Multi-objective bidding strategy for GenCo using non-dominated sorting particle swarm optimisation

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Abstract: This paper proposes a multi-objective bidding strategy for a generation company (GenCo) in a day-ahead uniform price spot market using non-dominated sorting particle swarm optimisation (NSPSO). NSPSO is introduced to solve the multi-objective strategic bidding problem considering expected profit maximisation and risk (profit variation) minimisation. Monte Carlo (MC) simulation is employed to simulate rivals’ bidding behaviour. Test results indicate that the proposed approach can provide an efficient non-dominated solution front. In addition, it can be efficiently used as a decision-making tool for a GenCo compromising between expected profit and the risk of profit variation in a spot market.

Keywords: optimal bidding strategy; particle swarm optimisation; PSO; non-dominated sorting; Monte Carlo simulation.


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1 Introduction

Since 1980, electric power industries have been restructured to promote competitions and efficient uses of energy resources. In a perfect competitive environment, suppliers and consumers could freely and openly trade electric energy with fairness of social welfare maximisation (David and Wen, 2000). However, in practice, several electricity markets are not fully competitive because of many factors such as limited numbers of suppliers, transmission constraints, power loss, and different capacities of suppliers, etc. Consequently, a generation company (GenCo) could develop an optimal bidding strategy to maximise its profit. However, in a competitive environment, electricity price fluctuations can significantly impact to GenCo’s profit. Therefore, in a modern optimal bidding strategy, the risk of profit variation should be concerned. And the risk-constrained optimal bidding strategy becomes a multi-objective optimisation problem.

Typically, a multi-objective optimisation problem adopts the trade-off technique that combines conflicted objective functions of the problem to be a single objective function using weight coefficients. A GenCo may prefer to maximise profit whereas the risk of profit variation needs to be considered. A higher profit bidding scenario would increase the profit variation since when GenCo’s profit can be gained by stepping up bid prices. Consequently, it would have a lower chance to win the bid. Using the trade-off technique, a GenCo needs to vary the weight coefficient to consider different bidding scenarios and then select the most appropriate set of bid prices. A frontier of optimal bidding solutions from various values of the weight coefficient is known as the Pareto front. In multi-objective optimisation, well-distributed optimal solutions along the Pareto front are required for GenCo to make a decision based on its risk attitudes.

In the recent years, evolutionary algorithms (EAs) are shown to be as effective tools in solving multi-objective optimisation problems (Zitzler et al., 2000; Deb, 2001). EA’s success is due to its generic ability to handle large complex real world problems. Non-dominated sorting particle swarm optimisation (NSPSO) is one of the most effective EA modified from particle swarm optimisation (PSO) for solving multi-objective optimisation problems. NSPSO allows direct comparison between offsprings and parents, which improves pressuring of particles to a Pareto optimal front. The solution front is
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In the proposed approach, fast and elitist non-dominated sorting algorithm which is used in the fast and elitist non-dominated sorting genetic algorithm (NSGA) so-called NSGA-II (Deb et al., 2000) is applied to reduce the execution time for a multi-objective bidding problem.

In this paper, a multi-objective bidding strategy for a GenCos including profit maximisation and risk minimisation is provided by NSPSO. Monte Carlo (MC) simulation is performed to simulate rivals’ behaviour in a day-ahead uniform price spot market. It is assumed that there is only the supply side participating in the spot market, and additional markets such as reserve markets and contract markets are not included in this work.

The rest of the paper is organised as follows: in Section 2, literature reviews of EAs for multi-objective optimisation and risk-constrained optimal bidding strategies are provided. In Section 3, notations used in the paper are declared. In Section 4, the problem formulation including the GenCo’s objective function, the technical constraints, and the market clearing model is proposed. In Section 5, the solution methodologies including NSPSO, MC simulation, and the solution algorithm are expressed. In Section 6, numerical examples and results are discussed. Finally, in Section 7, relevant points are concluded.

2 Literature reviews

There are two parts in this section. The first describes multi-objective optimisation techniques and their applications. The second reviews previous research works on risk-constrained optimal bidding strategies.

