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Optimized Self Scheduling of Power Producers in a Restructured Power Market

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Abstract: Generation scheduling and dispatch are determined by individual power producers' bids in a deregulated power market. The benefits obtained by a power producer will depend largely on how effectively it can incorporate the variation of the market price in its generation scheduling. This paper addresses the self-scheduling problem and design of optimal bidding strategy for a price-taker company. By restructuring the electric power systems, market participants are facing an important task of bidding energy to an Independent System Operator (ISO). This study proposes a model and a method for optimization-based bidding and self-scheduling where a utility bids part of its energy and self-schedules the rest. The model considers ISO bid selections and uncertain bidding information of other market participants. With appropriately simplified bidding and ISO models, closed-form ISO solutions are first obtained. These solutions are then plugged into the utility's bidding and self-scheduling model which is solved by using Lagrangian relaxation. Testing results depicts that the method has effective solutions with acceptable computation time.

Key word: Bidding strategies, lagrangian relaxation, self-scheduling

INTRODUCTION

With the deregulation of electrical power systems, market participants bid energy to an Independent System Operator (ISO). In the daily market, participants submit bids to the ISO who then decides Energy Clearing Prices (ECP) and hourly generation levels of each participant over a 24-hour period. The relationship between ISO and participants is shown in Fig. 1. In some regions, a utility bids part of the energy and self-schedules the rest, whereas an Independent Power Producer (IPP) bids all its energy. This study focuses on the daily bidding and scheduling of a utility.

For each participant, bidding strategies ideally should be selected to maximize its profit. Game theory is a natural platform to model such an environment (Owen, 1995; Krishna and Ramesh, 1997; Ferrero *et al*., 1997). In the literature, matrix games have been used for its simplicity, and bidding strategies are discredited, such as "bidding high","bidding low" or "bidding medium". With discrete bidding strategies, payoff matrices are constructed by enumerating all possible combinations of strategies, and an "equilibrium" of the "bidding game" can be obtained. It is difficult to incorporate self-scheduling in the method.

Modeling and solving the bid selection process by the ISO have also been discussed. In Hao *et al*. (1998), bids are selected to minimize total system cost, and the ECP is determined as the price of the highest accepted bid. In Alvey *et al*. (1998), a bid-clearing system is presented. Detailed models are used, including network, reserve, and ramp-rate constraints, and the problem is solved by using linear programming.

The purpose of the study is to present a model and a method for the bidding and self-scheduling problem from the viewpoint of a utility, say Participant 1. To obtain effective solutions with acceptable computation time, bids are represented as quadratic functions of power levels. For Participant 1, these parameters are to be optimized. For other participants, the parameters are assumed to be available as discrete distributions. Based on bids submitted, the ISO is to minimize the total system cost. The problem for Participant 1 is then formulated to minimize its expected cost, including generation costs and payment to the market.

PROBLEM FORMULATION

Representation of bids: A bid consists of price offers and the amount of load to be satisfied by the market for each hour. Price offers specify a stack of MW levels and the corresponding prices as illustrated in Fig. 2. By integrating a staircase price offer curve, the bidding cost function is piecewise linear. The amount of load to be satisfied by the market is denoted as pM*l* (t).

To reduce the number of parameters associated with a bid, the piece-wise linear bidding cost function is approximated by a quadratic Cl (pAl(t)) (often done in scheduling problems (Guan *et al*., 1994)):

$$Cl(p_{Al}(t)) = a_l(t)p_{Al}^2(t) + b_l(t)p_{Al}(t), \qquad l = 1, 2, \ldots, L \qquad (1)$$

where, l is the participant index, t the hour index, p_{Al} (t) the accepted level by ISO, $a_l(t)$ and b_l (t) are non-negative bidding parameters, and L the number of participants.

