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Optimal Integrated Bidding and Hydrothermal Scheduling with Risk Management and Self-Scheduling Requirements

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Abstract: With the power industry worldwide deregulated, electricity is primarily traded through bidding in a daily energy market. In the optimization of bidding strategies, hydrothermal scheduling is one of the key components, and is facing fundamental changes for adapting to the new environment. This paper first presents a novel formulation for integrated bidding and hydrothermal scheduling, where the market clearing price is modeled as a Markov chain and the risks are directly formulated in the objective function in terms of MCP variances. The self-scheduling requirements and the interactions between the energy and reserve markets are considered. A Lagrangian relaxation based algorithm is then developed to solve this problem, and a stochastic dynamic programming approach is developed to solve the unit subproblems. Since the bidding of pumped-storage units plays important roles in both the energy and reserve markets, and significantly affects thermal biddings, it is the focus in this paper. How self-scheduling constraints, risk management and reserve market affect the energy bidding strategies is analyzed. Numerical testing based on an 11-unit system in New England shows that the method can generate energy and reserve bid curves in 4-5 minutes, and risks of buying power at high market price are effectively reduced.

Key words: Deregulation, Bidding Strategies, Hydrothermal Scheduling, Risk Management, Pumped-storage Unit

I. INTRODUCTION

The electric power industry worldwide is experiencing unprecedented deregulation for introducing competition among generation companies (GenCos) and energy service companies (ESCos). Under the new environment, electricity is primarily traded through bidding in a daily energy market. GenCos submit non-decreasing "supply bid curves" for each generator, one for each hour of the next day, while ESCos submit hourly non-increasing "demand bid curves" reflecting its forecasted demand. The bid requirements may be different in different markets. For example, New England market requires step-wise bid curves ([2]), while California market requires piece-wise linear bid curves ([7]). Based on the bid curves, an independent systems operator (ISO) calculates the hourly market clearing prices (MCP), at which electricity will be traded. The power award to each bidder is then determined based on the individual bid curves and the MCP. After auction closes, each GenCo aggregates its power awards as the system demand, and performs hydrothermal scheduling to meet its obligations at minimum cost over the bidding horizon. It is through well-made bids in the competitive environment that a GenCo recovers its operation costs and garners its profits. Therefore, how to optimize the bidding strategies is vital for a GenCo to survive and to make profits.

There are many new challenging issues under the competitive market environment. First, the participants with different goals are involved and compete in the market, and the information available to each participant is limited, regulated, and received with significant time delay. These are compounded by the underlying uncertainties inherent in the market such as the demand for electricity, fuel prices, outages of generators, transmission capacities, and tactics by other market participants, etc. Consequently the market is full of uncertainties and risks, and the MCP could be quite volatile, especially when demand is high. How to handle MCP volatilities and reduce bidding risks has therefore become a major issue. Second, because bidding decisions are coupled with generation scheduling, generator characteristics have to be considered by performing generation scheduling to meet the accepted bids in the future before bids are submitted. To adapt to the new environment, generation scheduling is facing the fundamental changes. The optimization is based on the MCPs rather than the load demands as before. Also the final decisions are bid curves. Since high ancillary service prices can be frequently observed in many markets, how to allocate the limited generation capacity among different markets should also be considered. Third, a GenCo may have its own load from either the obligations of bilateral contracts or other long-term markets. This amount of own load is required by the market rules to buy from the market. As a strategic decision for risk management, a GenCo may want to cover at least a certain percentages of its own load and associated ancillary service requirements by itself. All these issues have made the integrated bidding and scheduling a challenging task for maximizing profits and reducing risks in competitive markets.

Some methods have been developed in the literature to address the bidding problem. It is natural that each participant will select the bidding strategies that maximize its profit; therefore game theory is a natural platform ([1, 3, 9, 13]). Other simulation methods for modeling and solving the energy and ancillary service bidding problems at different levels of the markets is also discussed in ([11]). Nevertheless, these tools to support the bidding process are far from satisfactory in view of the inherent complexity for practical systems ([7-8]). Computationally efficient and systematic approaches are critically needed to address these new challenges and to develop effective optimization-based bidding strategies.

