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INFLUENCE OF PRICE UNCERTAINTY MODELING ACCURACY ON BIDDING STRATEGY OF A MULTI-UNIT GENCO IN ELECTRICITY MARKETS*

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Abstract– In deregulated electricity markets, strategic bidding plays an important role in a generation company's (GENCO's) profit maximization. A reasonable profit making bidding strategy is presented in this paper, taking into account price uncertainty as well as generator cost characteristics. Price uncertainty is considered through various statistical distributions, ensuring success in bidding process with a specified degree of confidence. The screening curve, generally used for economic evaluation of generating units in planning and operation studies, is utilized to characterize generator costs. The logically developed bidding strategy is implemented on a GENCO, that owns five different generating units. Fixed, variable and no load cost of generating units is taken into consideration to calculate GENCO profit. No load cost occurs when unit loses bid and cannot shutdown due to unit commitment constraints. Historical data of PJM electricity market is used to model price uncertainty. Finally, a comparative analysis is carried out to access the influence of accuracy of price uncertainty modeling on the GENCO profit.

Keywords– Bidding Strategy, capacity factors, no load cost, price uncertainty, statistical distributions

1. INTRODUCTION

Restructuring of electricity markets reduces consumer payments and improves operational efficiency, but creates issues such as financial risk, transmission congestion, system security, resources scheduling, abuse of market power, *etc.* Liberalization or deregulation has changed the way of business in electricity markets. In the new environment, GENCOs sell their energy and ancillary services through bidding into electricity market. The independent system operator (ISO) manages market operations like market clearing and system stability [1-2].

Present electricity markets are oligopolistic due to presence of price-maker large GENCOs and consumers. They can manipulate market prices to enhance their benefits. Therefore, oligopolistic electricity markets have high price volatility. On the other hand, price-taker GENCOs are unable to affect market prices and require a reasonable level of profit to survive in oligopolistic electricity markets. They can develop their bidding strategies, considering price uncertainty and generator cost characteristics. In general, there are three ways to develop optimal bidding strategies: estimation of market clearing price (MCP) for the next trading period, estimation of rival participant's behavior and game theory approach [3]. These have been solved using different solution approaches, like mathematical optimization, intelligent & agent based and game theory based approaches [4-5]. Among these solution approaches, mathematical optimization is commonly used to formulate bidding strategy of price-taker GENCOs.

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Combined Lagrangian Relaxation and Stochastic Dynamic programming methods are useful tools for optimization of bidding strategy under price uncertainties and risks; they consume less computational time, and represent the bids as quadratic functions of power levels [6-8]. Ordinal optimization model has been used for bidding strategy formulation of hydrothermal GENCO [9], while optimal bidding strategy for suppliers can be derived by solving a set of differential equations [10]. Generators' strategic bidding considering demand elasticity has been discussed [11]. Generators' and large consumers' bidding strategy can be formulated as stochastic optimization problem and solved by Monte Carlo approach [12]. Markov Decision Process can be used as a solution algorithm for stochastic optimization problem [13]. Markov decision process is unable to handle multi-constrained stochastic problems. In addition, its application is restricted to discrete variables problem, whereas competitive bidding is a continuous variable problem.

Using price forecasting, generators can accurately value their contracts and schedule their resources in an economic manner. Common forecasting tools used are time series based dynamic regression & transfer function, ARMA, GRACH, artificial neural network, *etc*. [14-16]. Forecasting tools need historical data of market price but scarcity of historical electricity markets data makes it difficult to achieve accurate prediction. A statistical model can represent price uncertainty, under the assumption that price of any one period is a random variable [17-19]. In [20], the price based unit commitment (PBUC) method has been proposed to develop bidding strategies under price uncertainty. Based on the generation unit characteristics and unit availability, the GENCOs carry out PBUC for a range of price scenarios and thus determine the bidding strategies for each bidding period of the next day. PBUC considers various unit commitment constraints.

This paper presents a reasonable bidding strategy for a price-taker GENCO, that owns five different generating units, considering price uncertainty as well as generator cost characteristics. Price uncertainty is considered through various statistical distributions, ensuring success in bidding process with a specified degree of confidence. The screening curve is utilized to characterize generator costs, with associated economic range of capacity factors. The logically developed bidding strategy is non-iterative and simple. Unit commitment constraints, such as no-load cost, have been considered for profit calculation. A practical case study of PJM electricity market has been taken up. A comparative analysis is presented to illustrate influence of market price uncertainty modeling accuracy on generating units' profits. Profit obtained through the proposed approach is also compared with the maximum profit possible, had the MCP been known with certainty. Comparative results suggest that the proposed approach is effective and gives reasonable profit.

