RISK-CONSTRAINED OPTIMAL BIDDING STRATEGY FOR A GENERATION COMPANY USING SELF-ORGANIZING HIERARCHICAL PARTICLE SWARM OPTIMIZATION

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This article proposes optimal bidding strategies for a generation company (GenCo) considering risk of profit variation by self-organizing hierarchical particle swarm optimization with time-varying acceleration coefficients (SPSO-TVAC). Based on a trade-off technique, the expected profit maximization and risk minimization are achieved. Nonconvex operating cost functions of thermal generation units and minimum up/down time constraints are cooperated to provide the optimal bid prices in a day-ahead uniform price spot market. The rivals’ bidding behavior is estimated by Monte Carlo simulation. Test results indicate that SPSO-TVAC is superior to inertia weight approach particle swarm optimization (IWAPSO) and genetic algorithm (GA) in searching the optimal bidding strategy solutions.

INTRODUCTION

In a deregulated electricity market, generation companies (GenCos) could maximize their expected profits by developing bidding strategies (David and Wen 2000). In fact, they have to make a decision based on forecasted information. For example, a GenCo does not know the actual market clearing price (MCP) beforehand because it depends on bidding behavior of market participants. Thus, the market price uncertainty is a major concern for GenCos in energy trading.

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There has been much research on optimal bidding strategies in the energy market. The optimal bidding problem for a single trading period using a dynamic programming approach is introduced in David (1993). The game-based approaches are applied in order to find the equilibrium point of the bidding strategies. However, there are two main assumptions that might not be reasonable for bidding strategy problems. First, the operating cost functions of competitors are known (Ferrero, Shahidehpour, and Ramesh 1997; Soleymani, Ranjbar, and Shirani 2008). Second, the bidding behavior is modeled as discrete quantities (Ferrero, Rivera, and Shahidehpour 1998; Kian and Cruz 2005), in which the equilibrium state might not be easily found. In Zhang, Wang, and Luh (2000), Lagrangian relaxation is proposed to solve the simplified bidding and self-scheduling problems in which the market situation is modeled as discrete quantities. However, the model may not be appropriate for multi-participant environment. In Richter and Sheble (1998), a heuristic approach genetic algorithm (GA), is proposed to find equilibrium prices of a double auction market. This approach is attractive, but there are very few markets implementing the double auction model (David and Wen 2000). In Wen and David (2001), an overall bidding strategy in a day-ahead market based on GA is proposed. The same approach is extended for the spinning reserve market (Wen and David 2002). In Bajpai and Singh (2007), the optimal bidding strategy in a uniform-price spot market using fuzzy adaptive particle swarm optimization (FAPSO) is proposed. The Monte Carlo (MC) method is used to simulate the rivals’ behavior in the market. Multihourly trading in a uniform-price spot market using block bid model with a precise model of nonlinear operating cost functions and minimum up/down time constraints are considered. Because rivals’ bidding behaviors are statistically approximated, the GenCo could dispatch differently from the expectation; therefore, the risk of profit variation should be considered in the strategic bidding problem.

There are several researchers who are considering price risk in the strategic bidding problem. In Ma et al. (2005), a risk-constrained optimal bidding strategy for a GenCo is developed. Profit maximization and risk minimization with the trade-off technique are formulated as a stochastic optimization problem without considering technical constraints. In Rodriguez and Ander (2004), the bidding strategies are designed for different attitude participants—risk aversion and risk preference. This approach develops the price scenarios to deal with the uncertainty in the electricity market, whereas historical forecasted MCPs are needed. In Conejo et al. (2004), the self-scheduling problem of a price-taker producer is addressed. The profit and risk are simultaneously considered, and the operating constraints, ramp rate and minimum up/down time limits, are considered. However, this approach is simplified by the use of estimated MCP in determining the revenue. In Rahimiyan and Mashhadi (2007), the price risk obtained from bidding strategies in which the MCP is modeled as normal probability distribution.
function is analyzed. Even though the MCP can be precisely forecasted based on historical data, in an imperfect competitive market, the MCP could be influenced by bidding behaviors of market participants (David and Wen 2000). In Boonchuay and Ongsakul (2009), a risk-constrained optimal bidding strategy in a multihourly uniform-price spot market, using inertia weight approach particle swarm optimization (IWAPSO), is proposed. The minimum up/down time constraints are considered in providing the optimal bid prices. However, IWAPSO is not efficient in searching the optimal solution compared with a novel particle swarm optimization (PSO) (Ratnaweera, Halgamuge, and Watson 2004; Chaturvedi, Pandit, and Srivastava 2008).