In this paper, a novel formulation for integrated bidding and scheduling is first presented. The MCPs are assumed to be Markov random variables instead of a set of single predicted value, and the risks involved are formulated in terms of MCP variances. The reserve market and the self-scheduling requirements are considered. The problem is a constrained large-scale mixed-integer stochastic optimization problem. A Lagrangian relaxation-based (LR) algorithm is then developed to decompose the problem into a number of unit subproblems. Stochastic dynamic programming is then applied to solve the unit subproblems. Since pumped-storage units can provide large reserve at either pumping or generating, and the decision at one hour may affect the results of other hours in view of pond dynamics and limits, their bidding strategies play key roles in the interaction between the energy and reserve markets, and are the focus of this paper. Numerical testing based on an 11-unit system of New England market shows that the algorithm can generate the energy and reserve bid curves in several minutes. Our risk management is proved to be an effective way to avoid buying large amount of power at high MCP variances. We also show that pumped-storage units affect thermal bidding strategies significantly, and thus play important roles in both the energy and reserve markets.

II. PROBLEM FORMULATION

Consider a generation company in New England with I generators of thermal, hydro, and pumped-storage units. The problem is to select bid curves for each unit so as to maximize the profit while reducing risks over a time horizon T. The formulation involves market assumptions, the objective function to be minimized, and constraints to be satisfied.

In this paper, the "perfect market" is first assumed, i.e., the MCP is not affected by one participant. For simplicity the MCPs $\lambda_d(t)$ are further assumed to be a Markov chain, i.e., $\lambda_d(t)$ only depends on $\lambda_d(t-1)$. The same is also assumed for the reserve prices $\lambda_r(t)$. The MCPs and reserve prices may be dependent to each other, and form one Markov chain. In practice a "perfect market" may not exit, and the MCP is affected by the bids of the company itself, which is known as the cyclic nature. This issue will be discussed in section VI. Based on the price prediction and the analysis of historical data, suppose for each hour a possible set of MCPs $\{\lambda_d^k(t)\}$, (k=1, 2,...) and reserve prices $\{\lambda_r^j(t)\}$ (j=1, 2, ...) are given. The integrated bidding and scheduling problem is to determine the bid price $\lambda_d(p_i(t))$ as a function of generation level $p_i(t)$ for each unit i at time t, or equivalently to determine the generation level $p_i(\lambda_d^k(t))$ for each MCP value $\lambda_d^k(t)$. Similarly the reserve bid curve is determined in terms of the reserve level $r_i(\lambda_r^k(t))$ versus each reserve price $\lambda_r^k(t)$.

Suppose that the company has its "own load" $p_d(t)$ and the associated reserve requirement $p_r(t)$ at hour t. Since the load prediction is usually within a 2-percentage error based on our prediction experience, its uncertainty has less impact as compared to that of MCP, and is thus ignored in this paper. The amount of energy and reserve that the company has to buy (positive) from or sell (negative) to the market are $p_d(t)-\sum_{i=1}^{I} p_i(\lambda_d(t))$ and $p_r(t)-\sum_{i=1}^{I} r_i(\lambda_r(t))$, respectively. As a strategic decision for risk management, the company may want to cover at least a certain percentage of its own load and reserve requirements on the average. This "self-scheduling requirements" can be formulated as the expected constraints:

$$E\left(\sum_{i=1}^{I} p_i(\lambda_d(t))\right) \ge \alpha_d(t)p_d(t), \qquad \forall t, \tag{1}$$

and

$$E\left(\sum_{i=1}^{I} r_i(\lambda_r(t))\right) \ge \alpha_r(t)p_r(t), \qquad \forall t, \tag{2}$$

where $\alpha_d(t)$ and $\alpha_r(t) \in [0,1]$ are the self-scheduling coefficients. It should be pointed out that the algorithm developed can deal with the case having no above self-scheduling requirement without any modifications.