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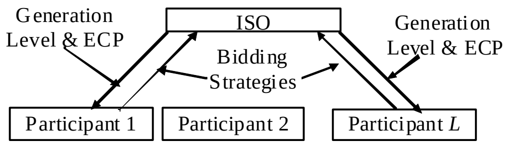

Fig. 1: The relationship between ISO and participants

	Rate $/MW	Level MW
Block 0	10	100
Block 1	15	60
Block 2	20	40

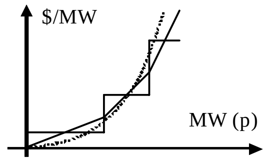

Fig. 2: An example of bids

The p_{Al} (t) is non-negative, and is upper bounded by a maximal value, i.e.,

$$0 \leq p_{Al}(t) \leq \overline{p}_{Al}(t) \quad (2)$$

Participant 1 does not have exact bids of others, but has probability distributions of {a*l*(t), b*l*(t) and pM*l*(t)}, *l* = 2, …, *L*, based on market information and experiences. The distributions are represented by J discrete sets of bids:

$$Bj = \{a^j_l, b^j_l, p^j_{ml}\ l = 2, \ldots L\},\ j = 1, 2, \ldots J \quad (3)$$

The probability of Bj is p_j with $\sum_{j-1}^{J} p^j = 1$. For Participants 1, $a_1(t)$, $b_1(t)$ and $p_{M1}(t)$ depend on its unit characteristics and others' bids, and are to be optimized.

The ISO model: The ISO decides hourly generation levels of participants to satisfy the total submitted load at the minimum cost over 24 h. Bids of all participants are available to the ISO, and the deterministic ISO problem is:

$$J_{ISO} = \min_{p_{Al}(t)} \sum_{t=l}^{T} \sum_{l=l}^{L} C_l(p_{Al}(t)) \quad (4)$$

subject to:

$$\sum_{l=l}^{L} p_{Al}(t) = \sum_{l=l}^{L} p_{Ml}(t) \quad (5)$$

where $p_{Ml}(t)$ is the amount of load that will be satisfied by the market for Participant *l* at hour t. Constraints (2) should be satisfied for all participants. For simplicity of derivation, however, they are only required to be satisfied for Participant 1 but are ignored for others.

The model of participant 1: Participant 1 is to decide the generation levels of each unit and a bidding strategy to maximize its profit, or to minimize its costs while satisfying various constraints. The costs include generation costs and payment to the market, with the payment equal to ECP multiplied by ($p_{M1}(t)$ - $p_{A1}(t)$). Only thermal units are considered to simplify presentation, however, there is no difficulty in incorporating hydro and pumped-storage units. The problem is therefore:

$$\min_{p_{M1}(t), a_1(t), b_1(t), p_{ti}(t)} J, \text{With } J \equiv E \sum_{t=1}^{T} \sum_{i=1}^{I} \left\{ C_{ti}(p_{ti}(t)) + \lambda^*_M(t)(p_{M1}(t) - p_{Al}(t)) \right\} \quad (6)$$

In the above, T is the number of hours, I the number thermal units, Cti the cost function of thermal unit i, $p_{ti}(t)$ the generation level of unit i at hour t, and $\lambda^*_M(t)$ the ECP at hour t. The expectation is taken with respect to uncertain bidding parameters reflected through $\lambda^*_M(t)$ and $p_{Al}(t)$.

For each hour, the load balance constraint requires that:

$$\sum_{i=l}^{I} p_{ti}(t) + E(p_{Ml}(t) - p_{Al}(t)) = p_d(t) \quad (7)$$

In the following, the of ISO scheduling will be solved first, followed by bidding and self-scheduling.

The ISO scheduling: From ISO's point of view, its problem is deterministic. When Participant 1 solves the ISO problem, however, it only has distributions of parameters, and has to solve the ISO problem for every set of bidding parameters. Solution of the ISO problem for the jth set Bj is derived as follows. The index j is omitted as appropriate for simpler presentation.

