Optimal Integrated Generation Bidding and Scheduling With Risk Management Under a Deregulated Power Market

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***Abstract*—In the deregulated power industry, a generation company (GenCo) sells energy and ancillary services primarily through auctions in a daily market. Developing effective strategies to optimize hourly offer curves for a hydrothermal power system to maximize profits has been one of the most challenging and important tasks for a GenCo. This paper presents an integrated bidding and scheduling algorithm with risk management under a deregulated market. A stochastic mixed-integer optimization formulation having a separable structure with respect to individual units is first established. A method combining Lagrangian relaxation and stochastic dynamic programming is then presented to select hourly offer curves for both energy and reserve markets. In view that pumped-storage units provide significant energy and reserve at generating and pumping, the offering strategies are specially highlighted in this paper. Numerical testing based on an 11-unit system with a major pumped-storage unit in the New England market shows that the algorithm is computationally efficient, and effective energy and reserve offer curves are obtained in 4–5 min on a 600-MHz Pentium III PC. The risk management method significantly reduces profit variances and, thus, bidding risks.**

***Index Terms*—Deregulation, offering/bidding strategies, pumped-storage unit, reserve market, risk management.**

I. Introduction

THE electric power industry is experiencing deregulation to introduce competitions among generation companies (GenCos) and to improve the services for customers ([3], [7]). In this competitive environment, energy and ancillary services are primarily traded through auctions in a daily market. GenCos submit hourly generation offers for individual or a portfolio of generators for the next day, while energy service companies (ESCos) submit hourly demand bids. Based on generation offers and demand bids, an independent systems operator (ISO) determines hourly market clearing prices (MCPs) and the power quantities awarded to each GenCo by solving a security-based unit commitment problem. After the auction closes, each GenCo aggregates the power awards as its system demand, and performs unit commitment to fulfill the market obligations at the minimum operation cost. In this process, how well a GenCo garners profits depends on how good its offering strategies are. In view of the MCP volatilities, developing effective and computationally efficient offering strategies with good risk management therefore becomes vital for a GenCo to maximize profits and to obtain competitive advantages.

There are many challenging issues in developing offering strategies. First, participants compete in a market, and the information available to each one is limited, regulated, and received with time delay. These are compounded by underlying uncertainties inherent in markets such as the demand for electricity, outages of generators and transmissions, and tactics used by participants. Consequently, the market is full of uncertainties and risks. Recent experiences showed that the MCP is volatile, and could be U.S.$ 30 or U.S.$ 1000 per megawatt hour. The volatility is especially serious for high-load situations such as very hot/humid summer or very cold/windy winter days, or with unexpected generation or transmission outages. These extreme or unexpected situations are critical to a GenCo, as a bad strategy may result in a loss of millions of dollars in a few days or even hours. How to handle the price volatilities and reduce bidding risks has been a major issue. Second, since energy and ancillary markets affect each other, and ancillary service prices are occasionally high (e.g., U.S.$1000 per megawatt hour for 10-min spinning reserve) as observed in many markets, a GenCo must consider how to allocate its limited generation capacities among these markets to maximize profits. This interaction among different markets adds difficulties in making offering strategies. Third, a GenCo may have its "own load" from its customers, bilateral contracts, and long-term obligations. As required by market rules, the GenCo needs to buy power from the market at MCPs to serve its own load. As a company strategy for risk management and because of gas/fuel supply contracts that may require a minimum consumption of gas and oil, a GenCo may want to cover by itself at least a certain percentage of its own load and the associated ancillary services. This "self-scheduling requirement" couples the offering strategies of different generators, making the problem more difficult. Finally, bidding decisions are coupled with generation scheduling, and the generator characteristics and how they will be used to satisfy the awarded bids in the future have to be considered before bids are submitted. If there are pumped-storage units in the system, both offering and bidding strategies need to be considered over the same bidding period. The optimization is difficult in view of operational constraints such as the pond level dynamics, pond level limits, and discrete operating regions. All of these issues have made the integrated generation offering and scheduling a very challenging task in a competitive market.

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Efforts have been made to address bidding problems ([1], [4]–[8], [11], [13]–[15], [19], [21]). Under the assumption that the probabilistic distributions of competitors' offering prices are known, an optimal offering strategy for a single power block at a particular hour is derived by ignoring intertemporal unit constraints in [11]. A bidding process considering offer uncertainties of other GenCos (e.g., bidding high or low) by simulating the ISO's offer-selection process is presented in [7]. Since bid information is revealed with a significant delay (e.g., five months in New England), assuming that the probabilistic distributions of offering prices for hundreds of generators are known may not be practical. An iterative auction structure is recommended in [14], [19], where GenCos are allowed to revise their offers iteratively, and the MCPs are updated and made public during the process until the market closes. Under this structure, a method based on genetic programming and finite state automata is presented in [19] for iteratively revising the offers, each consisting of one power block with a price. A Lagrangian relaxation-based method is presented for iteratively revising offers considering revenue adequacy in [14]. Unfortunately, there currently exist no power markets with the iterative auction structure. The recently developed ordinal optimization approach is applied to select "good enough with high probability" offers in [7], [8]. Game theory has also been applied to model market competitions (e.g., [4], [5]) for simplified systems. In view of the problem complexity, it may have difficulties to derive payoff matrices. To address the challenges mentioned in the previous paragraph, effective and computationally efficient methods are critically needed.

