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Simulation on Supplier Side Bidding Strategy at Day-ahead Electricity Market Using Ant Lion Optimizer

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Abstract: In this article, Ant Lion Optimizer (ALO) is used for supplier side optimal bidding strategy in a day-ahead Electricity Market (EM). Optimal bidding is one of the major challenges of EM after deregulation. Deregulation is nothing but abolishing the market rules and unbundling the vertically integrated utilities. In EM, the main objective of Generating Companies (GenCos) is to bid optimally that maximizes its profit. Thus, for attaining maximum profit every supplier makes a strategy for acquiring the profitable bids. The strategic bidding technique for a GenCo in a day-ahead market for multi-hour selling is developed. The challenge of determining the market clearing pricing, load dispatch, and bid cost under three distinct capacities and price blocks is handled by the algorithm using this procedure. In this model, different probability distribution functions are used to explain rivals bidding behavior: normal, lognormal, gamma, and Weibull. Monte Carlo simulations are also carried out. The ALO is applied to maximize the profit of GenCos. The described method was implemented in MATLAB (2019) and evaluated using a standard test case from the literature. The numerical simulations are also displayed and contrasted. It is worth noting that the offered strategy produces the best profit outcomes.

Keywords: electricity market, bidding strategy, Ant Lion Optimizer, probability distribution functions

Nomenclature

$P_{\min}$ Minimum limit of ith block of GenCo-C (MW)

$P_{\max}$ Maximum limit of ith block of GenCo-C (MW)

$U_{i(t)}$ Binary variable, which is equal to 1, if the ith block is committed at hour t; otherwise, 0

M_i^{ut} Minimum up time of ith block of GenCo-C (hr)

M_i^{dt} Minimum down time of ith block of GenCo-C (hr)

$h_{i(t)}^{on}$ At the end of hour t (hr), the number of hours the ith block of GenCo-C has been continually ON

$h_{i(t)}^{off}$ At the end of hour t (hr), the number of hours the ith block of GenCo-C has been continually OFF

$C_{\min(t)}$ GenCo's operating expenses for the ith block

$\bar{C}$ Bid price cap

1. Introduction

Since the 1980s, much effort has been put towards revamping the conventional monopolistic power industry in order to provide enough competitiveness and improve financial efficiency. The production of parts for power producers, as well as, in certain cases, massive buyers, to simply interchange energy, is at the heart of this transformation.

Preferably, the marketplace configuration and board instruments or instructions in Electricity Market (EM) are well planned and well coordinated among members in order to increase social government support. As a result, in a meticulously structured EM, no gaps can be abused, and no opportunity is left for gaming, which brings down duties and expenses. Regardless, the new EM structure resembles an oligopoly rather than a perfect market. This is due to unique structures of the energy industry, such as a specified number of generators, a large venture size (obstruction to passage), transmission requirements that inhibit consumers from reaching multiple generators, and transmission miseries that prevent customers from buying energy from distant providers. Every one of them makes it possible for a couple of new organizations to support a specific geographic area, and in this environment, every provider can maximize advantage by investigating strategic bidding (SB) aims.

One of the key tenets of SB research is to recognize the potential for market power misuse through escape clauses that can be exploited in marketplace configuration and executive rules, because these outcomes have substantial strategic insinuations. In recent years, there has been some research on developing optimal bidding methods for competitive generators and/or large buyers, as well as researching relevant market power in poolco-type EMs where the fixed bid closeout and uniform value rule are widely applied. David and Wen (2000) presented a detailed literature appraisal of numerous bidding systems in the Abhyankar (2013) and Khaparde (2013) presented a deregulation

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introduction in the power industry. Hogan (2002) offered an analysis of the history and identified some options for the future. Several research articles have been available on the optimal bidding issue in EMs, such as the enhancement of bidding procedures using dynamic programming (Ansari & Rahimi-Kian, 2015) and stochastic optimization (Bajpai & Singh, 2007; Herranz et al., 2012; Huse et al., 1999; Kazempour et al., 2014; Ma et al., 2002; Richter et al., 1999; Song et al., 2000; Wen & David, 2001) techniques.

Wen and David (2001) presented a dynamic programming method based on SB on England–Wales EM. Ansari and Rahimi-Kian (2015) devised a risk-limited bidding model for GenCos operating in a pool-based electricity sector. Huse et al. (1999) suggested a heuristic solution to address the SB difficulty in EM. Ma et al. (2002) suggested a Monte Carlo (MC) technique to find the best outcome in EM. The authors developed a bidding strategy model based on the Zhejiang provincial EM. Song et al. (2000) tackled a multistage probabilistic bidding choice problematic in the spot market. Wen and David (2001) devised two bidding topologies for a day-ahead energy market utilizing a Genetic Algorithm (GA) to construct bidding strategy.

Richter et al. (1999) developed a bidding method based on Genetic Programming (GP). Bajpai and Singh (2007) used a specific model of nonlinear operating cost function and unit commitment minimum up-down restraints to solve an effective bidding strategy for a thermal generator in a uniform price spot market. Herranz et al. (2012) provided a short-term EM and addressed the difficulty of SB in the face of uncertainty. Jalal et al. (2014) established a precise model for large consumers in order to regulate pool prices and design a robust competitive platform in bidding procedures. To model ambiguity, a stochastic complementary framework was utilized. Risk management modeling was not included in their study. Akash Saxena et al. (2018) suggested an intelligent Grey Wolf Optimizer (IGWO) to deal with profit maximization in constantly changing EM. Hybrid model using Salp Swarm Algorithm (SSA) optimization and neural network is suggested to optimize the issues of bidding strategy in EM (Jain & Saxena, 2021).

Techniques of optimization inspired by nature Swarm intelligence is a popular branch of artificial intelligence in which algorithms are created by replicating the smart behavior of various animals such as wolves, whales, ants, lions, crows, and bees.

Mirjalili (2015) introduced the ALO algorithm. It is a metaheuristic method. The antlions belong to the Myrmeleontidae native of predatory insects, which gets its name from their unusual dietary behavior as larvae. The ALO algorithm imitates the antlion's larval hunting mechanism. The casual walking process of ants, establishing a trap, capturing in the antlion's pits, sliding ants towards the antlion, grabbing the prey, and repairing the pit are the five key phases (Kılıç & Yüzgeç, 2017; Mirjalili, 2015).