2.1 EAs for multi-objective optimisation

There are number of multi-objective optimisation algorithms used to handle complexity of power system problems. In Palanichamy and Babu (2007), the trade-off technique is applied to provide economic and emission dispatch for thermal generation units. The research suggests that the trade-off technique is an effective and simple way to find the optimal solution by combining the two objective functions together using a price penalty factor. However, the solution highly depends on value of the penalty factor and it cannot provide a complete optimal solution front for decision-making. In Kennedy and Eberhart (1995), PSO is introduced as an effective algorithm for single objective optimisation problem and also shown its potentials for multi-objective optimisation in Coello and Lechuga (2002), Parsopoulos and Vrahatis (2002), Hu and Eberhart (2002), Tripathi et al. (2007) and Coello et al. (2002). However, PSO has a limitation in solving a multi-objective optimisation problem. Offsprings of PSO is influenced by the global best and personal best particles while comparison among personal best particles is impossible. This leads to weakling of pressure toward the actual Pareto optimal front. In Srinivas and Deb (1994), NSGA is introduced. NSGA uses the basic concept of genetic algorithm combined with non-dominated sorting concept. It is shown that the algorithm can provide effective optimal solutions for multi-objective optimisation problems. However, this algorithm required large computational effort. In Deb et al. (2000), NSGA-II is introduced with the fast and elitist non-dominated sorting process and crowding distance
assignment. The fast and elitist non-dominated sorting process could significantly reduce the NSGA-II execution time, while crowding distance assignment could maintain diversity of a non-dominated solution front. In Li (2003), NSPSO, which allows comparison between offsprings and personal best particles for all searching points, is introduced to solve multi-objective optimisation problems. The test results demonstrate NSPSO’s ability in solving the benchmark problems. In Ratnaweera et al. (2004), various types of PSO are compared in solving different benchmark problems. Their research suggests that the time varying acceleration coefficient (TVAC) approach has superior performance in providing the optimal solutions for test functions to the other optimisers. However, the value of inertia weight and coefficient has high influence on convergence trajectory (Cui et al., 2008). In Mollazei et al. (2007), PSO with fitness uniform selection strategy (FUSS) and random walk strategy (RWS) is introduced to handle high dimensional functions. The PSO performance drops when the number of decision variables rise. In van den Bergh and Engelbrecht (2006), multiple objective particle swarm optimisation (MOPSO) with sigma method is applied to find the optimal location of thyristor controlled series compensator (TCSC) and its parameter in order to increase total transfer capability. In Pindoriya and Singh (2009), MOPSO is proposed to find the Pareto optimal solution of generation scheduling for power producers while handling uncertainty of congestion and operation constraints. In Cai et al. (2009), a multi-objective chaotic particle swarm optimisation (MOCPSO) is developed to solve the environmental concerned economic dispatch problem. Numerical results show that MOCPSO could provide better solutions compared with typical MOPSO. In Benabid et al. (2009), NSPSO that is a novel version of MOPSO is applied to solve the multi-objective optimal location and parameter setting of static VAR compensator (SVC) and TCSC.

2.2 Risk-constrained optimal bidding strategies

In an imperfect competitive environment, a GenCo could develop bidding strategies to maximise its profit and also minimise the risk of price fluctuations. There are a number of researchers considering price risk in the strategic bidding problem. In Ma et al. (2005), a risk-constrained optimal bidding strategy for a GenCo is developed. The objective function includes profit maximisation and risk minimisation. Using the trade-off technique, the multi-objective optimisation problem is solved by traditional PSO. In Rodriguez and Ander (2004), optimal bidding strategies are developed for different risk attitudes, risk averse and risk seeker. This method provides price scenarios to handle the market price uncertainty. In this model, MCP is estimated from historical data. In Conejo et al. (2004), an optimal self-scheduling problem of a price-taker producer is addressed. The profit and risk are simultaneously considered with a number of technical constraints. This approach is simplified by using an estimated MCP based on an analytical approach to calculate the revenue. In Rahimiyani and Mashhadi (2007), price risk obtained from bidding strategies is analysed in which MCP is modelled as a normal probability distribution function. Even though MCP could be precisely estimated from historical data or analytical techniques, in an imperfect competitive market, the value of MCP could be influenced by bidding behaviours of participants. In Boonchuay and Ongsakul (2009), an efficient heuristic search method, inertia weight approach particle swarm optimisation (IWAPSO), is applied to solve a risk-constrained optimal bidding strategy. In this research, MC simulation is adopted to simulate rivals’ behaviours in the competitive electricity market. And the multi-objective optimisation problem is handled by the
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trade-off technique. With a specific value of the trade-off weight coefficient, the optimal solution could be provided. However, using discrete values of the coefficient, a well-distributed optimal solution front is hardly found.

