Congestion Influence on Optimal Bidding in Competitive Electricity Market

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Abstract— Electricity market plays an important role in improving the economics of electrical power system. Transmission network is vital entity in open access deregulated wholesale electricity market. Whenever transmission network congestion occurs in electricity market, it divides the market in different zones and the trading price of electricity will no longer remains the same for the whole system. Bidding strategies in electricity market, where by changing the bid, market player changes the revenue of every participant of the market. In this paper, the bidding strategy problem is modeled as an optimization problem and the congestion’s influence will be discussed in the bidding process. Particle Swarm Optimization (PSO) is used to solve the Bidding problem and compared with Genetic Algorithm (GA). The effectiveness of the proposed optimization problem and the congestion’s influence will be compared with the solution obtained using the Genetic Algorithm approach.

Index Terms— Bidding strategy, congestion management, Independent Power Producers (IPP), market clearing price, Particle Swarm Optimization (PSO).

I. INTRODUCTION

The success of privatization of most of the industries led people to think for the deregulation of electric power system. This yields to restructuring of currently vertically integrated utility (VIU) to the main three utilities, namely generation company (GENCO), transmission company (TRANSCO) and distribution company (DISCO). The success in the energy privatization in the countries like UK, USA, Norway and Australia has encouraged many more countries to privatize their electricity industry. India has also participated in the process and most of the states of India have restructured their electricity boards. Ever since the restructuring has taken place, the electric power industry has seen tremendous changes in its operation and governance. Electricity, being a concurrent entity, cannot be stored easily. This emphasize on generation and consumption of electricity at the same moment of time. Ascertain of electricity market gave new dimension on power system engineer and the economics of power system.

In developed countries Electricity market is already functioning and it is being started to introduce in developing countries. The sole purpose of introduction of deregulation and electricity market is to create a healthy competition among the participant of the market and to make electricity market more efficient, liquid and complete [1]. The fundamental objectives behind the establishment of electricity market are the secure operation of power system and facilitating an economic operation of the system. Key entities of the electricity market are Generating companies (GENCOs), independent system operator (ISO) many a times known as system operator (SO), Transmission companies (TRANSCOs) and Distribution companies (DISCOs) [2]. The development of electricity market also aims for the maximum participation from the electric utilities to provide transparent and non-discriminatory platform for energy producers.

The efficiency of market decreases in the event of transmission line congestion. The congestion results in price change and reduces the market efficiency. Congestion can be managed by different approaches. One of the approaches is real and reactive power rescheduling [3]. Strategic bidding is the gaming of players of the market by which the players in the market submits bid to accomplish maximum benefit [4].

In recent years, a considerable amount of work has been published. Ferrero [5] proposed Game Theory based bidding method. Weber and Zhang [6, 7] proposed optimization based bidding strategies. Richter [8] proposed comprehensive bidding strategies with GA. Strategic bidding problem has been formulated as a two level optimization problem [9–13], in which producers try to maximize their profit based on the market clearing price (or bid price), and dispatch quantity is obtained from an optimal power flow model. Using deterministic approach, it is difficult to obtain the global solution of such bi-level optimization problem because of non-convex objective functions and non-linear complementarity conditions [9, 10] to represent market clearing. These difficulties are avoided by representing the residual demand function by mixed integer linear programming (MILP) model [11, 12], in which unit commitment and uncertainties are also taken into account. In [13], the generators associated to the competitors’ firms have been explicitly modeled as an alternative MILP formulation based on a binary expansion of the decision variables (price and quantity bids).

In this paper, the bidding strategy problem is modeled as an optimization problem and the congestion’s influence will be discussed in the bidding process. Particle Swarm Optimization (PSO) is presented to solve the bidding strategy problem. The profit’s deviations of congestion’s influence for all participants are analyzed in detail. Cases studied based on a modified 6-bus system is presented as illustrations [14]. Numerical analysis will clarify congestion’s influence on price and bidding strategy. The result shows that PSO technique can...
generate better quality solution within shorter calculation time and stable convergence characteristic compared to GA.

II. ELECTRICITY MARKET ARCHITECTURE

The electricity market architecture comprises of main four entities namely GENCOs, TRANSOs, DISCOs and an Independent System Operator (ISO). GENCO is not necessary to have its own generating plants, but it can negotiate on behalf of generating companies. In ancillary market GENCO has opportunity to sell its reserves and reactive power. The GENCO will try to maximize its own profit, whatever way it can, by selling the power in the market. TRANSO transmit the power from power producer to power consumer. It also maintains the transmission system to increase overall reliability of power system. DISCO distributes the power to retail companies, brokers or to its own consumers. ISO is an independent body which maintains the instantaneous power balance in the system. ISO is also responsible for secure operation of the grid. There could be two types of ISO, one is known as MinISO and the other is MaxISO [2]. While MinISO, looking after the grid security and has no role in power market, MaxISO model includes power exchange (PX). The function of power exchange is to provide a competitive market place for all the participant of the market. ISO uses the assets of TRANSO for its functioning. The role of ISO also encompasses the fare use of transmission network, maximizing social welfare of the market, running Power Exchange (PX), and maintaining grid security and to run separate market for ancillary services.