Lagrangian multipliers $\lambda_M(t)$ are used to relax (5), and $\pi_1(t)$ and $\pi_2(t)$ to relax (2) The resulting Lagrangian is:

$$L_{ISO} = \sum_{t=l}^{T} \left\{ \sum_{l=l}^{L} C_l(p_{AL}(t)) + \lambda_M(t) \left[\sum_{l=l}^{L} p_{Ml}(t) - \sum_{l=l}^{L} P_{Al}(t) \right] \right\} - \sum_{t=1}^{T} \pi_1(t)\, p_{Al}(t) - \sum_{t=l}^{T} \pi_2(t)(p_{Al}(t) - \overline{p}_{Al}(t)). \quad (8)$$

In (8), $\pi_1(t)$, $\pi_2(t)$, and pA1(t) satisfy:

$$\pi_1(t)p_{A1}(t) = 0, \text{ and } \pi_2(t)p_{A1}(t) = 0$$

The three cases of ISO solutions are presented below:

Case 1: Accepted level in bound ($0<p_{Al}(t)<p^{-}_{Al}(t)$) With the given {$\lambda_M(t)$}, (8) can be decomposed into sub-problems. The sub-problem for participant *l* is:

$$L_l = \min_{p_{Al}(t)} \sum_{t=l}^{T} \left\{ a_l(t) p_{Al}^2(t) + b_l(t) p_{Al}(t) - \lambda_M(t) p_{Al}(t) \right\} \quad (9)$$

The solution for (9) is:

$$p_{Al}^*(t) = \frac{\lambda_M(t) - b_l(t)}{2a_l(t)} \quad (10)$$

In (10), $a_l(t)$ is assumed to be non-zero. If it is zero, a quadratic function with a small $a_l(t)$ is used to approximate the linear function following the idea of. With an analytical solution for each sub-problem, it is not necessary to iteratively update $\lambda_M(t)$ at the high level. Substituting (10) into (5), one obtains the:

$$\lambda_{M(t)}^* = \frac{\sum_{l=l}^{L} \left[\frac{b_l(t)}{a_l(t)} + 2P_{Ml}(t) \right]}{\sum_{l=l}^{L} \frac{l}{a_l(t)}}. \quad (11)$$

Substituting (11) into (10), one obtains the accepted level for Participant 1 at hour t as:

$$p_{Al}^*(t) = \frac{\sum_{l=l}^{L} 2p_{Ml}(t) \sum_{l=2}^{L} \frac{b_l(t) - b_1(t)}{a_l(t)}}{2 + 2a_1 \sum_{l=2}^{L} \frac{l}{a_l(t)}} \quad (12)$$

The energy clearing price $\lambda^*_M(t)$ and the accepted level $p^*_{A1}(t)$ for Participant 1 are functions of $a_1(t)$, $b_1(t)$ and $p_{M1}(t)$. To simplify (11) and (12), let:

$$c_0(t) \equiv 2\sum_{l=2}^{L} p_{Ml}(t) + \sum_{l=2}^{L} \frac{b_l(t)}{a_l(t)} \quad (13)$$

$$c_1(t) \equiv \sum_{l=2}^{L} \frac{1}{a_l(t)} \quad (14)$$

Then (11) and (12) can be rewritten as:

$$\lambda_M^*(t) = \frac{(c_0(t) + 2p_{M1}(t))a_1(t) + b_1(t)}{c_1(t) * a_1(t) + 1} \quad (15)$$

$$p_{Al}^*(t) = \frac{c_0(t)/2 + p_{M1}(t) - c_1(t)b_1(t)/2}{c_1(t) * a_1 + 1} \quad (16)$$

Participant 1 may be a buyer or a seller depending on the sign of ($p^*_{M1}(t)$ - $p_{A1}(t)$), where $p^*_{M1}(t)$ is the solution for $p_{M1}(t)$ to be derived later.