3 Nomenclature

The notations used in this paper are stated below.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_{itc}^i$</td>
<td>Production cost of $i$th unit of the GenCo at hour $t$ in $</td>
</tr>
<tr>
<td>$F$</td>
<td>Cumulative profit of the GenCo in $</td>
</tr>
<tr>
<td>$Var[F]$</td>
<td>Profit variation or risk in $</td>
</tr>
<tr>
<td>$MCP_t$</td>
<td>Market clearing price at hour $t$ in $/MWh</td>
</tr>
<tr>
<td>$n^m_i$</td>
<td>Spot market profit of $i$th unit for $m$th rival’s strategy in $</td>
</tr>
<tr>
<td>$P_{(o)}^i$</td>
<td>Optimal bid price of $i$th unit of the GenCo in $/MWh</td>
</tr>
<tr>
<td>$p_{\text{min}}$</td>
<td>Minimum bid price in MW</td>
</tr>
<tr>
<td>$p_{\text{max}}$</td>
<td>Maximum bid price in MW</td>
</tr>
<tr>
<td>$q_i$</td>
<td>Minimum output of $i$th unit of the GenCo in MW</td>
</tr>
<tr>
<td>$q_{\text{max}}$</td>
<td>Maximum output of $i$th unit of the GenCo in MW</td>
</tr>
<tr>
<td>$q_{(t)}$</td>
<td>Dispatched power of $i$th unit of the GenCo at hour $t$ in MW</td>
</tr>
<tr>
<td>$Q^r_n$</td>
<td>Bidding quantity of $i$th unit of $n$th rival in MW</td>
</tr>
<tr>
<td>$R_k^n$</td>
<td>Offspring particle at iteration $k$</td>
</tr>
<tr>
<td>$\mu_i^n$</td>
<td>Mean bid price of $i$th unit of $n$th rival in $/MWh</td>
</tr>
<tr>
<td>$\sigma_i^n$</td>
<td>Bid price standard deviation of $i$th unit of the $n$th rival in $/MWh</td>
</tr>
<tr>
<td>$u_{(o)}$</td>
<td>Binary variable which is equal to 1 if the $i$th unit is committed at hour $t$ otherwise equal to 0</td>
</tr>
<tr>
<td>$t_{\text{on}}^i$</td>
<td>Duration of up time in hours</td>
</tr>
<tr>
<td>$t_{\text{off}}^i$</td>
<td>Duration of down time in hours</td>
</tr>
<tr>
<td>$\tilde{p}_n^r$</td>
<td>Bid price of unit $n$ of rival $r$ in $/MWh</td>
</tr>
<tr>
<td>$\mu_n^r$</td>
<td>Mean value of $\tilde{p}_n^r$ in $/MWh</td>
</tr>
<tr>
<td>$\sigma_n^r$</td>
<td>Standard deviation of $\tilde{p}_n^r$ in $/MWh</td>
</tr>
</tbody>
</table>

4 Problem formulation

A GenCo provides optimal bidding strategies that make high expected profit with low risk of profit variation. The multi-objective bidding strategy formulation can be expressed as
Maximise \( \{E[F] - \text{Var}[F]\} \) \hspace{1cm} (1)

subject to:

1. generation limits
\[
q_i(t) u_i(t) \leq q_i(t) \leq q_i(t) u_i(t)
\] \hspace{1cm} (2)

2. bid price limits
\[
p_{\text{min}} \leq p_i(t) \leq p_{\text{max}}
\] \hspace{1cm} (3)

3. minimum up time
\[
(1 - u_{i(t-1)}) \text{MUT} \leq h_{i(t)}^m
\] \hspace{1cm} (4)

4. minimum down time
\[
u_{i(t-1)} \text{MDT} \leq h_{i(t)}^d
\] \hspace{1cm} (5)

The revenue is obtained by product of the market clearing price \( (MCP_i) \) and the dispatched power \( q_{i(t)} \). The cumulative profit is described as
\[
F = \sum_{t=1}^{T} \sum_{i=1}^{M} (MCP_i \times q_{i(t)} - c_{i(t)})
\] \hspace{1cm} (6)

The profit variation or the risk can be calculated by equation (7)
\[
\text{Var}[F] = \sqrt{\frac{1}{M} \sum_{m=1}^{M} (n_m^m - E[F])}
\] \hspace{1cm} (7)

Each generation unit of the concerned GenCo is modelled using the non-convex production cost function \( c_{i(t)}^p \), the non-linear start-up cost function \( c_{i}^u \), and the constant shut-down cost \( c_{i}^d \). The operating cost function \( c_{i(t)} \) can be written as
\[
c_{i(t)} = c_{i(t)}^p + c_{i}^u \left[ u_{i(t)} \left(1 - u_{i(t-1)} \right) \right] + c_{i}^d \left[ (1 - u_{i(t)}) u_{i(t-1)} \right]
\] \hspace{1cm} (8)

\[
c_{i(t)}^p = c_o \left( q_{i(t)} \right)^2 + c_1 (q_{i(t)}) + c_2 + \left| c_3 \sin \left( c_4 (q_{i(t)} - q_{i(t)}) \right) \right|
\] \hspace{1cm} (9)

\[
c_{i}^u = h + \delta \left[ 1 - \exp \left( -\frac{T_{off}}{\tau} \right) \right]
\] \hspace{1cm} (10)

In (10), the exponential function represents the start-up costs including the hot start-up cost \( h \) and the cold start-up cost \( \delta \).
5 The optimal bidding strategy algorithm based on NSPSO

NSPSO is proposed to provide a set of non-dominated solution of multi-objective bidding strategy expressed in (1) to be as close as Pareto optimal solutions (Li, 2003) while maintaining the diversity of the population. Here, fast non-dominated sorting and crowding distance assignment are proposed for NSPSO.

5.1 Fast non-dominated sorting algorithm

For NSGA-II (Deb et al., 2000), fast non-dominated sorting algorithm mechanism is used to sort the population into various front level in order to select the population in the first level to be the next generation by calculating two values for each individual:

1. domination count, the number of other solutions which dominate that individual
2. $S_p$, a set of solutions dominated by that individual.

Firstly, with those two values, the solutions which have domination count to be zero, they will be classified into the first domination front. Secondly, subsequent fronts can be acquired by checking for $S_p$ of each individual in the first front and its domination count is reduced by one. The solution which has domination count equal to zero belongs to the next front. This process is continued until all of the solution is classified.

5.2 Diversity preservation

To satisfy the need of maintaining diversity of solution, a niching method called crowding distance assignment (Deb et al., 2000; Li, 2003) is used. The principle of this process is to estimate density of particular solution $i$ by determining the distance from solution point $i-1$ and $i+1$ when sorted in decent (or ascent) order of each objective as shown in Figure 1.