From the Fig.1 the equilibrium point is known as Market Clearing Price (MCP). The ISO or PX accepts bids from all the players of the market and determines the MCP. Whenever there is no network congestion, MCP is the only one price for every node of the system. But because of the congestion the whole system is being segregated in different zones and zonal market clearing price is used for different zones.

III. NETWORK CONGESTION

Whenever the network component is overloaded the network is called congested network [6]. In a competitive market, network congestion has its own importance because of the complexity involved. This congestion may be due to overloading of transmission line or transformer. The problem of network congestion can be alleviated with the help of phase shifter, tap changing transformers and curtailment of loads. It can also be solved by removing the overloaded component from the system. But this might aggregate the network congestion.

IV. MODEL OF BIDDING STRATEGY

A. Bidding strategy without line flow constraints

The bidding problem consists of price offers and the amount of loads to be satisfied in the competitive market. The bid price curves for generators and customers are quadratic convex and concave functions, respectively. All participants submit a bidding strategy to maximize the social welfare while satisfying various constraints. The model of bidding strategy without line flow constraints can be first formulated as:

Max. \( \text{Obj} \quad f_1 = \sum_{i=1}^{NG} B_i (d_i) - \sum_{j=1}^{NL} C_j (p_j) \) \quad (1)

with \( B_i (d_i) = b_i d_i^2 - \frac{1}{2} d_i^2 q_{ij} d_i^2 \)

\( C_j (p_j) = b_j p_j^2 - \frac{1}{2} p_j^2 q_{jj} p_j^2 \)

s.t \( \sum_{j=1}^{NL} p_j = \sum_{i=1}^{NG} d_i \) \quad (2)

\( p_j^{\text{min}} \leq p_j \leq p_j^{\text{max}} \) \quad (3)

where,

- \( i, j \): generators and customer index
- \( NL \): the number of customers
- \( NG \): the number of generators
- \( C_j \): the cost (or bid) function of generator \( j \)
- \( B_i \): the benefit function of customer \( i \)
- \( P_j \): bid quantities of customer \( j \)
- \( d_i \): bid quantities of customer \( j \)
- \( p_j^{\text{min}}, p_j^{\text{max}} \): the lower and upper generation output

B. The regulation of bidding strategy by congestion

When the congestion occurs after the bidding process, suppliers will regulate the power output to meet the security constraints. In this paper, a DC load flow model is used with a Q-V sub-problem and transmission line loss is neglected. The curtailment algorithm can be formulated as:
\[
\begin{align*}
\text{Min } & \Delta P^T W \Delta P \\
\Delta P_i & \leq |P_{ij}| \leq P^\text{max}_j \quad (5) \\
\sum_{i \in G} \Delta P_i &= 0 \quad (6)
\end{align*}
\]

where \( \Delta P = [\Delta P_1, \Delta P_2, \ldots, \Delta P_n] \) is the vector of the supplier’s curtailment. \( \Delta P_i \) is the increased/decreased output of generator \( i \). If \( \Delta P_i > 0 \), \( i^{th} \) supplier must increase its output. \( P_j \) denotes the line flow. \( W \), which is a diagonal weight matrix, is set to 1 in this paper. Either increasing output or decreasing output, the curtailed power must sum up to 0 such as Equation (6). It is clear that the curtailed power will result in the loss profits of suppliers and their cost must be allocated among market participants. Thus, the new bidding strategy will be re-formulated as:

\[
\begin{align*}
\text{Max. } & ECP \times (P^* + \Delta P_i) - C_i(P_i + \Delta P_i) + \text{REG}_{\text{cost}} \\
\text{s.t. } & \sum_{j=1}^{NG} P_j = \sum_{i=1}^{NL} d_i \quad (8) \\
& P^\text{min}_j \leq P_j \leq P^\text{max}_j \quad (9) \\
& |P_{ij}| \leq |P_{ij}|^\text{max} \quad (10) \\
& \sum_{i \in G} \Delta P_i = 0 \quad (11)
\end{align*}
\]

\( \text{REG}_{\text{cost}} \) is the regulated cost for generators. It can be found as

\[
\text{REG}_{\text{cost}} = -\Delta P_i \times (ECP - B_i (P_i + \Delta P_i)).
\]

**V. SOLUTION ALGORITHM**

The PSO method introduced by Kennedy and Eberhart [16] is a self-educating optimization algorithm that can be applied to any nonlinear optimization problem. In PSO, the potential solutions, called particles, fly through the problem space by following the best fitness of the particles. It exhibits some evolutionary computation attributes such as initialization with a population of random solutions and search for optima by updating generations. PSO seems to be sensitive in tuning of parameters and many researches [17-19] are still in progress in regulating these to improve the performance.

