Bacteria Foraging Optimization Algorithm based Strategic Bidding in Electricity Markets

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Abstract— In an electricity market, suppliers are more concerned with maximizing their profit and minimizing risk. To achieve this, optimal bidding strategy of a supplier has been formulated as a Bi-Level Multi Objective Optimization Problem (BLMOOP), in which lower level problem represents market clearing process by System Operator (SO) for minimization of customers’ payments. Upper level problem is a multi objective formulation, which considers profit maximization and risk minimization simultaneously. An ε-constraint method has been used to obtain pareto-optimal solutions of the BLMOOP. A fuzzy approach has been used to derive the most efficient solution among the pareto-optimal solutions. Upper level objective functions are highly nonlinear. Therefore, Bacteria Foraging Optimization (BFO) algorithm, a relatively new heuristic approach, has been applied to obtain the best solution to the BLMOOP for day-ahead hourly market. The effectiveness of the proposed method has been established on 30-bus test system. The results, obtained using the BFO algorithm, have been compared with those obtained using Sequential Quadratic Programming (SQP) based approach, a classical optimization method.

Keywords—Bacteria Foraging Optimization (BFO), Bi-level multi objective optimization problem, Congestion management, ε-constraint method, Fuzzy approach, Optimal bidding strategy.

I. Introduction

In pool based day-ahead markets, maximizing the profit, minimizing the risk and gaining the competitive advantage by suppliers are possible through strategic bidding. For developing strategic bidding, a supplier has to estimate the market clearing price, either by forecasting it or by simulating the market, to decide the optimal output of their generators. However, supplier faces the trading risk due to volatile market clearing price. Therefore, the optimal bidding strategy is a conflicting bi-objective optimization problem viz. profit maximization and risk minimization for the supplier.

A state-of-the-art literature survey on bidding strategy in electricity markets can be found in [1]. In [2-3], effects of network constraints on transactions, nodal prices and market performance have been analyzed. An OPF based probabilistic LMP simulator to simulate LMPs with the estimation of the rivals’ bidding strategies was used in [4]. In a strategic bidding problem, market clearing price may be influenced by rivals’ bidding behavior. Therefore, in electricity markets, risk due to price volatility is a serious concern and it creates the need to perform the risk assessment. In [5-7], trade off between profit maximization and risk minimization is modeled using Value at Risk (VaR) and Conditional Value at Risk (CVaR). In [8], a risk constrained optimal bidding strategy is developed. The trade off between expected profit maximization and risk minimization is formulated as a stochastic mixed integer linear programming and solved by MIP solver. The risk in the self-scheduling problem was modeled in [9]. A detailed overview of risk assessment methods in energy trading was given in [18]. Risk due to units’ forced outage was studied in [19].

From the literature survey, it is observed that most of the work have focused on risk assessment of price taker Gencos, considering constant marginal price and longer time frame. Further, the multi-objective optimization problems are combined into a single objective function with the help of risk tolerance parameter, which reflects the Genco’s preference towards the risk. The main issue, in this approach, is the selection of the appropriate value of the risk tolerance parameter. Therefore, for Genco’s proper decision making, this paper utilizes the ε-constraint method to alleviate the problem of selecting appropriate risk tolerance parameter.

The prime aim of this work is to develop an optimal bidding strategy for a supplier in an hourly day-ahead market using nodal price and hourly price-volume bid, considering network constraints and rivals’ bidding behavior. A Bi-Level Multi Objective Optimization Problem (BLMOOP) has been formulated, in which lower level problem represents the market clearing process of System Operator (SO). Upper level problem is a multi objective formulation, which considered profit maximization and risk minimization problem of a supplier. A relatively new population based technique, Bacteria Foraging Optimization (BFO) algorithm, has been utilized to obtain best solution of the upper level problem. To obtain the pareto optimal solutions of BLMOOP and to derive the most efficient solution out of the pareto optimal solutions, ε-constraint method and fuzzy approach has been used, respectively. The effectiveness of the proposed BFO algorithm has been tested on IEEE 30-bus system.