In this article, the risk-constrained bidding strategy model extended from Boonchuay and Ongsakul (2009) is proposed. The GenCo’s objective function including the expected profit maximization and risk minimization is solved by a novel self-organizing hierarchical particle swarm optimization with time-varying acceleration coefficients (SPSO-TVAC). The MC approach is employed to simulate rivals’ behavior in the market environment. The proposed bidding strategy is illustrated on a day-ahead uniform-price spot market with step-wise bidding protocol. Nonconvex operating cost functions of thermal generating units and minimum up/down time constraints are considered. For comparison, SPSO-TVAC is compared to IWAPSO and GA in searching for the optimal bidding strategy solutions.

The rest of the paper is organized as follows. The next section describes GenCo’s expected profit and associated risk in the bidding problem. Then problem formulation of the risk-constrained optimal bidding strategy is expressed. Afterwards, the solution methodologies based on SPSO-TVAC and MC approaches for the optimal bidding problem are proposed. For test results, a numerical example is used to illustrate the bidding model and to compare optimal solutions. Finally, the conclusion of the research is provided.

**GENCO’S EXPECTED PROFIT AND ASSOCIATED RISK**

In energy bidding, major uncertainties are the result of bidders’ behaviors and the energy demands, resulting in diversity of the MCP. Thus, GenCo’s profit, calculated by \( MCP_t \cdot q_t - c_t \), is uncertain. If there are \( N \) scenarios of GenCo’s profit, the expected profit and the profit variance can be determined by

\[
E[F] = \frac{1}{N} \sum_{n=1}^{N} F_n
\]

\[
\text{var}[F] = \frac{1}{N} \sum_{n=1}^{N} (F_n - E[F])^2.
\]
Here, the profit variance is used as the risk information. The relation between the expected profit and risk of profit variation is shown in Figure 1. Each bidding scenario obtains a different expected profit and risk, provided by varying the risk penalty factor (Boonchuay and Ongsakul 2009). It should be noted that high variance of profit implies greater risk of the bidding strategy. A GenCo can select an appropriate bidding scenario in which the expected profit and the risk are acceptable.

**PROBLEM FORMULATION**

In general, a GenCo is interested in providing optimal bid prices that make a large profit with low risk of profit variation (Bjorgan, Liu, and Lawarrée 1999). The combination of two conflicting objectives including the expected profit maximization and the risk minimization can be achieved by a trade-off technique. The optimal bidding model can be expressed as

\[
\text{Max } E[F] - \alpha \cdot \text{var}[F].
\]  \hspace{1cm} (3)

Subject to:

1. Generation limits

\[
\underline{q} u_{i(t)} \leq q_{i(t)} \leq \overline{q} u_{i(t)}.
\]  \hspace{1cm} (4)

2. Minimum up time

\[
(1 - u_{i(t-1)}) \text{MUT}_i \leq h_{i(t)}^{on}.
\]  \hspace{1cm} (5)

3. Minimum down time

\[
u_{i(t-1)} \text{MDT}_i \leq h_{i(t)}^{off}.
\]  \hspace{1cm} (6)

*FIGURE 1* Relation between the expected profit and risk of profit variation in the bidding problem.
4. Bid price limits

\[ p_{\text{min}} \leq p_{i(t)} \leq p_{\text{max}}. \] (7)

In Equation (3), different values of \( x \) provide the efficient set of the optimal solution (Boonchuay and Ongsakul 2009). In Equation (4), the generation limit of each unit is considered. In Equations (5) and (6), all units of the concerned GenCo have to satisfy the minimum up/down time constraints. Finally, in Equation (7), the bid prices that are the decision variables are limited by the maximum and minimum bid prices.