In this paper, a formulation for optimizing energy and reserve offer curves for a hydrothermal power system under a deregulated daily market is first established in Section II. Based on the estimation of MCP probability density functions obtained by using a classification method developed in our previous work ([17]), the hourly energy and reserve prices are modeled as a Markov chain. The bidding risks are managed using a mean-variance like method by adding a *risk penalty term* related to price variances to the objective function. The self-scheduling requirements are modeled similarly to system demand in a unit commitment problem. The formulation obtained is a stochastic mixed-integer optimization problem with a separable structure in terms of individual units. A Lagrangian relaxation-based algorithm is then presented in Section III, and the problem is decomposed into a number of individual unit subproblems. Each subproblem is solved by using stochastic dynamic programming, providing a set of offering strategies for an integrated energy and reserve market: how much power and reserve each unit should provide for each pair of energy and reserve prices and at what probability. The energy and reserve offer curves are then constructed by projecting these strategies onto individual markets. As mentioned, the solution methodology for pumped-storage units is highlighted in this paper. Numerical testing based on an 11-unit system in the New England market is presented in Section IV, demonstrating that the algorithm is efficient, and effective offer curves for both energy and reserve markets are obtained in 4–5 minutes on a 600 MHz Pentium III PC. It is also demonstrated that our risk management can significantly reduce profit variances and thus reduce bidding risks. The concluding remarks are given in Section V.

II. Problem Formulation

Consider a bidding and scheduling problem for a GenCo with N generators of hydro, thermal, and pumped-storage units under a deregulated daily market. It is to determine hourly energy and reserve offer curves for each unit for the next day, and the objective is to maximize the profit while managing risks. The formulation involves market assumptions, the objective function to be minimized, and constraints to be satisfied.

Offer Curves: An hourly energy offer $\lambda_d(t, p_n(t))$ for unit n at time t is a power-price curve, providing the selling price per MWHr for any given amount of power within the unit generation limits. Since offer curves are required to be nondecreasing, a GenCo usually considers an offer curve in an equivalent but more convenient way: how much power would each unit generate as a function of energy price $\lambda_d(t)$. That is, the offer curve is represented as $p_n(\lambda_d(t))$, a price-power function. Requirements on offer curves may be different for different markets. For example, a piece-wise linear offer curve was required by the former California market ([7]), while a step-wise offer curve consisting of up to 10 power blocks each with an associated price is required in New England ([3]). The New England market also requires the same power blocks across hours over the bidding horizon for each unit. We will assume that the power blocks can be different for different hours, as the New England requirement can be satisfied with an additional step to be explained in Section III. And more importantly, in the up-coming "standard market design" which is expected to be in effective March 2003, a unit can be modeled by using hourly "virtual incremental offers," where no fixed power blocks are required.

Energy and Reserve Market Clearing Prices: Since there are various time-dependent operating constraints such as minimum up/down times and ramp rate limits, offer curves and thus the MCP's are correlated across hours. In addition, the energy market is coupled with the reserve market in view that the limited generation capacities contribute to both energy and reserve, resulting in correlated energy and reserve market clearing prices. To model such dependency and correlation in a tractable manner, $\lambda_d(t)$ and $\lambda_r(t)$ are jointly modeled as a Markov chain. In our previous work [17], the probability density functions (PDFs) of energy prices are estimated by using neural networks. By extending the results, the joint PDFs for energy and reserve prices can be estimated. Based on these PDFs, a set of possible price pairs $(\lambda_d^i(t), \lambda_r^j(t))$ $(i = 1, 2, \ldots, I,\ j = 1, 2, \ldots, J)$ are selected for each hour. The corresponding energy price variance $\sigma\overset{2}{\lambda}_d(t)$ and the reserve price variance $\sigma\overset{2}{\lambda}_r(t)$ are calculated to reflect price uncertainties. A Markov chain is then formed where a stage corresponds to one hour, and a state corresponds to a possible price pair. The transition probability between two states of adjacent stages can be obtained as the product of the state probabilities. In view of the complicated coupling between energy and reserve bids, the optimization is first done for a joint energy and reserve market, leading to a set of joint energy and reserve offer curves. The energy and reserve offers are then obtained by projecting these joint offer curves onto individual markets.

Self-Scheduling Requirements: A GenCo may have its "own load" $p_d(t)$ and the associated reserve requirement $p_r(t)$ for hour t from its customers or other contract obligations[1]. Based on market rules, the GenCo is required to buy power at MCPs to serve its own load. Therefore, if the energy price is $\lambda_d(t)$, then the power the GenCo sells (positive) to or purchases (negative) from the market is $\sum_{n=1}^{N} p_n(\lambda_d(t)) - p_d(t)$. Similarly, if the reserve price is $\lambda_r(t)$, the reserve the GenCo sells to or buys from the market is $\sum_{n=1}^{N} r_n(\lambda_r(t)) - p_r(t)$, where $r_n(\lambda_r(t))$ is the reserve that unit n provides to the market.

Because of gas/fuel supply contracts that may require a minimum consumption of gas/fuel and possibly other obligatory considerations, the GenCo may want to cover, on the average, at least a certain percentage of its own load and reserve requirements by itself. These "self-scheduling requirements" are formulated as follows:

$$E\left(\sum_{n=1}^{N} p_n(\lambda_d(t))\right) \geq \alpha_d(t)p_d(t), \quad \forall\, t \tag{1}$$

and

$$E\left(\sum_{n=1}^{N} r_n\left(\lambda_r(t)\right)\right) \geq \alpha_r(t)p_r(t), \quad \forall\, t \tag{2}$$

where $\alpha_d(t)$ and $\alpha_r(t) \in [0,1]$ are self-scheduling coefficients. It should be noted that the method covers the case without self-scheduling requirements with much reduced computation.

Profit Function at Hour t: The major objective of the problem is to maximize the profit. Let $C_d(p_d(t))$ be the revenue from own-load customers, $C_n(p_n(t))$ the production cost for unit n, and $S_n(t)$ the startup cost at hour t. Then the profit at hour t is the revenue from own load customers, and from energy and reserve markets minus the operating cost, that is

$$\begin{aligned} f_1(t) \equiv & C_d(p_d(t)) + \lambda_d(t)\left(\sum_{n=1}^{N} p_n(\lambda_d(t)) - p_d(t)\right) \\ & + \lambda_r(t)\left(\sum_{n=1}^{N} r_n(\lambda_r(t)) - P_r(t)\right) \\ & - \sum_{n=1}^{N} \left[C_n\left(p_n\left(\lambda_d(t)\right)\right) + S_n(t)\right]. \end{aligned}$$

In view that the own load revenue $C_d(p_d(t))$ is a constant for a given $p_d(t)$, and is not available in our database, it is set to zero, and $f_1(t)$ defined above is actually the negative total cost to serve the own load by taking the market as a flexible generator or a dispatchable load.

