A Genetic Algorithm Based Optimal Pricing Strategy in Electricity Market

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Abstract - *Increased penetration of distributed energy resources such as renewables and virtual power plants, make complex electrical market even more complicated. Therefore, traditional pricing strategies for electrical market are not efficient anymore. This paper proposed a new pricing strategy in electricity nodal market. A two-level optimization problem has been developed for maximizing the non-cooperative companies profit while satisfying network constraint. In this method market equilibrium points are considered as Nash equilibrium. To guarantee feasibility and to avoid local maximum points, genetic algorithm method has been used. The effectiveness of the proposed method is validated by carrying out a simulation based analysis on the WSCC 9-bus system and compare results of the proposed method with the normal method which is currently used in the electricity market.*

Key Words: Electricity market, Genetic Algorithm, Nash equilibrium, power market

1.INTRODUCTION

For decades, electrical companies had focused on decreasing electricity generation costs and maximizing generation side profits [1–3]. However, increased penetration of renewable energies such as solar and wind leads to more investment on demand side control strategies. Advancements in technologies related to Storage devices [4, 5], and power electronic converters [6–8,14], during the recent decade, reduce cost of renewables integration and increase quality of injected power (e.g. injecting power with unity power factor or swing reduction) into the grid [33]. To handle uncertainty from renewables, a large body of research is focused on modern techniques to allocate generation and reserve [34] as well as incentivizing the demand to be more flexible [35]. Advanced control strategies such as demand respond adds more active participants to the power systems that can provide flexibility for the grid operator by increasing, decreasing or shifting their power consumption [1, 2, 9–12] which makes power system operation more secure [12, 13]. For instance, in [32], optimal incentives and penalties in the emergency demand response programs are determined based on a novel model of customers inclination towards participating in demand response programs. Moreover, under high penetration of renewables, active participate of flexible and controllable moves the power system toward a sustainable system with no need of backup generators running in low power or even idling [15, 16]. High penetration of distributed energy resources in the power system, adds additional layers of complexity to the complicated electrical market and careful planning which takes uncertainty into account and utilize resources robustly is essential [17]. In the restructured power system market, the active participation of demand side bidding (DSB) leads to competitive fair market.

Performance of the system is evaluated based on an economical concept called social welfare which is a combination of the goods price (electricity in this case) in that system and what society would benefit from those goods [18, 19]. In [20], social welfare maximization in electricity market with transmission line congestion is considered. Also by considering generation capacity and consumers demand, an optimization model for demand respond in electricity market can be built as presented in [21, 22].

Recently, demand respond based pricing programs have been proposed. For example, the authors in [23] have leveraged reinforcement learning to solve a pricing strategy for DR without assuming any specific forms of user's response functions. The most important take away from these studies is that the in an ideal market, each generating unit can bid into the market and biding strategy for optimal price is same as bidding strategy for the marginal price. However, in a non- ideal market, a generating unit can bid higher than its marginal cost which is called strategic bidding [1, 24]. In general, if a generating unit succeed to profitably maintain price higher than marginal cost for significantly long time, that unit has the market power. Since market efficiency is reached by fair competition, market power is not desirable and can decrease economic efficiency.

In the past, companies may have used conventional bidding techniques such as experience base market analysis or utilizing market simulator. However, those methods are obsolete and have been replaced by scientific methods. In general, there are three main optimal bidding strategies. The first strategy is based on the market clearing price (MCP) for the next period of time, the second strategy is based on the bidding behaviour of the competitor companies and the third one is based on game theory [1, 2].

The simplest bidding strategy is to bid less than predicted MCP. Predicting MCP in a cooperative market required analysis based on demand forecast, transmission line congestion information and other companies' bidding prediction. However, this information is hard to predict accurately due to uncertain nature of the power system [25, 26]. Also, often, it is assumed that MCP would not be affected by the other companies bidding while for a significant period of time, this assumption does not hold. As a result, that simple method only would be used in absence of the advanced bidding strategies in the electricity market [8, 27].