2. PROBLEM DESCRIPTION

a) The bid problem

GENCOs submit non-decreasing bid curves to ISO. A typical five step bidding curve is represented in Fig. 1, where x-axis represents the bid quantity (MW) while y-axis reflects the bid price ($/MWh). The bid prices PB_1, PB_2, PB_3, PB_4 and PB_5 correspond to the quantities QB_1, QB_2, QB_3, QB_4 and QB_5 respectively. A non-decreasing nature of the bid curve at time t can be described as:

$$PB_{n-1,t} \le PB_{n,t} \;\; \forall N = 2,3,4,5 \tag{1}$$

$$QB_{n-1,t} \le QB_{n,t} \;\; \forall N = 2,3,4,5 \tag{2}$$

where, n is the index for bid blocks. After gate closure, market operator determines the MCP based on supply and demand bids. When MCP, PR_t of each period is determined, the outcome of each bid is known. The bid status $UB_{n,t}$ reflects bid acceptance or rejection that can be obtained by comparison of bid price and MCP.

For rejected bids:

$$UB_{n,t} = 0 \quad if \quad PR_t < PB_{n,t} \tag{3}$$

For accepted bids:

$$UB_{n,t} = 1 \quad if \quad PR_t \geq PB_{n,t} \tag{4}$$

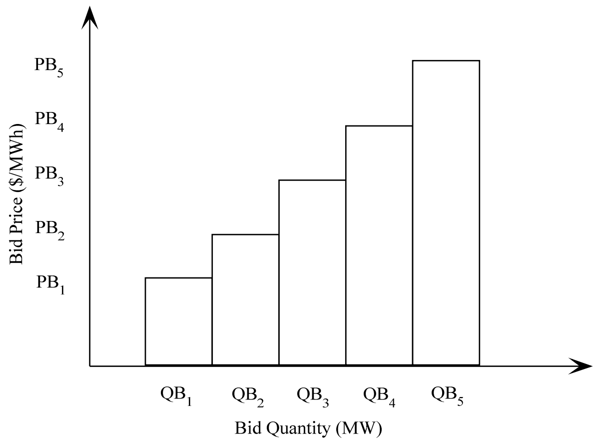

Fig. 1.Bidding curve with five steps

The bidding strategy aims to determine the bid quantities $QB_{n,t}$ and bid prices $PB_{n,t}$ such that the bid has a reasonable success rate and generates profit for the GENCO. Operation of generating units depends upon bid status.

b) Price uncertainty

Due to demand uncertainty, market power abuse and transmission congestion, electricity market prices fluctuate widely. Therefore, detailed knowledge of the electricity market price behavior is required to develop proper bid prices. A simple alternative is to represent a future spot price by a statistical distribution. The statistical models shown in this paper do not capture all empirically observable properties of electricity prices, such as mean reversion, jumps and spikes. Nevertheless, it offers the advantage of simplicity and may be adequate for operation planning studies of day-ahead markets. Only a few parameters are required to be estimated, which is advantageous for markets with short history [18].

In this paper, uncertainty of electricity market price is investigated through different statistical distributions. This is done under the assumption that MCP of one trading period is a random variable X , which has to be forecast. This random variable can be fitted in a specific statistical distribution, such as lognormal, Weibull and gamma, with the following parameters being investigated.

$$\begin{aligned} X &\approx Lognormal(\mu,\sigma) \\ X &\approx Gamma(\lambda,k) \\ X &\approx Weibull(\lambda,k) \end{aligned} \tag{5}$$

where, μ, σ, λ and k are mean, standard deviation, scale parameter and shape parameter of any particular period price data.

