

# A New Wholesale Bidding Mechanism for Enhanced Demand Response in Smart Grids

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**Abstract**— Calls to improve customer participation as a key element of smart grids have reinvigorated interest in demand-side features such as distributed generation, on-site storage and demand response. In the context of deregulated market structures, these features can improve flexibility of demand, but at the cost of added uncertainty. Therefore, how to implement these features under deregulated power markets is worth consideration. To address the problems induced by the demand-side participation features together with deregulated electricity markets, this paper presents a new bidding mechanism, which uses Price Elasticity Matrices (PEM) to model the concerned features. Three typical traditional bidding mechanisms are reviewed and compared with the proposed bidding mechanism. This paper also presents an algorithm guaranteeing better convergence to carry out the proposed bidding mechanism. The concept of a stepped supply curve's relative slope is defined in the algorithm. Multiple benefits induced are shown by numerical examples in a day-ahead wholesale electricity pool under real-time pricing.

**Index Terms**— smart grid, bidding mechanism, demand response, price elasticity matrix, deregulated electricity market, economic dispatch, market equilibrium.

## I. INTRODUCTION

**D**URING the past several decades, pressures to increase competition, reduce market power, improve reliability, and enable the use of cleaner renewable energy technologies have led to an increasing push for demand-side participation in competitive power markets, such as distributed generation, on-site storage and Demand Response (DR) programs [1]–[4]. One of the key features of the recent push for smart grids has been to enhance demand-side participation, especially in the form of increased price responsiveness of electricity demand. Whereas centrally administered demand-side management was an important feature of many regulated utilities throughout the past 2-3 decades, decentralized demand-side participation in competitive power markets have become the new paradigm for deregulated and restructured power systems.

This work was supported in part by the Masdar Institute of Science and Technology.

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DR has two primary categories: incentive-based demand response and time-based rates. Incentive-based demand response programs offer payments for end users to reduce their electricity usage during periods of system need or stress. By adjusting or curtailing a production process, shifting load to off-peak periods, or running on-site distributed generation, end users can reduce the level of demand that they place on distribution networks and the electric grid. End users who participate in incentive-based DR either receive discounted retail rates or separate incentive payments.

The second type of DR is comprised of time-based rates. A range of time-based rates are currently offered directly to end users; not all are dynamic, but their objective is to promote customer demand response based on price differentials across different time periods, and thus to move away from flat or averaged pricing and to promote more efficient markets. A typical example of this DR type is real-time pricing, under which the retail electricity price varies according to current system conditions [2].

For smart grids, although the emergence of demand-side participation features brings about more flexibility and options for both the supply and demand side, it also increases the uncertainties in their planning and operation. For example, when a forecasted real-time price is provided to end users in advance of their consumption, the final load amount may deviate from the forecasted value, leading to a real-time price that is inappropriate for the needed generation. Thus, in short-term power system operations, system operators may find it harder to predict the future demand and to commit or dispatch the correct amount of generation when there is an active demand response. While in long-term planning, planners may have difficulties deciding the needed generation and transmission capacity due to load forecasts that include both short- and long-term price elasticity of demand.

Therefore, in order for smart grids with demand-side participation features to have increased market efficiency, and not simply result in additional uncertainties, it is critical that information regarding load behavior is provided to the market administrator and incorporated into the appropriate market price [3]. For this reason, in smart grids, auctions in electricity markets considering demand response may have greater potential to increase efficiency than relying solely on a more passive demand response, where loads simply respond to real-time or forecasted prices.

One challenge of integrating demand response in energy auctions is the design of an appropriate bidding mechanism. The existing bidding mechanisms that allow demand-side participation [4], [5] have the problems of either only covering

a limited form of DR programs, such as Demand-Side Bid in Emergency market (DSBE) [6], or including numerous parameters physical load which produces the problem of calculation and information collection [7]. To solve these problems, this paper proposes a new demand-side bidding mechanism, in which demand-side bids include Price Elasticity Matrices (PEM) that represent any hour's load responsiveness to prices across time periods within the market's timeframe. The PEM concept was originally proposed to estimate demand response to real-time prices [8]–[12], but it has not yet been used in the context of a bidding mechanism. As a bidding mechanism, the application is very different from a forecast as the bidder (i.e., creator of the PEM) may have some control over its own price response. The proposed bidding mechanism allows for an easy and compact specification of end-user inter-temporal shifting constraints and other demand-side participation features, such as distributed generation and on-site storage. This feature is not observed under any current demand-side bidding mechanism.

This paper presents the proposed bidding mechanism in an hourly Day-Ahead (DA) wholesale electricity pool, which implements real-time pricing as the only DR program. However, the proposed bidding mechanism could be applied to a much more extensive context of under any other DR programs and to any wholesale electricity forward market that adopts a centralized auction to dispatch generation and determine market prices.

