(t)$ and $e_B(t)$ denotes the energy withdraw from the power grid at time step *t*. p_b is the battery depreciation cost and $b_d(t)$ denotes the battery discharge energy. Equation (8) describes the change in room temperature *T(t)* under air flow input *u(t)* from the HVAC system, which is linearized from a non-linear room thermal dynamics model as shown in [13], $dist(t)$ denotes the outside environment disturbance (e.g., sun radiation and ambient air temperature). Note that the linear model is only used for MPC control, while the original non-linear model is used for simulating the actual temperature revolution. The optimization problem is subject to HVAC system air flow volume constraint (9), lower and upper limits for room comfort temperature setting (10), building energy supply/demand constraint (11), battery charging and discharging constraint (13), temporal constraint associated with battery state-of-charge (14), lower and upper limits for state-of-charge (15) and end-of-the-day state-of-charge constraint (16).

$$\min \sum_{t=t_0}^{t_0+w-1} \left[p_g(t) \cdot (e_H(t) + e_B(t)) + p_b b_d(t)\right] \quad (7)$$

$$T(t+1) = An \cdot T(t) + Bn \cdot u(t) + En \cdot dist(t) \quad (8)$$

$$U_{lower}(t) \leq u(t) \leq U_{upper}(t) \quad (9)$$

$$T_{lower}(t+1) \leq Cn \cdot T(t+1) \leq T_{upper}(t+1) \quad (10)$$

$$e_H(t) + e_B(t) \geq 0 \quad (11)$$

$$e_H(t) = c_1 u(t)^3 + c_2 u(t)^2 + c_3 u(t) + c_4 \quad (12)$$

$$-d_r \times \tau \leq e_B(t) \leq c_r \times \tau \quad (13)$$

$$S(t+1) = S(t) + e_B(t) \quad (14)$$

$$E_{min} \leq S(t) \leq E_{max} \quad (15)$$

$$S(t+1) = E_0, if\ t\ mod\ N = 0 \quad (16)$$

In the above equations, w denotes predicting window length. N represents number of time intervals in a day. τ denotes the length of each operating interval. c_r and d_r represent maximum charging and discharging rate. $S(t)$ stands for battery's state of charge at operating interval t. E_{max} and E_{min} denote the maximum and minimum energy limit for the battery storage system. E_0 denotes initial state of charge for the battery storage system.

The MPC-based intelligent building energy scheduling algorithm is a non-linear optimization problem. The optimization problem is solved by using Yalmip [14] and IPOPT solver. The intelligent building energy scheduling algorithm provides the optimal energy schedule for each time interval given the real-time price forecasts. As we increase the price forecast for the current operating interval while keeping price forecasts for the rest of the time intervals fixed, the corresponding optimal energy schedule for the current operating interval decreases. The locus of points traced out in the price-quantity space when we gradually increase price forecast, is the building's price sensitive demand bid curve.

In practice, we could follow the steps shown in Figure 3 to construct the price sensitive demand bid curve. λ_l denotes the l-th segment electricity price forecast in current time interval i. First, λ_l is set to the lower bound of price forecast P_{lower}. Then the current interval's electricity price in real-time price profile is updated with price forecast λ_l. Next, based on the updated real-time electricity price profile, the MPC algorithm computes individual customers' demand bid quantity Q_l corresponding to electricity price λ_l. In each iteration, λ_l increases by P_{incr} until λ_l exceeds the upper bound of price forecast P_{upper}. During each iteration, the pair of electricity price forecast λ_l and the corresponding building demand bid quantity Q_l is saved to construct the final demand bid curve. There are in total L Price-Quantity pairs in the price sensitive demand bid curve. The price sensitive demand bid curve is a graphical representation of the relationship between quantity of electricity demanded and customer's willingness-to-pay. These individual demand bid curves will be aggregated by the distribution system operator and submitted to the wholesale market operator. A sample price sensitive demand bid curve of an individual customer is shown in Figure 4.