Case 2: Zero accepted level ($p_{A1}(t) = 0$)
In this case, the bidding prices of Participant 1 are high, causing $p_{A1}(t) = 0$. The derivation is similar to Case 1 with

$$\lambda_M^*(t) = \frac{2p_{M1}(t) + c_0(t)}{c_1(t)} \quad (17)$$

$$p_{A1}^*(t) = 0 \quad (18)$$

Case 3: Maximum accepted level:($p_{Al}(t) = (p^{-}_{A1}(t))$
In this case, Participant 1'sng price is low, resulting in ($p_{Al}(t) = (p^{-}_{A1}(t)$ and the following energy clearing prices.

$$\lambda^*_M(t) = \frac{\sum_{l=2}^{L} \left[\frac{b_l(t)}{al(t)} + 2p_{Ml}(t) \right]}{\sum_{l=2}^{L} \frac{l}{a_l(t)}} \quad (19)$$

The derivation is similar to Case 1 with ECP determined by other participants' bids.

Bidding strategy and self-scheduling: For Participant 1's problem, using multipliers $\lambda_1(t)$ to relax demand constraints (7) the Lagrangian can be written as:

$$\begin{aligned} L = E\sum_{t=1}^{T}\sum_{i=l}^{1}[c_{ti}(p_{ti}(t)) + \lambda^*_M(t)(p_{Ml}(t) - p^*_{Al}(t))] \\ + \sum_{t=1}^{T}\lambda_1(t)\left[p_d(t) - \sum_{i=l}^{I} p_{ti}(t) - E(p_{Ml}(t) p^*_{Al}(t)) \right] \end{aligned} \quad (20)$$

The RHS of (20) is separable for a given {$\lambda_1(t)$}, and can be decomposed into individual thermal unit subproblems and a bidding subproblem. A two-level algorithm is developed, where at the low level, individual subproblems are solved, and at the high level, {$\lambda_1(t)$} is updated.

Solutions of thermal subproblems: A Thermal Sub-problem is:

$$\min_{p_{ti}(t)} L_{ti}, with\, L_{ti} = \min_{p_{ti}(t)} \sum_{t=1}^{T} \left\{ C_{ti}(p_{ti}(t)) - \lambda_1(t) p_{ti}(t) \right\}$$

This minimization is subject to individual unit constraints. With $\{\lambda_1(t)\}$ given, the subproblem is deterministic, and can be solved by using the method presented in (Guan *et al*., 1992).

The solution of the bidding sub-problem: The bidding sub-problem is:

$$\min_{P_{M1}(t), a_l(t), b_l(t)} L_{B,} \quad with$$

$$L_B \equiv E\sum_{t-l}^{T}\{\lambda^*{}_M(t)[p_{Ml}(t) - p^*{}_{Al}(t)] \tag{21}$$
$$-\lambda_1(t)[p_{Ml}(t)p^*{}_{Al}(t)]$$

In (21), λ_M^* and $p^*_{A1}(t)$ are obtained from ISO scheduling as presented as below, and depend on bids of participants. This bidding sub-problem is therefore stochastic. In the following, the deterministic version of the sub-problem will be solved first. The stochastic version can be similarly solved except that the expectation of LB is optimized. Following the derivations of as below, three cases will be considered, i.e.,

$0 < p_{Al}(t) < \overline{p}_{Al}(t)$, pA1(t) = 0 and pA1(t) = $\overline{p}_{Al}(t)$

Case 1: Accepted level in bound: $(0<P_{Al}(t)<P^{-}{}_{Al}(t))$
The degeneracy of the bidding subproblem (21) will be analyzed first, and then a numerical method to obtain a solution is presented.

