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A Risk-Constrained Optimal Bidding Strategy for a Generation Company by IWAPSO

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***Abstract*—In this paper, an optimal bidding strategy for a generation company by the inertia weight approach particle swarm optimization (IWAPSO) is proposed. The expected profit maximization and risk (profit variance) minimization are combined into the objective function of the optimization problem. Nonconvex operating cost functions of thermal generation units and minimum up/down time constraints are formulated to find the optimal bid prices for multi-hourly trading in a uniform price spot market. The rivals' behavior is approximated through the Monte Carlo (MC) simulation. The proposed method based on the IWAPSO and MC simulation can provide the efficient set of bid prices which is the best combinations between expected profit and risk. The mean-standard deviation ratio (MSR) index is used to select the optimal risky bid prices. The proposed approach is a profitable tool for a producer who needs to compromise between expected profit and risk in spot market. Moreover, this approach can be applied to different market models.**

***Index Terms*—Bidding strategy, particle swarm optimization, Monte Carlo simulation, spot market, uniform price, risk assessment, optimal risky scenario.**

I. NOMENCLATURE

The notations used in this paper are stated below.

$c_{i(t)}^{p}$	Production cost of the *i*th unit of Producer-A at hour *t* in $.
c_i^u	Start-up cost of the *i*th unit of Producer-A in $.
c_i^d	Shut-down cost of the *i*th unit of Producer-A in $.
F	Cumulative profit of Producer-A in $.
h	Hot start-up cost in $.
$h_{i(t)}^{on}$	Duration the *i*th unit of Producer-A has been continuously ON at the end of hour *t* in hours.
$h_{i(t)}^{off}$	Duration the *i*th unit of Producer-A has been continuously OFF at the end of hour *t* in hours.
MCP_t	Market clearing price at hour *t* in $/MWh.
MDT_i	Minimum down time of the *i*th unit of Producer-A in hours.
MUT_i	Minimum up time of the *i*th unit of Producer-A in hours.
$p_{i(t)}$	Optimal bid price of the *i*th unit of Producer-A in $/MWh.
$p_{\min}$	Minimum bid price in MW.
$p_{\max}$	Minimum bid price in MW.
$\underline{q}_i$	Minimum output of the *i*th unit of Producer-A in MW.
$\overline{q}_i$	Capacity of *i*th unit of Producer-A in MW.
$q_{i(t)}$	Dispatched power of the *i*th unit of Producer-A at hour *t* in MW.
Q_i^n	Bidding quantity of the *i*th unit of *n*th rival in MW.
T_{off}	Duration the unit 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, equal to 0.
τ	Cooling time constants in hours.
δ	Cold start-up cost in $.
μ_i^n	Mean bid price of the *i*th unit of *n*th rival in $/MWh.
σ_i^n	Bid price standard deviation of the *i*th unit of the *n*th rival in $/MWh.
α	Risk tolerance parameter.

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II. INTRODUCTION

IN competitive electricity markets, participants have to submit their price and quantity bids to the market operator for each hour in day-ahead or any trading period [1]. The market operator will settle the energy price for each hour as a uniform price or a pay-as-bid price. The settlement depends on the market clearing price (MCP) which is obtained through the intersection of the aggregate supplies and demands. In a uniform price basis, all winning bidders are paid at the MCP while, in a pay-as-bid basis, they are paid at the offered prices. In addition, due to limitation of the power transmission, the transactions have to be settled according to the physical constraints of the electricity network. Therefore, different nodal prices might arise when a constraint is binding [2].

A challenge problem that electricity producers always face is the development of bidding strategies to maximize their profits. Producers have to make a decision based on imperfect information on the market conditions, the MCP and the market clearing quantity (MCQ). Therefore, producers have to estimate their rivals' behavior to set the bid prices [3]. However, the risk consideration is necessary for producers to select the best strategy compromising between profit and risk.

There are many researches on optimal bidding strategies in power markets. The optimal bidding problem for a single trading period using a dynamic programming approach was firstly introduced in [4]. The game based approaches have been applied to find the equilibrium point of the optimal bidding strategy problems [5], [6]. The heuristic based bidding strategy with MC simulation was presented in [7]. In [8], an overall bidding strategy in a day-ahead market based on genetic algorithm was proposed. The same approach was extended for spinning reserve market [9]. However, the mentioned approaches were not included the inter-temporal operation constraints that may impact on the feasible bidding strategies.

In [10], the optimal bidding strategy in a uniform price spot market based on the fuzzy adaptive particle swarm optimization (FAPSO) was proposed. The MC method was used to simulate the rivals' behavior. Multi-hourly trading in a day-ahead market using block bid model with the precise model of nonlinear operating cost functions, and minimum up/down constraints were considered.

This paper proposes an optimal bidding strategy including expected profit maximization and risk (profit variance) minimization for a generation company by the IWAPSO. The MC simulation is performed to simulate the rivals' behavior in the market environment. The tradeoff technique [11] is used to combine both objectives that are to maximize expected profit and to minimize risk in spot market. In addition, the MSR index based method is used to select the optimal bid prices.