Section II first reviews three traditional demand-side bidding mechanisms, including Emergency Demand Side Bidding (EDSB), the Single Hourly Bidding (SHB) and a new demand responsive bidding mechanism proposed in [8]. Section III formulates our proposed bidding mechanism for a DA auction in a wholesale electricity pool. Section IV presents a market-interaction algorithm that improves the convergence properties for the proposed bidding mechanism. Finally, section V examines the proposed bidding mechanism under a 6-bus power system with various system status and end-user types. The conclusion of this paper is given in section VI.

## II. TRADITIONAL BIDDING MECHANISMS

In order to better understand the characteristics and deficiencies of existing bidding mechanisms for smart grids, this section reviews three representative demand-side-unbundled bidding mechanisms: Emergency Demand-Side Bidding (EDSB), Single Hourly Bidding (SHB) and an alternative demand responsive bidding mechanism proposed in [7].

### A. Emergency Demand-Side Bidding (EDSB) program and Single Hourly Bidding (SHB)

Emergency Demand-Side Bidding (EDSB) is an incentive-based DR program that is carried out in forward market auctions. This bidding mechanism is designed to reduce power usage through the voluntary partial curtailment of energy intensive processes by large power users. Companies, mostly industrial and commercial, and retailers sign up to take part in the programs. The implementation frequencies of EDSB

depend on the forecasts of emergencies' occurrences. Based on the program, the timeframe of EDSB varies from day ahead to hour ahead.

A practical example of this bidding mechanism is the NYISO's Day-Ahead Demand Response Program (DADRP). DADRP allows energy users to bid their load reductions, or "negawatts", into the Day-Ahead energy market as generators do. Offers determined to be economic are paid at the market clearing price [14].

Compared to EDSB, Single Hourly Bidding (SHB) happens on a more regular basis: it is adopted in regular dispatching rather than only coping with emergency situations. In a DA market, all generators and retailers are required to submit their bids before a deadline. However, in this case, the retailers bid for the electricity to consume (MW) and the unit price of consumption (\$/MW), as opposed to the quantity and price offered for emergency curtailment [15].

SHB operates quite differently from EDSB in practice and has several advantages over EDSB as described below:

- **Regular operation and reduction of market power:** EDSB is implemented only when emergencies are forecasted and participants submit bids responding to the ISO's calling for a few time spots. The SHB is held on a regular basis, such as in the DA market, and participants submit bids for a fixed and longer auction period, such as 24 hours. Studies show that this bundled 24 hourly bids instead of a separated hourly bid can reduce market power [13].
- **Larger social surplus:** EDSB only accepts bids to minimize the total generation cost (with a limited number of demand-side curtailment bids). On the contrary, the SHB regularly accepts bids to maximize the total social surplus, which should lead to a more efficient market [16].
- **More demand-side participation:** In the EDSB, demand-side participants sign up for the program voluntarily and will have a regular non-bid consumption over most periods. The SHB encourages more regular participation by requiring retailers that aggregate scattered end users to participate in regular auctions.
- **Efficient equilibrium in DA markets:** the EDSB operates independently of the DA market, and extra financial rewards are needed to motivate demand-side participation. The SHB is held as part of the DA dispatching. In the SHB, the DA market motivates the demand side by itself.

Even with these advantages over an EDSB program, SHB ignores loads' operating constraints and inter-temporal shiftability. (This is the reason why this bidding mechanism is named as the single hourly bidding). Usually, the change of one hour's electric consumption may affect the electric consumption during all the other hours across the timeframe. For example, some loads need continuous operation, thus their power consumption at a certain hour is coupled with the nearby hours. Ignoring the inter-temporal constraints will lead to the actual load's operation deviating from the optimal DA dispatching, thereby reducing the market's efficiency.

### B. An improved bidding mechanism by Su and Kirschen

To incorporate load operation constraints into auctions in DA electricity pools, Su and Kirschen [7] propose a new bidding mechanism.

Su and Kirschen's bidding mechanism improves upon SHB by considering load inter-temporal constraints. However, it has several limitations: firstly, the load response ramping limits only constrain load shifting limits across neighboring hours rather than across the whole auction timeframe. Although there is a constraint on the total energy that can be shifted over the whole timeframe, this single parameter cannot precisely specify a bidders' willingness to shift between any two hours (e.g, moving peak load to the morning when the peak price is high enough). Secondly, the information required from retailers' bids includes specific physical characteristics of the load, such as ramping limits and least continuous operating time, which may be difficult for a load aggregator to estimate. For example, if a retailer were responsible for 500 different discrete loads, multiple distributed generation and on-site storage units, it would have to generate a bid  $B_T^m$  for each one. Moreover, this bidding mechanism's optimization formulation for the Unit Commitment (UC) and Economic Dispatch (ED) would be subjected to a large number of load operation constraints, which would be time-consuming to solve and difficult to guarantee the existence of feasible solutions.