In an ideal competitive market, number of sellers and buyers is such that exiting one seller or buyer has no effect on the price and both sellers and buyers are forced to bid in marginal price or would be eliminated from the market. But, in actual electricity market, sellers try to bid higher that MCP and similarly buyers tend to bid lower than MCP.

This behaviour is modeled in various works such as [28, 29] where cost curve is multiplied by cost coefficient k that takes effects of other companies bidding on MCP into account. In this paper, that work is extended such that effects of consumers' behaviour on MCP are also considered. This consideration moves the electricity market toward more competitive market which benefits costumers by decreasing the final electricity prices.

Pricing optimization which is a trending research challenge for making the use of renewable resources in the most optimum way, needs different tools and algorithms to be calculated in a minimum way. Particle swarm optimization (PSO) is one of these methods that gives the best answer with respect to cost criteria [30]. In this paper, Genetic Algorithm (GA) is used as the tool for optimizing the same criteria and constraints as [30] instead of PSO algorithm. In computer science and operations research (OR), a genetic algorithm (GA) is a meta-heuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA). Based on its powerful abilities, GA has been widely used in the literature to solve complicated nonlinear optimization problems [30, 31]. In this work, instead of binary based, decimal based has been used which accelerate solving time significantly.

2.MODELING ELECTRIC UTILITIES BIDDING BEHAVIOUR IN ELECTRICITY MARKET

Different electric utilities bidding in a competitive electricity market such that maximize their economical profit which can be modeled as a game. In this paper Nash equilibrium is used to reach the maximum profit. We assume bidding strategy of other utility remain the same during this process. If after finite number of iterations each utility bidding price converges to a certain price, these prices form Nash equilibrium points. In this work, we present how optimal power flow (OPF) formulation can be modified to include different bidding strategies. Therefore, by an appropriate modeling, all other utilities bidding strategies can be taken into account. In this work as a common practice in power system, the power flow problem can be linearized around the operating point to form DCOPF problem which can be solved in fast time scale. Generation cost of each unit, C can be shown as

$$C(P_G) = aP_G + bP_G^2 \tag{1}$$

where a and b are linear and quadratic cost function. By getting derivative of (1), nodal price, p can be reached as

$$p = \frac{dC(P_G)}{dP_G} \tag{2}$$

Then generating power can be derived as a function of price

$$P_G(p) = \frac{1}{2b}(p-a) = m(p-p_{\min}) \qquad [MW] \tag{3}$$

and similarly, nodal price can be shown as generating power

$$p(P_G) = \frac{1}{m}P_G + p_{\min} \tag{4}$$

Equation (4) is known as marginal price for a generation unit. Similarly expected profit curve of costumers can be defined as

$$B(D) = aD + bD^2 \tag{5}$$

where D is consuming power.

By getting derivative of (5), nodal price can be shown as

$$p = \frac{dB(D)}{dD} \tag{6}$$

requesting power as a function of price can be shown

$$d(p) = \frac{1}{2b}(p-a) = -m_D(p-p_{\max}) \tag{7}$$

and similarly, price can be shown as a function of requesting power of the unit

$$p(D) = \frac{1}{-m_D}D + p_{\max} \tag{8}$$

where p and D represent nodal price, and requested power respectively. Marginal cost of each costumer can be described by (8). Based on supply and demand curves, cost of generation can be determined. By multiplying supply and demand bidding curves in coefficients k_S and k_D we can derive supply and demand sides bidding behaviour as

$$p(S) = k_S(\frac{1}{m_S}s + p_{min}) \tag{9}$$

$$p(D) = k_D(\frac{-1}{m_D}D + p_{max}) \tag{10}$$

To maximize supply and demand sides profit, each side should tune these coefficients properly.