The updates of particles are accomplished according to the following equations. Equation (12) calculates a new velocity for each particle \( r \), based on its previous velocity \( (V^k_r) \), the particle’s location at which the best fitness has been achieved \( (P^\text{best}_r) \) so far, and the best particle among the neighbors \( (G^\text{best}) \) at which the best fitness has been achieved so far. The learning factors \( a_1 \) and \( a_2 \) are the acceleration constants that change the velocity of a particle towards \( P^\text{best}_r \) and \( G^\text{best} \), and \( rand_1 \) and \( rand_2 \) are uniformly distributed random numbers in \([0, 1]\). Each particle’s position is updated using (13) in the solution hyperspace. It is concluded in [20] that the PSO with a linearly decreasing (LD) inertia weight \( W \) in each iteration \( k \), from maximum value \( W_{\text{max}} \) to minimum value \( W_{\text{min}} \), can make a significant improvement on convergence to the global optimum within a reasonable number of iterations

\[
V^{k+1} = w^k V^k + a_1 \text{rand} \times (P^{\text{best}}_r - X^k_r) + a_2 \text{rand} \times (G^{\text{best}} - X^k_r) \quad (12)
\]

\[
X^{k+1} = X^k + V^{k+1} \quad (13)
\]

\[
w^k = \frac{W_{\text{max}} - W^k_{\text{min}}}{W_{\text{max}} - W_{\text{min}}} \times k \quad (14)
\]

where \( k \) is the iteration counter and \( k_{\text{max}} \) is the maximum iteration number.

The velocity update expression (12) can be explained as follows [21]. Without the second and third terms, the first term (representing inertia) will keep a particle flying in the same direction until it hits the boundary. Therefore the first term tries to explore new areas and corresponds to the diversification in the search procedure. In contrast, without the first term, the velocity of the flying particle is only determined by using its current position and its best positions in history. Therefore the second (representing memory) and third terms (representing cooperation) try to converge the particles to their \( P^{\text{best}}_r \) and/or \( G^{\text{best}} \) and correspond to the intensification in the search procedure. Namely, the PSO has a well-balanced mechanism to utilize the diversification and the intensification in the search procedure efficiently.

A. PSO algorithm for bidding problem

The computational steps in optimal strategy searching process using PSO algorithm are described below:

Step1. Give input parameters of the system and specify the lower and upper limits of each variable

Step2. Initialize the particles (strategic variable) of population randomly. These initial particles must satisfy the constraints of bidding generators.

Step3. Calculate the fitness value of each particle in the population using fitness function (7)

Step4. Update the iteration counter; \( k = k + 1 \)

Step5. Update the inertia weight \( w \) using (14) and modify the velocity and position of each particle using (12) and (13), respectively. If a particle violates its position limits in any dimension, set its position at proper limit.

Step6. If the iteration counter reaches predefined maximum iteration \( k_{\text{max}} \), then Stop; else go to step 4.

Step7. The particle that generates the latest \( G^{\text{best}} \) is the optimal value.

PSO uses random initialization, but it gives almost the same optimal solution in asset of simulations within a given case. It shows its immunity to the start point. The number maximum iterations required to obtain the global solution is dependent on the nature and size of the problem. The system has been solved for DC power flow and the loading of the lines is calculated. Fig 2 shows the flow chart of the proposed approach.
VI. CASE STUDY

In this paper, a 5-bus power system with three competitive generators and two customers interconnected by six transmission lines is used for test as shown in Figure 3. The associated bid functions and desired profits for participants are listed in Table 1. To analyze the congestion’s influence on the bidding strategy and price, the situation is first performed when the transmission line has no congestion. The bid quantities and cost for participants are allocated by using proposed algorithm as shown in Table 2. The social welfare using PSO is more compared to GA without considering congestion.