Let $C_i(p_i(t))$ be the fuel cost[1] for unit i to operate at $p_i(t)$, and $S_i(t)$ the startup cost at hour t. The profit at hour t then equals the revenue from the two markets minus the operation costs, i.e.,

$$\lambda(t)\left(\sum_{i=1}^{I} p_i(\lambda_d(t))-P_d(t)\right)+\mu(t)\left(\sum_{i=1}^{I} r_i(\lambda_r(t))-P_r(t)\right)-\sum_{i=1}^{I}\left(C_i(p_i(\lambda_d(t)))+S_i(t)\right).$$

With transition probabilities of market prices known, the variances $\sigma^2_{\lambda_d}(t)$ and $\sigma^2_{\lambda_r}(t)$ at hour t can be calculated, and they reflect market uncertainties. According to the historical data, the MCP may jump from its normal value of \$20 or \$30 to over \$1000 per megawatt hour. To avoid risks and capture potential spike prices, a GenCo usually prefers to sell power when the market has large uncertainty, and buy power when the market has low uncertainty. This idea suggests managing the risks by minimizing following product of the price variances and the purchased amount of energy,

$$\sigma^2_{\lambda_d}(t)\left(P_d(t)-\sum_{i=1}^{I} p_i(\lambda_d(t))\right)+\sigma^2_{\lambda_r}(t)\left(P_r(t)-\sum_{i=1}^{I} r_i(\lambda_d(t))\right)\Bigg\}.$$

Combining the above analyses, the objective function to be minimized is a weighted sum of the negative *profit* and the *risk* terms over the time horizon T, that is,

$$\begin{aligned}C=E\Bigg\{\sum_{t=1}^{T}\Bigg[&-\lambda_d(t)\left(\sum_{i=1}^{I} p_i(\lambda_d(t))-P_d(t)\right)-\lambda_r(t)\left(\sum_{i=1}^{I} r_i(\lambda_r(t))-P_r(t)\right)\\&+\sum_{i=1}^{I}\left(C_i(p_i(\lambda_d(t)))+S_i(t)\right)\\&+w(t)\left(\sigma^2_{\lambda_d}(t)\left(P_d(t)-\sum_{i=1}^{I} p_i(\lambda_d(t))\right)+\sigma^2_{\lambda_r}(t)\left(P_r(t)-\sum_{i=1}^{I} r_i(\lambda_r(t))\right)\right)\Bigg]\Bigg\},\end{aligned} \tag{3}$$

where $w(t) \ge 0$ is the weight to balance the profit versus risks.

The problem is also subject to individual unit constraints. The constraints for thermal and hydro units are the same as before deregulation, and have been presented in [4, 6, 11]. The operation rules of pumped-storage units after deregulation have been changed and are different from those presented in [5]. Furthermore a pumped-storage unit can provide large reserve when either pumping or generating, and the decision at one hour may affect the results of other hours in view of pond dynamics and limits. The bidding strategies for pumped-storage units play key roles in the interactions between the energy and reserve markets. Therefore only the constraints for a pumped-storage unit are presented in the following.

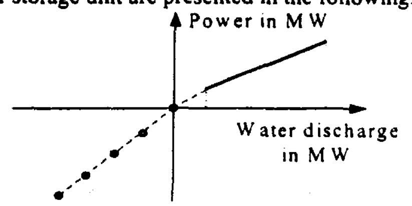

Figure 1 Water-power conversion for a pumped-storage system

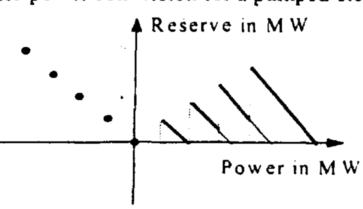

Figure 2 Power-reserve relationship

There are usually multiple generators associated with one pond in a pumped-storage system. Unlike the operation rules before deregulation where the whole continuous operating region is allowed as shown by the dashed line in Figure 1, each generator can only operate at its pumping capacity or at generating within a continuous operating region. For example, the water-power conversion is shown in Figure 1 for a pumped-storage system with four identical generators associated with a pond, where the water discharge has been converted into megawatts. At pumping, the reserve contribution of a pumped-storage unit is the same as the pumping level since the unit can be shut down very quickly to reduce the demand. At

[1] There are no fuel and startup costs for pumped-storage or hydro units.

generating, the reserve equals the generation capacity of online generators minus the current generation level. The power-reserve relationship for a pumped-storage unit is shown in Figure 2.

A pumped-storage system i has following pond constraints.

- Pond level dynamics

$$v_i(t+1) = v_i(t) - w_i(t), \qquad \forall t, \tag{4}$$

where $w_i(t)$ is the water discharged (positive) from or pumped (negative) to the pond, and $v_i(t)$ the pond level at time t.