There have been a few research published in the works about implementing practical optimization or improving the ALO algorithm's performance. Multi-objective optimal generation scheduling (Chopra & Mehta, 2015), optimal nonconvex and dynamic economic load (Kamboj et al., 2017), automatic generation control of interconnected power industry (Gupta & Saxena, 2016), optimal flexible process planning (Petrović & Miljković, 2017), optimal route planning for unmanned aerial vehicle (Yao & Wang, 2017), decisive optimal coefficients of infinite impulse response (IIR) filters (Nair et al. 2017), proportional integral derivative (PID) controller parameter design (Saikia & Sinha, 2016), and feature selection problem (Emary & Zawbaa, 2019; Gupta & Saxena, 2016; Zawbaa et al., 2018) are some of them.

The unvarying price spot market, in which all successful supply bidders receive the same market clearing price, has been explored in this work. Probability distribution functions are used to model the bids of other competitors (Bialek et al., 1996). These distribution functions can be created by analyzing past market data. The evaluation of a provider's bidding choice is expressed as a stochastic optimization problem, which is then turned into a deterministic counterpart using MC simulation (Boyle, 1977).

The following are the significant contributions to this work.

- Using the block bid concept, bidding techniques for multi-hourly trading a day-ahead market have been devised.
- Intertemporal operational limitations (Arroyo & Conejo, 2000) have been introduced, such as minimum up and minimum down times.
- The running cost function includes a sinusoidal nonlinear manufacture cost and an exponential start-up cost function (Wood et al., 2013). Some other type of cost function, on the other hand, can be added into the calculation.
- The SB problem was defined in a continuously changing context with frequent changes in load and generation.
- The ALO was introduced for the bidding problem. The effectiveness of ALO algorithm in appraisal of bidding strategies in an economical EM has been established on four cases.

2. Problem Statement

This section provides a brief description about GenCo's bidding strategy with mathematical formulation of the problem. The following subsections go through it all mentioned earlier.

2.1. Bidding strategy

In order to thrive in a competitive climate, a GenCo must operate at a high level of efficiency. However, in the energy marketplace, successful implementation may not be enough because it must offer its products at competitive prices in order to make the most profit.

A GenCo's profit is influenced by various factors, including its own bids, bids submitted by rivals, total energy requirements, and so on. Although a generating firm has no influence over its rivals' bids or the energy demand, it can devise its own strategy for placing a bid that maximizes profit while minimizing risk explained in Figure 1.

Figure 1
Supplier side's bidding strategy
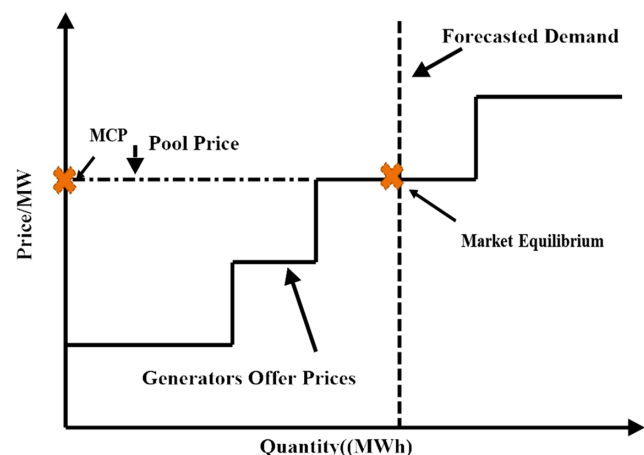
2.2. Mathematical formulation

After receiving the bids from the GenCos, the system operator plots a supply curve in upward sloping and a vertical line is drawn for the forecasted demand. The point at which the two curves intersect each other is equilibrium of the market and the horizontal line from equilibrium point on *y*-axis determines the market clearing price of the system (Jain & Saxena, 2021).

2.2.1. Objective function

The profit of GenCo is calculated using the given equation.

$$Genco_{i,profit} = Revenue - Genco_{i,cost} \qquad (1)$$

Here,

$$Revenue = MCP \times P_i \qquad (2)$$

$$Genco_{i,cost} = a_i P_i + b_i P_i^2 \qquad (3)$$

where P_i is the amount of quantity of ith GenCo trade in the market. a_i and b_i are the cost coefficients.

2.2.2. Operating constraints

(i) Generation limits

$$P_{\min} U_{i(t)} \leq P_{i(t)} \leq P_{\max} U_{i(t)}, \quad \forall t \in T \qquad (4)$$

(ii) Intertemporal constraints

$$(1 - U_{i(t+1)}) M_i^{ut} \leq h_{i(t)}^{on}, \quad if \ U_{i(t)} = 1 \qquad (5)$$

$$U_{i(t+1)} M_i^{dt} \leq h_{i(t)}^{off}, \quad if \ U_{i(t)} = 0 \qquad (6)$$

(iii) Bid price limits

$$C_{\min(t)} \leq Genco_{i,cost} \leq \tilde{C} \qquad (7)$$

3. Ant Lion Optimizer

ALO algorithm is a metaheuristic algorithm that is offered by Mirjalili (2015). The ALO metaheuristic algorithm mimics the antlions' adaptive approach when hunting ants in the field. In this division, the motivation and mathematical model of the ALO algorithm are detailed.

3.1. Motivation

Antlions are members of the Myrmeleontidae group, which is part of the Neuroptera class. Antlions have dual stages in their life cycle: larvae and adults. Their normal whole life span upmost to 3 years, with the majority of that time spent as larvae (adulthood lasts just 3–5 weeks). Their labels come from their distinct hunting performance and desired target. An antlion larvae house a cone-shaped pit inside the sand by crawling in a round motion and throwing sand out with its huge jaw. The larvae hide beneath the base of the cone after excavating the traps and wait for targets (ideally ants) to be surrounded in the pit. When an antlion notices a prey is caught in a trick, it attempts to catch it. Insects, on the other hand, rarely get trapped right away and strive to flee the

trap. In this case, antlions ingeniously hurl sands towards the pit's edge, allowing the prey to sink into the pit's base. When a prey is captured in the mouth, it is dragged underneath the earth and eaten (Mirjalili, 2015). The ALO algorithm is based on how ants and antlions behave in a trap. Ants are obligatory to move throughout the search space(s) in order to mimic such interactions, while antlions are free to kill insects and become fitter utilizing traps. It is worth noting that ants are similar to particle swarm optimization (PSO) particles or GA individual. An ant's position denotes the criteria for a certain solution.