The revenue is obtained by the product of the MCP and the generation dispatch. Thus, the GenCo’s cumulative profit is determined by

\[ F = \sum_{t=1}^{T} \sum_{i=1}^{I} (MCP_t \cdot q_{i(t)} - c_{i(t)}). \] (8)

Using uniform-price basis, MCP can be determined by the intersection between aggregate supply and demand curves. The nonconvex operating cost function of each unit can be written as (Bajpai and Singh 2007)

\[ c_{i(t)} = c^p_{i(t)} + c^u_i \{ u_{i(t)} (1 - u_{i(t-1)}) \} + c^d_i \{ (1 - u_{i(t)}) u_{i(t-1)} \} \] (9)

\[ c^p_{i(t)} = c_0 (q_{i(t)})^2 + c_1 q_{i(t)} + c_2 + \left| c_3 \sin(c_4(i - q_{i(t)})) \right| \] (10)

\[ c^u_i = h + \delta \left( 1 - \exp \left( \frac{-T_{\text{off}}}{\tau} \right) \right). \] (11)

**SOLUTION METHODS**

**Self-Organizing Hierarchical PSO with TVAC (SPSO-TVAC)**

SPSO-TVAC is an efficient population-based optimization technique, which is appropriate for nonconvex optimization problems (Chaturvedi, Pandit, and Srivastava 2008). Mathematically, it is defined as (Ratnaweera, Halgamuge, and Watson 2004)

\[ v_{id}^{k+1} = a_1^k \cdot \text{rand}_1 \cdot (p_{id}^k - x_{id}^k) + a_2^k \cdot \text{rand}_2 \cdot (p_{g_id}^k - x_{id}^k) \] (12)

\[ x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1}. \] (13)

In Equation (12), the first component is the cognitive component that represents the individual experience of each particle. The last component
is the social collaboration of the particles in finding the global optimal solution. The position of the $i$th particle on the $d$th dimension is updated by Equation (13). With the time-varying acceleration coefficient concept, the cognitive and social coefficients are given as

$$a^k_1 = a_{1i} - \frac{a_{1f}}{k_{max}} \cdot k$$

$$a^k_2 = a_{2i} - \frac{a_{2f}}{k_{max}} \cdot k.$$  \hspace{1cm} (14)

$$a^k_2 = a_{2i} - \frac{a_{2f}}{k_{max}} \cdot k.$$  \hspace{1cm} (15)

In addition, SPSO-TVAC has reinitialized velocity to enhance its performance when particles stagnate during the search. The pseudocode is shown as follows:

Main procedure
Velocity update equation in (12)
if $v_{id} = 0$
  if $\text{rand}3 < 0.5$
    $v_{id} = \text{rand}4 \cdot v_{dmax}$
  else $v_{id} = -\text{rand}5 \cdot v_{dmax}$
end if
end if
$v_{id} = \text{sign}(v_{id}) \cdot \min(\text{abs}(v_{id}, v_{dmax}))$
Position update equation in (13),

where $v_{id}$ is the velocity of the $i$th particle on the $d$th dimension, and $v_{dmax}$ is the maximum velocity limit on the $d$th dimension, which could be set between 10% to 15% of the dynamic range of the variable on each dimension (Chaturvedi, Pandit, and Srivastava 2008).

**Monte Carlo Simulation for Strategic Bidding Problem**

MC simulation is a stochastic computational technique that is performed by statistical sampling experiments. It needs a probability density function (PDF) of uncertainty source for simulation. For strategic bidding problems, the uncertainties come from bidding behaviors of market participants. A PDF that appropriately represents the distribution of historical bidding behaviors could be used. However, in this article, a normal PDF is employed to estimate rivals’ bidding behaviors, which can be expressed as (Bajpai and Singh 2007)

$$PDF\left(\hat{\mu}_i^n \right) = \frac{1}{\sqrt{2\pi} \hat{\sigma}_i^n} \cdot \exp\left(-\frac{(\hat{p}_i^n - \mu_i^n)^2}{2(\hat{\sigma}_i^n)^2}\right).$$  \hspace{1cm} (16)
**Optimal Bidding Strategy Algorithm Based on SPSO-TVAC and MC Simulation**

The main steps of the optimal bidding strategy algorithm based on SPSO-TVAC and MC simulation are as follows:

1. **Step 1**: Read generator data, rivals’ data, and load data.
2. **Step 2**: Specify maximum iteration of updating, \( \text{iter\_max} \), and maximum number of MC simulation, \( \text{mc\_max} \), and the risk weighting factor \( a \).
3. **Step 3**: Initialize bid prices of the GenCo or particles.
4. **Step 4**: Adjust the bid prices of the GenCo to satisfy the bid price limits in Equation (7).
5. **Step 5**: Set the iteration counter \( \text{iter} = 1 \).
6. **Step 6**: Execute the first MC simulation, \( \text{mc} = 1 \), as
   1. Generate rivals’ bid prices based on their PDF.
   2. Arrange all offered bids.
   3. Settle the MCP and quantity for all periods using the uniform-price basis.
   4. Check if \( \text{mc} < \text{mc\_max} \), \( \text{mc} = \text{mc} + 1 \) and go to step 6.1. Otherwise go to step 7.
7. **Step 7**: Evaluate the fitness function, which consists of the objective function in Equation (3) and a penalty function.
8. **Step 8**: Define local and global best particles.
9. **Step 9**: Update particles using Equations (12) to (14). If Equation (12) equals zero, the particle velocity will be reinitialized.
10. **Step 10**: Check if \( \text{iter} < \text{iter\_max} \), \( \text{iter} = \text{iter} + 1 \) and go to step 6. Otherwise stop.

The optimal bid prices of the GenCo with a fixed-risk weighting factor can be obtained by the proposed procedure.

**NUMERICAL RESULTS**

A day-ahead uniform-price spot market with step-wise bidding protocol is illustrated. A forecasted day-ahead demand is shown in Table 1. The probability distribution parameters of rivals’ bid prices are shown in Table 2. It is assumed that the rivals’ bidding behaviors can be expressed by the normal distribution (Bajpai and Singh 2007). The parameters of all units of the GenCo are shown in Table 3. The minimum and maximum bid price limits are set as 0 and 50 $/MWh, respectively.
Three different stochastic search approaches including SPSO-TVAC, IWAPSO, and GA are compared in searching the optimal bidding strategy solutions. For the PSO parameters, the maximum number of iterations is set as 300 with the swarm size of 50 particles. For SPSO-TVAC, the coefficient of cognitive component \( a_1 \) is decreased from 2.5 to 0.5 and the social learning factor \( a_2 \) is increased from 0.5 to 2.5. For IWAPSO, the inertia weight is varied from 0.9 to 0.4 and the acceleration coefficients are equal to 2. For the GA parameters, the maximum number of generation, population size, and mutation and crossover probabilities are set as 300, 50, 0.2, and 0.6, respectively. A 3 GHz Pentium IV personal computer with 1GB RAM is performed using MATLAB software.

### TABLE 1  Forecasted Day-Ahead Power Demand

<table>
<thead>
<tr>
<th>Hour</th>
<th>Load (MW)</th>
<th>Hour</th>
<th>Load (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1500</td>
<td>13</td>
<td>2500</td>
</tr>
<tr>
<td>2</td>
<td>1300</td>
<td>14</td>
<td>3000</td>
</tr>
<tr>
<td>3</td>
<td>1300</td>
<td>15</td>
<td>3500</td>
</tr>
<tr>
<td>4</td>
<td>1500</td>
<td>16</td>
<td>3500</td>
</tr>
<tr>
<td>5</td>
<td>2000</td>
<td>17</td>
<td>3500</td>
</tr>
<tr>
<td>6</td>
<td>2000</td>
<td>18</td>
<td>3000</td>
</tr>
<tr>
<td>7</td>
<td>2000</td>
<td>19</td>
<td>3000</td>
</tr>
<tr>
<td>8</td>
<td>2500</td>
<td>20</td>
<td>2500</td>
</tr>
<tr>
<td>9</td>
<td>3000</td>
<td>21</td>
<td>2000</td>
</tr>
<tr>
<td>10</td>
<td>3500</td>
<td>22</td>
<td>2000</td>
</tr>
<tr>
<td>11</td>
<td>3500</td>
<td>23</td>
<td>1500</td>
</tr>
<tr>
<td>12</td>
<td>3500</td>
<td>24</td>
<td>1500</td>
</tr>
</tbody>
</table>

### TABLE 2  Data of Rivals’ Bidding Parameters

<table>
<thead>
<tr>
<th>Unit 1</th>
<th>Unit 2</th>
<th>Unit 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q_n ) (MW)</td>
<td>( Q_n ) (MW)</td>
<td>( Q_n ) (MW)</td>
</tr>
<tr>
<td>( \mu_n^i ) ($/MWh)</td>
<td>( \mu_n^i ) ($/MWh)</td>
<td>( \mu_n^i ) ($/MWh)</td>
</tr>
<tr>
<td>( \sigma_n^i ) ($/MWh)</td>
<td>( \sigma_n^i ) ($/MWh)</td>
<td>( \sigma_n^i ) ($/MWh)</td>
</tr>
</tbody>
</table>