- Pond level limits

These constraints require that the pond level should be within its upper and lower bounds at any time. With the MCPs as random variables, it is very difficult to deal with the pond level constraints mathematically for all the possible MCP realizations because of large number of possibilities. These constraints are thus required in an expected sense, i.e.,

$$\underline{V}_i \le E(v_i(t)) \le \overline{V}_i, \qquad \forall t. \tag{5}$$

where $\underline{V}_i$ is the minimum pond limit, and $\overline{V}_i$ the maximum pond limit.

- Initial and end pond levels

The initial pond level V_i^0 specifies the amount of water available at the beginning of bidding period, and is formulated as

$$v_i(0) = V_i^0. \tag{6}$$

The end pond level V_i^T specifies the desired amount of water available for next bidding cycle. Similarly, it is formulated in an expected sense, i.e.,

$$E(v_i(T)) = V_i^T. \tag{7}$$

III. SOLUTION METHODOLOGY

The above integrated bidding and scheduling problem is a mixed-integer stochastic optimization problem to determine the generation level $p_i(\lambda_d^k(t))$ of each unit i for each MCP value $\lambda_d^k(t)$, and the reserve $r_i(\lambda_r^k(t))$ for each reserve price $\lambda_r^k(t)$. One way to solve this problem is to perform scenario analysis. However, in view of the possibilities of MCP realizations, it is difficult to solve the problem within a reasonable amount of CPU time for systems of practical sizes. Lagrangian relaxation is applied in this paper to deal with the self-scheduling constraints by taking the advantage of the separable problem structure, and a stochastic dynamic programming approach is developed to solve the subproblems, one for each unit.

By relaxing the constraints (1) and (2) using two sets of multipliers $\nu_d(t) \ge 0$ and $\nu_r(t) \ge 0$, respectively, a two-level optimization is formed. Given a set of multipliers $\nu_d(t)$ and $\nu_r(t)$, the relaxed problem is

$$\min_{p_i(\lambda_d(t))} L(\beta_d, \beta_r, p_i(\lambda_d(t))), \tag{8}$$

with

$$L(\beta_d, \beta_r, p_i(\lambda_d(t))) \equiv E\Bigg(\sum_{t=1}^{T} \sum_{i=1}^{I} \Big[C_i(p_i(\lambda_d(t))) + S_i(t)$$

$$- \big(\lambda_d(t) + w(t)\sigma_{\lambda_d}^2(t) + \nu_d(t)\big) p_i(t) - \big(\lambda_r(t) + w(t)\sigma_{\lambda_r}^2(t) + \nu_r(t)\big) r_i(t) \Big] \Bigg). \tag{9}$$

By regrouping (9), the subproblem for unit i is formulated as

$\min L_i$, with

$$L_i \equiv E\Bigg(\sum_{t=1}^{T} \Big[C_i\big(p_i(\lambda_d(t), \lambda_r(t))\big) + S_i(t)$$

$$- \mu_d(t) p_i(\lambda_d(t), \lambda_r(t)) - \mu_r(t) r_i(\lambda_d(t), \lambda_r(t)) \Big] \Bigg), \tag{10}$$

subject to individual unit constraints. In the above,

$$\mu_d(t) \equiv \lambda_d(t) + w(t)\sigma_{\lambda_d}^2(t) + \nu_d(t), \tag{11}$$

and

$$\mu_r(t) \equiv \lambda_r(t) + w(t)\sigma_{\lambda_r}^2(t) + \nu_r(t). \tag{12}$$

The multipliers $\nu_d(t)$ and $\nu_r(t)$ are updated at the high level to maximize the dual function $q(\nu_d, \nu_r)$, i.e.,

$$\max_{\nu_d \ge 0, \nu_r \ge 0} q(\nu_d, \nu_r), \text{ with } q(\nu_d, \nu_r) \equiv \min_{p_i(\lambda_d(t))} L(\nu_d, \nu_r, p_i(\lambda_d)). \tag{13}$$

The two levels iterate until a stopping criterion is achieved. Based on subproblem solutions, the bid curves are constructed after the dual procedure terminates. These steps are described next.

Solving Subproblems

The unit subproblem (10) is similar to that of a hydrothermal scheduling problem as in [5, 7, 16], with the exception that the marginal energy and reserve costs $\mu_d(t)$ and $\mu_r(t)$ are random variables depending on market prices $\lambda_d(t)$ and $\lambda_r(t)$. The solution is a set of strategies: how much power should each unit provide for each pair of $\lambda_d^k(t)$ and $\lambda_r^j(t)$ at what probability?