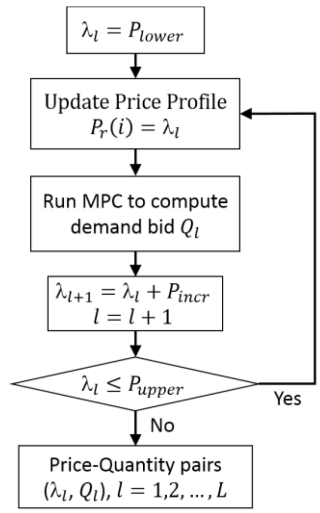

Figure 3. Demand Bid Curve Creation Diagram

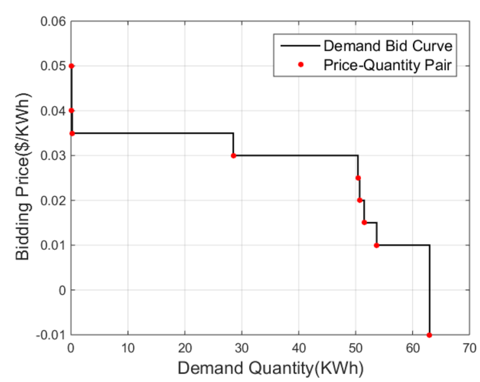

Figure 4. Sample Price Sensitive Demand Bid Curve

IV. NUMERICAL STUDY

A. Simulation Setup

Numerical studies are conducted on a 5-bus system [15] as shown in Figure 5 to demonstrate the effectiveness of proactive demand participation scheme.

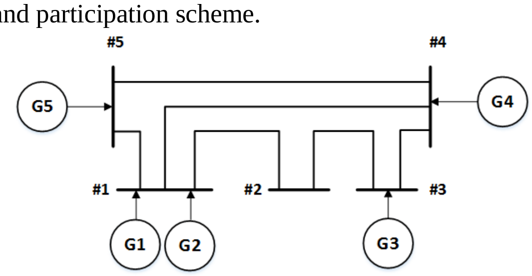

Figure 5. 5-bus Test System

HVAC control system and battery storage system are assumed to be the major flexible loads of a typical building model in the simulation. In this simulation, each building has a HVAC system with a maximum power consumption of 100 kW. In addition, a battery storage system with an energy rating of 200 kWh and a power rating of 50 kW is installed in each building. Each building also has certain amount of fixed loads. The fixed loads have the same daily profile as the test case in [11]. In the 5-bus test system, it is assumed that 2000 buildings are connected to each bus in the transmission system. Five different types of buildings, each with a distinct flexible-to-fixed load ratio, are modeled at each bus. By varying the composition of five different types of buildings on each bus, the total flexible load level in the power network can be set to any designated ratio.

B. Passive DR Versus Proactive Demand Participation

We start from an initial electricity price profile which has been calibrated based on the test system. In the passive demand response scheme, customers are assumed to be under the real-time pricing program. As illustrated in Figure 6, the customers schedule their HVAC system and battery system energy usage based on the initial real-time electricity price forecasts using the MPC approach [12]. The individual customer's energy consumption schedules are sent to the system operator. The system operator then solves the security constrained economic dispatch (SCED) problem [16] with fixed loads from customers. In contrast, in the proactive demand participation scheme, the customers construct their price sensitive demand bid curves at each decision step (every hour in the simulation) as described in section III. For simplification purposes, the individual demand bid curves are aggregated at the transmission level without considering distribution network losses. The market operator then solves the SCED problem based on the aggregated demand bid curve to derive the LMPs and dispatch instructions.