Rival 1: 200 10 2.5 300 20 3
Rival 2: 300 15 3 400 30 2
Rival 3: 250 10 2 300 15 2.5
Rival 4: 300 20 4 350 25 5

### TABLE 3  GenCo’s Data

<table>
<thead>
<tr>
<th>Unit 1</th>
<th>Unit 2</th>
<th>Unit 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c_0 ) ($/MW^2h)</td>
<td>( c_1 ) ($/MWh)</td>
<td>( c_2 ) ($/h)</td>
</tr>
<tr>
<td>( c_3 ) ($/h)</td>
<td>( c_4 ) (rad/MW)</td>
<td>( \eta ) (MW)</td>
</tr>
<tr>
<td>( s ) (MW)</td>
<td>MUT (h)</td>
<td>MDT (h)</td>
</tr>
<tr>
<td>( h ) ($)</td>
<td>( \delta ) ($)</td>
<td>( \tau ) (h)</td>
</tr>
<tr>
<td>( c_d ) ($)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Unit 1: 0.00482 7.97 78 150 0.063 200 50 1 1500 1500 1 100
Unit 2: 0.00194 15.85 310 200 0.042 400 100 2 1500 2500 1 200
Unit 3: 0.001562 32.92 501 300 0.0315 600 100 4 2000 4000 8 400
Monte Carlo Simulation Trials

The expected profit of the GenCo and the execution time are compared with the different numbers of MC simulation. In the test, SPSO-TVAC is employed to maximize the GenCo’s expected profit without considering risk. The average values from 20 runs of the simulation are shown in Table 4.

With different numbers of MC simulations from 500 to 10,000 trials, the GenCo’s expected profit is not diverse. The expected profit of the 500-trial MC approach differs from the expected profit of the 10,000-trial MC approach by 0.23%. Nevertheless, the execution time proportionally increases with the number of MC simulations. The 500-trial MC approach requires 9.07 minutes, whereas the 10,000-trial MC approach needs 179.12 minutes.

<table>
<thead>
<tr>
<th>Number of MC simulation</th>
<th>Expected profit ($)</th>
<th>Execution time (min.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>129929.39</td>
<td>9.07</td>
</tr>
<tr>
<td>1000</td>
<td>129763.81</td>
<td>17.35</td>
</tr>
<tr>
<td>5000</td>
<td>129648.88</td>
<td>89.45</td>
</tr>
<tr>
<td>10000</td>
<td>129634.56</td>
<td>179.12</td>
</tr>
</tbody>
</table>

Searching Performance Comparison

Here, various stochastic search approaches—including GA, IWAPSO, and SPSO-TVAC—are used to maximize the GenCo’s expected profit. The risk weighting factor is set as zero. The 1000-trial MC approach is performed to estimate the rivals’ behavior. With 20 runs of the simulation, the statistical test results and the execution time are compared in Table 5.

In Table 5, SPSO-TVAC provides the highest expected profit of $130,190.86, whereas IWAPSO and GA provide $129,772.49 and $129,458.54, respectively. The lowest and average values of the GenCo’s expected profit provided by SPSO-TVAC is higher than the solutions of both IWAPSO and GA. The standard deviation (SD) implies the stability of the optimizers in which the SPSO-TVAC solution has the least SD. Finally, on

<table>
<thead>
<tr>
<th></th>
<th>Expected profit ($)</th>
<th>Execution time (min.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>129458.54</td>
<td>122923.54</td>
</tr>
<tr>
<td>IWAPSO</td>
<td>129772.49</td>
<td>128770.30</td>
</tr>
<tr>
<td>SPSO-TVAC</td>
<td>130190.86</td>
<td>129662.77</td>
</tr>
</tbody>
</table>
average, SPSO-TVC requires 17.35 minutes to provide the solution, whereas IWAPSO and GA require 18.20 minutes and 32.16 minutes, respectively.

In Figure 2, the convergence characteristics of SPSO-TVC, IWAPSO, and GA are shown. The best solutions from each optimizer are compared. At the beginning of the search, IWAPSO can reach higher expected profit solutions than the other optimizers. However, after the 70th iteration, SPSO-TVC provides the highest expected profit solution. Because of the reinitialized process, SPSO-TVC can provide a better solution during the search, whereas IWAPSO keeps a local optimal solution. For GA, the solution convergence is slow compared with the other optimizers.