Solution degeneracy analysis: From the ISO load balance constraints (5), the net energy exchange between Participant 1 and the market is:

$$p_{M1}(t) - p_{A1}(t) = \sum_{l=2}^{L}[p_{Al}(t) - p_{Ml}(t)] \tag{22}$$

By substituting (22) into (21), L_B can be rewritten as:

$$L_B = \sum_{t=1}^{T}\left\{[\lambda_M^*(t) - \lambda_1(t)]\sum_{l=2}^{L}[p_{Al}(t) - p_{Ml}(t)]\right\} \tag{23}$$

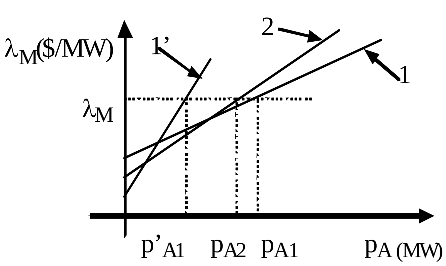

Fig. 3: Degeneracy of the deterministic bidding subproblem

By substituting (10), (13) and (14) into (23), L_B becomes:

$$L_B = \sum_{t=1}^{T}\frac{1}{2}\Big\{c_1(t)\lambda_M^{*2}(t) - \tag{24}$$
$$[c_1(t)\lambda_1(t) + c_0(t)]\lambda_M^* + \lambda_1(t)c_0(t)\Big\}$$

It is separable in time. To obtain its minimum, the partial derivatives with respect to $a_1(t)$, $b_1(t)$ and $p_{M1}(t)$ are set to zeros, i.e.,

$$\frac{\partial L_B(t)}{\partial a_1(t)} = \frac{\partial L_B(t)}{\partial \lambda^*{}_{M(t)}}\frac{\partial \lambda_M^*(t)}{\partial a_1(t)} = 0$$
$$\frac{\partial L_B(t)}{\partial b_1(t)} = \frac{\partial LB(t)}{\partial \lambda^*{}_{M(t)}}\frac{\partial \lambda^*{}_M}{\partial b_1(t)} = 0 \tag{24}$$

$$\frac{\partial L_B(t)}{\partial P_{M1}(t)} = \frac{\partial L_B(t)}{\partial \lambda^*{}_{M(t)}}\frac{\partial \lambda_M^*(t)}{\partial P_{M1}(t)} = 0 \tag{25}$$

where,

$$\frac{\partial \lambda_M^*(t)}{\partial a_1(t)} = \frac{c_0(t) + 2p_{M1}(t) - c_1(t)b_1(t)}{[c_1(t)a_1(t)+1]^2}$$
$$\frac{\partial \lambda_M^*(t)}{\partial b_1(t)} = \frac{1}{c_1(t)a_1(t)+1} \tag{26}$$
$$\frac{\partial \lambda_M^*(t)}{\partial_{M1}(t)} = \frac{2a_1(t)}{c_1(t)a_1(t)+1}$$

It is clear that $\frac{\partial \lambda_M^{*(t)}}{\partial b_1(t)}$ cannot be zero, therefore, the simultaneous Eq. (24), (25) and (26) degenerate to:

$$\frac{\partial L_B(t)}{\partial \lambda_M(t)} = c_1(t)\lambda_M^{*2}(t) - [c_1(t)\lambda_M^*(t) + c_0(t)] = 0 \tag{27}$$

With three variables and one constraint (27) for each t, the bidding subproblem has an infinite number of solutions. The degeneracy can be seen from Fig. 3 with the case of two participants. Suppose that Line 2 is the bidding price curve of Participant 2, and Line 1 is an optimal bidding strategy of Participant 1 with optimal a_1, b_1, p_{A1}, p_{M1} and p_{lM}. Another bid of Participant 1 is an equivalent solution if it satisfies 0 < b’1 < $_{lM}$ and $p'_{M1} = p_{M1} - (p_{A1} - p'_{A1})$ because it results in the same energy clearing price $_{lM}$ and the net energy exchange $(p_{M1} - p_{A1})$.