For optimization, a fitness (objective) function is used to evaluate individual ant, and the fitness values of all the ants are recorded in the following matrix (Kılıç & Yüzgeç, 2017; Mirjalili, 2015).

$$OA_M = \begin{bmatrix} f([A_{1,1}, \ldots., A_{1,Dim}]) \\ f([A_{2,1}, \ldots., A_{2,Dim}]) \\ \vdots \\ \vdots \\ \vdots \\ f([A_{N,1}, \ldots., A_{N,Dim}]) \end{bmatrix} \qquad (8)$$

where OA_M is the matrix of preserving every ant's fitness, $A_{i,j}$ is the value of the xth ant's yth dimension, N is the quantity of ants, and f is the objective function in (8).

The antlions, in accumulation to ants, are thought to be hidden somewhere in the search space. The accompanying matrices [see (9) and (10)] are used to save their locations and fitness values.

$$Antlion_M = \begin{bmatrix} AL_{1,1,} & \ldots & \ldots & AL_{1,Dim} \\ AL_{2,1} & \ldots & \ldots & AL_{2,Dim} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ AL_{N,1} & \ldots & \ldots & AL_{N,Dim} \end{bmatrix} \qquad (9)$$

where $Antlion_M$ is the antlion position saving matrix. $AL_{x,y}$ denotes the value of the xth antlion's yth dimension, and Dim denotes the size of the antlion variable count (dimension).

$$OAL_M = \begin{bmatrix} f([AL_{1,1}, \ldots., AL_{1,Dim}]) \\ f([AL_{2,1}, \ldots., AL_{2,Dim}]) \\ \vdots \\ \vdots \\ f([AL_{N,1}, \ldots., AL_{N,Dim}]) \end{bmatrix} \qquad (10)$$

where OAL_M is the matrix for preserving each antlion's fitness and $AL_{x,y}$ is the xth antlion's yth dimension value.

3.2. Characteristics

The random movement of prey (ant), antlion pit trapping, constructing traps, ant moving towards the antlion, and prey capture and trap re-building are the five key processes of prey hunting (Mirjalili, 2015).

3.2.1. Random movement of prey (ant)

At each stage of optimization, ants use random walk to modify positions themselves. The random walks are standardized by the subsequent equation (min–max normalization) to maintain them within the search space.

$$Z_x^l = \frac{(Z_x^l - a_x) \times (b_x - c_x^l)}{(d_x^l - a_x)} + c_x \tag{11}$$

3.2.2. Antlion pit trapping

Antlion trapping alter antlions' random walks, as previously mentioned. The set of equations is presented in Saikia and Sinha (2016) to numerically model this premise.

$$c_x^l = Antlion_y^l + c^l \tag{12}$$

$$d_x^l = Antlion_y^l + d^l \tag{13}$$

where c^l represents the least of all variables at the lth iteration, c_x^l represents the lowest of all variables for the xth ant, d^l represents the vector comprising the extreme of all variables at the lth iteration, d_x^l represents the extreme of all variables for the xth ant, and $Antlion_y^l$ represents the position of the selected yth antlion at the lth iteration. In a hypersphere defined by the vectors c and d, ants walk around a designated antlion, as shown in (12) and (13).

3.2.3. Constructing traps

In Mirjalili (2015), a roulette wheel is used to depict the antlion's hunting capability. It is supposed that the ants are only held inside by one antlion. Throughout optimization, the ALO algorithm must use a roulette wheel operator to identify antlions depending on their fitness. The healthier antlions have a higher risk of contracting ants because of this technique.

3.2.4. Prey (ant) moving towards the antlion

Antlions can build traps that are comparative to their fitness level, and ants wander at random. When an ant is caught in the trap, though, antlions hurl sands outwards from the pit's center. This behavior is carried out by the surrounded ant who is attempting to flee. According to the mathematical behavior, the radius of the ant's random walks hypersphere is flexibly lowered. In accordance with Kılıç & Yüzgeç (2017), the set of analysis equations is utilized.

$$c^l = c^l / R \tag{14}$$

$$d^l = d^l / R \tag{15}$$

where R is a ratio, c^l is the lth iteration's least of all variables, and d^l is the vector containing the lth iteration's maximum of all variables.

In (14) and (15), $R = 10\ wi/I$, where i is the present iteration, I is the maximum number of iterations, and w is a constant determined by the current iteration.

$$w = \begin{cases} 2 & \text{if } i > 0.1I \\ 3 & \text{if } i > 0.5I \\ 4 & \text{if } i > 0.75I \\ 5 & \text{if } i > 0.9I \\ 6 & \text{if } i > 0.95I \end{cases}$$

Essentially, this constant w can be used to vary the level of exploitation precision.

3.2.5. Prey capture and trap re-building

The hunt is over when an ant hits the lowest of the pit and is captured in the antlion's jaws. The antlion then drags the ant into the sand and eats it at this point. To replicate this procedure, it is hypothesized that ants get fitter (travel deeper into the sand) than their counterpart antlion. To improve its prospects of getting new prey, an antlion must appraise its position to the most recent position of the chased ant. This theory is represented by the equation (Kılıç & Yüzgeç, 2017).

$$Antlion_y^l = Ant_x^l \quad if \quad f(Antlion_y^l) \leq f(Ant_x^l) \tag{16}$$

where l denotes the present iteration, $Antlion_y^l$ signifies the location of the yth antlion at the lth iteration, and Ant_x^l signifies the position of the xth antlion at the lth iteration.

3.2.6. Elitism

Each iteration best antlion is preserved and regarded as exceptional. The superior one must be effective in influencing the movements of all the ants throughout iterations because it is the fittest antlion. As a result, it is thought that every ant, guided by the roulette wheel and the elite, wanders around a picked antlion at random, as shown below (Mirjalili, 2015).

$$Ant_x^l = \frac{(R_a^l + R_e^l)}{2} \tag{17}$$

where R_a^l represents the random walk round the antlion designated by the roulette wheel at the lth iteration, R_e^l represents the random movement round the elitist at the lth iteration, and Ant_x^l represents the location of the xth ant at the lth iteration.