II. Bacteria Foraging Optimization (BFO)

Bacteria foraging is a recent evolutionary computational technique proposed by Passino [10]. It mimics the foraging behavior of E.Coli bacteria present in our intestine. The
foraging strategy is dictated by four steps viz. Chemo taxis, Swarming, Reproduction and Elimination and Dispersal. The chemo taxis process decides the search direction of the bacteria with the help of swimming (movement in a predefined direction) and tumbling (movement in different directions). In swarming process, the bacterium, which has searched the optimum path for reaching towards the best food location, provides an attraction signal to other bacteria for swarming together to reach the desired location. During the reproduction process, the least healthy bacteria die and each of the other healthier bacteria split into two bacteria, and placed in the same location, keeping the population of bacteria constant. The foraging strategy of the bacteria may be affected by certain events, which may either kill all the bacteria in a region or may disperse a group of bacteria to other locations. This may either destroy the chemo tactic progress or may assist in chemo taxis, since dispersal may place bacteria at better locations. Hence, each bacterium in the population is subjected to elimination-dispersal with some probability. To keep the number of bacteria constant, if one of the bacterium is eliminated, the other is dispersed to a random location on the optimization domain. Thus, elimination and dispersal prevents bacteria from being trapped in local optima.

III. Problem Formulation

In a day-ahead pool-operated electricity market, optimal bidding strategy of a supplier is to determine the optimal bid quantity and price to maximize its profit. To compute the profit, the supplier needs to estimate market clearing price either by forecasting it or by simulating the market clearing process. Once market is cleared, suppliers receive the uniform Market Clearing Price (MCP) and dispatch output of generator at the price. The supplier needs to estimate market clearing price to maximize its profit. To compute the above formulation, are utilized by generator-i, while the lower level optimization problem is solved by generator-i. The LMPs and the dispatched quantities, obtained from the lower level problem, are utilized by generator-i in the upper level problem for profit maximization. Therefore, lower level problem, along with bounds on the bidding strategy vector, is modeled as constraints in (7) for the upper level problem.

A. Market Clearing Model

It is assumed that the SO utilizes Security Constrained Economic Dispatch (SCED), based on DC power flow, to clear the market. Objective of the SO is to minimize customer payments subject to various equality and inequality constraints. Accordingly, dispatch output of generators and Locational Marginal Prices (LMPs) at generators buses can be calculated as follows [11]:

\[
\text{Min } CP = \sum_{i=1}^{N} P_i \rho_i * P_i
\]  

Subject to,

\[
B \theta = P_g - P_d
\]  

\[
F_i^{\text{min}} \leq F_i \leq F_i^{\text{max}} \quad \forall i \in L
\]  

\[
P_i^{\text{max}} \leq P_i \leq P_i^{\text{min}} \quad \forall i \in N
\]

where, \(N\) is the number of generators, \(\rho_i\) is bidding price of generator-i in $/MWh, \(P_i\) is bidding quantity of generator-i in MW, \(B\) is bus susceptance matrix, \(\theta\) is vector of bus voltage angles, \(P_g\) is vector of bus generation, \(P_d\) is vector of bus loads, \(F_i\) is power flow in line \(i\) in MW, \(F_i^{\text{min}}\) is the lower flow limit in line \(i\) in MW, taken as zero in this work, \(F_i^{\text{max}}\) is the upper flow limit in line \(i\) in MW, \(L\) is number of lines in the system, \(P_i^{\text{max}}\) is minimum generation capacity of \(i\)th generator, \(P_i^{\text{max}}\) is maximum generation capacity of \(i\)th generator.