Risk Management: Measuring and managing bidding risks are major issues under a competitive and uncertain environment. For a GenCo with high own load obligation, the risk consideration is mostly for high market prices. Typically price spikes appear in extreme situations such as very hot/humid summer days or very cold/windy winter days, or with unexpected generation or transmission outages. These situations are critical as a bad bidding strategy may result in a loss of millions of dollars within a few days or even hours. Unfortunately, it is difficult for MCP forecaster to capture such extreme situations in view of scarce training data and limited information ([2]). Fig. 1 shows the MCP prediction error (prediction—actual) distribution for the New England Market from July 1 to December 1, 2000, for a neural network that is currently in production use on a daily basis by a utility company. Though the prediction error is fairly well distributed, the distribution has a fat negative tail, indicating the price spikes were not well captured. As demonstrated in [2], however, large uncertainties (as implied by large predicted variances) could be detected even with limited data points. To reduce bidding risks, a GenCo may prefer to stay "long" (sell power) when the market uncertainties are high to capture potential price spikes, and to stay "short" (buy power) when the market uncertainties are low to avoid risks.

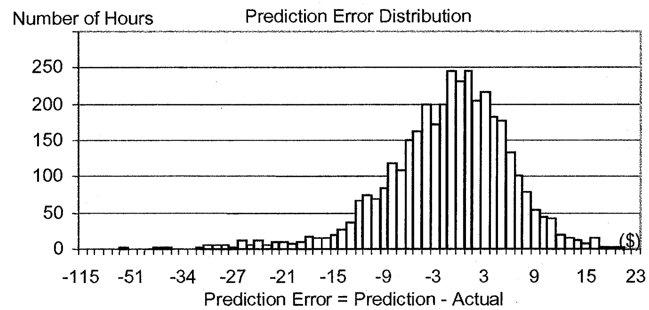

Fig. 1. Prediction error distribution.

As mentioned, the MCPs are correlated across time. Under the Markovian price assumption, historical information is summarized at the bidding preparation time. Based on the current market structure, bids for different hours of the next day must be submitted at the same time, and once they are submitted, they cannot be revised. Therefore, it provides little help to correlate the price of different hours of next day in our risk management. In view that variances $\sigma^2_{\lambda_d}(t)$ and $\sigma^2_{\lambda_r}(t)$ well reflect market uncertainties at hour t, the idea in the previous paragraph suggests managing risks by using a mean-variance-like approach often applied within the context of control theory (i.e., having variance-related risk terms in the objective function). The risk terms in our context are defined as the product of the price variances and the level of energy and reserve purchases, that is

$$\begin{aligned} f_2(t) \equiv \sigma^2_{\lambda_d}(t) & \left(P_d(t) - \sum_{n=1}^{N} p_n\left(\lambda_d(t)\right)\right) \\ & + \sigma^2_{\lambda_r}(t)\left(P_r(t) - \sum_{n=1}^{N} r_n\left(\lambda_d(t)\right)\right). \end{aligned}$$

Combining the above analyses and considering the price randomness, the objective function to be minimized is an expected weighted sum of the *negative profit* and the *risk* term over the bidding time horizon, that is

$$C = E\left\{\sum_{t=1}^{T} \left[-f_1(t) + \omega(t) f_2(t)\right]\right\} \tag{3}$$

[1]Since load prediction error is usually within 2% per our experience, the prediction uncertainty has less impact as compared to that of MCP, and is ignored in this paper.

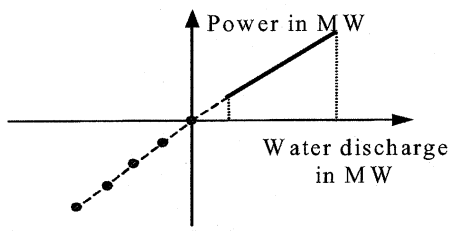

Fig. 2. Water-power conversion for a pumped-storage system.

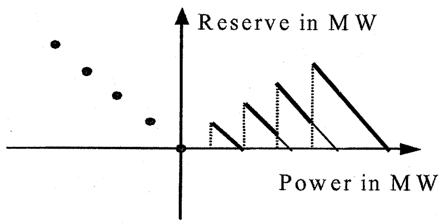

Fig. 3. Power-reserve relationship.

where $\omega(t) \geq 0$ is the weight balancing the profit versus risks.

Individual Unit Constraints: The bidding problem is also subject to individual unit constraints. The constraints for thermal and hydro units are the same as those before deregulation, and have been presented in [9], [10], and [16]. The operation rules of pumped-storage units in the New England market after deregulation are different from those presented in [9]. Therefore, the constraints for a pumped-storage unit are presented next.

There are usually multiple units associated with one pond in a pumped-storage system. Fig. 2 shows the water-power conversion for a system with four identical generators, where the water discharge has been converted into megawatts. Unlike the operation rules before deregulation where the operating region is continuous as shown by the dashed line in Fig. 3, each unit can pump at its pumping capacity, be idle, or generate within a continuous operating region as shown by the solid line and five additional dots in the figure. The spinning reserve is the same as the pumping level or the online generation capacity minus the generation level. The power-reserve relationship for the pumped-storage unit is shown in Fig. 3.

A pumped-storage system has following pond constraints.

- Pond level dynamics

$$v_n(t+1) = v_n(t) - w_n(t), \quad \forall\, t. \tag{4}$$

- Pond level limits.

These constraints require that the pond level should be within its upper and lower bounds at any time. Since it is difficult to deal with the pond level constraints mathematically for all the possible market realizations, these constraints are modeled in an expected sense, that is

$$\underline{V}_n \leq E(v_n(t)) \leq \overline{V}_n \quad \forall\, t. \tag{5}$$

- End pond levels.