3.TWO LEVELS OPTIMIZATION ALGORITHM

In this section, a two-level optimization algorithm for utilities' bidding strategies has been developed based on the genetic algorithm (GA). At the first level, bidding coefficients, k_S and k_D are determined such that maximizing their profit. To calculate these coefficients, an iterative method such as Gauss-Seidel has been used. At the first level, at each iteration, while all coefficients remain constant, k_S^i (k_D^i) has been changed until Nash equilibrium of the market is achieved.

At the second level, independent system operator (ISO), solving DCOPF by GA to maximize utilities profit. Assume a power system with N bus, N_g generators, N_l loads and N_b branches. Then (9) and (10) can be shown as

$$p(S^i) = k_S^i(a_i S_i + b_i), \quad i = 1, ..., N_g \qquad (11)$$

$$p(D^i) = k_D^i(c_i D_i + d_i), \quad i = 1, ..., N_l \qquad (12)$$

Under no congestion in transmission lines, nodal price of all buses over the system are equal

$$p(S^1) = ... = p(S^{N_g}) = p(D^1) = ... = p(D^{N_l}) \qquad (13)$$

$$k_S^1(a_1 S_1 + b_1) = ... = k_S^{N_g}(a_{N_g} S_{N_g} + b_{N_g}) = k_D^1(c_1 D_1 + d_1) = ... = k_D^{N_l}(c_{N_l} D_{N_l} + d_{N_l}) \qquad (14)$$

Then, all supply and demand can be calculated based on one generation or consumer unit. Without loss of generality consumer unit N_l is picked and

$$D_j = \frac{\frac{k_D^{N_l}}{k_D^j}(c_{N_l} D_{N_l} + d_{N_l}) - d_j}{c_j}, \quad j = 1, ..., N_l - 1 \qquad (15)$$

$$D_j = \frac{\frac{k_D^{N_l}}{k_D^j}(c_{N_l} D_{N_l} + d_{N_l}) - d_j}{c_j}, \quad j = 1, ..., N_l - 1 \qquad (16)$$

In a loss-less system, supply and demand should exactly match

$$S_1 + S_2 + ... + S_{N_g} = D_1 + D_2 + ... + D_{N_l} \qquad (17)$$

By placing (15) and (16) in (17), for a range of different values of k_S^i and k_D^i, S_i and D_j of all buses can be calculated. Physical constraints of the problem should be satisfied at all steps of solving the problem such as

$$\sum_{i=1}^{N_g} S_i = \sum_{j=1}^{N_l} D_j \qquad (18)$$

$$S_i^{min} \leq S_i \leq S_i^{max} \quad i = 1...N_g \qquad (19)$$

$$D_i^{min} \leq D_i \leq D_i^{max} \quad i = 1...N_l \qquad (20)$$

$$-P_k^{max} \leq P_k \leq P_k^{max} \quad k = 1...N_t \qquad (21)$$

where P_k is the power flow and P_k^{max} is the power rating of line number k. Bidding coefficient should be calculated such that maximizing each utilities profit

$$\max(B_S^i = \frac{2k_S^i - 1}{2} a_i S_i^2 + (k_D^i - 1) b_i S_i) \;\; i = 1, ..., N_g \qquad (22)$$

$$\max(B_D^j = \frac{-2k_D^j + 1}{2} c_j D_j^2 + (-k_D^j + 1) d_j D_j) \;\; j = 1, ..., N_l \qquad (23)$$

Where B_S^i and B_D^j represent profit curve of the generation unit i and demand unit j. To solve mentioned problem, iterative numerical method such as GA has been solved repetitively, correcting K_S and K_D at each iteration until they are converged at Nash equilibrium.

In genetic algorithm, each cluster includes some chromosome containing control variables. In our problem, each chromosome includes profit curve, supply, demand and generating and consuming coefficients such as

$$[\text{profit curve}, S_1 ... S_{N_g} D_1 ... D_{N_l} k_S^1 ... k_S^{N_g} k_D^1 ... k_D^{N_l}] \qquad (24)$$

and in both level of optimization, same chromosomes are used. The overview of the two-level optimization algorithm is presented in fig 1.