![Crowding distance evaluation](image)

Figure 1 Crowding distance evaluation
5.3 Particle updating approach

There are a number of methods to calculate current velocity of particles. However, in this paper, the updating equation of TVACs (TVAC-PSO) is used and expressed as (Ratnaweera et al., 2004)

\[
V_i^k = \omega^k V_i^{k-1} + a_1 \text{rand}_1 (P_{best_i}^k - P_i^k) + a_2 \text{rand}_2 (P_{g}^k - P_i^k)
\]  \hspace{1cm} (11)

\[
\omega^k = \omega_{\text{max}} - \left( \frac{\omega_{\text{max}} - \omega_{\text{min}}}{k_{\text{max}}} \right) \times k
\]  \hspace{1cm} (12)

\[
a_1 = a_{1i} - \left( \frac{a_{1i} - a_{2j}}{k_{\text{max}}} \right) \times k
\]  \hspace{1cm} (13)

\[
a_2 = a_{2i} - \left( \frac{a_{2i} - a_{2j}}{k_{\text{max}}} \right) \times k
\]  \hspace{1cm} (14)

\[
P_i^k = P_i^k + V_i^k
\]  \hspace{1cm} (15)

As shown in equation (11), for updating its velocity, every particle needs to know:

1. the velocity of the last iteration \(V_i^{k-1}\)
2. the local best particle \(P_{i,\text{best}}^k\) which is the particle that give the best rank and diversity (details in Sections 5.1 and 5.2) among the points where the particle has travel through
3. global best particle \(P_{g}^k\) is the best particle among the neighbours in iteration \(k\).

**Figure 2** Particle flow of NSPSO (see online version for colours)
The rest are constants factors to adjust the acceleration of $P_i^k$. The acceleration factors, $a_1$ and $a_2$, which vary from $a_{1i}$ to $a_{1j}$ and $a_{2i}$ to $a_{2j}$ along with iteration count, respectively. $rand_1$ and $rand_2$ are random numbers between 0 to 1 with uniform distribution. Finally, after calculating each particle velocity $V_i^k$, the particle’s position can be updated by (15). The production offspring and the next generation of population are shown in Figure 2.

5.4 MC simulation

To handle the uncertainty of rival’s bidding, MC simulation is adopted. MC simulation is a stochastic computational technique which is performed by statistical sampling experiments on a computer. It uses random numbers to model an uncertainty process based on the probability density function (PDF) of the uncertainty source. In a strategic bidding problem, a challenge is uncertainty from rivals’ bidding behaviours, which its PDF needs to be provided. However, assuming that the rivals’ bid prices are normally distributed, the PDF can be expressed as (Bajpai and Singh, 2007)

$$pdf\left(\hat{p}_n\right) = \frac{1}{\sqrt{2\pi \sigma_n^2}} \exp\left(-\frac{\left(\hat{p}_n - \mu_n\right)^2}{2\left(\sigma_n^2\right)^2}\right)$$

(16)

5.5 Uniform price market settlement

In this paper, the electricity market considers only a uniform price spot market without demand elasticity. All GenCos are requested to submit their bid prices and quantities to the market operator. The market clearing price (MCP) will be settled at the intersection between the supply curve and actual demand as illustrated in Figure 3. All winning bidders will be equally paid at the MCP.

**Figure 3** MCP determination (see online version for colours)
5.6 Solution procedure

The main steps of the optimal bidding strategy algorithm based on NSPSO and MC simulation are shown as below.

Step 1  **Input data**: Generator data, rivals’ data and load data are given. The generator data includes operating cost functions and constraints. The rivals’ data includes statistical bid prices and quantities of other GenCos.

Step 2  **Initial value and population**: The decision variable, bid price and quantity, of each unit belong to the producer are initialised with random real numbers within bid price and quantity ranges. The initial value of velocity $V_i^0$ is initialised by random numbers in the range of the decision variable with 50% probability for the opposite direction. The value of $P_{i, best}^k$ is set as the particle current position $P_i^k$. The maximum numbers of iterations for NSPSO and MC simulation are specified.

Step 3  **Reset MC counter**: Set the MC counter $mc = 1$ and the iteration counter $k = 1$.

Step 4  **Rivals’ strategy simulation**: The rivals’ bid prices are generated based on their PDF.

Step 5  **Market settlement process**: The uniform price basis is performed to provide the MCPs and quantities. All winning bidders will be paid at the MCP.