This modeling of electricity price in the market enables the representation of next day price at any one hour, with the desired level of probability. Statistical representation of the price is helpful for planning and operation in competitive markets. The benefits to be realized from the correct statistical characterization of the market price data can be verified by way of different simulation studies. Hypothesis test can investigate whether the forecasted price data emerges from a specific statistical distribution or not. Ansari-Bradley test is used for testing hypothesis of considered distributions at 5% significance level. A comparison of the histogram and the density function reflects the suitability of a distribution function for a set of forecasted data.

c) Generators cost analysis

Optimal and economic operation of different generating units, with their relative merits, is represented by screening curves [17]. These curves define the annual revenue requirement (ARR) per MW of generating units as a function of capacity factor. ARR of generating units depends on the following three factors: fixed cost (FC), variable cost (VC) and capacity factor (CF). FC is a non-fuel operation and maintenance (O&M) cost of a generating unit, which does not vary significantly with its electricity generation. In the traditional power system, the scheduling of generators considers only the marginal cost, as the fixed costs are taken care of in the process of energy rate making. Following the same logic, the fixed cost may not seem relevant in daily bidding process in the competitive market, because for an existing Genco, fixed cost is sunk cost and it should not influence operation of the unit in any period. However, consideration of the average costs becomes necessary to ensure the viability of a generating unit. This is also an important parameter for long-term planning and operation of generating units. VC incurred when generating units generate electric power, which depends on their fuel cost parameters [19, 20].

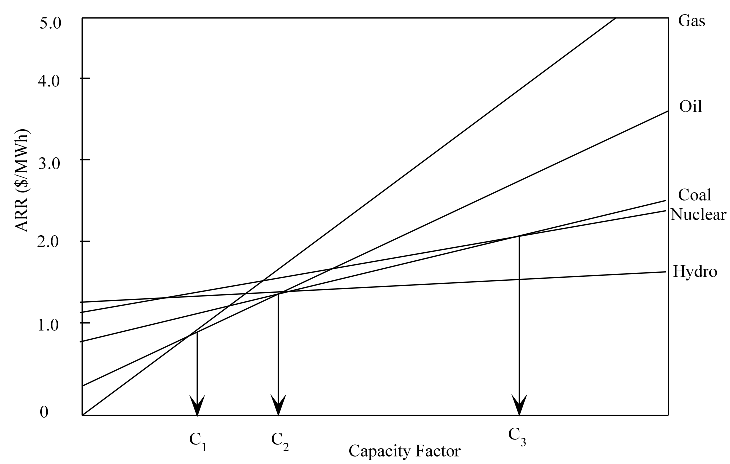

Fig. 2. Screening curves of the mix generation units

Figure 2 shows a typical screening curve to illustrate the combined operation of five generating units. This graph shows that the nuclear unit with very high capital and operation cost would be an economic option, if it is operated with a capacity factor higher than C_3. Similarly, coal unit is most economical with capacity factor between C_2 and C_3. The hydro unit has a high capital cost and low operation cost, and is economical if the capacity factor value is higher than C_2. Gas unit with low capital cost and a high fuel cost rate would be most economical when operated with a capacity factor less than C_1. In the same way, oil unit is the best choice for generating unit capacity factor between intervals C_1 and C_2.

3. BIDDING STRATEGY

Bidding strategy optimizes the bidding curves submitted by GENCOs to the system operator, for recovering their costs and attaining profit. Development of bidding curves would be of little importance even if bid price is known along with cost characteristic of units, but accurate forecasting is not available. For a price-taker GENCO, if the cost of its generating units is always high or less than market price, bidding strategy would be formulated easily. However, the problem arises when the cost of generating units fluctuates high and low, as compared to the market prices, which is a realistic situation in competitive electricity market. Therefore, the present paper aims to develop bidding strategy approach for price-taker GENCO, considering price uncertainty and cost characteristics of generating units, in order to obtain reasonable profit and desired bid success rate. Using the proposed approach, GENCO can operate its generating units economically for the entire year of operation rather than individual bidding period. Therefore, the proposed approach does not follow the marginal cost of generating units and analyses are provided on an annual basis.