The end pond level V_n^T specifies the desired amount of water available for next bidding cycle. Similar to the pond level limits, it is formulated in an expected sense, that is

$$E(v_n(T)) = V_n^T. \tag{6}$$

The above formulation is a stochastic mixed-integer optimization problem. The key feature is the separable structure with respect to units as only the self-scheduling requirements (1) and (2) couple the decisions of different units. Therefore, Lagrangian relaxation can be effectively applied by taking the advantage of the separable structure. For the case without the self-scheduling requirements, the problem can be solved in one iteration where the multipliers are all zeros.

III. Solution Methodology

A. Lagrangian Relaxation Framework

Since the constraints (1) and (2) couple the decisions among individual units, they are relaxed by using two sets of multipliers $v_d(t) \geq 0$ and $v_r(t) \geq 0$, respectively, and a two-level optimization is formed. Given a set of multipliers $v_d(t)$ and $v_r(t)$, the relaxed problem is

$$\min_{p_n(\cdot), r_n(\cdot)} L(\nu_d, \nu_r, p_n(\cdot), r_n(\cdot)), \text{ with} \tag{7}$$

$$\begin{aligned} &L(\nu_d, \nu_r, p_n(\cdot), r_n(\cdot)) \\ &\quad \equiv -\sum_{t=1}^{T} C_d(p_d(t)) \\ &\qquad + E\Bigg(\sum_{t=1}^{T}\sum_{n=1}^{N}\Big[C_n(p_n(\lambda_d(t))) + S_n(t) \\ &\qquad\qquad - \big(\lambda_d(t) + \omega(t)\sigma_{\lambda_d}^2(t) + \nu_d(t)\big)\, p_n(\lambda_d(t)) \\ &\qquad\qquad - \big(\lambda_r(t) + \omega(t)\sigma_{\lambda_r}^2(t) \\ &\qquad\qquad\quad + \nu_r(t)\big)\, r_n\left(\lambda_r(t)\right)\Big]\Bigg). \end{aligned} \tag{8}$$

Define

$$\mu_d(t) \equiv \lambda_d(t) + \omega(t)\sigma_{\lambda_d}^2(t) + \nu_d(t) \text{ and} \tag{9}$$

$$\mu_r(t) \equiv \lambda_r(t) + \omega(t)\sigma_{\lambda_r}^2(t) + \nu_r(t). \tag{10}$$

Compared with traditional unit commitment problems, $\mu_d(t)$ and $\mu_r(t)$ play the role of the marginal energy and reserve costs at t, respectively.

By regrouping (8), the above subproblem is formulated as $\min_{\mathbf{p}_n(\cdot), \mathbf{r}_n(\cdot)} L_n$, with

$$\begin{aligned} L_n \equiv E\Bigg(\sum_{t=1}^{T}\Big[&C_n(p_n(\lambda_d(t))) \\ &+ S_n(t) - \mu_d(t)p_n(\lambda_d(t)) - \mu_r(t)r_n(\lambda_r(t))\Big]\Bigg) \end{aligned} \tag{11}$$

subject to individual unit constraints.

The multipliers $v_d(t)$ and $v_r(t)$ are updated at the high level to maximize the dual function $q(v_d, v_r)$, (i.e., $\max_{v_d \geq 0, v_r \geq 0} q(v_d, v_r)$), with

$$q(\nu_d, \nu_r) \equiv \min_{p_n(\cdot), r_n(\cdot)} L(\nu_d, \nu_r, \mathbf{p}_n(\cdot), \mathbf{r}_n(\cdot)) + \sum_{t=1}^{T} \Big[(\alpha_d(t)\nu_d(t) - \lambda_d(t)) P_d(t) + (\alpha_r(t)\nu_r(t) - \lambda_r(t)) P_r(t) \Big]. \quad (12)$$

The two levels iterate until a stopping criterion is satisfied. The offer curves are then constructed based on subproblem solutions. These steps are described next.

B. Solving Subproblems

A unit subproblem (11) is similar to that for a unit commitment problem as in [9], [10], [16]. The key differences are that the marginal energy cost $\mu_d(t)$ and the reserve cost $\mu_r(t)$ are now random variables depending on $\lambda_d(t)$ and $\lambda_r(t)$, and the solution is a set of offering strategies: how much power should each unit provide for each pair of $\lambda_i d(t)$ and $\lambda_j r(t)$ at what probability.

Solution methodologies for different types of units are different. In view of limited space, only the method for pumped-storage subproblems will be presented. The method for thermal units can be derived by extending the deterministic case ([9], [10]) to a stochastic one.

Without fuel and startup costs, the subproblem for pumped-storage unit n can be described as $\min_{\mathbf{p}_n(\cdot), \mathbf{r}_n(\cdot)} L_n$, with

$$L_n \equiv E\left(\sum_{t=1}^{T} [-\mu_d(t) p_n(\lambda_d(t)) - \mu_r(t) r_n(\lambda_r(t))]\right) \quad (13)$$

subject to operation constraints (4)–(6).

In view of the discontinuous operating regions as shown in Figs. 3 and 4, the subproblem involves both integer and continuous decision variables. The idea to solve this subproblem is to substitute out the pond dynamics (4), and to relax the two sets of pond level limit constraints (5) and the end pond level requirement (6) by using three additional sets of multipliers $\gamma_1(t)$, $\gamma_2(t)$ $(t = 1, 2, \ldots, T-1)$, and γ_3, respectively. A new sub-Lagrangian is then formed as

$$\tilde{L}_n \equiv E\Bigg\{ \sum_{t=1}^{T} [-\mu_d(t) p_n(\lambda_d(t)) - \mu_r(t) r_n(\lambda_r(t))] + \sum_{t=1}^{T-1} \gamma_1(t) \left(\sum_{\tau=1}^{t} w_n(\tau) - V_n^0 + \underline{V}_n \right) + \sum_{t=1}^{T-1} \gamma_2(t) \left(V_n^0 - \overline{V}_n - \sum_{\tau=1}^{t} w_n(\tau) \right) + \gamma_3 \left(V_n^T - V_n^0 + \sum_{\tau=1}^{T} w_n(\tau) \right) \Bigg\}.$$