Subproblems for different types of units are different. In view of the limited space, only the solution methodology for pumped-storage subproblems will be presented since their bidding strategies play a key role in the interactions between the energy and reserve markets. Methods for thermal units will be presented in a future paper.

Without fuel and startup cost, the pumped-storage subproblem i can be described as

$$\min L_i, \text{ with } L_i \equiv E\left(\sum_{t=1}^{T} \big[-\mu_d(t) p_i(t) - \mu_r(t) r_i(t) \big] \right), \tag{14}$$

subject to operation constraints (4) – (7).

In view of the discontinuous operating regions as shown in Figures 1 and 2, the subproblem is a stochastic optimization problem with both integer and continuous decision variables. Our basic idea to solve this subproblem is to substitute out the pond dynamics and to relax the pond level limit constraints (5) and end pond level requirement (7) by using three sets of multipliers $\gamma_1(t)$, $\gamma_2(t)$ ($t = 1, 2, \ldots, T$-1) and γ_3, respectively. A new sub-Lagrangian is formed as

$$\hat{L}_i \equiv E\Bigg\{ \sum_{t=1}^{T} \big[-\mu_d(t) p_i(t) - \mu_r(t) r_i(t) \big] + \sum_{t=1}^{T-1} \gamma_1(t) \left(\sum_{n=1}^{t} w_i(n) - V_i^0 + \underline{V}_i \right)$$

$$+ \sum_{t=1}^{T-1} \gamma_2(t) \left(V_i^0 - \overline{V}_i - \sum_{n=1}^{t} w_i(n) \right) + \gamma_3 \left(V_i^T - V_i^0 + \sum_{n=1}^{T} w_i(n) \right) \Bigg\}.$$

An intermediate level is thus generated, where the multipliers $\gamma_1(t)$, $\gamma_2(t)$ and γ_3 are updated by using the subgradient or bundle method. At the low level with multipliers given, the sub-Lagrangian can be further decomposed into stage-wise functions, i.e.,

$$\min \hat{L}_i, \text{ with } \hat{L}_i \equiv E\left(\sum_{t=1}^{T} h_i(t)\right), \tag{15}$$

where

$$h_i(w_i(t)) \equiv -\mu_d(t)p_i(w_i(t)) - \mu_r(t)r_i(t) + w_i(t)\left(\gamma_3 + \sum_{n=t}^{T-1}[\gamma_1(n) - \gamma_2(n)]\right) + \gamma_2(t)\left(V_i^0 - \bar{V}_i\right) - \gamma_1(t)\left(V_i^0 - \underline{V}_i\right),\ t = 1, 2, \ldots, T\text{-}1, \tag{16}$$

and

$$h_i(w_i(T)) \equiv -\mu_d(t)p_i(w_i(T)) - \mu_r(t)r_i(w_i(T)) + \gamma_3 w_i(T), \tag{17}$$

are the stage-wise cost functions.

The problem in (15) is to minimize an expected sum of the stage-wise cost functions with random coefficients. Based on transitions of Markovian MCPs, a scenario tree can be constructed. A stochastic dynamic programming approach is thus developed, where a stage corresponds to an hour and a state at hour t to a pair of MCP $\lambda_d^k(t)$ and reserve price $\lambda_r^j(t)$ (k, j=1, 2, ...). Since there is no stage-wise constraints, the optimal generation level $p_i(\lambda_d^k(t),\lambda_r^j(t))$ and reserve level $r_i(\lambda_d^k(t),\lambda_r^j(t))$ for each state are obtained by optimizing the stage-wise cost function, subject to the operating regions. Therefore the optimal generation level for each state only depends on $\pi(t)$ and $\kappa(t)$. It should be pointed out that in view of discontinuous operating regions as in Figures 1 and 2, the optimal generation level may change significantly with a slight change of $\pi(t)$ and $\kappa(t)$, resulting in a significant change in bid curves. The probability $P_i(\lambda_d^k(t),\lambda_r^j(t))$ for each state to be reached is then calculated based on the transition probabilities of Markovian prices. These strategies obtained will be used to construct bid curves.