Power balance constraints are the DC power flow equations. The LMPs at the generator and load buses are the Lagrange multipliers associated with the power flow constraints. The equality constraints are the transmission line constraints and the generation capacity constraints, respectively. The equality and inequality constraints in the above formulation are linear equations and can be generalized as follows including the slack variables.

\[
Ax = b
\]

\[
0 \leq x \leq u
\]

IV. PROPOSED BI-LEVEL MULTI OBJECTIVE OPTIMIZATION PROBLEM (BLMOOP)

The proposed BLMOOP for bidding strategy has two objective functions. The first is the main objective \((F_1)\), the profit maximization of the generator-i. The second objective \((F_2)\) is the minimization of the risk using Value at Risk (VaR) methodology [12].

\[
\begin{align*}
\text{Max } F_1 &= \lambda_i * P_i - C(P_i) \\
\text{Min } F_2 &= \alpha \sqrt{P_c'V_xP_c}
\end{align*}
\]

Subject to,

\[
S_i^{\text{min}} \leq S_i \leq S_i^{\text{max}}
\]

\[
\text{Min } CP
\]

\[
\text{Subject to,}
\]

\[
B \theta = P_g - P_d
\]

\[
F_i^{\text{min}} \leq F_i \leq F_i^{\text{max}} \quad \forall i \in L
\]

\[
P_i^{\text{max}} \leq P_i \leq P_i^{\text{min}} \quad \forall i \in N
\]

where, \(C(P_i) = (a_u * P_i^2 + b_u * P_i + c_u)\), \(\lambda_i\) is LMP of generator-i, \(S_i\) is bidding strategy variable of generator-i, \(S_i^{\text{min}}\) is lower bound of bidding strategy vector of generator-i, \(S_i^{\text{max}}\) is upper bound of bidding strategy vector of generator-i, \(\alpha\) is confidence level, \(P_{c'}\) is column vector \((N\times1)\) containing generators’ schedule, \(V_x\) is covariance matrix.

The above formulation (6)–(7) is a BLMOOP, in which the upper level represents the trade off between profit maximization without incorporating rivals’ bidding strategies, and monetary risk minimization for generator-i, while the lower level optimization problem is used by the SO for market clearing. The LMPs and the dispatched quantities, obtained from the lower level problem, are utilized by generator-i in the upper level problem for profit maximization. Therefore, lower level problem, along with bounds on the bidding strategy vector, is modeled as constraints in (7) for the upper level problem.

A. Value at Risk (VaR)

In electricity markets, VaR determines the monetary risk, at given confidence level, associated with generation schedule \(P_g\) and fluctuations in LMPs. Expression of VaR in terms of generation schedule \(P_g\) and fluctuations in LMPs [12] is,

\[
\text{VaR} = \alpha \sqrt{P_c'V_xP_c}
\]

where, \(V_x\) is the covariance matrix.

B. Approach for Estimation of Rivals’ Strategy

In an electricity market, it is necessary for a supplier to model its rivals’ unknown information i.e. bid price to maximize its profit. An immediate problem for each supplier is how to model rivals’ bidding behavior. For
modeling rivals’ bidding behavior, it is more practical to assume that a generator builds its optimal bidding strategy based on the possible strategies of the other generators that can be estimated probabilistically from historical market data. For each rival generator \( j \in J \), the possible strategies and their associated probabilities estimated by the \( i^{th} \) generator, for which bidding is to be framed, can be denoted by matrices \([13]\),

\[
\begin{bmatrix}
S_{pi} & \ldots & S_{pj}
\end{bmatrix}
\quad \text{and} \quad
\begin{bmatrix}
pr_{pi} & \ldots & pr_{pj}
\end{bmatrix}
\]

(9) respectively, where \( j = \{1, 2, \ldots, i-1, i+1, \ldots, N\} \) is the reduced set of generators excluding \( i^{th} \) generator. \( K_i \) is the maximum number of blocks to bid and \( G_i \) is the maximum number of strategies for \( i^{th} \) GenCo. For each opponent GenCo \( J_j \), there is \( N_j \) number of possible strategy combinations, defined as \( \Phi_j = \{\Phi_{ji}, \Phi_{j1}, \ldots, \Phi_{jm}, \ldots, \Phi_{jp}\} \) and their probabilities are represented as \( \eta_j = (\eta_{j1}, \eta_{j1}, \ldots, \eta_{jm}, \ldots, \eta_{jp}) \), where, \( N_j = K_j \times G_j \). The set of all possible strategic combinations of opponents \( \Psi = (\Psi_1, \Psi_2, \ldots, \Psi_{N}) \), is defined as cross product of all \( j \) sets \( \Phi_1, \Phi_2, \ldots, \Phi_j \) denoted by \( \Phi_1 \times \Phi_2 \times \ldots \times \Phi_j \). This consists of all ordered \( J \) tuples \( \{\varphi_1, \varphi_2, \ldots, \varphi_j\} \), where, \( \varphi_1 \in \Phi_1, \varphi_2 \in \Phi_2, \ldots, \varphi_j \in \Phi_j \). If probability of \( \varphi_j \) is defined as \( PR(\varphi_j) \), then the respective probability of each strategy combination is expressed as,