An intermediate level is thus created, where the multipliers $\gamma_1(t)$, $\gamma_2(t)$, and γ_3 are updated by using the subgradient or

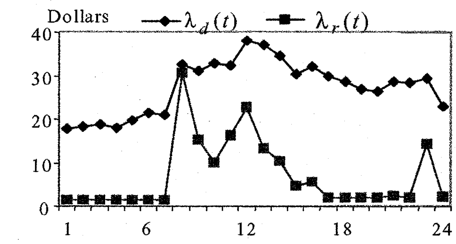

Fig. 4. MCP $\lambda_d(t)$ and reserve price $\lambda_r(t)$ on July 12, 1999, New England market.

the bundle method. At the low level with multipliers given, the subproblem is described as

$$\min_{p_n(\cdot), r_n(\cdot)} \tilde{L}_n, \text{ with } \tilde{L}_n \equiv E\left(\sum_{t=1}^{T} h_n(t, p_n(\cdot), r_n(\cdot))\right), \quad (14)$$

where

$$h_n(t) \equiv -\mu_d(t) p_n(w_n(\lambda_d(t), \lambda_r(t))) - \mu_r(t) r_n(\lambda_d(t), \lambda_r(t)) + w_n(\lambda_d(t), \lambda_r(t)) \left(\gamma_3 + \sum_{n=t}^{T-1} [\gamma_1(n) - \gamma_2(n)] \right) + \gamma_2(t) \left(V_n^0 - \overline{V}_n \right) - \gamma_1(t) \left(V_n^0 - \underline{V}_n \right), \quad t = 1, 2, \ldots, T-1, \quad (15)$$

and

$$h_n(T) \equiv -\mu_d(t) p_n(w_n(\lambda_d(T), \lambda_r(t))) - \mu_r(t) r_n(w_n(\lambda_d(T), \lambda_r(T))) + \gamma_3 w_n(\lambda_d(T), \lambda_r(T)), \quad (16)$$

are the stage-wise cost functions.

The problem in (14) is to minimize an expected sum of the stage-wise cost functions with random coefficients. In view of the Markovian assumption on MCPs, a stochastic dynamic programming approach is developed where a stage corresponds to an hour and a state at hour t to a pair of $(\lambda_d^i(t), \lambda_r^j(t))$ $(i = 1, 2, \ldots, I;\ j = 1, 2, \ldots, j)$. Since all intertemporal constraints have been relaxed, the optimal generation $p_n(\lambda_d^i(t), \lambda_r^j(t))$ and reserve $r_n(\lambda_d^i(t), \lambda_r^j(t))$ for each state are obtained by optimizing the stage-wise cost function, subject to operating region constraints as depicted in Figs. 3 and 4. The optimal generation level for each state thus depends only on $\mu_d(t)$ and $\mu_r(t)$. It should be pointed out that in view of discontinuous operating regions, the optimal generation level may change considerably with a slight change of $\mu_d(t)$ and $\mu_r(t)$, resulting in significantly different offer curves. The probability $P_n^r(\lambda_d^i(t), \lambda_r^j(t))$ for each state is then calculated based on the transition probabilities of Markovian prices. The solution obtained here is a set of high dimensional offering strategies for the joint energy and reserve market: how much power and reserve should each unit provide for a possible pair of $(\lambda_d^i(t), \lambda_r^j(t)$, and at what probability. These strategies $p_n(\lambda_d^j(t), \lambda_r^j(t))$ are used to construct offer curves.

C. Solving the Dual Problem

After the subproblems are solved, the multipliers $\gamma_1(t), \gamma_2(t)$, and γ_3 are updated at the intermediate level, and the multipliers $v_d(t)$ and $v_r(t)$ are updated at the high level by using a subgradient or bundle method. In our testing, the trust region bundle method in [12], [22] is used.

D. Constructing Offer Curves

The strategies obtained are a set of joint offer curves for a combined energy and reserve market. Since the energy and reserve are traded separately in two markets, the strategies need to be projected onto individual markets. To do this, a joint offer curve is first projected to the energy market by taking expectation of generation levels $p_n\left(\lambda_d^i(t), \lambda_r^j(t)\right)$ over $\lambda_r^j(t)$ $(j = 1, 2, \ldots, J)$, that is

$$\hat{p}_n(\lambda_d^i(t)) = \frac{\sum_{j=1}^{J} p_n(\lambda_d^i(t), \lambda_r^j(t)) P_n^r(\lambda_d^i(t), \lambda_r^j(t))}{\sum_{j=1}^{J} P_n^r(\lambda_d^i(t), \lambda_r^j(t))}, \quad \forall\, i, n, t. \quad (17)$$

Since the operating regions of a unit may be discontinuous, the result $\hat{p}_n\left(\lambda_d^i(t)\right)$ obtained in (17) may be infeasible (i.e., may fall in a forbidden range). The above result is therefore further projected onto the nearest feasible operating region to obtain a near-optimal generation level $p_n\left(\lambda_d^i(t)\right)$. The energy offer curves are then constructed based on these generation levels $p_n\left(\lambda_d^i(t)\right)$ $(i = 1, 2, \ldots, I)$ and their associated prices. The reserve offer curves can be similarly constructed. It is easy to verify that an offer curve obtained in this way is nondecreasing and satisfies the market requirements.

In the New England market, the power blocks in offer curves for a unit are fixed across the bidding horizon. In this case, the power blocks are typically given, and the problem is to optimize the offer price for each block. The method developed here can be used in such cases by projecting $\hat{p}_n\left(\lambda_d^i(t)\right)$ to the nearest block. As will be demonstrated in the numerical testing section, the performance degradation is not significant.