For an n-unit GENCO, n-bid blocks can be formulated as follows. The quantity and price of blocks are determined by utilization of statistical model and screening curve. The quantities QBs and prices PBs of n-steps block are:

$$QB_n = \sum PG_n \tag{6}$$

where, PG_n is the MW capacity of n^{th} generation unit. One bid block is considered for one generation unit. Multiple block bidding for a unit can be modeled by preparing screening curves for different cost characteristics, at various output levels of the generators. Multi-level bidding is beyond the scope of this paper. The bid prices are calculated by the following price probability relationship.

$$PB_n = P_n \ such\ as\ prob\left(Price \geq P_n\right) = \alpha_n \% \tag{7}$$

Equation (7) implies that if the bid price PB_n for the n^{th} unit is set as P_n, probability of the bid being successful during market clearing is $\alpha_n\%$. The bid success rate $\alpha_n\%$ of any of the units can be determined probabilistically by using screening curves. The bid for a generating unit should be developed in a manner, such that the probability of its success lies in the range of capacity factors corresponding to the most economic generating unit. For any additional bid quantity, the bid price is identified such that the probability of the market price exceeding the last bid quantity should lie in the range. The revenue of GENCO can be computed as follows:

$$\mathrm{Re}venue = \sum_{t\in\Omega^T} \sum_{n\in\Omega^N} PR_t QB_{n,t} UB_{n,t} \tag{8}$$

where, Ω^T is a set of indices of hours and Ω^N is a set of indices of bid blocks (units). PR_t is a market clearing price at time t in $\$/MWh$. Short-term profit of GENCO mainly depends on its variable cost, other costs may be neglected. However, in long-term operation, the profit of GENCO depends on its variable cost as well as fixed cost. The cost is computed as follows:

$$Cost = \sum_{t\in\Omega^T} \sum_{n\in\Omega^N} FC_{n,t} + VC_{n,t} UB_{n,t} + NLC_{n,t}\left(1 - UB_{n,t}\right) \tag{9}$$

where, $FC_{n,t}$, $VC_{n,t}$ and $NLC_{n,t}$ are fixed cost, variable cost and no load cost of n^{th} generation unit at time t. Fixed cost of a generating unit is calculated using the following formula:

$$FC_{n,t} = \frac{r.OC_{n,t}}{1 - e^{-rT}} \tag{10}$$

where,

$OC_{n,t}$ = Overnight cost of n^{th} generating unit at time t (\$/MWh)

r = Discount rate (% per year)
T = Life of generating unit (years)

Overnight cost is the total construction cost of generating unit without any interest [23]. Variable cost of generating units is calculated according to their fuel cost parameters. The variable cost and revenue of generating unit would be incurred only when it's bid is successful. Thus, generation unit is committed to run, that is, bid status $UB_{n,t} = 1$. Along with fixed cost and variable cost, another cost component that cannot be ignored in profit calculation is the no load cost. No load cost occurs when the units lose the bid, but are not shut down due to minimum up and down time constraints. When bid status $UB_{n,t} = 0$, no load cost is included in generators cost.

Adopting the proposed bidding strategy, the GENCO's profit can be expressed as

$$Profit = \sum_{t \in \Omega^T} \sum_{n \in \Omega^N} PR_t QB_{n,t} UB_{n,t} - FC_{n,t} - VC_{n,t} UB_{n,t} - NLC_{n,t} \left(1 - UB_{n,t}\right) \tag{11}$$

The bid status depends on the MCP at each operating period. The bid quantity and corresponding bid price, as formulated earlier, are expected to produce appropriate levels of bidding success and produce reasonable amount of profit, considering the market price behavior and the generator cost characteristics.

The proposed bidding strategy formulation approach is simulated through the algorithm discussed below:

Step: 1 Set $t = 1$ (for hour 1).
Step: 2 Determine bid quantities & bid prices from (6) & (7).
Step: 3 Forecast the market clearing price through considered statistical distribution.
Step: 4 Determine the bid status & unit status by comparing the bid prices & the MCP.
Step: 5 Calculate revenue for different units, based on the bid status.
Step: 6 Calculate the fixed cost, variable cost and no load cost for different units, based on bid status.
Step: 7 If $t \in \Omega^T$, set $t = t + 1$ & go back to step 2, otherwise go to next step.
Step: 8 Summarize the variable cost, no load cost and the revenue of different units.
Step: 9 Calculate the profit as the difference of the revenue and the fixed, variable & no-load cost.

This algorithm calculates profit of the GENCO with forecasted MCP. To evaluate the influence of price uncertainty modeling on GENCO profit, MCP is forecasted through various statistical distributions (lognormal, Weibull and gamma) and the profit obtained using this algorithm is compared. In addition, obtained GENCO profit through the forecasted MCP by different statistical distributions is also compared with GENCO profit calculated for actual price data to validate the proposed bidding strategy.