### III. THE PROPOSED NEW BIDDING MECHANISM

To improve upon the existing bidding mechanisms described in section II, we propose a new bid format that models end-user response by PEMs. The PEM concept was firstly proposed for demand response estimation, but has not been applied in any bidding mechanism so far [7]-[11].

#### A. Price Elasticity Matrix

Under a real-time pricing DR program of timeframe  $T$ , electricity of all time-periods can be treated as products that substitute or complement each other. Therefore, the price elasticity of electricity is defined as the change in electricity consumption at a scheduled hour  $t$  due to a change in the electricity price of that same hour  $t$  or any other hour  $\tau$ . When perturbations are small, the price elasticity can be linearized around reference demand at hour  $t$ ,  $P_{t,ref}$  and reference price at hour  $\tau$ ,  $p_{\tau,ref}$ , and further the normalized by  $P_{t,ref}/p_{\tau,ref}$ . The normalized price elasticity is denoted as:

$$\epsilon_{t\tau} = \frac{P_t - P_{t,ref}}{p_{\tau} - p_{\tau,ref}} = \frac{\Delta P_t}{\Delta p_{\tau}} \quad (1)$$

when  $t = \tau$  in (1), the elasticity is defined as *own-elasticity*, representing demand's change responding to the price's change at the same time period; when  $t \neq \tau$ , the elasticity is defined to be a *cross-elasticity*, representing demand's change due to the price's change over any other time period. During a timeframe  $T$ , all time-period price influence on electricity demand can be summarized in a PEM as:

$$\epsilon_{T \times T} = \begin{bmatrix} \epsilon_{11} & \epsilon_{12} & \dots & \epsilon_{1T} \\ \epsilon_{21} & \epsilon_{22} & \dots & \epsilon_{2T} \\ \vdots & \vdots & \ddots & \vdots \\ \epsilon_{T1} & \epsilon_{T2} & \dots & \epsilon_{TT} \end{bmatrix} \quad (2)$$

The PEM allows us to calculate the demand's change during  $T$  by:

$$\Delta P = \epsilon_{T \times T} \Delta p \quad (3)$$

where  $\Delta P$  and  $\Delta p$  are the vector representations of the changes in demand change and price over all the time periods in  $T$ . Using a PEM, end-user response and inter-hour tradeoffs can be represented in a very compact and intuitive form. This form has advantages when solving for market clearing prices as well, as will be shown later.

End-user response depends on the end-user load type. The loads of a single or multiple end users can fall into three categories: fixed, curtailable, and shiftable loads. All these load types are described by a unique PEM topology:

- Fixed loads are inelastic to price, and therefore all entries for this load type are equal to zero in the PEM.
- Curtailable loads represent inessential loads that can be shed (but not shifted) in the presence of high prices or incentives. They are represented by a PEM with negative values along the diagonal and zero values for all off-diagonal entries.
- Shiftable loads can be moved to other periods during the day. Thus, their PEMs have negative on-diagonal entries and positive off-diagonal entries distributed in different patterns corresponding to various end-user types. Table I briefly summarizes some end-user types of shiftable loads.

TABLE I  
END-USER TYPES OF SHIFTABLE LOADS AND THEIR PEMs

End-User Types	PEM Topologies	Shifting Behavior
Early shifting		End users schedule load to early time periods to take advantage of the hours of lowest prices.
Late shifting		End users schedule load to late time periods to take advantage of the hours of lowest prices.
Forward shifting		End users react to a high price by postponing their consumption to later time periods.
Backward shifting		End users react to a high price by moving their consumption to earlier time periods.
Flexible		End users have the ability to reschedule loads over a long period with equal preference over each time periods.
Real-world		End users have the ability to reschedule loads during $T$ but with higher preference over the originally scheduled time periods.

PEM topology presentations based on other classifications of end-user response are given in earlier works [8], [11], [12]. The PEM presentations and the end-user response's

classification in this paper are chosen to better fit the proposed bidding mechanism.

Shiftable loads are said to be lossless if the total energy use over the full timeframe is the same as before shifting. A lossless PEM would have the following property:

$$\sum_t \epsilon_{t\tau} = 0 \quad (4)$$

where  $\epsilon_{t\tau}$  is the row  $t$  and column  $\tau$  entry of the PEM  $\epsilon_{T \times T}$ .