Table 1. The Bids Data for Participants

<table>
<thead>
<tr>
<th>Generators</th>
<th>Cost functions($)</th>
<th>$p_1^{min}$</th>
<th>$p_1^{max}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gen.1</td>
<td>560+7.92$p_1$+0.001562$p_1^2$</td>
<td>0(MW)</td>
<td>200(MW)</td>
</tr>
<tr>
<td>Gen.2</td>
<td>310+7.85$p_1$+0.001944$p_1^2$</td>
<td>0(MW)</td>
<td>150(MW)</td>
</tr>
<tr>
<td>Gen.3</td>
<td>78+7.97$p_1$+0.004822$p_1^2$</td>
<td>0(MW)</td>
<td>150(MW)</td>
</tr>
<tr>
<td>Customers</td>
<td>Profit functions($)</td>
<td>Peak load</td>
<td></td>
</tr>
<tr>
<td>Cust.1</td>
<td>100$d_1$ - 0.175$d_1^2$</td>
<td>200(MW)</td>
<td></td>
</tr>
<tr>
<td>Cust.2</td>
<td>110$d_2$ - 0.15$d_2^2$</td>
<td>150(MW)</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. The Social Welfare without Congestion

<table>
<thead>
<tr>
<th>Generators</th>
<th>Output/ Loads</th>
<th>Costs($)</th>
<th>Output/ Loads</th>
<th>Costs($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gen.1</td>
<td>153.65</td>
<td>1813.78</td>
<td>158.299 MW</td>
<td>1852.87</td>
</tr>
<tr>
<td>Gen.2</td>
<td>141.75</td>
<td>1461.74</td>
<td>145.497 MW</td>
<td>1493.22</td>
</tr>
<tr>
<td>Gen.3</td>
<td>44.58</td>
<td>442.94</td>
<td>46.0936 MW</td>
<td>455.611</td>
</tr>
<tr>
<td>Total cost for Generators</td>
<td>350MW</td>
<td>3718.46</td>
<td>350 MW</td>
<td>3801.701</td>
</tr>
<tr>
<td>Customers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cust.1</td>
<td>200</td>
<td>14184.87</td>
<td>200 MW</td>
<td>14184.74</td>
</tr>
<tr>
<td>Cust.2</td>
<td>150</td>
<td>20049.01</td>
<td>150 MW</td>
<td>20048.84</td>
</tr>
<tr>
<td>Total benefit for customers</td>
<td>350</td>
<td>34233.880</td>
<td>350 MW</td>
<td>34233.58</td>
</tr>
<tr>
<td>Social welfare ($)</td>
<td>30515.420</td>
<td>30475.173</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3 shows the line flow before and after congestion management. From the Table 3, line #4 violates the flow limit after bidding strategy and it is regulated from 253.30MW to 246.07MW after congestion management.

Table 3. Line flow before and after congestion management

<table>
<thead>
<tr>
<th>Line No.</th>
<th>Line flow after bidding strategy</th>
<th>Line limits</th>
<th>Line flow after congestion management (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>173.65</td>
<td>250</td>
<td>156.50</td>
</tr>
<tr>
<td>#2</td>
<td>23.91</td>
<td>250</td>
<td>23.09</td>
</tr>
<tr>
<td>#3</td>
<td>48.82</td>
<td>250</td>
<td>35.73</td>
</tr>
<tr>
<td>#4</td>
<td>253.30</td>
<td>250</td>
<td>246.07</td>
</tr>
<tr>
<td>#5</td>
<td>72.80</td>
<td>250</td>
<td>80.82</td>
</tr>
<tr>
<td>#6</td>
<td>77.20</td>
<td>250</td>
<td>69.177</td>
</tr>
</tbody>
</table>

Due to the line #4 is overload after bidding strategy; ISO has to curtail the power in order to keep the security operation. The simulation results are summarized in Table 4. Gen.2 curtails the output from 141.75 MW to 31.206 MW and the lost profit is $904.884. Similarly, Gen.1 and Gen.3 increase the output for meeting the load demand. The social welfare after congestion management using PSO is $30515.420, which is more than the social welfare by using GA.
In this paper, application of PSO for bidding strategy approach is proposed. In this approach, each participant tries to maximize its profit with the help of information announced by operator. The curtailment decisions are performed to keep system operation within security limits. It can be seen that the congestion will result in lost profit of social welfare. The profit's deviations of congestion's influence for all participants are analyzed in detail. The results are compared with the GA. The results obtained using PSO gives more profit (social welfare) and takes less CPU time compared to GA. Numerical analysis will clarify that congestion’s influence on bidding strategy will reduce the market efficiency and also social welfare.

### VII. CONCLUSION

In this paper, application of PSO for bidding strategy approach is proposed. In this approach, each participant tries to maximize its profit with the help of information announced by operator. The curtailment decisions are performed to keep system operation within security limits. It can be seen that the congestion will result in lost profit of social welfare. The profit’s deviations of congestion’s influence for all participants are analyzed in detail. The results are compared with the GA. The results obtained using PSO gives more profit (social welfare) and takes less CPU time compared to GA. Numerical analysis will clarify that congestion’s influence on bidding strategy will reduce the market efficiency and also social welfare.

### VIII. REFERENCES