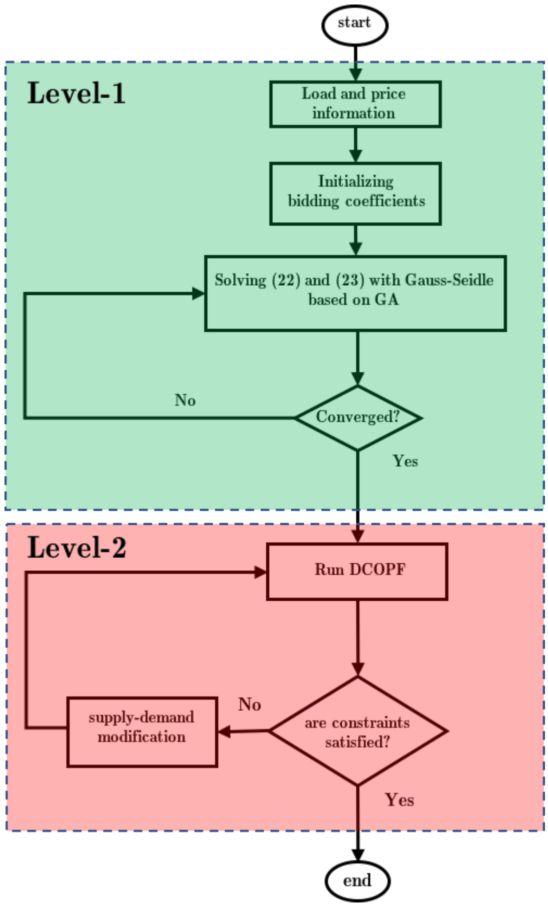

Figure1: Overview of the two-level optimization algorithm

4.SIMULATION RESULTS

To evaluate effectiveness of the proposed method, simulation based analysis is carried out on the modified WSCC 9- bus system includes 9 generators and 9 loads. The simulation considers both normal and under congestion performance of the system. Optimum bidding coefficients after each iteration is shown in fig 2. Since generator 7 and 9 has the largest and smallest coefficients in the cost curves, K_S^7 and K_S^9 has the largest and smallest values. Similarly, K_D^{1-7} are larger than $K_D^{8,9}$.

Nodal price, generated and consumed power and power flow results are shown in table I. Since there is no congestion in the power system, nodal price of all buses are the same. Power flows on each line has been shown in table II.

To make transmission line congestion in the system, power rating of line connecting bus 7 and 8 is limited to 150 MW. This means part of power should be redirected through other lines. Power generation and consumption as well as nodal price and power flow results under this assumption are shown in table III and table

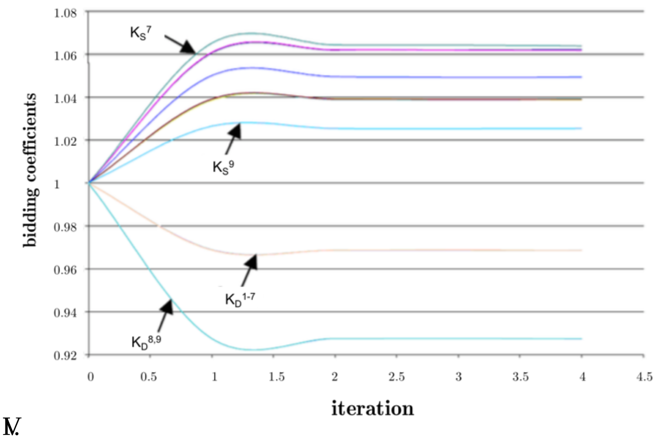

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Figure 2: Bidding coefficients after each iteration