\[
\Omega_a = \prod PR(\varphi_j) \quad \forall \psi_m \subset \psi \quad \forall m \subset M
\]

(10) where, \( M \) is total number of possible strategy combinations of the rivals, given by:

\[
M = \prod_{j=1}^{N_j} N_j = \prod_{i=1}^{N} (i-1, i+1, \ldots, N)
\]

(11) After incorporating the rivals’ bidding strategies, the BLMOO of \( i^{th} \) generator (6-7) will be modified as,

\[
\begin{align*}
\text{Max} & \quad F_i = \sum_a \Omega_a \cdot \lambda_{ai} \cdot P_{ma} - C(P_{ma}) \\
\text{Min} & \quad F_j = \sum_a \Omega_a \cdot \mu_a \cdot P_{jma} - C(P_{jma})
\end{align*}
\]

subject to,

\[
\begin{align*}
S_{mi} & \leq S_{mi} \leq S_{mi}^m \\
\forall \psi_m & \subset \psi \\
\text{s.t.:}
\end{align*}
\]

\[
\begin{align*}
A & = b \\
\varphi & \leq u
\end{align*}
\]

where, \( \lambda_{ai} \) is the LMP at \( i^{th} \) generator bus and \( P_{ma} \) is the dispatched quantity of the \( i^{th} \) generator, for \( m^{th} \) strategic combination of the opponents.

C. \( \varepsilon \)-Constraint Method

To alleviate the difficulties faced by the weighted sum approach in solving MOOP, the \( \varepsilon \) constraint method is used. This method converts the MOOP into single objective optimization problem by keeping \( F_i \) as the main objective function and considering other objective functions as constraints \([14]\),

\[
\text{Max} \quad F_i(x)
\]

Subject to,

\[
F_i(x) \leq e_{i1}, F_i(x) \leq e_{i2}, \ldots, F_i(x) \leq e_{ip}
\]

(14) where, subscript \( p \) indicates number of competing objective functions. To apply the \( \varepsilon \)-constraint method, user specified values of \((p-1)\) objective functions are needed, which will be used as grid points. These values can be calculated from the payoff table \([15]\) as described below,

1. At first, optimum value of each objective function is calculated, \( F_i^\ast \) indicates the optimum value of \( F_i (i=1,2,\ldots, p) \).
2. Calculate the value of the other objective functions utilizing the solution obtained in step-1. It is represented by \( F_j^\ast, F_j^\ast, \ldots, F_j^\ast \). Calculate all the rows of the payoff table in this way.
3. Then the \( i^{th} \) row of payoff table is \( F_j^\ast, F_j^\ast, \ldots, F_j^\ast \). Calculate all the rows of the payoff table in this way.
4. Obtain the maximum and minimum values of the objective function \( F_i \) from the \( J^\ast \) column of the payoff table for the \( \varepsilon \)-constraint method.
5. Divide the range of the objective function \( F_i \) and \( F_j \) into \( q_i \) and \( q_j \) equal intervals, respectively. Considering maximum and minimum values of the range, \( q_i + 1 \) and \( q_j + 1 \) equidistant grid points are produced for \( F_i \) and \( F_j \), respectively.
6. Solve \((q_i + 1) \times (q_j + 1)\) optimization sub problems considering the constraints. Sub problem \((i,j)\) has the following form,

\[
\begin{align*}
\text{Max} \quad F_i(x) & \quad \text{Subject to,} \\
F_i(x) & \leq e_{i1}, F_i(x) \leq e_{i2}, F_i(x) \leq e_{ip} (18)
\end{align*}
\]

\[
e_{i1} = F_i^\ast - \left[ \frac{F_i^\ast - F_i^{\text{min}}}{q_i} \right] i = 0, 1, \ldots, q_i
\]

(15) where, \( \text{max} \) and \( \text{min} \) represents the maximum and minimum values of the individual function, obtained from the payoff table. By solving all the optimization sub problems, \((q_i + 1) \times (q_j + 1)\) pareto optimal solutions are obtained.