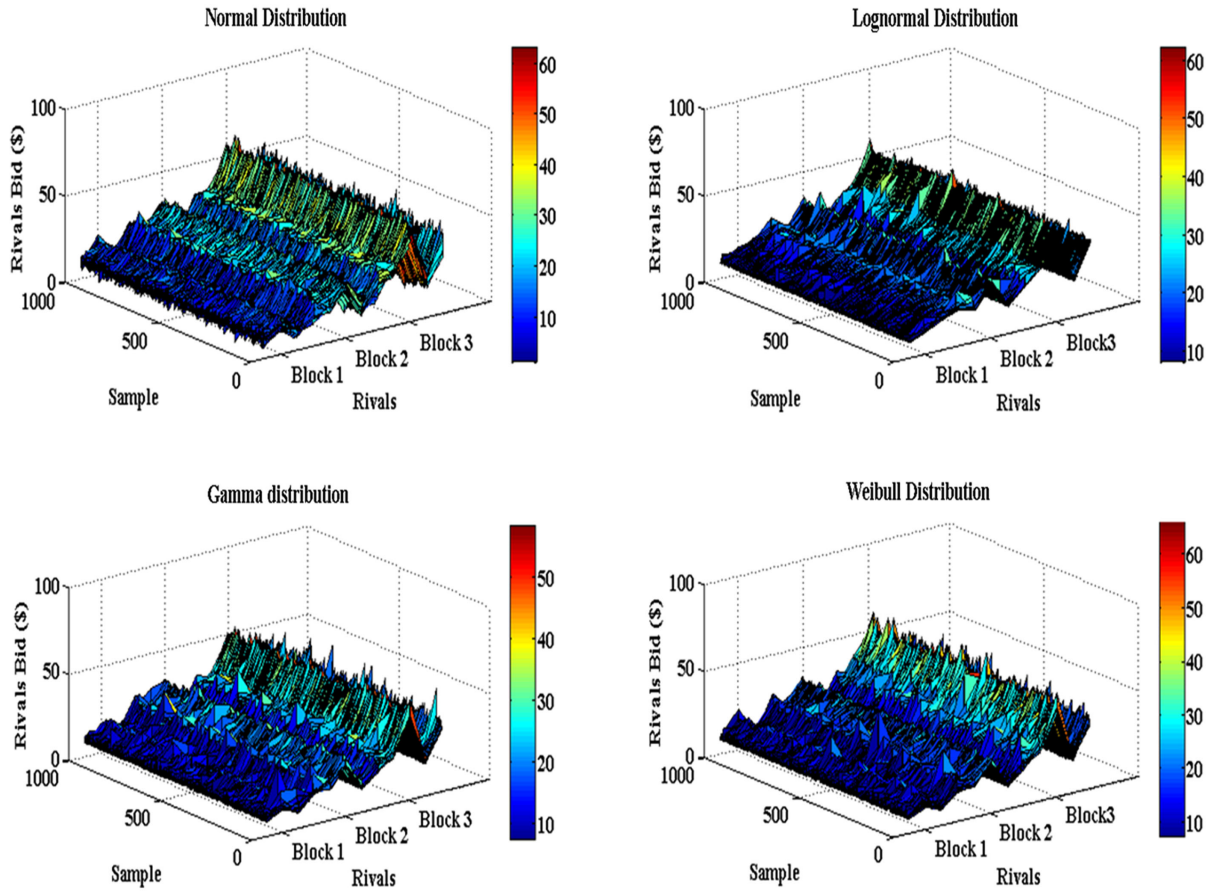The flowchart of ALO for the application of optimal bidding is displayed in Figure 2.

Figure 2
Flowchart of ALO for optimal bidding problem of EM
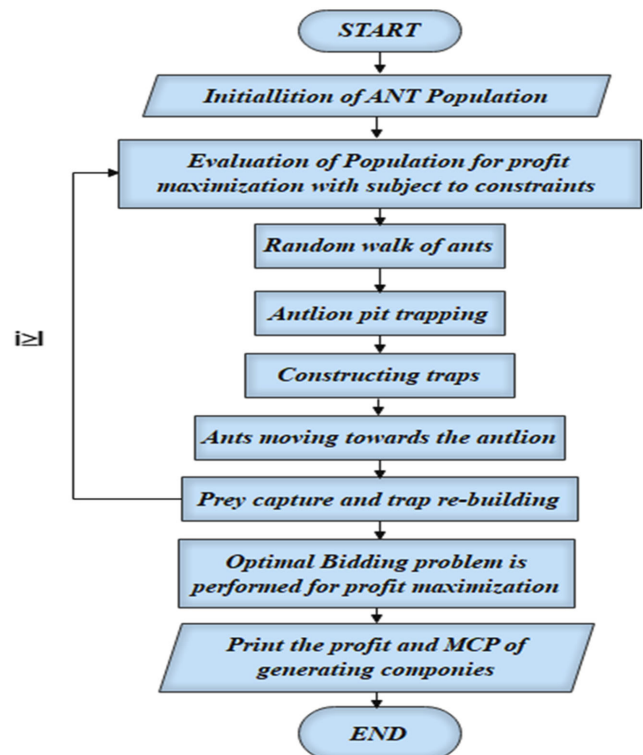
Figure 3
Cost modal of different distributions

4. ALO for the Application of Optimal Bidding in EM

The variant is programmed in MATLAB 2019 and runs on an i5 processor CPU, 4.00 GHz and 8 GB of RAM. To draw an evaluation of optimization routines, the number of iterations and population size for all algorithms are maintained the same (i.e., maximum number of iteration = 500 and number of search agents = 50). The efficacy of the suggested ALO is experimented over IEEE-14 bus system constructed for the problem described in Section II. The optimization process is examined for a dynamically varying setting and bidding strategies are acquired for a day-ahead EM in multi-hour power system. GenCo-C, along with its four competitors, attempts to trade energy through a mart in this trade. The bid proposals are analyzed and arranged from minimum to maximum value. The MCP is calculated by the bid price of the previous executed block once the system demand has been met. Table 6 lists the cost coefficients for generator C as well as other pertinent information such as up and down time, block capacities, and other time constants. For all committed blocks, a consistent MCP is taken into account. Blocks with a low bid price and a large bid amount can earn good profits. It is vital to remember that the ideal bid price for each block commit should be less than or similar to the marginal trading price. The optimization technique defined in Section II resolves the procedure in such a way that the optimum bid price is less than the marginal bid price, allowing for the commitment of the maximum unit of GenCo-C. The results of the suggested approach are shown below.

In this work, the bidding cost of the competitors and system demand is exhibited as per Figures 3 and 4, respectively. The particulars of the rivals bid mean, cap size, and standard deviations for three blocks are displayed in Table 1.

The parameters of all three blocks of GenCo-C are given in Table 2 (David, 1993).