Solving Dual Problem

After solving the subproblems, the subgradient associated with the energy self-scheduling constraints (1) is

$$g_{\beta_d}(t) = \alpha_d p_d(t) - \sum_{i=1}^{I} E(p_i(\lambda_d^k(t),\lambda_r^j(t)),\ \forall t. \tag{18}$$

The multipliers $v_d(t)$ can then be iteratively updated by using a subgradient or bundle method at the high level. The updating of $v_r(t)$ and the intermediate level multipliers $\gamma_1(t)$, $\gamma_2(t)$ and γ_3 is similar. In our testing, the trust region bundle method as presented in [12, 14].

Generating and Selecting Bid Curves

After the dual procedure converges, the bid curves for each unit are constructed based on the strategies provided in subproblem solutions. The generation level for $\lambda_d^k(t)$ is the expectation of $p_i(\lambda_d^k(t),\lambda_r^j(t))$ over $\lambda_r^j(t)$ (j=1, 2, ...). Since the operating regions of a unit may be discontinuous, the result obtained is then projected onto the nearest feasible operating region to obtain the optimal generation level $p_i(\lambda_d^k(t))$. This procedure can be described as

$$p_i(\lambda_d^k(t)) = proj\left(\frac{\sum_j p_i(\lambda_d^k(t),\lambda_r^j(t))P_i(\lambda_d^k(t),\lambda_r^j(t))}{\sum_j P_i(\lambda_d^k(t),\lambda_r^j(t))}\right), \forall k, \forall t. \tag{19}$$

In New England market, a bid curve is a set of power blocks, each associated with a price. Therefore the bid curve for each unit at hour t is then constructed as $\left\{\lambda_d^k(t), p_i(\lambda_d^{k+1}(t)) - p_i(\lambda_d^k(t))\right\}$. The reserve bid curves can be constructed Similarly. If at any $\lambda_d^k(t)$, a unit would like to generate more power, then we say it bids at lower price.

Since larger dual value does not always mean better feasible solution, bid curves are generated for the last several iterations, and are sorted by using a simplified ordinal optimization method [8]. The best one is selected.

IV. Analysis Of Self-Scheduling, Market Interaction And Risk Management

Since $\mu_d(t)$ plays the role of marginal energy cost and $\mu_r(t)$ the marginal reserve cost in (10), their values determine the generation level $p_i(\lambda_d^k(t),\lambda_r^j(t))$ and thus the bid curves as in (19). From (11)-(12) and (16)-(17), one can see the impact of self-scheduling constraints, risk management, and the interaction of the energy and reserve markets.

The self-scheduling constraints couple the different units via $v_d(t)$ and $v_r(t)$, and affect the bidding by changing $\mu_d(t)$ and $\mu_r(t)$ as in (11) and (12). For example, if the self-scheduling requirement at hour t is high, $v_d(t)$ will be large, making $\mu_d(t)$ large. Consequently, the units will bid at low prices.

The tradeoff in allocating the limited generation capacity in the energy and reserve markets depends on the market prices $\lambda_d(t)$ and $\lambda_r(t)$. At normal situations when $\lambda_d(t)$ is much higher than $\lambda_r(t)$, the bidding is primarily based on $\lambda_d(t)$. Occasionally, when the reserve price $\lambda_r(t)$ is relatively high as observed in many markets, the pumped-storage bidding strategies may change significantly in view of the discrete operating regions. Since the bidding strategies of a pumped-storage unit are coupled at different hours because of the pond dynamics and limits, the decision at one hour will affect results of other hours. Furthermore, their bidding strategies also affect thermal bids in view of self-scheduling constraints. The pumped-storage units thus play a key role in both energy and reserve markets.

The risk management affects bidding strategies through the changes of $\mu_d(t)$ and $\mu_r(t)$ depending on the variances $\sigma_{\lambda_d}^2(t)$ and $\sigma_{\lambda_r}^2(t)$. If $\sigma_{\lambda_d}^2(t)$ is high indicating large uncertainty on $\lambda_d(t)$, then $\mu_d(t)$ will be large. Consequently the optimal generation level for each state is large, resulting in large $p_i(\lambda_d^k(t))$ as in (19). As a result, the units will bid at low price such that the company can sell more power at potential price spikes, or to avoid buying a large amount of power at a potential high MCP.