D. Fuzzy Decision Maker

In this paper, a fuzzy decision maker has been proposed \([16]\) to select the most efficient solution among the pareto optimal solutions, which will satisfy profit maximization and risk minimization objectives to the extent possible. The linear membership functions for both the objectives \( F_i \) and \( F_j \) can be expressed mathematically as,

\[
\mu_i = \begin{cases} 
1; & F_i \geq F_i^\ast \\
\frac{F_i - F_i^\ast}{F_i^{\text{max}} - F_i^\ast}; & F_i^{\text{min}} < F_i < F_i^\ast \\
0; & F_i \leq F_i^{\text{min}}
\end{cases}
\]

(17)

\[
\mu_i = \begin{cases} 
1; & F_i \leq F_i^\ast \\
\frac{F_i - F_i^\ast}{F_i^{\text{max}} - F_i^\ast}; & F_i^{\text{min}} < F_i < F_i^{\text{max}} \\
0; & F_i \geq F_i^{\text{max}}
\end{cases}
\]

(18)

where, \( F_i^{\text{max}} \) and \( F_i^{\text{min}} \) indicate the range of the objective function. \( \mu^\ast \) is calculated based on its individual membership functions as follows:
Fig. 1. proposed BFO based optimal bidding strategy is given in MATLAB optimization toolbox. A flow chart for the lower level problem is solved by a FMINCON function of has been used for solving the upper level problem, while the optimization method to get the best optima. BFO algorithm solved using a heuristic algorithm and a conventional ($/Mw^2h), and generators’ data have been taken from the assumed to be 283.3 MW. The covariance matrix generators and 41 lines [17]. The total load demand is tested on IEEE 30-bus system, which comprises of 6.

\[
\mu' = \frac{\sum_{i=1}^{M} \mu'_i}{\sum_{i=1}^{p} \sum_{j=1}^{p} \mu'_i}
\]

where, \( M \) is the number of non dominated solutions, and \( p \) is the number of objective functions. The solution with the maximum membership function \( \mu' \) is considered as the most efficient solution.

v. Solution Algorithm

The BLMOOP is a non convex problem, which has been solved using a heuristic approach and a conventional optimization method to get the best optima. BFO algorithm has used for solving the upper level problem, while the lower level problem is solved by a FMINCON function of MATLAB optimization toolbox. A flow chart for the proposed BFO based optimal bidding strategy is given in Fig. 1.

![Flowchart for the proposed optimal bidding strategy using BFO](image)

VI. Simulation Results

The effectiveness of the proposed methodology has been tested on IEEE 30-bus system, which comprises of 6 generators and 41 lines [17]. The total load demand is assumed to be 283.3 MW. The covariance matrix ($/Mw^2h), and generators’ data have been taken from the ref. [7], and [13] respectively. The lower and upper bound on the bid price of the Genco, whose strategy has been estimated, has been considered marginal cost and three times of marginal cost. Rivals’ bidding strategies have been predicted using probabilistic approach. It is assumed that all the generators are bidding hourly price-volume bid (single block). The performance of the BFO algorithm depends on the optimal settings of their control parameters. The control parameters in the BFO algorithm are number of bacteria, chemo tactic steps, swing length, reproduction steps, and number of elimination-dispersal events. In this work, the optimal values of these control parameters have been decided by hit and trial, and the parameters, which resulted in the maximum value of the fitness function, were selected as optimal. For this system, BFO parameters are set as, number of bacteria (S) = 6, chemo tactic steps (Nc) = 3, swing length(Ns) = 3, reproduction steps (Nre)= 4, elimination-dispersal events (Ned)= 2, Probability of elimination and dispersal (Ped)= 0.25, run length unit (C) =0.01.