Obtaining a solution: Having shown the degeneracy of (21) above, it is straightforward to obtain one of its solutions. Substituting $\lambda^*_M(t)$ in (15) and p*A1(t) in (16) into (21), the subproblem cost at hour t can be:

$$LB(t) = \left\{ \begin{aligned} &\left(\left(\frac{c_0(t)a_1(t) + 2p_{M1}(t)a_1(t) + b_1(t)}{c_1(t)a_1(t)+1} \right) - \lambda_1(t) \right) \\ &\times \left(p_{M1}(t) - \frac{c_0(t)/2 + p_{M1}(t) - c_1(t)b_1(t)/2}{c_1(t)a_1(t)+1} \right) \end{aligned} \right\} \tag{28}$$

To minimize $L_B(t)$, any two of its three decision variables $a_1(t)$, $b_1(t)$, are $p_{M1}(t)$ are fixed first, and the third one is optimized by a gradient method.

Case 2: Zero Accepted Level: ($p_{A1}(t) = 0$)
In this case, the accepted level for Participant 1 is zero, therefore the bidding sub-problem cost is obtained by substituting (17) and (18) into (21):

$$L_B(t) = \frac{2}{c_1(t)} p^2_{M1}(t) + \left[\frac{c_0(t)}{c_1(t)} - \lambda_1(t) \right] p_{M1}(t) \tag{29}$$

Minimizing (29), the solution is:

$$p^*_{M1}(t)\left[\lambda_1(t)c_1(t) - c_0(t)\right]/4 \tag{30}$$

Participant 1 purchases $p^*_{M1}(t)$ from the market at the energy clearing price of the hour.

Case 3: Maximum accepted level: ($p_{Al}(t) = p^-_{Al}$)
In this case, Participant 1's accepted level $p_{A1}(t)$ reaches the maximum, and the ECP is determined by bids of others. A solution to this bidding subproblem is to set $a_1(t)$ equal to 0, and $b_1(t)$ equal to Participant 1's marginal cost without bidding. This leads to ($p_{Al}(t) = p^-_{Al}$) if Participant 1's generation cost is low.

The stochastic bidding subproblem and solution: Now consider the stochastic version. Following (21) and (28), the subproblem is changed to:

$$\min E\left[L_B(t)\right] = \sum_{j=1}^{J} L^j_B(t)\, p^j \tag{31}$$

In the above, L^j_B (t) is similar to LB(t) in (28), and E[LB(t)] is a function of $a_1(t)$, $b_1(t)$ and $p_{M1}(t)$. With a derivation similar to that for the deterministic case, it can be shown that (25) and (26) degenerate to one as can be seen from Fig. 4. Suppose that Participant 2 has two possible bidding prices, Line $_{2L}$ (bidding at low prices) and 2H (bidding at high prices), and Line 1 is an optimal bidding strategy for Participant 1. Another bid of Participant 1 is an equivalent solution if it satisfies $0 < b'_1 < \lambda_{ML}$, $a'_1 = a_1$ and $p'_{M1} = p_{M1} - (p_{A1L} - p'_{A1L})$. The difference between this and the deterministic case is that a'_1 is required to be equal to a1 so that Line 1′ is parallel to Line 1, and p'_{M1} also satisfies $p'_{M1} = p_{M1} - (p_{A1H} - p'_{A1H})$ to result in the same expected net energy exchange.

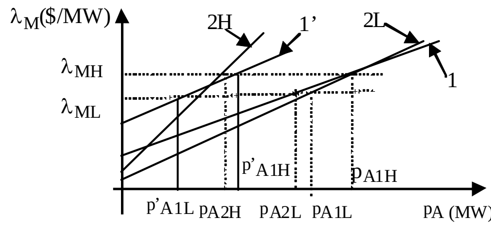

Fig. 4: Degeneracy of the stochastic bidding subproblem

In solving the sub-problem, b_1 is fixed, and p_{M1} and a_1 are optimized using the gradient method.