4. CASE STUDY

A practical case of PJM electricity market is considered in this paper [21]. Historical data of day-ahead market price from year 2010 to 2012 is taken for price uncertainty modeling while year 2013 data is used for validation of obtained results. MCP for first hour of PJM electricity market is shown in Fig. 3. From this figure, it is visualized that MCP of PJM electricity market is highly volatile in terms of both mean and standard deviation. The market price uncertainty is modeled by different statistical distribution functions. The density functions adopting lognormal, Weibull and gamma distribution, along with the actual histogram for representative first hour price data of PJM electricity market is shown in Fig. 4. A cumulative probability plot along different distributions is shown in Fig. 5. From these figures, it is observed that lognormal distribution fits accurately on first hour MCP of PJM electricity market.

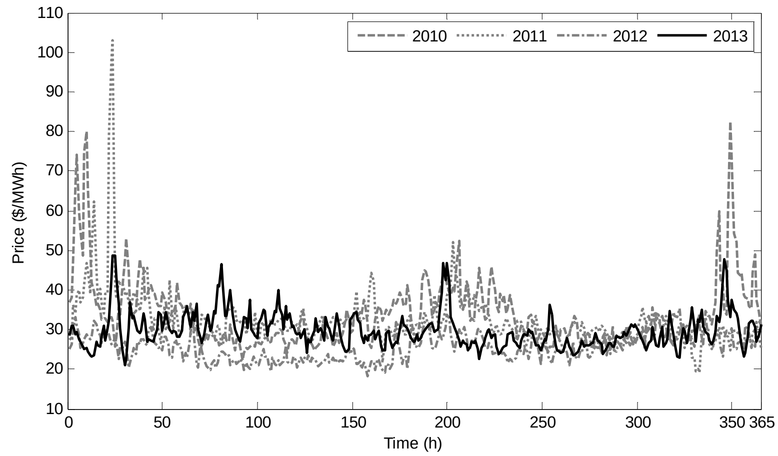

Fig. 3. PJM electricity market price volatility for Hour 1.

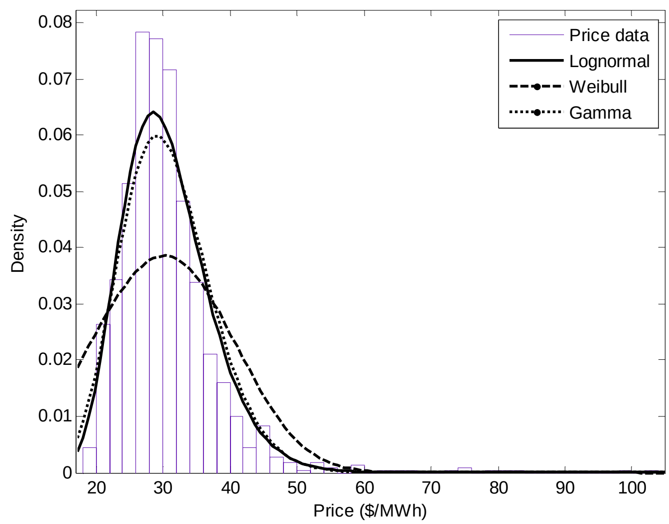

Fig. 4. Probability plots of three distributions for Hour 1

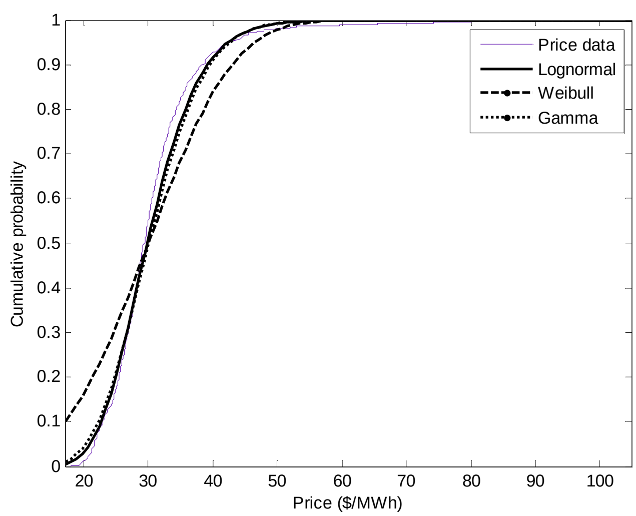

Fig. 5. Comparison of three density functions for Hour 1

Ansari-Bradle hypothesis test is conducted for 24 hours. On the basis of percentage of acceptance of null hypothesis, it can be seen from Table 1 that lognormal distribution is the best model for representing price data of PJM electricity market, as compared to Weibull and gamma distributions. The Statistical Toolbox of MATLAB® is used for this analysis [22].