An optimal bidding strategy of generator-1 has been developed for the following three cases considering transmission constraints and rivals’ bidding strategy.

Case I: All rivals are bidding at their marginal cost.
Case II: Rivals 2 and 3 are bidding strategically, rivals 4, 5, 6 are bidding at their marginal cost.
Case III: All rivals are bidding strategically.

A. Case I simulation results

In this case, constrained market clearing simulation has been carried out, assuming that all the rival are bidding at their marginal cost. The solution of market clearing has been used as input to the upper level problem, which is solved using BFO algorithm, to determine profit and risk of generator-1, simultaneously. The results obtained with the BFO algorithm have been compared with those obtained using the SQP. Pay-off table, obtained using the BFO algorithm and the SQP, is shown in Table I. From the pay-off Table I, it can be observed that the expected profit obtained using BFO algorithm is higher in comparison to SQP, when the objective is to maximize the profit.

The ε-constraint method has been used to obtain the pareto optimal solutions of the BLMOOP. A fuzzy decision maker has been used to select the most efficient solution, which satisfies both the objective functions, among the pareto optimal solutions. The solution with the highest membership value has been selected as the best solution. The optimal solution of bidding strategy of generator-1, obtained using fuzzy approach, is shown in Table II.

<table>
<thead>
<tr>
<th>Method</th>
<th>Expected profit maximization</th>
<th>Expected profit minimization</th>
<th>Risk $/h</th>
<th>Value of decision variable $</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFO</td>
<td>239.49</td>
<td>227.19</td>
<td>40.19</td>
<td>2.04</td>
</tr>
<tr>
<td>SQP</td>
<td>213.48</td>
<td>189.70</td>
<td>39.10</td>
<td>2.17</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>Expected profit $/h</th>
<th>Risk $/h</th>
<th>Bidding strategy variable ($)</th>
<th>Computation time</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFO</td>
<td>236.40</td>
<td>39.30</td>
<td>2.15</td>
<td>171</td>
</tr>
<tr>
<td>SQP</td>
<td>207.53</td>
<td>38.80</td>
<td>2.32</td>
<td>18.57</td>
</tr>
</tbody>
</table>

LMPs and dispatched output of generators are shown in Table III. It can be seen that the expected profit and risk are $ 236.40 and $ 39.30 per hour, respectively using the BFO algorithm whereas, these are $ 207.53 and $ 38.80 per hour, respectively, using the SQP.
B. Case II simulation results

In this case, generator-1 builds its optimal bidding strategy based on the estimated bidding strategies of rivals 2 and 3, as shown in Table IV.

The simulation results depicting upper and lower values of expected profit and risk are given in Table V. Optimal solution of bidding strategy of generator-1, and LMPs and dispatched output of generators are shown in Tables VI and VII. In this case, profit of generator-1 has been increased as compared to the case-I. The reason behind this is that due to strategic bidding of the generators 2 and 3, LMP at bus-1 has increased as compared to the case-I. In this case, simulation time has increased as compared to the case-I, because of the increased strategic combinations of the rivals.

Since, maximum number of bidding strategies for rivals 2 & 3 are two (Gj=2), and for rivals 4, 5, 6, it is one (Gj=1). Therefore, as per equation (16), rivals’ strategic combinations are 2^2=4.

C. Case III Simulation Results

The estimated bidding strategies of the rivals are given in Table VIII. From the Table VIII, it can be seen that the maximum number of bidding strategies, chosen by all the rivals, are two (Gj=2). Therefore, as per the equation (16), total number of possible strategic combinations of rivals is 2^3=8.