Step 6  **Profit and variance evaluation**: Cumulative profit and profit variance of the concerned GenCo are calculated using (6) and (7). This finishes one trial of MC simulation.

Step 7  **MC loop stopping criteria**: If the maximum number of the MC iterations is not reached, go to Step 4 and increase the MC counter by 1. Otherwise, go to the next step.

Step 8  **Particle ranking (1)**: Sort $P^k$ based on fast non-dominated sorting criterion and assign crowding distance.

Step 9  **Particle updating**: The global best particle $P_{g}^k$ can be selected from the top 5% of the non-dominated list from Step 8. Then, all particles are updated by (11) to (15) to generate offspring $R^k$.

Step 10  **Particle ranking (2)**: Combine $P^k$ and $R^k$ together and sort them based on fast non-dominated sorting and assign crowding distance again. Note that size of the population is now 2N.

Step 11  **Select population for next generation**: Select the particle that has the best ranking until the population size of the next generation particles is equal to $N$.

Step 12  **PSO loop stopping criteria**: If the iteration counter is less than the maximum number of iterations, go to Step 3 and increase the PSO counter by 1. Otherwise, stop.
6 Simulation and discussion

In this section, the proposed NSPSO is performed to solve three benchmark problems and a multi-objective bidding strategy problem.

6.1 Test problems

NSPSO is tested in solving three benchmark problems in Deb et al. (2000). Test results are shown in Appendix.

6.2 Numerical results

NSPSO is applied to determine an optimal bidding strategy of the GenCo in a day-ahead spot market using a uniform price basis with step-wise bidding protocol. It is assumed that there is only the supply side participating in the spot market, and other markets such as reserve markets and contract markets are not considered. The probability distribution parameters of rivals’ unit bid prices are shown in Table 2, and it will be performed by the normal PDF. The parameters of all units of the concerned GenCo are shown in Table 3.
For PSO parameters, the maximum number of iterations is set at 300 with the swarm size of 200 particles. The parameters associated with the TVAC-PSO are $a_1$ varying from 2.5 to 0.5 and $a_2$ varying from 0.5 to 2.5. The linearly decreasing inertia weight is from 0.9 to 0.4 with iteration cycle. A 2.1 GHz Intel Core 2Duo CPU T8100 with 2 GB of RAM is performed for the simulation under the MATLAB software.

**Table 1** Data of rival bidding parameters

<table>
<thead>
<tr>
<th>Rival 1 ($n = 1$)</th>
<th>Rival 2 ($n = 2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(MW)</td>
<td>($$/MWh)</td>
</tr>
<tr>
<td>Unit 1 ($i = 1$)</td>
<td>200</td>
</tr>
<tr>
<td>Unit 2 ($i = 2$)</td>
<td>300</td>
</tr>
<tr>
<td>Unit 3 ($i = 3$)</td>
<td>400</td>
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</table>

<table>
<thead>
<tr>
<th>Rival 3 ($n = 3$)</th>
<th>Rival 4 ($n = 4$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(MW)</td>
<td>($$/MWh)</td>
</tr>
<tr>
<td>Unit 1 ($i = 1$)</td>
<td>250</td>
</tr>
<tr>
<td>Unit 2 ($i = 2$)</td>
<td>350</td>
</tr>
<tr>
<td>Unit 3 ($i = 3$)</td>
<td>450</td>
</tr>
</tbody>
</table>

**Table 2** Data of generation unit of concerned GenCo

<table>
<thead>
<tr>
<th>$c_0$ ($$/MW^2h$)</th>
<th>$c_1$ ($$/MWh$)</th>
<th>$c_2$ ($$/h$)</th>
<th>$c_3$ (rad./MW)</th>
<th>$\bar{q}$</th>
<th>$q$</th>
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<tr>
<td>Unit 1</td>
<td>0.00482</td>
<td>7.97</td>
<td>78</td>
<td>0.063</td>
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<tr>
<td>Unit 2</td>
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<td>Unit 3</td>
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<td>561</td>
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<table>
<thead>
<tr>
<th>MUT</th>
<th>MDT</th>
<th>$h$</th>
<th>$\delta$</th>
<th>$r$</th>
<th>$c_i^d$</th>
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<tbody>
<tr>
<td>Unit 1</td>
<td>1</td>
<td>1</td>
<td>1,000</td>
<td>1,500</td>
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</tr>
<tr>
<td>Unit 2</td>
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<tr>
<td>Unit 3</td>
<td>4</td>
<td>2</td>
<td>2,000</td>
<td>4,000</td>
<td>8</td>
</tr>
</tbody>
</table>