V. Numerical Testing

Numerical testing is performed for a system with 10 thermal units and a pumped-storage system with 4 identical generators associated with a large pond. The energy and reserve prices on July 12 of New England market, as shown in Figure 3, are used in the testing. The price distributions at each hour are assumed to be Gaussian. The mean is set as the corresponding price, and the standard deviation $\sigma(t)$ as ten percent of the corresponding price. 15 price values uniformly distributed in the 99.7% confidential region $[-3\sigma(t), 3\sigma(t)]$ are generated for each hour. The own load curve is shown in Figure 4, and the reserve requirements are set to 15% of the loads. The self-scheduling is assumed to be 80%. For better presentation, the bid curves of thermal units are aggregated, and only the bid curves in $[-3\sigma(t), 3\sigma(t)]$ are shown.

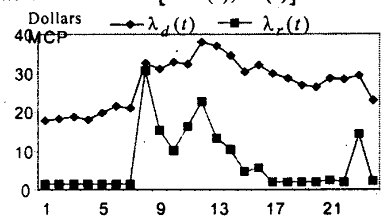

Figure 3 The MCP $\lambda_d(t)$ and reserve price $\lambda_r(t)$ on July 12, 1999, New England market

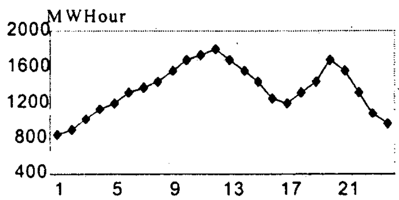

Figure 4 The own load $p_d(t)$

Example 1: The impact of risk management

Example 1 is to show the impact of our risk management strategy on biddings. For simplicity, the reserve market is ignored in this example. Two cases (Cases 1 and 2) are tested and compared. The risk management is not considered, i.e., $w = 0$ in Case 1, but is considered in Case 2 with $w = 0.8$. The bid curves of pumped-storage unit at hours one and eight for these two cases are shown in Figures 5 and 6, respectively. Since $\sigma_{\lambda_d(t)}$ is set to be proportional to $\lambda_d(t)$, the higher $\lambda_d(t)$ is, the high the variance is. As compared with Case 1, the pumped-storage unit tries to generate more power at hour eight by bidding lower prices in Case 2 in view of high uncertainty on MCP $\lambda_d(t)$. Similar results are observed for other hours with high MCP variances. Conversely the pumped-storage unit bids higher prices at hour one in Case 2 to make sure that it could pump more water for later use as shown in Figure 5. The results show that our risk management can effectively avoid buying large amount of power from the market at hours with high MCP uncertainties, implying that the risks have been reduced.

Example 2: The impact the pumped-storage unit and reserve market

This example is to show the effects of the pumped-storage unit on the thermal units, and how the reserve market affects the biddings of pumped-storage unit. To achieve this purpose,

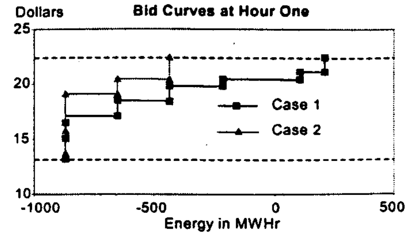

Figure 5 Bid curves of pumped-storage unit at hour one

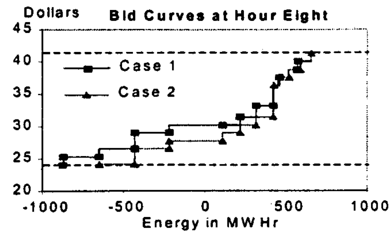

Figure 6 Bid curves of pumped-storage unit at hour eight

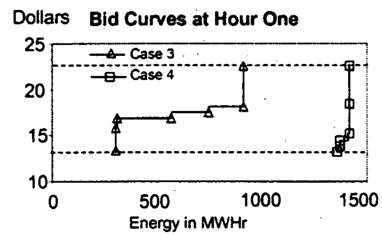

Figure 7 Aggregated thermal bid curves at hour one

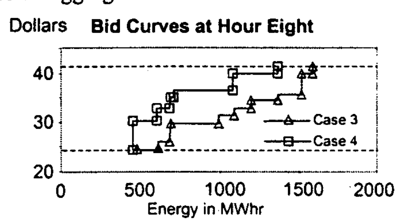

Figure 8 Aggregate thermal bid curves at hour 8

the 10-thermal-unit system is generated and tested (Case 3) for comparison with the system with the pumped-storage unit (Case 4). The reserve market is also considered in this example. The aggregated bid curves of thermal units at hours one and eight are respectively shown in Figures 7 and 8. And the bid curves for Case 4 are also shown. The pumped-storage bid curves at hours one and eight are shown in Figure 9.