The three load categories include additional price responsive features such as distributed generation and on-site storage. Therefore, these demand-side features can be modeled by a PEM with the appropriate topology. Distributed generation (DG) has a PEM with the same form as for curtailable loads, as it is turned on during high prices and essentially contributes to a negative load. For the same reason, on-site storages have the PEM topology of shiftable loads for a flexible end-user (see Table I).

In smart grids, the price elasticity values for a PEM can potentially be determined by the user-end load control algorithms or be estimated through loads' consumption data collected by smart meters. In discussing price elasticity values, it is important to note that the PEM is not used here to forecast a price response (as in previous PEM work), but to *specify inter-hour shifting constraints*, for which the retailer is assumed to have some control. Exploring how a retailer would choose elasticity values that best match its mix of loads and DG resources in order to minimize its purchasing cost or reduce risk exposure to volatile prices in DA and real-time markets is an area for future work.

### B. Operation of the Proposed Bidding Mechanism

When applied in a DA wholesale electricity pool, after the DA auction is started, all generators and retailers are required to submit their bids before a deadline. The bids of retailers take the form as:

$$B_T^r = \langle P_t^{ref}, p_t^{ref}, \epsilon_{T \times T} | t \in T \rangle, r \in \mathcal{R} \quad (5)$$

where  $T$  indicates the transaction time horizon of the DA market,  $\mathcal{R}$  is the set of retailers  $r$ ;  $P_t^{ref}$  is the reference consumption active power of retailers at hour  $t$  (MW), and  $p_t^{ref}$  reference selling price of the retailer at hour  $t$  (\$/MW·h). The reference price  $p_t^{ref}$  and demand  $P_t^{ref}$  should be a point on the retailer's end-user demand curve. The reference demand  $P_t^{ref}$  should be in the neighborhood of the forecasted demand of the next day. Sometimes, the bid profile includes  $P_{max}$  and  $P_{min}$  to state end-user response range. One retailer's bid can contain multiple PEMs and their corresponding reference points in order to retain the capacities of the loads under each PEM.

The bid profile (5) provides information that essentially approximates a multi-dimensional demand curve, which states the self price-demand relation as well as cross price-demand relation. Two key assumptions are required for this approximation. They are:

- the total consumption quantity submitted by the retailer is much larger than the consumption pattern

of each load. Without this assumption, the demand curve is constructed by energy blocks, and thus is not continuous and differentiable;

- the demand curve can be linearized around the reference points of price and demand.

The proposed bidding mechanism allows retailers' bids to describe their end-user inter-temporal constraints in a compact and straightforward manner with PEM. In the UC and ED the optimization problem does not have to include to all loads' discrete physical constraints and thus can be solved without much added complication. Generator dispatch schedules and market clearing prices can therefore be found more realistically representing end-user constraints and preferences for load shifting.

## IV. ALGORITHM

The proposed bidding mechanism can be carried out by an iterative market clearing algorithm first proposed David [8] and Kirschen [11]. This algorithm cannot converge to a solution when generators' supply curves are too steep or when demand clears the market (both cases will be described in the present section). For this reason, we propose an extension of the original market clearing algorithm that guarantees convergence in the two situations described above.

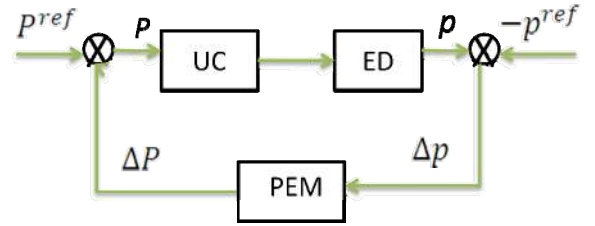


Fig. 1. The market interaction algorithm. In the figure, the UC and ED blocks refer to the unit commitment and economic dispatch.  $D$  and  $p$  are the demand and price.  $D_{ref}$  and  $p_{ref}$  are the reference points of demand and price.  $\Delta D$  and  $\Delta p$  are the deviation of demand and price from their reference points.

David and Kirschen's algorithm consists of two steps: implementing the demand-side-bundled UC and ED, and evaluating demand response to the market clearing price, as shown in Fig. 1. The algorithm can be described by its iterations: in the first iteration, the algorithm conducts demand-side-bundled unit commitment with the hourly demand as  $P_t^{(0)}$  (which is denoted in retailers' bids as their reference load,  $P_t^{ref}$ ). The unit commitment gives the initial market clearing price as  $p_t^{(0)}$ . The algorithm compares  $p_t^{(0)}$  with the reference price  $p_t^{ref}$  and calculates the difference,  $\Delta p_t^{(0)}$ . With (3), the algorithm determines the demand deviation  $\Delta P_t^{(0)}$ . The sum of  $P_t^{ref}$  and  $\Delta P_t^{(0)}$  gives the end-user response to price  $p_t^0$ , which updates  $P_t^{(0)}$  to  $P_t^{(1)}$ . The iterations are repeated until the following condition is satisfied:

$$|P_t^{(K)} - P_t^{(K+1)}| < \xi \quad (6)$$

where  $\xi$  is a small positive real number. At that point, the  $K$ th iteration is the converged iteration, and the market clearing price  $p_t^k$  and its corresponding generation schedules are at the market equilibrium.