Update of multipliers at the high level: Multipliers are updated to maximize dual function f $\phi(\lambda_1)$:

$$\max_{\lambda_1 \geq 0} \phi(\lambda_1) \text{ with } \phi(\lambda_1) \equiv \min_{p_{M1}(t), a_1(t), b_1(t), p_{ti}(t)} L \tag{32}$$

where, L is defined in (20). With a given set of subproblem solutions obtained at the low level, this is a deterministic problem. The subgradient of f $\phi(\lambda_1)$ is a T′1 vector gl_1, and the t-th element is

$$g\lambda_1(t) = P_d(t) - \sum_{i=1}^{I} P_{ti}(t) - (p_{M1}(t) - p^*_{A1}(t)) \tag{33}$$

The dual problem is usually solved by a sub-gradient method (Shaw, 1995), and is solved in this paper by the bundle trust region method (BTRM) to improve the convergence. BTRM is a kind of bundle method that accumulates sub-gradients obtained thus far in a bundle, and uses a convex combination of these sub-gradients to find a search direction. Obtaining the convex combination coefficients involves quadratic programming that is recursively solved in BTRM to reduce time requirements.

NUMERICAL RESULTS

The method has been implemented in C++ based on our hydrothermal scheduling code (Guan *et al*., 1994; Guan *et al*., 1995; Guan *et al*., 1992). A data set provided by Northeast Utilities (NU) is used to demonstrate the capabilities of the method in handling various market situations. To simplify testing, all other market participants are aggregated as Participant 2 with three possible bidding strategies, bidding low (L), bidding

Table 1: Bidding parameters of participant 2

	$b_2(t)$ (%)			p_{M2} (t) (%)		
Case	L	M	H	L	M	H
1	80	100	120	20	30	40
2	80	100	120	10	30	50
3	60	100	140	20	30	40
4	100	120	140	20	30	40
5	20	40	60	20	30	40

Table 2: Cost comparison of mean method and stoch method

Case	Mean Meth ($)	Stoc. Meth ($)	Savings (%)
1	106.169	105.759	0.39
2	100.930	100.365	0.56
3	102.420	101.431	0.97
4	103.076	102.682	0.38
5	105.334	104.800	0.51

medium (M), and bidding high (H) each with the same probability 1/3. The High value for $a_2(t)$ is 0.09, Medium 0.05, and Low 0.01. Participant 2's $b_2(t)$ and $pM_2(t)$ are varied to represent different market situations. With Case 1 as the base, four additional cases are created where $b_2(t)$ as a percentage of Participant 1's original marginal cost (without bidding) and $p_{M2}(t)$ as a percentage of Participant 1's original load are listed in Table 1.

The method is compared with the "mean method" which considers Participant 2's bidding model as deterministic with each parameter set to its mean value. Comparison of testing results for Participant 1 based on 100 simulation runs is presented in Table 2. Case 2 represents a volatile market with a large variance on pM2(t), and the saving of the stochastic method over the mean method is increased as compared with the base case. Case 3 also represents a volatile market with large variance on $b_2(t)$, and the saving is increased as compared with the base case. Cases 2 and 3 therefore show that the method works better than the mean method in volatile markets. Case 4 represents a more expensive market with the mean value of $b_2(t)$ increased by 20%, and the saving over the mean method is 0.38%. Case 5 represents a the cheap market with the mean value decreased by 40%, and saving is 0.51%. Cases 4 and 5 therefore show that the method works well in both expensive and cheap market situations.

The average CPU time for the mean method is 70 sec, and that of the stochastic method is about 95 sec. The CPU time requirements are close because both methods solve the bidding subproblem using a gradient method, and there is only one stochastic bidding sub-problem.

$b_2(t)$ (%): $b_2(t)$ as a percentage of Participant 1's marginal cost without bidding.

$p_{M2}(t)$ (%): $p_{M2}(t)$ as a Percentage of Participant 1's Load.

CONCLUSION

In this research study a method is proposed for optimized bidding and self-scheduling where a utility bids part of its energy and self-schedules the rest. An innovative model and an efficient Lagrangian relaxation-based method are presented to solve the bidding and self-scheduling problem. Numerical testing depicts that the model properly handles various market situations.

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