**Table 3** Hourly expected dispatched power of each unit of GenCo

<table>
<thead>
<tr>
<th>Hour</th>
<th>Unit 1</th>
<th>Unit 2</th>
<th>Unit 3</th>
<th>Hour</th>
<th>Unit 1</th>
<th>Unit 2</th>
<th>Unit 3</th>
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<tr>
<td>1</td>
<td>200.00</td>
<td>0.00</td>
<td>0.00</td>
<td>13</td>
<td>200.00</td>
<td>387.6</td>
<td>0.00</td>
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<tr>
<td>2</td>
<td>199.20</td>
<td>0.00</td>
<td>0.00</td>
<td>14</td>
<td>200.00</td>
<td>397.60</td>
<td>0.00</td>
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<tr>
<td>3</td>
<td>198.20</td>
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<td>0.00</td>
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<td>24</td>
<td>198.60</td>
<td>0.00</td>
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</table>
Here, NSPSO is applied to provide optimal bidding strategy for the next 24 hours with the forecast demand shown in Figure 5. The minimum bid price is simply specified using the marginal cost. Therefore, in this case, the minimum bid price of unit 1, unit 2 and unit 3 are set to 9.89 $/MWh, 17.40 $/MWh and 34.79 $/MWh, respectively.

Figure 5  Forecast power demand by system operator

6.3 Simulation results and discussion

In Figure 6, the first front of optimal solution is shown. Using the proposed NSPSO with 500-trial MC simulation, the algorithm can provide the optimal set of expected profit and profit variance within 150 minutes. The maximum expected profit is $129,540 with $5,796 standard deviation of profit. The minimum expected profit is $70,339 with $2,776 standard deviation. The simulation result shows the good diversity among the non-dominated front. Note the front of solution is not smooth because of the non-convex generation cost functions.

According to the objective function, the efficient solution could be selected depending on preference of the GenCo. However, in order to select the optimal risky bidding solution, the index of the mean-standard deviation ratio (MSR) could be adopted in this problem. The MSR index which is the Sharpe index (Haugen, 2001) without the risk-free asset is defined by (Boonchuay and Ongsakul, 2011)

$$MSR_i = \frac{E[F_i]}{\sigma_i}$$  \hspace{1cm} (17)

In (17), $E[F_i]$ and $\sigma_i$ are expected profit and standard deviation of $i^{th}$ solution, respectively. The solution with the maximum MSR implies the optimal risky strategy. In this case, the highest MSR solution has the expected profit of $123,600 with $4,862 standard deviation.

Table 3 shows the expected dispatch power of concerned GenCo. The results show that unit 1 obtains the maximum expected dispatch at the almost entire trading periods, while unit 2 obtains the maximum expected dispatch power only during hours 9 to 19. And unit 3 is not expected to be dispatched in any operating hours. In hours 5 to 7 and 21 to 22, unit 2’s expected dispatch power is lower than its minimum capacity. Thus, unit 2 might not be scheduled to supply the load during these off-peak periods.
Figure 6  Expected profit versus profit variance of concerned GenCo (see online version for colours)

Figure 7  Optimal bid price and expected MCP (see online version for colours)

In Figure 7, the expected bid prices of the concerned GenCo in the 24-hour trading period are shown. Bid prices of unit 1 are lower than the expected MCPs in the entire trading period while bid prices of unit 2 are under the expected MCPs during hours 9 to 20. But,
unit 3’s bid prices are higher than the expected MCPs for the entire operating hours. During the peak demand periods, units 1 and 2 are fully dispatched and the expected MCPs increase to the maximum. This causes the GenCo’s expected profit is very high compared with the profit during the off-peak periods.