Table 1. Characteristics of Statistical Distributions for PJM Electricity market period 1 Price Data

Distribution	Mean	Variance	Null Hypothesis Acceptance (%)
Lognormal	30.5630	43.34	95.39
Weibull	30.6295	98.5066	90.67
Gamma	30.1143	46.2444	86.8

The case of five units GENCO is considered for implementing the proposed algorithm. Nuclear and coal are base units, hydro is considered as intermediate unit while oil & gas are peak units. The information about unit's capacities, cost parameters and no load cost per hour is mentioned in Table 2. The overnight cost of generating units is taken from a recently available annual report of U.S. Energy Information Administration [23]. Most economic capacity factor ranges are shown in Table 3.

Table 2. Cost Characteristics of Generating Units

Unit Type	Capacity MW	Overnight cost \$/MWh	Marginal cost \$/MWh	No Load Cost \$/h
Nuclear	600	20	4.4235	256.41
Coal	300	37	12.4049	372.15
Hydro	250	21	0.001	0.0025
Oil	200	40	57.2208	0
Gas	150	25	48.5947	0

Table 3. Screening Curve Analysis Result of Generating Units

Unit Type	Size (MW)	Most Economical CF (%)
Nuclear	600	80-100
Coal	300	30-100
Hydro	250	30-100
Oil	200	15-30
Gas	150	0-15

Based on the statistical distributions and screening curve analysis, bid prices are selected with a probability of 80%, 70%, 30%, 15%, and 5% for the bid quantity 600 MW, 900 MW, 1150 MW, 1350 MW and 1500 MW, respectively. The bid prices at each bid period are derived from the cumulative density function (CDF) corresponding to the probability density function (PDF), as shown in Fig. 6. The analysis uses the actual historical price data and is simulated in three continuous distributions, as described in Section 2.

To evaluate the impact of price uncertainty modeling on GENCO's hourly profit and bid success rate, the proposed algorithm is simulated for the first hour. Obtained generating units bid prices, along with forecasted MCP using different statistical distributions for the first hour are shown in Fig. 7. Profit earned by the generating units using different statistical distribution for the first hour is shown in Fig. 8. From this figure, it is visualized that bid price of generating units are less than forecasted MCP using lognormal distribution. Therefore, all bids are successful. However, nuclear, coal and hydro unit bids are successful when market price is forecasted by Weibull distribution. The profit is negative for the units who have lost the bid, because of fixed and no load cost. Forecasted MCP using Gamma distribution is higher than only nuclear unit bid price, therefore only nuclear unit have winning bid.

As a result of higher bid success rate, the profit eared by GENCO using lognormal distribution is significantly higher than other distributions. Similarly, daily profit earned by GENCO using lognormal distribution is also higher than other distributions, as visualized in Table 4.

To analyze the strength of the proposed algorithm on GENCO annual profit, simulations were again performed with the proposed algorithm, and the results are shown in Table 5, 6 and 7, with different success rates. The results reflect that the profit obtained through forecasted prices, by lognormal distribution, has minimum deviation from profit obtained through actual prices. Therefore, bidding strategy considering the price behavior as a lognormal distribution, achieves the maximum profit as compared to other distribution functions. The results justify the characteristics of distribution functions shown in Table 1. Therefore, accurate representation of price uncertainty increases the profit.

Simulations are performed on MATLAB® platform, on Windows based personal computer with 1.73 GHz processor and 2.50GB RAM.