E. Performing Unit Commitment to Satisfy the Market Obligations

After the market closes, the GenCo takes the energy and reserve awards as the system demand and reserve requirements, respectively, and performs unit commitment and economic dispatch to minimize its total operation cost while satisfying market obligations. If the generators are located in multiple zones, multiarea unit commitment may be needed, and transmission constraints may also need to be considered.

F. Analyzing Self-Scheduling, Market Interaction, and Risk Management

Since $\mu_d(t)$ plays the roles of marginal energy cost (9) and $\mu_r(t)$ the marginal reserve cost in (10), their values determine the generation and reserve levels and thus offer curves. To be specific, we shall demonstrate how self-scheduling constraints, risk management, and the interaction of the energy and reserve markets affect offers though (9) and (10), (15), and (16). For simplicity, the focus will be on energy offers, as reserve offers can be similarly analyzed.

The self-scheduling constraints affect the offers by changing $\mu_d(t)$ and $\mu_r(t)$ through $v_d(t)$ and $v_r(t)$ as in (9) and (10). If the self-scheduling requirement on energy at hour t is high, $v_d(t)$ will be large, making $\mu_d(t)$ large. Consequently, the generation level $p_n\left(\lambda_d^i(t), \lambda_r^i(t)\right)$ will be large for a given offer price $\lambda_d^i(t)$. Equivalently, the offer price will be low for a given generation level so that a large amount of power can be sold to the market to satisfy the self-scheduling requirements.

The tradeoff in allocating the limited generation capacity between the energy and reserve markets is made based on $\lambda_d(t)$ and $\lambda_r(t)$. At normal situations, $\lambda_d(t)$ is much higher than $\lambda_r(t)$, making $\mu_d(t)$ much higher than $\mu_r(t)$. Consequently, energy offer curves are primarily based on $\mu_d(t)$. Occasionally, the reserve price $\lambda_r(t)$ is significant as observed in many markets, making $\mu_r(t)$ high. As a result, the GenCo will allocate more capacity into the reserve market by offering low prices for reserve and high prices for energy.

Since a pumped-storage unit contributes significant energy and reserve at pumping or generating, it plays important roles in both markets. Its offering strategies, however, are coupled across hours through intermediate level multiples $\gamma_1(t)$, $\gamma_2(t)$, and γ_3 in view of the pond limits and dynamics as shown in (15). A decision at one hour affects the pond level (4), thus affects multiples $\gamma_1(t)$, $\gamma_2(t)$, and γ_3 afterwards through the iterative multiplier updating process. These multipliers affect the decisions at previous hours when optimizing the stage-wise cost (15) in stochastic dynamic programming. If the lower pond level constraint cannot be satisfied at hour t leading to a high $\gamma_2(t)$, then the unit has to either generate less or pump more before that hour. The pumped-storage strategies also affect thermal offers through high level multiples $v_d(t)$ and $v_r(t)$ as a pumped-storage unit significantly affects self-scheduling obligations on thermal units by pumping or generating (1–2). Therefore, pumped-storage units also play a key role in the interaction between energy and reserve markets.

The risk management scheme (3) affects offering strategies by changing of $\mu_d(t)$ and $\mu_r(t)$ via $\sigma_{\lambda_d}^2(t)$ and $\sigma_{\lambda_d}^2(t)$. If $\sigma_{\lambda_d}(t)$ is high, indicating high uncertainty on $\lambda_d(t)$, then $\mu_d(t)$ is high. Consequently, the optimal generation level for each state is high, resulting in high $p_n\left(\lambda_d^i(t)\right)$. As a result, the GenCo offers low energy price to capture potential price spikes. For a pumped-storage unit, the risk management method typically forces the unit to pump more water during offpeak hours in view of relatively low prices and low uncertainties to be used during onpeak hours with high prices and high uncertainties.

IV. Numerical Testing Results

Numerical testing has been performed for a system consisting of ten thermal units with piece-wise linear production costs and a large pumped-storage unit with four identical generators associated with one large pond in New England. Three examples are presented. The first one shows how our risk management scheme affects offering strategies and the profit

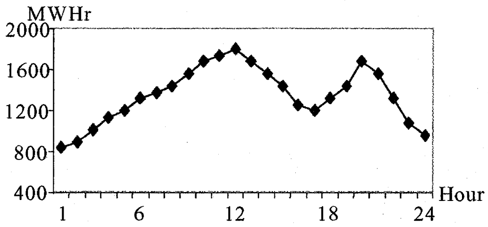

Fig. 5. Own load $p_d(t)$.

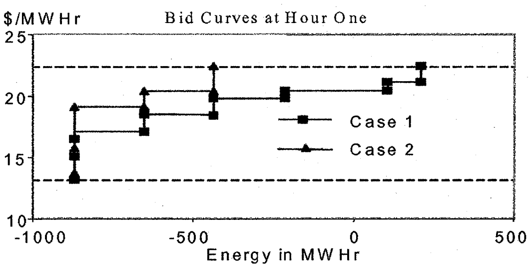

Fig. 6. Offer curves of the pumped-storage unit at hour one.

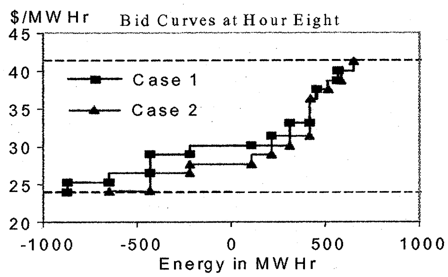

Fig. 7. Pumped-storage offer curves at hour eight.

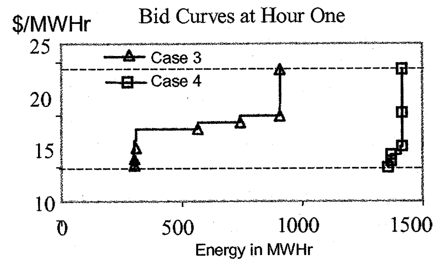

Fig. 8. Aggregated thermal offer curves at hour one.