David and Wen (2000) following four cases are taken to show the efficacy of the optimizer on the application of optimal bidding in EM. In these cases, the bidding data of opponents are constructed using these four different probability distribution functions:

Case I: Normal Distribution
Case II: Lognormal Distribution
Case III: Gamma Distribution
Case IV: Weibull Distribution

Figure 4
System demand for a day-ahead EM
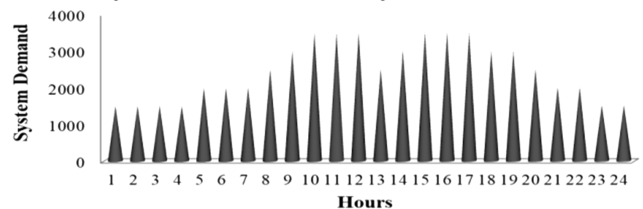
Table 1
Data of opponent's bidding parameters (Bajpai & Singh, 2007)

	Block 1			Block 3			Block 3		
	Q_I	μ_i^n	σ_i^n	Q_I	μ_i^n	σ_i^n	Q_I	μ_i^n	σ_i^n
Opponent 1 ($n=1$)	200	10	2.5	300	20	3	400	30	3
Opponent 2 ($n=2$)	300	15	3	400	30	2	500	50	4
Opponent 3 ($n=3$)	250	10	2	300	15	2.5	300	20	2.5
Opponent 4 ($n=4$)	300	20	4	350	25	5	450	40	5

The bidding performance of rivals is modeled in this case study, as seen in Figure 3. Table 1 provides information about opponent bid cap size, mean, and standard deviations for all blocks in a normal distribution. Table 2 indicates the power block details of GenCo-c.

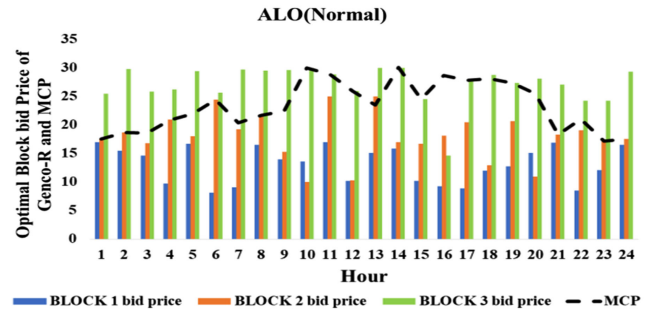## 4.1. Case I: Normal distribution

The normal probability distribution is used in this case. ALO provides a solution to the difficulty of achieving optimal bidding strategy. We saw that the ALO results resist and deliver optimum profit for the GenCo-C for multi-exchanging hour in a day market. Figure 5 shows the optimal block bid price and MCP of GenCo-C using a normal distribution and the ALO method. The bidding prices of GenCo-C in three blocks are shown in this diagram with MCP.

Figure 6 depicts the profit obtained by ALO using the MCP curve. The profitability of the GenCo-C increases dramatically in the 10th and 14th hours, reaching $6535 and $7195, correspondingly. The profit for block 2 dropped sharply to $4834 at the 13th hour due to a drop in MCP to 23.51 $/MWh. Due to the high MCP of 30.13 $/MWh, the profits increase to $7195 at the 14th hour. The total profit, as computed by ALO, is $110,467.
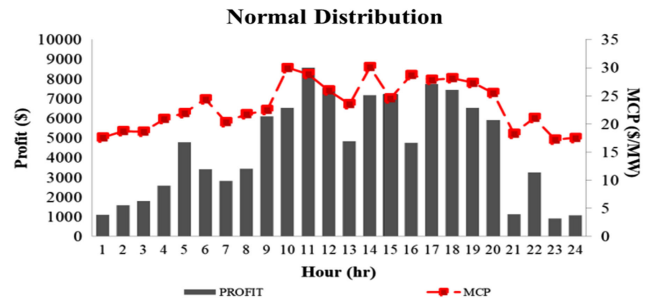
Table 3 presents the load dispatch acquired from ALO algorithm for all the GenCos participating in a mart under a uniform MCP.

- Because of its high manufacturing cost and small system demand, the third block of GenCo-C is not dispatched during the hours of adverse profit (from 1 to 9 hr).
- Because it has been shut down for a long period, cold start-up costs are accounted for in the manufacturing cost of third block when it is delivered at 10 hr (9 hr).
- At the end of the 12-hr period, the third block is no longer sent due to low system demand, and the minimum downtime constraint kicks in at 13–14 hr.
- The third block is dispatched again at 15–17 hr, and the cost of a hot start-up is included in the hour's production cost because it was shut down for a brief time.

Figure 5
Optimal block bids and MCP graph using normal PDF

- Due to low system demand, the third block will not be dispatched from 20 to 24 hr.
- Optimal bid price of third block is shown zero during 1–9, 13–14, 18, and 20–24 hr, when it is nondispatched.

4.2. Case II: Lognormal distribution

The lognormal probability distribution is used in this case. Figure 7 shows the optimal block bid price and MCP of GenCo-C using a normal distribution and the ALO method. The bidding prices of GenCo-C in three blocks are shown in this diagram with MCP.

Figure 8 displays the profit chart acquired by ALO. A sharp rise in the profit is perceived in the 9th and 14th hour as the profit of the GenCo-C becomes $7737 and $7994, respectively. For block 2, the profit trails a sharp decrement to $5356 in at 13th hour due to the drop in MCP to 24.57 $/MWh. Cumulative profit calculated through ALO is $180,616.

Figure 6
Profit and MCP graph using normal PDF

Table 2
Data of GenCo-C power blocks

	C_0 (MW^{2}h)	C_1 ($/MWh)	C_2 ($/h)	C_3 ($/h)	C_4 (rad./MW)	Q_{max} (MW)	Q_{min} (MW)	MUT (hr)	MDT (hr)	H ($)	δ ($)	τ (hr)	C_i^d ($)
Block 1	0.00482	7.97	78	150	0.063	200	50	1	1	1000	1500	1	100
Block 2	0.00194	15.85	310	200	0.042	400	100	1	1	1500	2500	1	200
Block 3	0.001562	32.92	561	300	0.0315	600	100	1	1	2000	4000	8	400