However, this algorithm has two situations which will cause non-convergence even when a market equilibrium exists. The first non-convergent situation occurs when the generators' supply curve is too steep. This disadvantage is illustrated by a single hour case in Fig. 2.

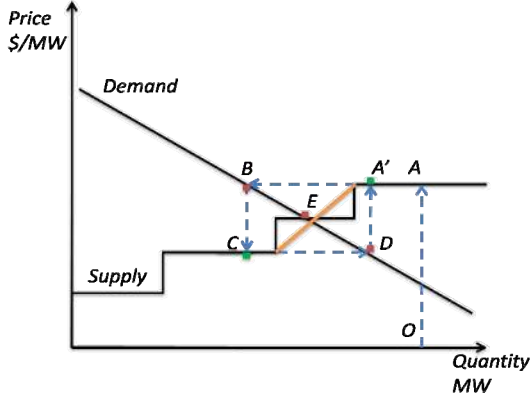


Fig. 2. Non-convergence caused by steep local relative slope of the supply curve. The straight line is the demand curve, and the step curve represents the supply curve derived from the costs of generators' energy blocks. The dash arrowed lines are the searching path of David and Kirschen's algorithm.

Based on the original supply curve, an iteration that starts with demand at point  $O$ , will remain trapped triggers the end-user response as  $P_B$  and thus generates an optimal price  $p_c$  which in turn triggers the end-user response as  $P_D$ . However, since demand  $P_D$  gives the original price  $P_{A'}$ , the following iterations will be trapped in the four points  $A', B, C$  and  $D$  but will be never able to reach the market equilibrium  $E$ . This result is caused by a demand response from  $B$  to  $D$  that is larger than the total capacity of what should be the marginal unit (i.e., the generator with a marginal cost  $\lambda(G_E)$  at point  $E$ ). By defining a local relative slope  $k_{A,C}$  of the stepped generators' supply curve, and letting  $k$  represent the linear slope of the demand curve, we formulate this condition of non-convergence at  $A, C$  as:

$$k \leq k_{A,C} \quad (7)$$

where

$$k_{A,C} = \frac{\lambda(G_A) - D_k^{-1}(\text{cap}(G_A))}{\text{cap}(G_A) - P_k(\lambda(G_A))} \quad (8)$$

where  $k_{A,C}$  is initially defined in this paper as the relative slope of the step-sized supply curve segment,  $G_A$  to  $G_C$ ;  $\text{cap}(G_A)$  is the generation capacity summation from the least expensive generation unit to the generation unit that has a marginal cost only less than  $G_A$ ;  $\lambda(G_A)$  is the marginal cost of  $G_A$ ;  $P_k(p)$  is the demand curve function with slope  $k$  and independent variable as price  $p$ ;  $P_k^{-1}(P)$  is the inversed function of demand curve  $P_k$  with independent variable as quantity  $P$ .

By applying (7) and (8), we can detect non-convergence due to steep local relative slopes of generator's supply curve.

The second non-convergent situation is when demand clears the market, which means the total demand at the market equilibrium is on the border of the marginal unit or exceeds the total generation. Fig. 3 illustrates this situation. In this case, David and Kirschen's algorithm will be also unable to reach the market equilibrium but cycles among the market equilibrium  $E$ 's neighborhood,  $A, B, C$  and  $D$ .

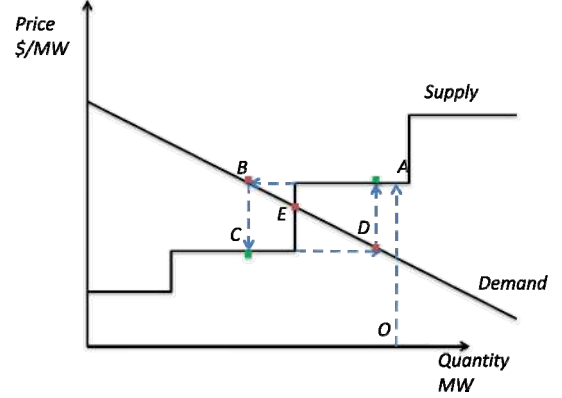


Fig. 3. Non-convergence caused by demand clears the market. In this case, the market clearing price can be set by the marginal cost of neither  $G_A$  nor  $G_B$ , which means supply doesn't clear the market. The market is cleared at  $E$  by searching along the demand curve.