TABLE I
SIMULATION RESULTS

	Case 1	Case 2	Diff.	Rel. Diff.
Total Cost	709,828	710,862	1,034	0.15%
Std. Dev.	22,636	18,819	3,817	–16.86%

variance. The second demonstrates the interaction between the energy and reserve markets, and how the pumped-storage unit affects thermal offering strategies. In the above two examples, the hourly market prices are obtained by adding randomness around actual New England MCPs. The third example presents bidding results where hourly MCPs are predicted by using a neural network. For better presentation of results, thermal offer curves are aggregated, and only curves within $[-3\sigma_d(t), 3\sigma_d(t)]$ are presented for all of the examples.

Example 1: Impact of Risk Management: In this example, New England market data on July 12, 1999 are used. The actual energy and reserve prices are shown in Fig. 5, the GenCo's own load is shown in Fig. 6, and the reserve requirements are set to 15% of the corresponding loads. The MCP distribution at each hour is assumed Gaussian with the actual market price as the mean. The standard deviation $\sigma_d(t)$ is set as 10% of the corresponding hourly MCP. Fifteen price values uniformly distributed within the 6 $\sigma_d(t)$ confidential region (with 99.73% coverage) are generated for each hour. The self-scheduling requirement is assumed to be 80% of the GenCo's own load. For simplicity, the reserve market is ignored in this example.

Two cases are tested, where risk management is not considered in Case 1 but considered in Case 2 with $?(\omega) = 0.045$. The offer curves for the pumped-storage unit at hours one and eight are shown in Figs. 7 and 8, respectively. In view of the high MCP uncertainty at hour eight, the pumped-storage unit generates more or pumps less by having lower offer prices in Case 2 as compared to Case 1. However, it has higher offer prices at hour one to generate less or pump more to preserve water for future use.

To investigate the impact of risk management on the expected profit, Monte Carlo simulation was performed, and 500 sets of market clearing prices were randomly generated based on price distributions. For each scenario, a unit is awarded based on its offer curves and the MCPs. By taking the awarded energy as the demand requirements, unit commitment is then performed to generate a schedule to fulfill market obligations at a minimum cost. An expected total cost is then calculated over scenarios. The testing results are summarized in Table I.

It can be seen that our risk management scheme reduces the standard deviation of total cost by 16.86% at a cost of increasing the expected total cost by 0.15%. In reality, the MCPs may not be Gaussian, especially for extreme or unexpected situations where high MCP uncertainties most likely imply high prices. In those cases, the MCP could be underestimated in view of few similar historical samples, and our risk management may reduce operation costs as well as bidding risks, as to be demonstrated in Example 3.

To evaluate how good the results are under New England market rules where power blocks for each unit are fixed over a bidding horizon, the solutions are projected to corresponding blocks. The same Monte Carlo simulation is performed for 500 runs, and the average total costs are obtained at U.S.$ 710 327 for Case 1 (with a 0.07% increase as compared to the results reported in Table I) and U.S.$ 711 431 for Case 2 (with a 0.08% increase).

Finally, the unit commit problem is solved where the own load is exactly supplied by the 11 units. The total cost is obtained at U.S.$ 735 866. By taking the market as a flexible generator or a dispatchable load, the expected total cost is reduced by 3.5% without risk management and 3.4% with risk management.

Example 1: Impact of Risk Management: This example uses the same data set of example 1 except that the reserve market is included. To show how the pumped-storage unit affects thermal offers, the pure thermal-unit system (Case 3)

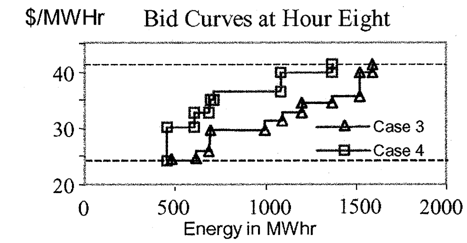

Fig. 9. Aggregated thermal offer curves at hour 8.

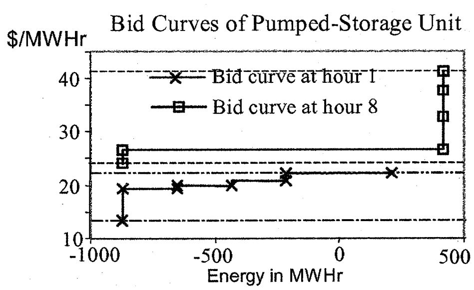

Fig. 10. Pumped-storage offer curves in case 4.

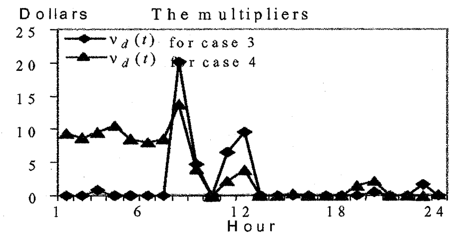

Fig. 11. Multipliers associated with self-scheduling energy constraints.

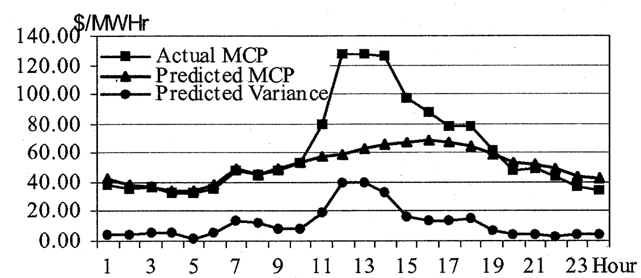

Fig. 12. Actual versus predicted MCP of August 8, 2000 New England.

is tested, and the result is compared with that for the system with the pumped-storage unit (Case 4). The aggregated offer curves for thermal units at hours one and eight are shown in Figs. 9 and 10, respectively, and the pumped-storage offer curves are shown in Fig. 11.