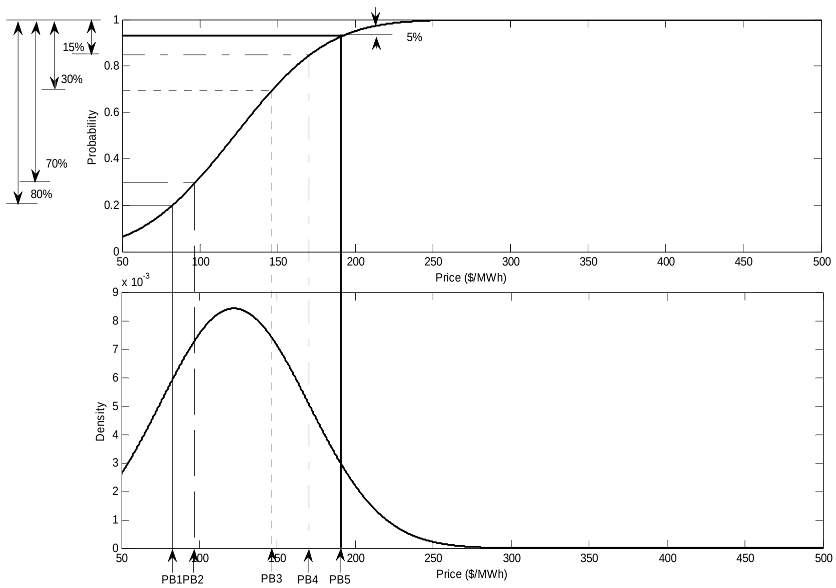

Fig. 6. PDF and CDF of the price distribution

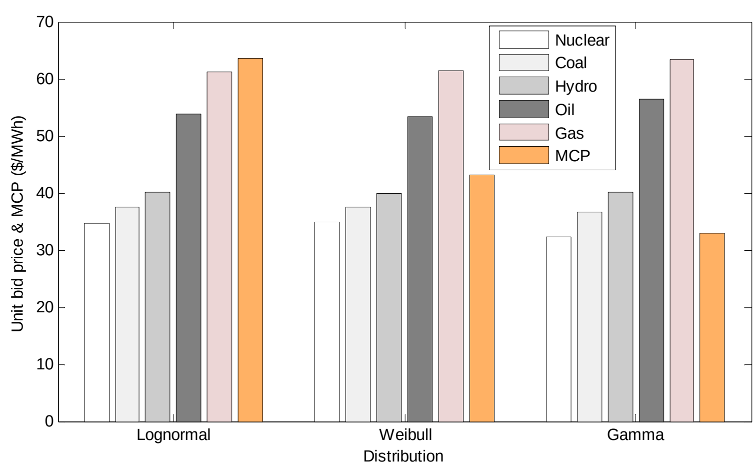

Fig. 7. Offered bid prices of generating units and forecasted MCP for Hour 1

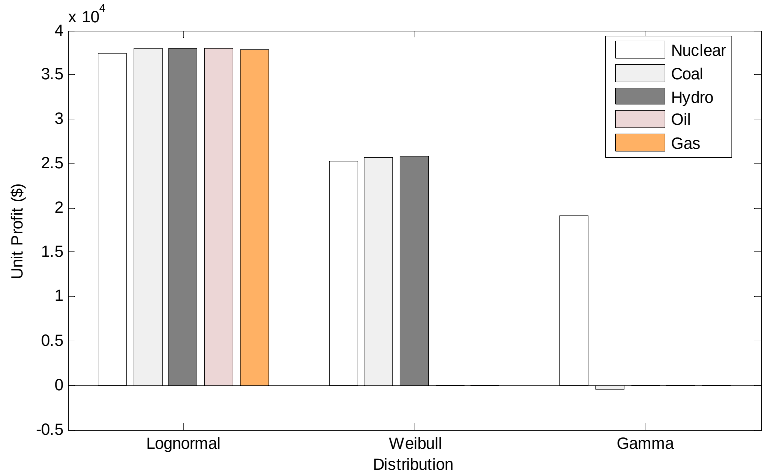

Fig. 8. Profit obtained by generating units at hour 1

Table 4. Daily profit obtained by generating units in different distributions

Unit Type	Lognormal	Weibull	Gamma
Nuclear	668408.70	610978.30	565940.80
Coal	617966.50	578913.60	537251.40
Hydro	592308.30	554093.80	504911.20
Oil	68159.43	159900.60	57056.57
Gas	27231.99	86404.01	0