Because of the two non-convergent situations, we propose an improved heuristic algorithm. The new algorithm starts by running David and Kirschen's algorithm. In every iteration  $k$ , the algorithm determines if the market equilibrium is found by checking the condition (6). When the condition is not satisfied, it further checks whether the current searching path is non-convergent. Once the non-convergence is detected, the improved algorithm decides the non-convergent causes by considering the two situations mentioned. If the market clearing price of the recent several iterations oscillates between two generators which marginal cost are ordered next to each other, then the non-convergence is caused by demand clearing the market. Otherwise, the non-convergence is caused by a relative slope of the supply curve that is locally steeper than that of the demand curve. In the first case, the algorithm starts searching for a market equilibrium on the demand curve. In the second case, the improved algorithm changes the searching path by reversing the searching path. In multi-period cases, the searching can become much more complex. Detailed searching algorithm for multi-period cases is presented in [18].

## V. NUMERICAL EXAMPLES

The proposed bidding mechanism's performance is examined in a 24 hourly DA wholesale pool under real-time pricing. The testing power system is a 6-bus system with three generation units and three retailers.

The improved market interaction algorithm is used to solve the above formulation. To better observe the end-user demand response procedure, only the generators' capacity limits are considered in the simulations but all the other generation and network constraints are neglected.

The reference loads,  $P_{ref}$ , for the three retailers are derived from actual load data of Long Island, New York state on August 9, 2008 [19]. For presentation convenience, the reference loads are normalized by twice their maximum value 3389 (MW). The reference price,  $p_{ref}$ , is set to a constant value of 10.4 (\$/MW·h). Fig. 4 depicts the reference points.

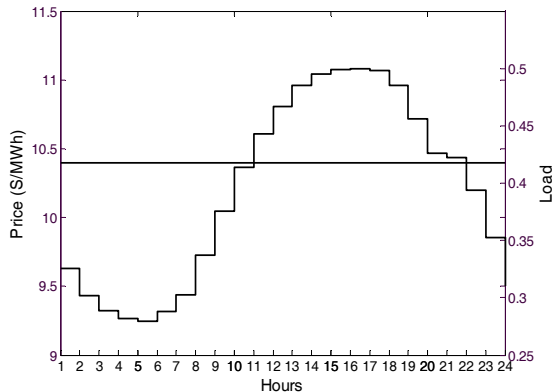


Fig. 4. Reference load and price of 24-period retailers' bids. The stepped curve is the load reference, which is normalized by 3389 (MW). The line is the price reference corresponding to the load reference.

The PEMs for the three retailers are set identical as of the real-world end-user type, with a self-elasticity of  $-0.2$  and cross-elasticity under a Gaussian distribution ( $\mu = 0.2, \sigma^2 = 0.7$ ) along each column and centered along the diagonal. The end users shift loads in a lossless manner, so the PEMs satisfy (4). The transaction timeframe of the DA market is equal to 24 hours. In addition, we set the demand response range as  $P_{max} = 1.0$  and  $P_{min} = 0.0$ .

Table II presents bids of the three generation units, which are normalized by G1's rated capacity.

TABLE II  
GENERATORS' PARAMETERS

Generator No.	Capacity	Marginal Cost (\$/MW·h)
G1	1.0	9.8
G2	0.7	10.7
G3	0.5	12.6

Two types of major generation-side contingencies are considered happening to G2. The first type is a sudden change in generation costs, shown in Fig. 5, and the second type is a sudden loss of generation, shown in Fig. 6.

Fig. 7 shows the bidding results for the two bidding mechanisms after the market equilibrium is reached under the contingency of G2's cost change. For the proposed bidding mechanism, Fig. 7 a shows that G1 clears the market from H1 to H8, H10 and H24, which is reflected by its marginal cost shown in Fig. 7 b. The market price at H8 is at a value between the marginal costs of G1 and G2, as demand clears the market for this period, which is verified by the fact that G1 outputs its full capacity. In addition, Fig. 7 a shows that G2 clears the market from H10 to H23 except for H10 and H15. At H10, G1 clears the market with a positive output of G2, because G2's marginal cost at the hour decreases to a value less than that of G1; at H15, G3 clears the market while G2 is not dispatched, since G2's marginal cost at the hour increases above G3's marginal cost. The cost change of G2 affects the

market price at H10 and H15 but not at H5 when the total demand can be satisfied by G1.

For the SHB, the generation dispatching results and the market clearing price can be described in a similar way. It is observed from Fig. 7 b that the demand clears the market at H1 and H8, which results in a higher market price than that under the proposed bidding mechanism.