Table 3
Load dispatch using normal PDF

		Opponent 1			Opponent 2			Opponent 3			Opponent 4			GenCo-C		
		B1	B2	B3	B1	B2	B3	B1	B2	B3	B1	B2	B3	B1	B2	B3
Hour	Load	200	300	250	300	200	300	400	300	350	400	400	500	300	450	600
1	1500	200	300	n/d	300	n/d	n/d	250	n/d	n/d	n/d	n/d	n/d	200	250	n/d
2	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
3	1500	200	n/d	n/d	300	n/d	n/d	250	n/d	n/d	150	n/d	n/d	200	400	n/d
4	1500	200	300	n/d	300	n/d	n/d	250	n/d	n/d	n/d	n/d	n/d	200	250	n/d
5	2000	200	n/d	n/d	300	n/d	n/d	250	300	300	n/d	n/d	n/d	200	400	n/d
6	2000	200	300	n/d	300	n/d	n/d	250	n/d	300	300	n/d	n/d	200	150	n/d
7	2000	200	n/d	n/d	300	n/d	n/d	250	300	300	50	n/d	n/d	200	400	n/d
8	2500	200	300	n/d	300	n/d	n/d	250	300	300	300	n/d	n/d	200	350	n/d
9	3000	200	300	n/d	300	400	n/d	250	300	n/d	300	350	n/d	200	400	n/d
10	3500	200	300	200	300	200	n/d	250	300	300	300	n/d	n/d	200	400	550
11	3500	200	300	200	300	400	n/d	250	300	n/d	300	350	n/d	200	400	300
12	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
13	2500	200	300	n/d	300	n/d	n/d	250	300	n/d	300	350	n/d	200	300	n/d
14	3000	200	300	400	300	n/d	n/d	250	300	n/d	300	350	n/d	200	400	n/d
15	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	n/d	n/d	200	400	600
16	3500	200	300	350	300	n/d	n/d	250	300	300	300	n/d	n/d	200	400	600
17	3500	200	300	400	300	n/d	n/d	250	300	300	300	350	n/d	200	400	200
18	3000	200	300	n/d	300	100	n/d	250	300	300	300	350	n/d	200	400	n/d
19	3000	200	300	n/d	300	400	n/d	250	300	300	300	n/d	n/d	200	400	50
20	2500	200	300	n/d	300	n/d	n/d	250	300	300	250	n/d	n/d	200	400	n/d
21	2000	200	n/d	n/d	300	n/d	n/d	250	300	n/d	300	350	n/d	200	100	n/d
22	2000	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	350	n/d	200	400	n/d
23	1500	200	n/d	n/d	300	n/d	n/d	250	n/d	n/d	300	n/d	n/d	200	200	n/d
24	1500	200	n/d	n/d	300	n/d	n/d	250	250	n/d	n/d	n/d	n/d	200	250	n/d

Load Dispatch of Normal Distribution Using ALO of 5 GenCos and 3 Blocks

Figure 7
Optimal block bids and MCP graph using lognormal PDF
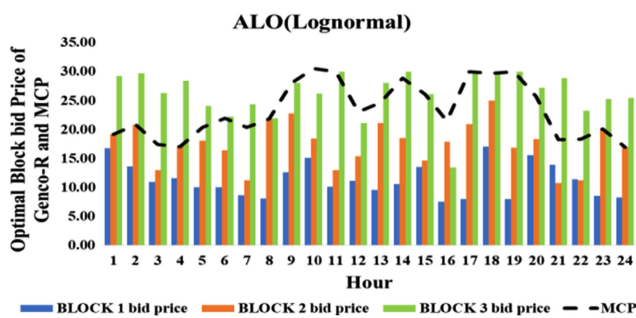
Figure 8
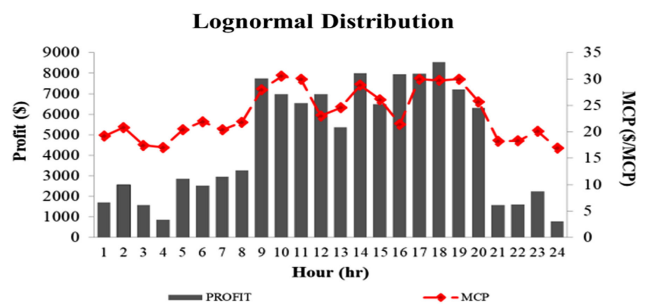**Profit and MCP graph using lognormal PDF**

Table 4 presents the load dispatch achieved from ALO algorithm for all the GenCo's partaking in a mart underneath a uniform MCP.

- Because of its high manufacturing cost and small system demand, the third block of GenCo-C is not dispatched during the hours of negative profit (from 1 to 8 hr).
- Because it has been shut down for a long period, cold start-up costs are included for in the manufacturing cost of third block when it is transmitted at 9 hr (8 hr).
- After 12 hr, the third block is no longer sent due to low system demand, and the minimal downtime constraint persists for another 2 hr.
- The third block is re-dispatched at 15 hr, and the cost of a hot start-up is included in the hour's manufacture cost because it was shut down for a brief period.

- Owing to reduced system demand, the third block will not be dispatched from 20 to 24 hr.
- Optimal bid price of third block is shown zero during 1–8, 13–14, 18, and 20–24 hr, when it is nondispatched.

## 4.3. Case III: Gamma distribution

The gamma probability distribution is used in this case. Figure 9 shows the optimal block bid price and MCP of GenCo-C using a normal distribution and the ALO method. The bidding prices of GenCo-C in three blocks are shown in this diagram with MCP.

ALO's profit graph is depicted in Figure 10. Given the high MCP 28.89 $/MWh and 27.86 $/MWh, the profit of the GenCo-C

Table 4
Load dispatch using lognormal PDF

		Opponent 1			Opponent 2			Opponent 3			Opponent 4			GenCo-C		
		B1	B2	B3	B1	B2	B3	B1	B2	B3	B1	B2	B3	B1	B2	B3
Hour	Load	200	300	250	300	200	300	400	300	350	400	400	500	300	450	600
1	1500	200	300	n/d	300	300	n/d	n/d	300	n/d	n/d	n/d	n/d	200	200	n/d
2	1500	200	n/d	n/d	300	n/d	n/d	100	300	n/d	n/d	n/d	n/d	200	400	n/d
3	1500	200	300	n/d	300	300	n/d	n/d	300	n/d	n/d	n/d	n/d	200	200	n/d
4	1500	200	n/d	n/d	300	n/d	n/d	n/d	300	n/d	300	n/d	n/d	200	200	n/d
5	2000	200	300	n/d	300	300	n/d	250	300	n/d	n/d	50	n/d	200	400	n/d
6	2000	200	n/d	n/d	300	n/d	n/d	250	300	n/d	300	50	n/d	200	400	n/d
7	2000	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	350	n/d	200	400	n/d
8	2500	200	300	n/d	300	300	n/d	250	300	n/d	300	250	n/d	200	400	n/d
9	3000	200	300	400	300	300	n/d	250	300	300	300	n/d	n/d	200	400	50
10	3500	200	300	n/d	300	300	n/d	250	300	300	300	350	n/d	200	400	600
11	3500	200	300	400	300	300	n/d	250	300	300	300	n/d	n/d	200	400	550
12	3500	200	300	n/d	300	300	n/d	250	300	300	300	350	n/d	200	400	600
13	2500	200	300	n/d	300	300	n/d	250	300	n/d	300	250	n/d	200	400	n/d
14	3000	200	300	450	300	300	n/d	250	300	300	300	n/d	n/d	200	400	n/d
15	3500	200	300	n/d	300	300	n/d	250	300	300	300	350	n/d	200	400	600
16	3500	200	300	n/d	300	300	n/d	250	300	300	300	350	n/d	200	400	600
17	3500	200	300	n/d	300	300	n/d	250	300	300	300	350	n/d	200	400	600
18	3000	200	300	400	300	300	n/d	250	300	n/d	300	350	n/d	200	400	n/d
19	3000	200	300	n/d	300	300	n/d	250	300	n/d	300	350	n/d	200	400	400
20	2500	200	300	n/d	n/d	300	n/d	250	300	300	300	250	n/d	200	400	n/d
21	2000	200	50	n/d	300	50	n/d	250	300	n/d	300	n/d	n/d	200	400	n/d
22	2000	200	n/d	n/d	300	n/d	n/d	250	300	300	50	n/d	n/d	200	400	n/d
23	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
24	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	250	n/d	n/d	200	250	n/d