TABLE III. LMPS AND OUTPUT OF THE GENERATORS FOR CASE-I (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Generator number</th>
<th>BFO algorithm</th>
<th>SQP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LMPs ($/MWh)</td>
<td>Generation (MW)</td>
</tr>
<tr>
<td>G1</td>
<td>6.56</td>
<td>53.62</td>
</tr>
<tr>
<td>G2</td>
<td>6.31</td>
<td>60.22</td>
</tr>
<tr>
<td>G3</td>
<td>12.13</td>
<td>39.54</td>
</tr>
<tr>
<td>G4</td>
<td>7.98</td>
<td>30.00</td>
</tr>
<tr>
<td>G5</td>
<td>7.50</td>
<td>40.00</td>
</tr>
<tr>
<td>G6</td>
<td>6.50</td>
<td>40.00</td>
</tr>
</tbody>
</table>

TABLE IV. STRATEGIES OF GENERATORS 2 AND 3 ESTIMATED BY GENERATOR-1 FOR CASE-II (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Generator(j)</th>
<th>S11</th>
<th>P11</th>
<th>S12</th>
<th>P12</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1.2</td>
<td>0.6</td>
<td>1.4</td>
<td>0.4</td>
</tr>
<tr>
<td>3</td>
<td>1.2</td>
<td>0.7</td>
<td>1.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Since, maximum number of bidding strategies for rivals 2 & 3 are two (Gj=2), and for rivals 4, 5, 6, it is one (Gj=1). Therefore, as per equation (16), rivals’ strategic combinations are 2^2=4.

TABLE V. PAYOFF TABLE FOR MULTI OBJECTIVE BIDDING STRATEGY FOR CASE-II (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Method</th>
<th>Objective function</th>
<th>Expected profit ($/h)</th>
<th>Risk ($/h)</th>
<th>Value of decision variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFO</td>
<td>Expected profit maximization</td>
<td>338.21</td>
<td>39.45</td>
<td>2.80</td>
</tr>
<tr>
<td></td>
<td>Risk minimization</td>
<td>332.04</td>
<td>38.92</td>
<td>3.00</td>
</tr>
<tr>
<td>SQP</td>
<td>Expected profit maximization</td>
<td>326.78</td>
<td>38.58</td>
<td>2.72</td>
</tr>
<tr>
<td></td>
<td>Risk minimization</td>
<td>320.54</td>
<td>38.01</td>
<td>2.79</td>
</tr>
</tbody>
</table>

TABLE VI. OPTIMAL SOLUTIONS OF BIDDING STRATEGY FOR CASE-II (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Method</th>
<th>Expected profit ($/h)</th>
<th>Risk ($/h)</th>
<th>Bidding strategy variable ($/h)</th>
<th>Computation time (sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFO</td>
<td>333.50</td>
<td>39.10</td>
<td>2.74</td>
<td>472</td>
</tr>
<tr>
<td>SQP</td>
<td>324.00</td>
<td>38.29</td>
<td>2.75</td>
<td>74</td>
</tr>
</tbody>
</table>

TABLE VII. LMPS AND OUTPUT OF GENERATORS FOR CASE-II (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Generator number</th>
<th>BFO algorithm</th>
<th>SQP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LMPs ($/MWh)</td>
<td>Generation (MW)</td>
</tr>
<tr>
<td>G1</td>
<td>8.21</td>
<td>56.98</td>
</tr>
<tr>
<td>G2</td>
<td>7.88</td>
<td>57.01</td>
</tr>
<tr>
<td>G3</td>
<td>16.33</td>
<td>39.40</td>
</tr>
<tr>
<td>G4</td>
<td>10.30</td>
<td>50.00</td>
</tr>
<tr>
<td>G5</td>
<td>7.77</td>
<td>40.00</td>
</tr>
<tr>
<td>G6</td>
<td>7.25</td>
<td>40.00</td>
</tr>
</tbody>
</table>

TABLE VIII. STRATEGIES OF OPPONENT GENERATORS ESTIMATED BY GENERATOR-1 FOR CASE III (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Generator(j)</th>
<th>S11</th>
<th>P11</th>
<th>S12</th>
<th>P12</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1.2</td>
<td>0.7</td>
<td>1.4</td>
<td>0.3</td>
</tr>
<tr>
<td>3</td>
<td>1.3</td>
<td>0.25</td>
<td>1.25</td>
<td>0.75</td>
</tr>
<tr>
<td>4</td>
<td>1.4</td>
<td>0.3</td>
<td>1.6</td>
<td>0.7</td>
</tr>
<tr>
<td>5</td>
<td>1.5</td>
<td>0.8</td>
<td>1.2</td>
<td>0.2</td>
</tr>
<tr>
<td>6</td>
<td>1.6</td>
<td>0.4</td>
<td>1.2</td>
<td>0.6</td>
</tr>
</tbody>
</table>