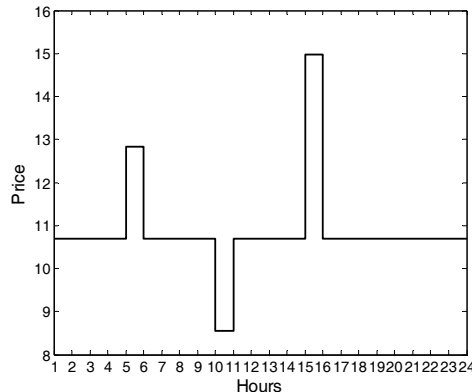


Fig. 5. G2's generation cost. G2's marginal cost is bid as 10.7. This marginal cost is forecasted to suddenly increase at Hour 5 and Hour 15 to 12.84 and 14.98, and decrease at Hour 10 to 8.56.

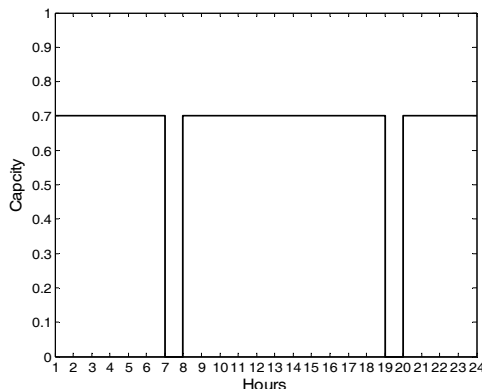


Fig. 6. G2's generation capacity. G2's capacity is bid as 0.7. This capacity is forecasted to be lost (i.e. drop to 0.0) at Hour 7 and Hour 19.

Fig. 7 c shows the load profiles responding to the market prices. For the proposed bidding mechanism, when the market price is higher than the reference price, for example at H 15, the end users redistribute their loads more to the nearby hours and less to the further away hours and vice versa. For the SHB, since no shifting effects are considered, it is estimated that loads are increased when the price is lower than the reference price and vice versa. The two resultant load profiles illustrate an important point: while the SHB mechanism expects an ideally improved load profile with higher valley and lower peak, the actual load profile for an end user with inter-temporal shifting constraints may be quite different. Even lower valley and higher peak around the previous peak values may appear due to the shifting behaviors of real-world end users.

Fig. 8 shows the bidding results after reaching the market equilibrium under the contingency of G2 losing capacity. It is observed from Fig. 8 b that the demand clears market at H1 and H8 under the SHB and at H8 under the proposed bidding

mechanism. The loss of G2's capacity causes a price spike at H19 under both bidding mechanisms. The setting of the market price can be reflected by the generation dispatching schedule shown in Fig. 8 a. In addition, responding to the market price, the load profile under both the bidding mechanisms are shown in Fig. 8 c. The interpretation of Fig. 8 follows a similar description of Fig. 7 and won't be repeated here.