Figure 9
Optimal block bids and MCP graph using gamma PDF
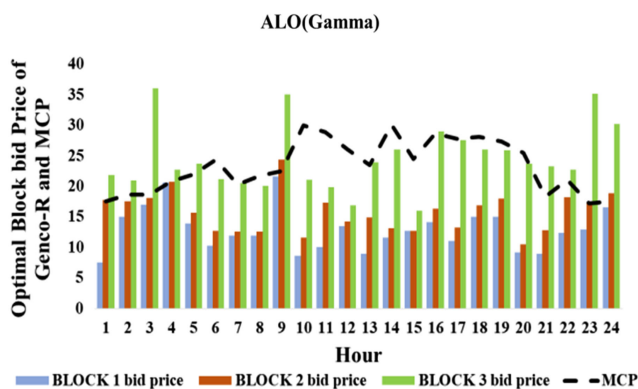
Figure 10
Profit and MCP graph using gamma PDF
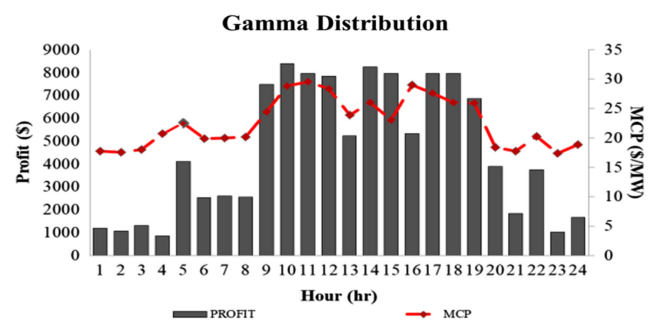
increases dramatically in the 11th and 17th hours, reaching $8588 and $7745, respectively. The profit for block 2 fell sharply at the 13th hour to $4834 due to a drop in MCP from 26 $/MWh to 23.5 $/MWh. Due to the high MCP of 30.13 $/MWh, the profit of $7195 increases again at the 14th hour. ALO calculated a total profit of $108,410 for the year. Table 5 presents the load dispatch attained from ALO algorithm for all the GenCo's partaking in a mart under a uniform MCP.

- Because of its high manufacturing cost and low system demand, the third block of GenCo-C is not dispatched during the hours of negative benefit (from 1 to 9 hr).

- Because the third block has been shut down for a long period, the cold start-up cost is accounted for in the manufacturing cost when it is dispatched at 10 hr (9 hr).
- After 12 hr, the third block is no longer sent due to low system load, and the minimal downtime constraint is active for 1 hr.
- The third block is re-dispatched at 14 hr, and the price of a hot start-up is included in the hour's output cost since it was shut down for a brief period.
- Due to reduced system load, the third block will not be dispatched from 20 to 24 hr.
- Best bid price of third block is shown zero during 1–9, 13, and 20–24 hr, when it is nondispatched.

Table 5
Load dispatch using gamma PDF

		Opponent 1			Opponent 2			Opponent 3			Opponent 4			GenCo-C		
		B1	B2	B3	B1	B2	B3	B1	B2	B3	B1	B2	B3	B1	B2	B3
Hour	Load	200	300	250	300	200	300	400	300	350	400	400	500	300	450	600
1	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
2	1500	200	n/d	n/d	n/d	n/d	n/d	250	300	n/d	300	n/d	n/d	200	250	n/d
3	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
4	1500	200	300	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	150	n/d	n/d
5	2000	200	300	n/d	300	n/d	n/d	250	300	50	n/d	n/d	n/d	200	400	n/d
6	2000	200	n/d	n/d	300	n/d	n/d	250	300	50	300	n/d	n/d	200	400	n/d
7	2000	200	300	n/d	300	n/d	n/d	250	300	n/d	50	n/d	n/d	200	400	n/d
8	2500	200	250	n/d	300	n/d	n/d	250	300	200	300	350	n/d	200	400	n/d
9	3000	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	n/d
10	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
11	3500	200	300	100	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
12	3500	200	300	n/d	300	350	n/d	250	300	300	300	n/d	n/d	200	400	600
13	2500	200	300	n/d	300	n/d	n/d	250	300	n/d	300	n/d	n/d	200	350	n/d
14	3000	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	100
15	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
16	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
17	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
18	3000	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	100
19	3000	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	100
20	2500	200	300	n/d	300	n/d	n/d	250	300	250	300	n/d	n/d	200	400	n/d
21	2000	200	50	n/d	300	n/d	n/d	250	300	n/d	300	n/d	n/d	200	400	n/d
22	2000	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	350	n/d	200	400	n/d
23	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
24	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d

The table title row "Load Dispatch of Gamma Distribution Using ALO of 5 GenCos and 3 Blocks" spans the full width above the opponent headers.