TABLE IX. PAYOFF TABLE FOR MULTI OBJECTIVE BIDDING STRATEGY FOR CASE-III (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Method</th>
<th>Objective function</th>
<th>Expected profit ($/h)</th>
<th>Risk ($/h)</th>
<th>Value of decision variable (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFO</td>
<td>Expected profit maximization</td>
<td>344.63</td>
<td>39.84</td>
<td>2.81</td>
</tr>
<tr>
<td></td>
<td>Risk minimization</td>
<td>339.83</td>
<td>39.33</td>
<td>3.00</td>
</tr>
<tr>
<td>SQP</td>
<td>Expected profit maximization</td>
<td>306.91</td>
<td>41.04</td>
<td>3.00</td>
</tr>
<tr>
<td></td>
<td>Risk minimization</td>
<td>306.91</td>
<td>41.04</td>
<td>3.00</td>
</tr>
</tbody>
</table>

TABLE X. OPTIMAL SOLUTIONS OF BIDDING STRATEGY FOR CASE III (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Method</th>
<th>Expected profit ($/h)</th>
<th>Risk ($/h)</th>
<th>Bidding strategy variable ($/h)</th>
<th>Computation time (sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFO</td>
<td>342.23</td>
<td>39.58</td>
<td>2.90</td>
<td>1674</td>
</tr>
<tr>
<td>SQP</td>
<td>306.91</td>
<td>41.04</td>
<td>3.00</td>
<td>128</td>
</tr>
</tbody>
</table>

TABLE XI. LMPS AND OUTPUT OF GENERATORS FOR CASE III (30 BUS SYSTEM)

<table>
<thead>
<tr>
<th>Generator number</th>
<th>BFO algorithm</th>
<th>SQP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LMPs ($/MWh)</td>
<td>Generation (MW)</td>
</tr>
<tr>
<td>G1</td>
<td>8.31</td>
<td>38.94</td>
</tr>
<tr>
<td>G2</td>
<td>8.11</td>
<td>59.44</td>
</tr>
<tr>
<td>G3</td>
<td>15.83</td>
<td>40.69</td>
</tr>
<tr>
<td>G4</td>
<td>10.31</td>
<td>50.00</td>
</tr>
<tr>
<td>G5</td>
<td>9.40</td>
<td>40.00</td>
</tr>
<tr>
<td>G6</td>
<td>9.36</td>
<td>34.31</td>
</tr>
</tbody>
</table>

Simulation results are given in Tables IX, X & XI. In this case, profit of the generator-1 has increased as compared to the previous two cases, because of LMP at bus-1 has increased. In this case, simulation time has increased in comparison with the previous cases, because of 32 possible combinations of the rivals.

In all the three cases, it has been observed that the BFO outperformed the SQP in terms of solution accuracy, because the BFO avoids the local optima by combining the gradient information and heuristic in the search process. Further, it has been observed that the financial risk has increased with the increase of profit. However, the change in the risk as compared to the change in the profit is less due to less variation in the dispatched output of generator-1.

VII. Conclusion

A bi-level multi objective optimization problem has been proposed to develop the optimal bidding strategy of a generator. The lower level problem solves the market
clearing problem performed by the SO, and the upper level problem maximizes the individual generators’ profit and minimizes their risk. Probabilistic approach has been used to model the rivals’ bidding behavior. The proposed multi objective problem optimizes the two conflicting objective functions of the profit maximization and the risk minimization, simultaneously. The ε-constraint method has been used to obtain the pareto-optimal solutions of proposed multi-objective problem. A fuzzy approach has been used to determine the most efficient solution among the pareto optimal solutions of the BLMOOP. BFO algorithm has been used to compare those obtained using the SQP. The performance of the BFO algorithm is found to be superior to the SQP due to its better search capability in all the three cases studied.

References