In Table 6, the different values of the risk weighting factor are considered to provide the optimal bidding strategies by SPSO-TVC, IWAPSO, and GA. Based on 20 runs of the simulation, the best fitness solutions from each optimizer are shown. The results indicate that SPSO-TVC could provide the highest fitness solutions for all risk-attitude bidding strategies compared with the other optimizers.

**TABLE 6** Optimal Bidding Strategy Solutions with Different Risk Attitudes by GA, IWAPSO, and SPSO-TVC

<table>
<thead>
<tr>
<th>Alpha</th>
<th>Optimizer</th>
<th>Expected Profit ($)</th>
<th>SD of Profit ($)</th>
<th>Best Fitness Value ($)</th>
</tr>
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<tbody>
<tr>
<td>0</td>
<td>GA</td>
<td>129458.54</td>
<td>5731.93</td>
<td>129713.35</td>
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<tr>
<td></td>
<td>IWAPSO</td>
<td>129772.49</td>
<td>5808.15</td>
<td>130118.55</td>
</tr>
<tr>
<td></td>
<td>SPSO-TVC</td>
<td>130190.86</td>
<td>5850.61</td>
<td>130190.86</td>
</tr>
<tr>
<td>0.005</td>
<td>GA</td>
<td>100295.84</td>
<td>2999.95</td>
<td>55297.16</td>
</tr>
<tr>
<td></td>
<td>IWAPSO</td>
<td>118500.56</td>
<td>3231.77</td>
<td>66278.71</td>
</tr>
<tr>
<td></td>
<td>SPSO-TVC</td>
<td>124250.75</td>
<td>3364.19</td>
<td>67661.80</td>
</tr>
<tr>
<td>0.01</td>
<td>GA</td>
<td>94596.62</td>
<td>2880.55</td>
<td>11620.93</td>
</tr>
<tr>
<td></td>
<td>IWAPSO</td>
<td>113584.83</td>
<td>3139.06</td>
<td>15047.85</td>
</tr>
<tr>
<td></td>
<td>SPSO-TVC</td>
<td>114168.75</td>
<td>3069.26</td>
<td>19964.60</td>
</tr>
</tbody>
</table>
Solutions with Different Risk Attitudes

The optimal solutions with different values of the risk factor in Table 6 are extensively illustrated here. The risk-neutral (Alpha = 0) and the risk-averse (Alpha = 0.01) strategies are compared. With the risk-neutral strategy, the optimal bid prices of unit 1 to 3 of the GenCo and the expected MCP in day-ahead spot market are shown in Figure 3.

In Figure 3, the unit-1’s entire period bid prices and the unit-2’s bid prices of hours 1 to 22 are lower than the expected MCP. It implies that both units 1 and 2 have expectation to dispatch power during these periods. On the other hand, the unit-3’s entire period bid prices and the unit-2’s bid prices of hours 23 and 24 are higher than the expected MCP to prevent the negative profit. In Figure 4, the solution of the risk-averse strategy is a bit different to the risk-neutral strategy solution. In hours 1, 2, 7 to 9, and 20 to 24, the unit-2 bid prices are higher than the expected MCP. The expected generation dispatch of the GenCo with different risk-attitude bidding strategies is shown in Table 7.

In Fig. 5, the GenCo’s hourly expected profits and standard deviation of profit with different degree of risk aversion are shown. With the risk-neutral bidding strategy, during hours 10 to 13 and hours 15 to 17, the expected profit is the highest because it is during the peak demand periods. With the risk-averse bidding strategy, there is the negative profit of $2990.89 on hour 3 because the unit-2 start-up cost is considered. In addition, during hours 7 to 9 and hours 20 to 24, the risk-averse bidding strategy provides the lowest risk of profit variation.

FIGURE 3 Optimal bid prices of the GenCo and expected MCP when Alpha = 0.
FIGURE 4 Optimal bid prices of the GenCo and expected MCP when \( \alpha = 0.01 \).