Figure 11
Optimal block bids and MCP graph using Weibull PDF

Figure 12
Profit and MCP graph using Weibull PDF
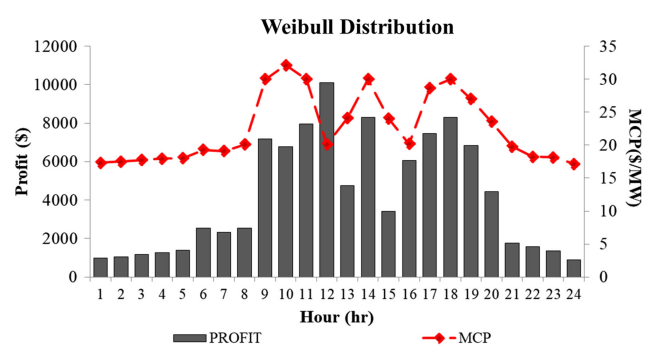
4.4. Case IV: Weibull distribution

The Weibull probability distribution is used in this case. Figure 11 shows the optimal block bid price and MCP of GenCo-C using a normal distribution and the ALO method. The bidding prices of GenCo-C in three blocks are shown in this diagram with MCP.

ALO's profit graph is depicted in Figure 12. Due to the high MCP, the profit of the GenCo-C increases dramatically in the 12th and 14th hours, reaching $10,104 and $8306 correspondingly. The profit for block 2 dropped dramatically at the 13th hour, to $4749. The total profit, as determined by ALO, is $115,206.9064.

Table 6 shows the load dispatch calculated using the ALO algorithm for all units participating in an auction with the same MCP.

- Because of its high manufacturing cost and low system consumption, the third block of GenCo-C is not dispatched during the hours of negative benefit (from 1 to 8 hr).
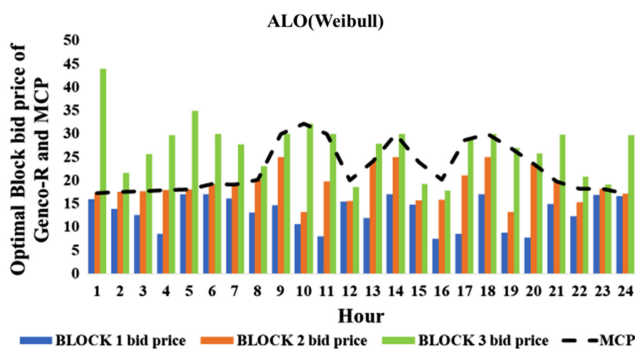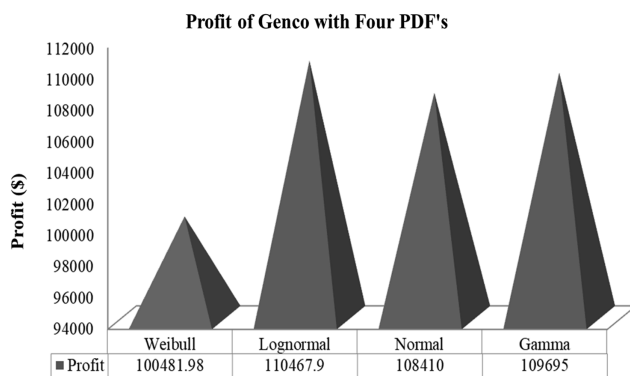- Because it has been stopped down for a long period, cold start-up costs are included for in the production cost of third block when it is dispatched at 9 hr (8 hr).

Table 6
Load dispatch using Weibull PDF

Hour	Load	Opponent 1			Opponent 2			Opponent 3			Opponent 4			GenCo-C		
		B1 200	B2 300	B3 250	B1 300	B2 200	B3 300	B1 400	B2 300	B3 350	B1 400	B2 400	B3 500	B1 300	B2 450	B3 600
1	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	250	n/d	n/d	200	250	n/d
2	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
3	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
4	1500	200	n/d	n/d	n/d	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
5	2000	200	n/d	300	300	n/d	n/d	250	300	n/d	50	n/d	n/d	200	400	n/d
6	2000	200	n/d	n/d	300	n/d	n/d	250	300	50	300	n/d	n/d	200	400	n/d
7	2000	200	300	n/d	300	n/d	n/d	250	300	50	n/d	n/d	n/d	200	400	n/d
8	2500	200	300	n/d	300	n/d	n/d	250	300	300	300	n/d	n/d	200	350	n/d
9	3000	200	300	n/d	300	n/d	n/d	250	300	n/d	300	350	n/d	200	400	400
10	3500	200	300	400	300	n/d	n/d	250	300	n/d	300	350	n/d	200	400	500
11	3500	200	300	n/d	300	400	n/d	250	300	300	300	n/d	n/d	200	400	600
12	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
13	2500	200	300	n/d	300	n/d	n/d	250	300	300	300	n/d	n/d	200	350	n/d
14	3000	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	100
15	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
16	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	600
17	3500	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	500
18	3000	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	100
19	3000	200	300	n/d	300	n/d	n/d	250	300	300	300	350	n/d	200	400	100
20	2500	200	300	n/d	300	n/d	n/d	250	300	300	300	n/d	n/d	200	350	n/d
21	2000	200	300	n/d	300	n/d	n/d	250	300	n/d	300	n/d	n/d	200	100	n/d
22	2000	200	50	n/d	300	n/d	n/d	250	300	n/d	300	n/d	n/d	200	400	n/d
23	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d
24	1500	200	n/d	n/d	300	n/d	n/d	250	300	n/d	n/d	n/d	n/d	200	250	n/d

Figure 13
Profit comparison chart for the four cases

Profit of Genco with Four PDF's

	Weibull	Lognormal	Normal	Gamma
■ Profit	100481.98	110467.9	108410	109695

- At the end of the 12-hr period, the third block is no longer dispatched due to low system consumption, and the minimal downtime constraint is in effect (1 hr).
- The third block is re-dispatched at 14 hr, and the cost of a hot start-up is included in the hour's output cost because it was closed down for a brief period.
- Due to low system consumption, the third block will not be dispatched from 20 to 24 hr.
- Best bid price of third block is shown zero during 1–8, 13, and 20–24 hr when it is nondispatched.

Figure 13 shows the profit comparison chart for the above four distribution cases. From the figure it is clear that the profit earn by using lognormal PDF is larger than the others.

5. Conclusion and Future Scope

The application of ALO for bidding strategy problem of providers and large customers in a competitive energy market is recommended in this research. In this technique, each participant uses the information provided by the system operator to try to maximize his or her profit.

The differences between symmetrical and asymmetrical competitive information are addressed, and it is concluded that individuals with defective information will lose money. The ALO approach is efficient and preferable due to the benefits of interacting with only one operation and the capacity to maintain convergence. These benefits of ALO are also proven by the simulation findings of this research.

For stiffer competition in the real-time operations of power grids under deregulation, a more realistic SB dilemma for producing companies and consumers can be established.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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