In Figure 8, the hourly expected profits of the concerned GenCo without the risk constraint are shown. During hours 10 to 13 and 15 to 17, the total expected profit is the highest because the expected MCP is maximum during the peak demand periods. For unit 3, the expected profit is equal to zero since its bid prices are set over the expected MCP to avoid negative profit from the expensive operation cost. In hours 5 to 8, unit 2’s profit is slightly negative since the start up cost is considered.

Figure 8 Hourly expected profit curves of concerned GenCo (see online version for colours)

7 Conclusions

The multi-objective bidding strategy problem including profit maximisation and risk minimisation for a GenCo in a day-ahead uniform price spot market is effectively solved by NSPSO. A major modification on NSPSO is that the fast and elitist non-dominated sorting and crowding distance assignment are adopted to reduce computational effort and to obtain a well-distributed optimal solution front. Based on the non-dominated sorting technique, the first front of optimal solutions is selected to be the best solution set since it is closest to the Pareto optimal front. Also diversity on a non-dominated front is handled by the crowding distance assignment which measures distance among particles. The numerical results indicate that the proposed solution algorithm based on NSPSO and MC simulation is an effective approach in providing the optimal bid prices and quantities for the concerned GenCo. However, the GenCo needs to select an appropriate bidding strategy based on its risk attitude. This work also suggests the highest MSR solution as
the optimal risky bidding strategy. The proposed approach is a beneficial decision-making tool for a GenCo in managing spot market price risk. For future works, the proposed model could be extended to consider reserve markets, bilateral transactions, and locational marginal price-based markets.

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References


Multi-objective bidding strategy for GenCo using NSPSO


Appendix

Table 4  Test functions and optimal solutions

<table>
<thead>
<tr>
<th>Problem</th>
<th>n</th>
<th>Variable bounds</th>
<th>Objective functions</th>
<th>Optimal solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCH</td>
<td>1</td>
<td>$[-10^{-3}, -10^{-3}]$</td>
<td>$f_1(x) = x^2$ $f_2(x) = (x - 2)^2$</td>
<td>$x \in [0, 2]$</td>
</tr>
<tr>
<td>KUR</td>
<td>3</td>
<td>$[-5, 5]$</td>
<td>$f_1(x) = \sum_{i=1}^{n-1} \left(-10 \exp \left(-0.2 \sqrt{x_i^2 + x_{i+1}^2} \right)\right)$ $f_2(x) = \sum_{i=1}^{n} \left</td>
<td>x_i^{0.8} + 5 \sin x_i\right</td>
</tr>
<tr>
<td>ZDT2</td>
<td>30</td>
<td>$[0, 1]$</td>
<td>$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \left(x_1 / g(x)\right)^2\right] $ $g(x) = 1 + 9 \left(\sum_{i=2}^{n} x_i / (n-1)\right)$</td>
<td>$x_i \in [0, 1]$ $x_i = 0$ $i = 2, \ldots, n$</td>
</tr>
</tbody>
</table>

Source: Deb et al. (2000)

The simulation results of problem SCH solved by NSPSO are shown in Figures 9(a) and 9(b). In Figure 9(a), the plots of $f_1(x)$ and $f_2(x)$ versus $x$ are shown. The value of $x$ is in the range of given optimal solution. In Figure 9(b), relation between $f_1(x)$ and $f_2(x)$ is illustrated. For the KUR and ZDT2 problems, NSPSO could find the similar solution fronts to NSGA-II (Deb et al., 2000) as illustrated in Figures 10(a), 10(b), 11(a), and 11(b) respectively.

Figure 9  SCH solutions solved by NSPSO (see online version for colours)
Multi-objective bidding strategy for GenCo using NSPSO

Figure 10  KUR solutions compared between NSPSO and NSGA-II (see online version for colours)

Figure 11  ZDT2 solutions compared between NSPSO and NSGA-II (see online version for colours)