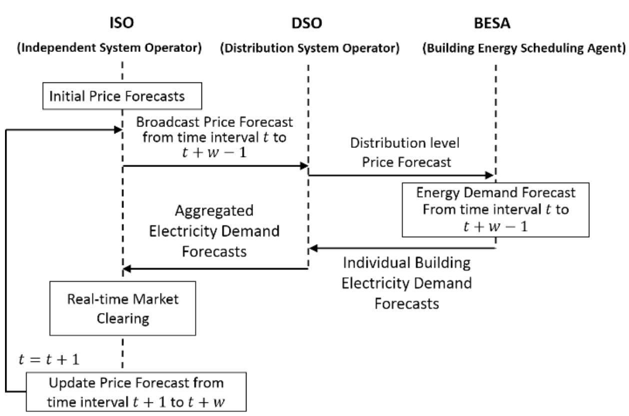

Figure 6. Passive Demand Response Flowchart

C. Effectivenss of Proactive DR Scheme

The building energy consumptions and LMPs under the proactive demand participation scenario and the passive price-based demand response scenario are shown in Figures 7 and 8. In this experiment, the total flexible load ratio in the power network is set to 50%. The flexible load ratio in our experiments is calculated by dividing energy consumption from flexible loads by energy consumption from all types of loads. We assume all customers either use proactive demand response scheme or use passive demand response strategy in each scenario.

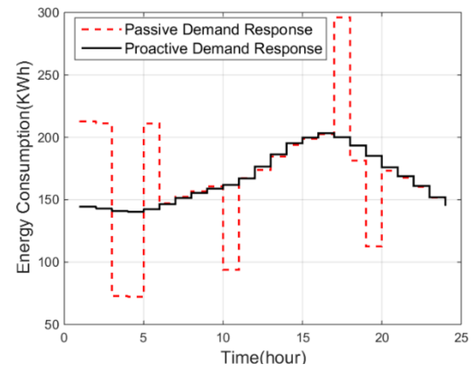

Figure 7. Building Energy Consumption

It can be seen from Figure 7 that the total energy consumption profile under the proactive demand participation scenario is much smoother than that of passive scenario. This is due to the direct representation of price sensitive demand bids, which enables better scheduling coordination between flexible loads and generators. The coordinated scheduling result also leads to lower total system generation cost in the proactive demand participation scenario. As demonstrated in Figure 8, real-time LMPs volatility is much lower in the proactive demand participation scenario.

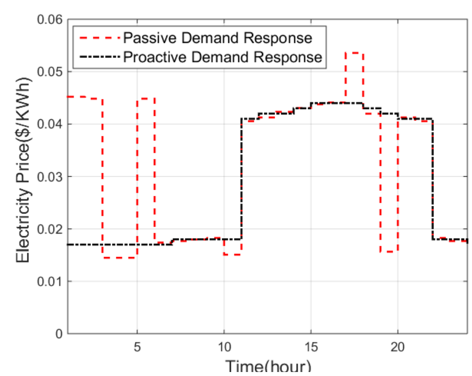

Figure 8. Real-time Locational Marginal Price

D. Impact of Flexible Load Level and Proactive DR Ratio

Experiments are conducted to study how changes in flexible load penetration level and proactive demand response participation ratio impact the overall system generation cost. The flexible load penetration level $R^{flexible}$ and proactive demand response participation ratio $R^{proactive}$ are defined in equations (17) and (18).

$$R^{flexible} = \frac{Flexible\ Load\ Energy\ Consumption}{Total\ Energy\ Consumption} \tag{17}$$

$$R^{proactive} = \frac{Numer\ of\ Customer\ in\ Proactive\ DR\ Program}{Total\ Number\ of\ Customers} \tag{18}$$

In this experiment, we first vary flexible load ratio in the power network from 0% to 100% while maintaining the level of total system peak demand. All customers are assumed to be adopting the proactive demand response strategy. The percentage of total generation cost reduction is calculated by comparing the generation costs in the passive demand response scheme and proactive demand participation scheme. The passive demand response scheme is treated as the benchmark case.

As shown in Figure 9, the total generation cost reduction percentage increases as we increase the penetration level of flexible loads in the power system. The proactive demand participation scheme is much more effective in reducing total system cost when the flexible load penetration level is higher. The proactive demand participation scheme can achieve up to 18% generation cost reduction compared with the conventional passive demand response strategy.