### TABLE 7 GenCo’s Expected Power Dispatch

<table>
<thead>
<tr>
<th>Hour</th>
<th>Expected Dispatch, MW (( \alpha = 0 ))</th>
<th>Expected Dispatch, MW (( \alpha = 0.01 ))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unit 1</td>
<td>Unit 2</td>
</tr>
<tr>
<td>1</td>
<td>199.90</td>
<td>311.75</td>
</tr>
<tr>
<td>2</td>
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<td>4</td>
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<td>302.75</td>
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<tr>
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CONCLUSION

In this article, the optimal bidding strategies for a GenCo considering risk of profit variation based on SPSO-TVAC and MC simulation are proposed. The GenCo’s strategies depend on the risk attitude in which the risk weighting factor has to be specified. A higher value of the risk weighting factor implies a more risk-averse bidding strategy. For the entire risk-attitude bidding strategies, SPSO-TVAC provides the highest fitness solutions with less solution diversity compared with IWAPSO and GA. The proposed approach could be a beneficial decision-making tool for a GenCo in energy trading. For future works, more informative risk-assessment approaches such as Value-at-Risk (VaR) and conditional VaR (CVaR) will be adopted in the strategic bidding problem.

NOMENCLATURE

\(a_k^1, a_k^2\) Acceleration coefficients of cognitive and social components at the \(k\)th iteration, respectively
\(a_1^i, a_2^i\) Initial values of cognitive and social acceleration coefficients, respectively
\(a_{1f}, a_{2f}\) Final values of cognitive and social acceleration coefficients, respectively
\(c_0, c_1, c_2\) Production cost coefficients of GenCo
\(c_3, c_4\) Constants of the valve point loading effect
\(c_{i(t)}\) Operating cost of the \(i\)th unit of GenCo at hour \(t\) in $
\(c_{i(t)}^p\) Production cost of the \(i\)th unit of GenCo at hour \(t\) in $
\(c_{i}^u\) Start-up cost of the \(i\)th unit of GenCo in $
\(c_{i}^d\) Shut-down cost of the \(i\)th unit of GenCo in $

FIGURE 5 GenCo’s expected hourly profit (bold lines) and standard deviation of profit (thin lines) with different degrees of risk aversion.
$F$  Cumulative profit of GenCo in $ 

$h$  Hot start-up cost in $ 

$h_{on}^{i(t)}$  Duration of the $i$th unit of GenCo which has been continuously ON at the end of hour $t$ in hours 

$h_{off}^{i(t)}$  Duration of the $i$th unit of GenCo which has been continuously OFF at the end of hour $t$ in hours 

$k_{max}$  Maximum number of iterations 

$k$  Iteration index 

$MCP_t$  Market clearing price at hour $t$ in $$/MWh 

$MDT_i$  Minimum down time of the $i$th unit of GenCo in hours 

$MUT_i$  Minimum up time of the $i$th unit of GenCo in hours 

$p_i^{(t)}$  Bid price of the $i$th unit of GenCo at hour $t$ in $$/MWh 

$p_i$  Bid price of unit $i$ of rival $n$ in $$/MWh 

$p_{min}$  Minimum bid price in $$/MWh 

$p_{max}$  Minimum bid price in $$/MWh 

$p_{best}^{d}$  Best position of the $i$th particle for the $d$th dimension reached at the $k$th iteration 

$p_{global}^{d}$  Global best particle for the $d$th dimension reached at the $k$th iteration 

$q_i^{(t)}$  Dispatched power of the $i$th unit of GenCo at hour $t$ in MW 

$q_i$  Minimum output of the $i$th unit of GenCo in MW 

$q_i^n$  Capacity of $i$th unit of GenCo in MW 

$Q^n_i$  Bidding quantity of the $i$th unit of $n$th rival in MW 

$rand_i$  Random number between 0 and 1, $i = 1, 2, \ldots, 5$ 

$T_{off}$  Duration of the unit which has been continuously OFF in hours 

$u_{i(t)}$  Operating status of the $i$th unit which is equal to 1 if it is committed at hour $t$, otherwise 0 

$v_{id}^k$  Velocity of the $i$th particle for the $d$th dimension at the $k$th iteration 

$x_{id}^k$  Position of the $i$th particle for the $d$th dimension at the $k$th iteration 

$\alpha$  Risk weighting factor 

$\delta$  Cold start-up cost in $ 

$\mu_i^n$  Mean bid price of the $i$th unit of $n$th rival in $$/MWh 

$\sigma_i^n$  Bid price standard deviation of the $i$th unit of the $n$th rival in $$/MWh 

$\tau$  Cooling time constants in hours

REFERENCES