In Figures 7 and 8, the thermal bid curves have significantly changed with the existence of the pumped-storage unit. Since the pumped-storage unit tries to pump at hour one in view of low MCP, the thermal units have to generate more power to satisfy the self-scheduling requirement. Therefore, they bid lower prices as compared with Case 3. In view of the high reserve price at hour eight, all the units should provide as much reserve as possible to maximize the profit. For pumped-storage unit, since the reserve contribution is the same as the pumping level or the online capacity minus the generation level, the 4 pumped-storage generators should either pump at pumping capacity at an almost zero price, or generate at the minimum generation limit so as to provide maximum reserve. These two strategies are all depicted in its bid curve as shown in Figure 9. In this testing, the pumped-storage unit trends to generate for the risk management purpose since the variance of MCP at that time is large. Compared with Case 2 in Figure 6, the bid of pumped-storage unit has significantly changed with the consideration of reserve market. For thermal units, they could be able to contribute less power in view of lower self-scheduling requirement as compared with Case 3. Therefore they bid higher prices so as to provide more reserve.

To better understand the impact of the pumped-storage unit, the multipliers $v_d(t)$ and $v_r(t)$ for the two cases are also plotted in Figure 10 to show the self-scheduling requirements of energy and reserve. With the pumped-storage unit, the reserve self-scheduling requirement can be easily satisfied since the multipliers $v_r(t)$ in Case 4 are all zeros. In fact, the pumped-storage unit can also contribute significant reserves to the reserve market in addition to satisfying the reserve self-scheduling requirements. At the same time, the pumped-storage unit contributes a large amount of power, and thus reduces marginal costs $\mu_d(t)$ and $\mu_r(t)$ at hours of peak MCPs or peak own loads. This is similar to the case in hydrothermal scheduling, where a pumped-storage unit can cut the load peak. Therefore the pumped-storage unit plays important roles in both the energy and reserve markets.

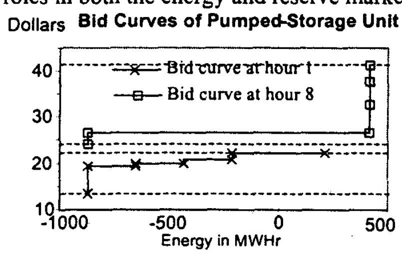

Figure 9 Bid curves of the pumped-storage unit in case 4

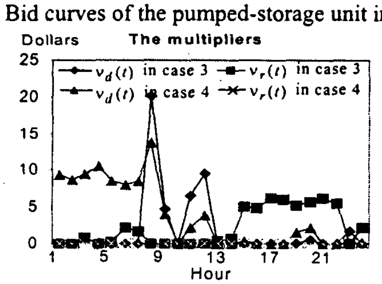

Figure 10 The multipliers

The CPU time is about 4-5 minutes on a PC with a 600-MHz Pentium III processor; therefore the algorithm is efficient for daily use.

VI. Conclusion And Future Work

A novel formulation and an optimization-based algorithm for integrated bidding and hydrothermal scheduling have been presented in this paper. The MCP is explicitly model as a Markov chain, the self-scheduling requirement and the interaction between energy and reserve market are considered. The bidding risk is also managed in a systematic way. The testing based on an 11-unit system shows that the algorithm can produce generation and reserve bid curves in 4-5 minutes, and the risks to buy a large amount of power at high MCP are effectively reduced. The performance of algorithm is to be tested via simulation.

Since a real market may not be perfect, the MCP is affected by the bids of the company itself, which is known as the cyclic nature. To estimate the impact on the MCP of the company's bids, a neural network is under development, where the aggregated bid curves are also part of inputs to the neural network in addition to market information. The trained network can then be integrated into the algorithm to deal with the issue of MCP cyclic nature. The basic idea is that the MCP distribution is modified based on the bid curves obtained at previous iteration. The ordinal optimization ([8]) is also applied to select the best set of bid curves with consideration the bid impact on the MCP.

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