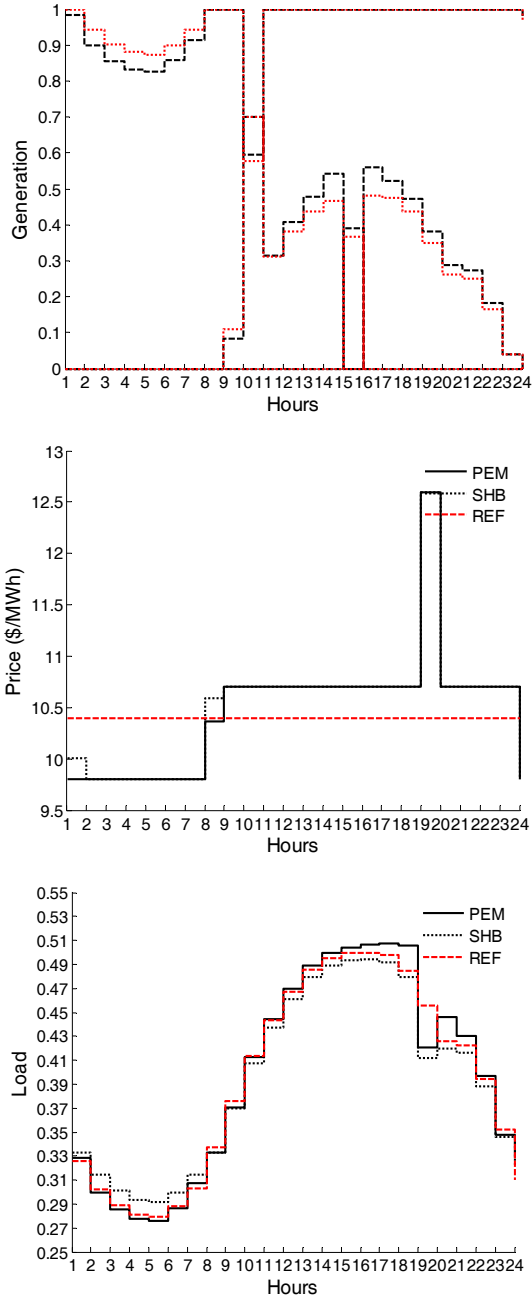


Fig. 7. DA auction bidding results of the proposed bidding mechanism. The capacity of G2 is shown in Fig. 5. From top to bottom: (a) the three generators' dispatching schedule, (b) market clearing price, and (c) final estimated load profile with demand response. Reference values are shown in the load and price figures.

## VI. CONCLUSION

Calls to improve customer participation as a key element of smart grids have reinvigorated interest in demand-side features such as distributed generation, on-site storage and demand response. In order for these features to result in increased market efficiency, and not simply create additional uncertainty, it is critical that information regarding load behavior, which can be monitored and controlled by smart grids, is provided to the market administrator and incorporated into the dispatch market price. For this reason, this paper proposes a new bidding mechanism that uses a Price Elasticity Matrix to incorporate more complex features of demand response, in particular, inter-temporal shifting effects.

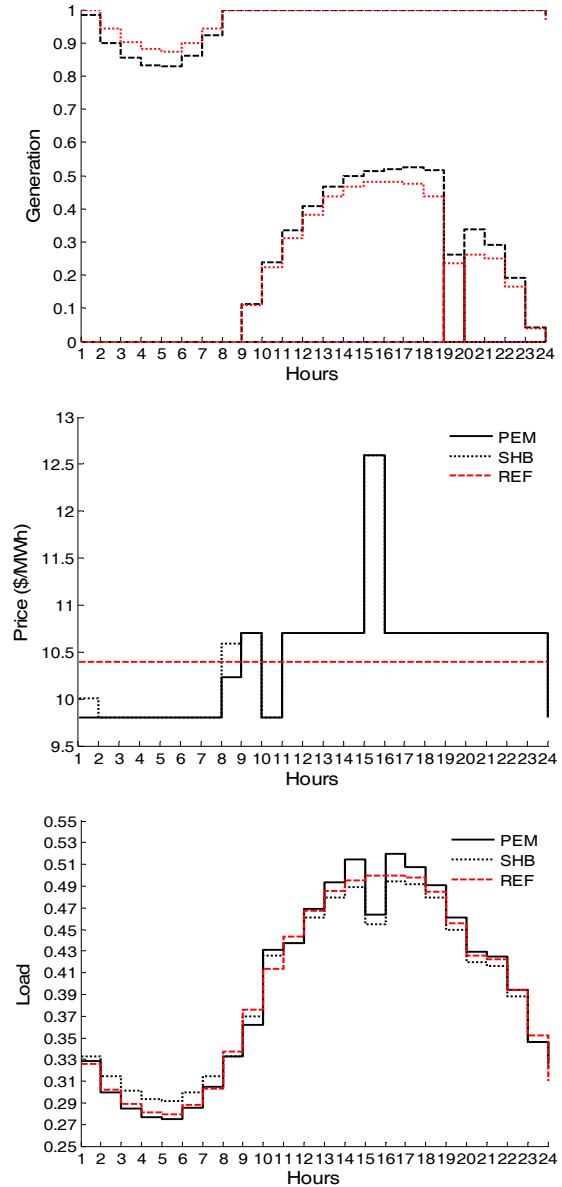


Fig. 8. DA auction bidding results of the PEM bidding mechanism and the SHB. The cost of G2 is shown in Fig. 6. From top to bottom: (a) the three generators' dispatching schedule, (b) market clearing price, and (c) final estimated load profile with demand response. Reference values are shown in the load and price figures.

The proposed bidding mechanism is formulated for a Day-Ahead (DA) auction in a wholesale electricity pools. In addition, this paper proposes an algorithm to solve for the market clearing price under two typical non-convergence cases: demands clearing the market, and a excessively steep supply curve. The concept of a stepped supply curve's relative slope is defined to address non-convergence issues for the later case.

A numerical example for a 6-bus test system is presented to illustrate the ability of the new bidding mechanism to capture more subtle inter-hour shifting constraints, as compared to a Single Hourly Bidding (SHB) mechanism. By using the proposed bidding mechanism in a Day-Ahead market, the market administrator would more accurately capture the actual real-time load behavior and therefore determine a more appropriate dispatch schedule and market price.

Future work may involve estimation methods of PEM for given smart grids' technologies. Another prospective direction is to include the representation of demand response in long-term power system planning.

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