Table I: generated and consumed power, nodal price and power flow results

Bus	V_{mag} (pu)	V_{ang}(deg)	Supply (MW)	Demand (MW)	λ (\$ / MWh)
1	1	0	268.4	155	47.9
2	1	-1.3	268.4	155	47.9
3	1	-6.5	176.4	155	47.9
4	1	-8.1	176.4	155	47.9
5	1	-9.9	176.4	155	47.9
6	1	-12.7	176.4	155	47.9
7	1	-7.4	278.4	155	47.9
8	1	-13.2	226.4	388.6	47.9
9	1	-19.2	115.3	388.6	47.9

Table II: Power flows on the lines

from bus	to bus	power flows (MW)
1	2	24.68
1	7	88.74
2	3	74.04
2	7	64.06
3	4	24.68
3	5	70.82
4	5	46.14
5	6	9.04
5	9	129.39
6	7	-89.85
6	9	120.35
7	8	186.37
8	9	23.82

Table III: generated and consumed power, nodal price and power flow results

Bus	V_{mag} (pu)	V_{ang}(deg)	Supply (MW)	Demand (MW)	λ(\$ / MWh)
1	1	0	268.4	155	47.9
2	1	-1.3	268.4	155	47.9
3	1	-6.5	176.4	155	47.9
4	1	-8.1	176.4	155	47.9
5	1	-9.9	176.4	155	47.9
6	1	-12.7	176.4	155	47.9
7	1	-7.4	278.4	155	47.9
8	1	-13.2	226.4	388.6	47.9
9	1	-19.2	115.3	388.6	47.9

As expected, nodal price changed significantly, especially at those buses that connected through the congested line. To have a better understanding of the effectiveness of the proposed method, bidding coefficients of the proposed method are compared to the bidding coefficients calculated by the normal method and results are tabulated in table V.

Table IV: Power flows on the lines.

from bus	to bus	power flows (MW)
1	2	24.68
1	7	88.74
2	3	74.04
2	7	64.06
3	4	24.68
3	5	70.82
4	5	46.14
5	6	9.04
5	9	129.39
6	7	-89.85
6	9	120.35
7	8	186.37
8	9	23.82

Table V: comparing bidding coefficients under normal and proposed method

bidding coefficients	proposed method	normal method
k_S^1	1.0621	1.0643
k_S^2	1.0621	1.0643
k_S^3	1.0391	1.04
k_S^4	1.0391	1.04
k_S^5	1.0391	1.04
k_S^6	1.0391	1.04
k_S^7	1.0643	1.0655
k_S^8	1.0496	1.0502
k_S^9	1.0254	1.0263

As it is shown, bidding coefficients in the proposed method are smaller than normal method and as a result, utilities profit would be maximized by employing this method. Nodal price at each bus under proposed method and normal methods are compared in table VI. Results verified that employing proposed method leads to smaller nodal price which means higher cost for utilities.

Proposed method, also significantly faster than the normal method. As an example, computational time of the proposed method for a 118-bus system is almost 4 minutes which is much faster than 30 minutes of the normal methods.

Table VI: comparing nodal price at buses under normal and proposed method

bus number	proposed method λ	normal method λ
1	45.74	46.34
2	46.18	46.78
3	47.49	48.09
4	47.93	48.53
5	48.37	48.97
6	47.93	48.53
7	45.30	45.90
8	54.08	54.65
9	50.13	50.72

5.CONCLUSIONS AND FUTURE WORKS

In this paper, we proposed a new bidding strategy in a restructured power system. It is shown that active demand side participation in the electricity market can move the market toward and ideal competitive market. A two-level optimization method based on the GA is used to find Nash equilibrium as a point that maximize utilities profit and effectiveness of the proposed method has been evaluated and verified by the simulation based analysis. For the future work, we are trying to extend this work to include reactive power and line losses and consider different types of uncertainties in the power system.

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