Table 5. Results for lognormal distribution of market price

	Using forecasted prices						Using actual prices	
Unit Type	Bid Success Rate %	Revenue M$	Operating cost M$	No Load Cost M$	Fixed Cost M$	Profit M$	Bid Success Rate %	Profit M$
Nuclear	79.98	257.267	18.5946	0.4655	6.3821	231.8048	85.42	208.5148
Coal	69.94	135.193	26.6016	1.1431	3.5454	200.451	61.93	187.4110
Hydro	59.87	84.9637	0.00130	0.0008	5.0653	198.8232	52.05	187.7532
Oil	14.75	18.8688	14.7885	0	3.7483	38.0722	12.98	23.8322
Gas	4.57	4.7276	2.9156	0	1.8994	14.0954	4.00	22.8654
Total						683.2466		660.3766

Table 6. Results for weibull distribution of market price

	Using Forecasted Prices						Using Actual Prices	
Unit Type	Bid Success Rate %	Revenue M$	Operating cost M$	No Load Cost M$	Fixed Cost M$	Profit M$	Bid Success Rate %	Profit M$
Nuclear	79.69	253.259	18.5282	0.4721	6.3821	227.8585	75.29	267.3085
Coal	69.67	132.6800	26.4974	1.1535	3.5454	196.2385	58.21	185.1085
Hydro	59.18	82.9494	0.00129	0.0008	5.0653	193.9755	49.69	184.9955
Oil	14.87	20.0515	14.9117	0	3.7483	41.4944	13.78	64.5644
Gas	4.83	5.5312	3.0833	0	1.8994	17.1420	6.24	29.0120
Total						676.7089		730.9889

Table 7. Results for gamma distribution of market price

	Using Forecasted Prices						Using Actual Prices	
Unit Type	Bid Success Rate %	Revenue M$	Operating cost M$	No Load Cost M$	Fixed Cost M$	Profit M$	Bid Success Rate %	Profit M$
Nuclear	78.80	250.8980	18.3212	0.4928	6.3821	225.6835	70.32	245.7935
Coal	69.39	132.1748	26.3932	1.1640	3.5454	195.4662	58.54	198.2562
Hydro	59.47	83.1178	0.0013	0.0008	5.0653	194.3953	52.44	196.8853
Oil	14.78	19.3584	14.8201	0	3.7483	39.5069	17.38	66.6569
Gas	4.99	5.3611	3.1853	0	1.8994	16.3596	6.77	23.4296
Total						671.4115		731.0215

To evaluate the impact of price uncertainty modeling on GENCO's hourly profit and bid success rate, the proposed algorithm is simulated for the first hour. Obtained generating units bid prices, along with forecasted MCP using different statistical distributions for the first hour are shown in Fig. 7. Profit earned by the generating units using different statistical distribution for the first hour is shown in Fig. 8. From this figure, it is visualized that bid price of generating units are less than forecasted MCP using lognormal distribution. Therefore, all bids are successful. However, nuclear, coal and hydro unit bids are successful when market price is forecasted by Weibull distribution. The profit is negative for the units who have lost the bid, because of fixed and no load cost. Forecasted MCP using Gamma distribution is higher than only nuclear unit bid price, therefore only nuclear unit have winning bid.

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Simulations are performed on MATLAB® platform, on Windows based personal computer with 1.73 GHz processor and 2.50GB RAM.

5. CONCLUSION

The paper proposes a novel bidding strategy for generators in electricity markets, based on price uncertainty and generator cost characteristics, while considering their no load cost. Different statistical distributions have been evaluated for price forecasting. Screening curve is used to set the probability of bid success in the range of capacity factor that makes the generating unit most economical. Historical price data from PJM Electricity Market, from the year 2010 to 2012, is used to generate the price distribution curves and bid price selections. The simulations are based on a five-unit GENCO system. The statistical analysis shows that the lognormal distribution is most appropriate and results obtained by the proposed bidding strategy verify this analysis. Obtained results show that the null hypothesis acceptance percentage for lognormal distribution is higher than other statistical distributions. In addition, profit obtained using the proposed approach for lognormal distribution has minimum deviation from profit calculated when actual MCP is known. The proposed approach is simple, non-iterative and effective for multiple unit GENCOs bidding strategy formulation in competitive environment. The optimal setting of the bid success rates and risk measures are important aspects of bidding strategy, which require further investigation.

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