Comparing the thermal offer curves for the two cases, we can see that with the pumped-storage unit, thermal units offer lower energy price for hour one but higher price for hour eight. In view of low price at hour one, the pumped-storage unit most likely pumps as shown in Fig. 10, resulting in higher self-scheduling energy requirement on thermal units. Therefore, the thermal units have to offer low energy price for generating more power to satisfy the self-scheduling requirement. On the contrary, the pumped-storage unit would most likely generate (see the offer curve in Fig. 11) in view of high price at hour eight, alleviating the self-scheduling energy requirement on thermal units. Therefore, the thermal units offer high energy price at hour eight, allocating more capacity to the reserve market. The thermal offer curves have been significantly changed with the pumped-storage unit.

In view of the high reserve price at hour eight, all units should provide as much reserve as possible to maximize the profit. Since the reserve contribution of a pumped-storage unit is the same as the pumping level or the online capacity minus the generating level (see Fig. 4), the four generators should either pump at pumping capacity, or generate at the minimum generation limit to provide maximum reserve. These two optimal strategies are obtained in the offer curve of Fig. 11. In this case, the pumped-storage unit would most likely generate in view of the high self-scheduling energy requirement and high MCP uncertainty at hour eight. As a result, the self-scheduling requirements on thermal units are reduced, and more thermal capacity is allocated to the reserve market by offering higher energy prices for thermal units, as shown in Fig. 10. The pumped-storage offer curve at hour eight is totally changed due to the reserve market as compared with those in Case 2 (see Figs. 8 and 11).

To further understand how the pumped-storage unit affects the system's operation, the multipliers $v_d(t)$ associated with the self-scheduling energy requirements for the Cases 3 and 4 are plotted in Fig. 12. At peak hours (e.g., hours 8, 9, 11, 12), the pumped-storage unit generates power on average and, thus, reduces marginal costs $v_d(t)$ by alleviating self-scheduling energy requirements on thermal units. This is similar to the case in unit commitment, where pumped-storage units cut the peak load. From the testing results, it is also observed that the pumped-storage unit contributes to the reserve market in addition to satisfying the self-scheduling reserve requirements. The pumped-storage unit plays important roles in both the energy and reserve markets.

Example 3: Offering Strategies Based on MCP Prediction: In the above examples, optimizing offer curves is based on actual market prices. In this example, the energy market price is predicted by using a classification-based neural network developed in [17]. The particular day selected is for August 8, 2000, a relatively hot day in a mild summer, in New England. The actual and predicted MCPs are shown in Fig. 12 where the predicted hourly variance is also plotted. In view of the very low reserve prices, Gaussian distribution is assumed with actual prices as the means and 10% of the prices as the standard deviations for the reserve prices.

By solving the bidding problem, a total cost of U.S.$ 738 580 is obtained without risk management, and U.S.$ 724 006 with risk management. Since the MCP uncertainty is predicted higher during the onpeak hours than that of offpeak hours, the pumped-storage unit pumps more water during the offpeak hours. Consequently, it generates more power during the onpeak hours, leading to a 1.97% saving on the total cost, as the actual MCP is substantially higher than the prediction.

To evaluate the solution quality, the problem is also solved assuming that the actual MCPs are known, and a total cost is obtained at U.S.$ 708 480. Therefore, the offer strategies obtained in this case is within 2.2% from the optimal solution with actual MCP known.

The CPU time is about 4–5 min on a PC with a 600-MHz Pentium III processor, making the algorithm computationally efficient for daily use.

V. Conclusions

An optimization-based algorithm has been presented to provide efficient energy and reserve offering strategies for a hydrothermal power system under deregulated power markets. A stochastic mixed-integer optimization formulation is established to systematically handle the MCP uncertainties, bidding risk management, and self-scheduling requirements. An optimal solution methodology combining Lagrangian relaxation and stochastic dynamic programming method is then presented. Numerical testing results show that the algorithm is computationally efficient, and effective offer curves for both energy and reserve markets are obtained in 4–5 min on a PC. The risk management is proved to be an effective way to reduce profit variances, thus the bidding risks. This paper also demonstrates how the reserve market affects generation offering strategies, and how a pumped-storage unit affects the thermal offers.

Appendix
A List of Notations

N and n	number of units and unit index;
T and t	bidding time horizon and time (hour) index;
$\lambda_d(t)$ and $\lambda_r(t)$	energy and reserve prices at t, respectively, in dollars per megawatt hour;
$\lambda_d^i(t)$	a set of predicted energy price at t, in in dollars per megawatt hour $i = 1, 2, \ldots, I$;
$\lambda_r^j(t)$	a set of predicted reserve price at t, in in dollars per megawatt hour $j = 1, 2, \ldots, J$;
$\sigma^2_{\lambda_d}(t)$ and $\sigma^2_{\lambda_r}(t)$	price variance prediction for energy and reserve at t respectively;
$\lambda_d(t, p_n(t))$	hourly energy offering price curve for unit n as a function of generation level, in dollars per megawatt hour;
$p_n(\lambda_d(t))$	hourly energy offer for unit n as a function of price, in megawatts;
$r_n(\lambda_r(t))$	hourly reserve offer for unit n as a function of price, in megawatts;
$p_d(t)$ and $p_r(t)$	The company's "own load" and the corresponding reserve at t, respectively, in megawatts;
$\alpha_d(t)$ and $\alpha_r(t)$	self-scheduling coefficients for energy and reserve, respectively;
$C_n(p_n(t))$	production cost curve for unit n as a function of generation;
$S_n(t)$	startup cost for unit n at t;
$C_d(p_d(t))$	revenue from own loads, a constant in the bidding problem;
$\omega(t)$	weight coefficient at t for balancing the profit versus risks;
$w_n(t)$	water discharged (positive) from or pumped (negative) to the pond at time t for pumped-storage unit n;
$v_n(t)$	pond level at t for pumped-storage unit n;
$\underline{V}_n$ and $\overline{V}_n$	min and max pond limits for pumped-storage unit n respectively;
$v_d(t)$ and $v_d(t)$	multipliers associated with the energy and reserve self-scheduling requirements at t, respectively;
$\gamma_1(t)$, $\gamma_2(t)$ and γ_3	multipliers associated with the minimum and maximum pond limits at t, and the end pond level constraint, respectively.

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