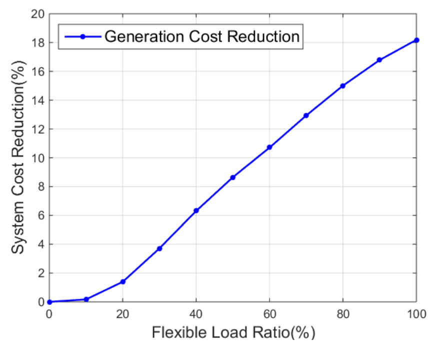

Figure 9. Generator Cost Reduction vs. Flexible Load Level

Next, we conduct experiments to quantify the impact of proactive demand response participation level on the system generation cost. Figure 10 shows the trend of system generation cost reduction when the proactive demand response participation level increases. The flexible load ratio in the power network is fixed at 100% in this experiment. We gradually increase the participation rate of proactive demand response customers, and calculate the system cost reduction in the proactive DR participation scheme compared to the passive DR scheme. In Figure 10, we can see that the system generation cost reduces significantly with increasing participation level of proactive demand response customers.

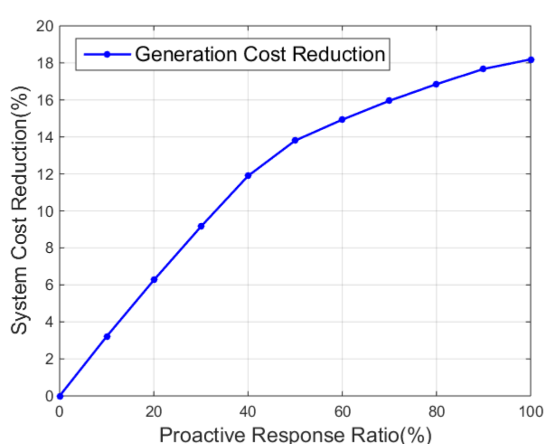

Figure 10. Generator Cost Reduction vs. Proactive Response Level

Figure 11 shows the capacity factors which represent the utilization ratio of the 5 generators in the test system. In our experiment, generators 3 and 4 have higher heat rate than generators 1, 2 and 5. As shown in Figure 11, in proactive demand participation scheme, the capacity factors of expensive generators 3 and 4 are lower than that of passive demand response scheme. The capacity factors of efficient generators 1, 2 and 5 in proactive demand participation scheme are higher than that of passive demand response regime. This result demonstrates that direct representation of price sensitive demand bids in the real-time market clearing process results in more efficient scheduling coordination between flexible loads and generators, and higher market efficiency.

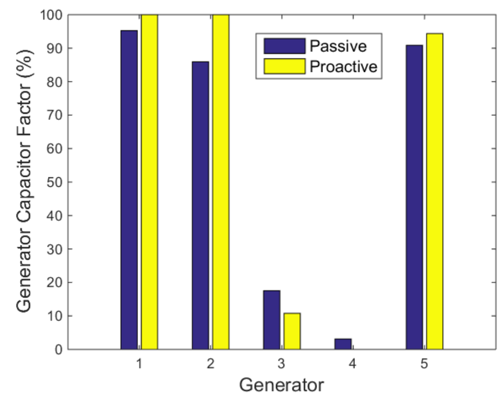

Figure11. Generator Cost Reduction vs. Price Sensitive Demand Level

V. Conclusions and Future Work

This paper proposes an innovative proactive demand participation scheme which fundamentally transforms the way retail customers interact with wholesale power markets. To implement proactive demand participation, a framework for integrated market operations in transmission and distribution system is developed. This paper also develops a demand bid curve construction methodology based on intelligent building energy scheduling algorithm. The simulation results show that the proactive demand participation scheme leads to higher market efficiency and lower price volatility compared with the passive demand response approach.

In order to move the proactive DR regime and integrated wholesale and retail market operations framework from vision to implementation, the following questions need to be further explored and addressed. First, how to prevent market manipulation by end-use customers from misrepresenting their demand bid curves? Second, will implementation cost of the proposed integrated market operations and proactive DR framework outweigh its benefits? Third, how to design privacy protection mechanisms to protect the end-use customers' sensitive information such as their demand bid curves?

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