A uniform price spot market with step-wise bidding protocol is considered in this paper. Nonlinear operating cost functions of thermal generation units and minimum up/down time constraints are formulated to provide the optimal bidding strategy. Producers submit their bids in terms of quantity and price for each hour in 24-h horizon to compete in a day-ahead market. This is assumed that there is only the supply side participating in the market, and transmission constraints are not considered. Moreover, other markets such as reserve markets and contract markets are not included in this paper.

The rest of the paper is organized as follows: Section III expresses the problem formulation of this work. Section IV proposes the optimal bidding strategy algorithm based on the IWAPSO and the MC simulation. Section V illustrates the model through a numerical example. Section VI discusses about the proposed strategic bidding approach and its results. Finally, Section VII provides some relevant conclusions.

III. Problem Formulation

In general, a producer is interested in providing optimal bid prices that makes a large profit with low risk (profit variance) [12]. The combination of the both objectives, the expected profit maximization and the profit variance minimization, can be achieved by the tradeoff technique [11] as

$$\max_{p_{i(t)}} \quad \mathrm{E}\left[F\right]-\alpha * \mathrm{var}[F] \tag{1}$$

s.t.

1) Generation limits

$$\underline{q}_i u_{i(t)} \le q_{i(t)} \le \overline{q}_i u_{i(t)}. \tag{2}$$

2) Minimum up time

$$\left(1-u_{i(t-1)}\right) MUT_i \le h_{i(t)}^{on}. \tag{3}$$

3) Minimum down time

$$u_{i(t-1)} MDT_i \le h_{i(t)}^{off}. \tag{4}$$

4) Bid price limits

$$p_{\min} \le p_{i(t)} \le p_{\max}. \tag{5}$$

In (1), F is the cumulative profit of the concerned producer, Producer-A, and α is the risk tolerance parameter. The different values of α provide the efficient frontier [13]. In (2), $\underline{q}_i$ and $\overline{q}_i$ are the lower and upper limits of dispatched power output, and $u_{i(t)}$ is a binary variable which is equal to 1 if the ith unit is committed at hour t; otherwise, equal to 0. In (3) and (4), $h_{i(t)}^{on}$ and $h_{i(t)}^{off}$ are the duration of up and down times, respectively. In (5), the bid price $p_{i(t)}$ is limited by the minimum bid price $p_{\min}$ and the bid price cap $p_{\max}$. The minimum bid price may be specified by their marginal cost.

The revenue is obtained by product of the market clearing price (MCP_t) and the dispatched power ($q_{i(t)}$). The cumulative profit is expressed as

$$F = \sum_{t=1}^{T}\sum_{i=1}^{I}\left(MCP_t * q_{i(t)} - c_{i(t)}\right) \tag{6}$$

Each unit of the concerned producer, Producer-A, is represented by the non-convex production cost function $c_{i(t)}^{p}$ that is composted of the nonlinear 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 [10]

$$c_{i(t)} = c_{i(t)}^{p} + c_i^u\left\{u_{i(t)}\left(1-u_{i(t-1)}\right)\right\} + c_i^d\left\{\left(1-u_{i(t)}\right)u_{i(t-1)}\right\} \tag{7}$$

$$c_{i(t)}^{p} = c_0\left(q_{i(t)}\right)^2 + c_1\left(q_{i(t)}\right) + c_2 + \left|c_3 \sin\left(c_4\left(\underline{q}_i - q_{i(t)}\right)\right)\right| \tag{8}$$

$$c_i^u = h + \delta\left(1-\exp\left(\frac{-T_{off}}{\tau}\right)\right). \tag{9}$$

In (8), c_0, c_1 and c_2 are production cost coefficients and c_3 and c_4 are the constants of the valve point loading effect. In (9), the exponential function represents the start-up costs including the hot start-up cost h and the cold start-up cost δ.

IV. The Optimal Bidding Strategy Algorithm Based on IWAPSO

In this section, the optimal bidding strategy algorithm based on the IWAPSO is proposed. The MC method is performed to simulate the rivals' behavior in the market environment. The optimal bid prices of the concerned producer, Producer-A, is provided by the proposed algorithm.

IWAPSO is a modified version of the classical PSO presented in [14]. The updating equations of IWAPSO are expressed as [15]

$$V_i^{k+1} = \omega^k V_i^k + a_1 rand_1 * \left(P_{best\,i}^k - X_i^k\right) + a_2 rand_2 * \left(G_{best}^k - X_i^k\right) \tag{10}$$

$$\omega^k = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{k_{\max}} * k \tag{11}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1}. \tag{12}$$

A new velocity for each particle based on its previous velocity V_i^k is updated by (10). The particle's location at which the best fitness ($P_{best\,i}^k$) and the best particle among the neighbors (G_{best}^k) have been achieved. The inertia weight ω^k which controls the exploration properties of the algorithm is updated by (11). The learning factors, a_1 and a_2, are the acceleration constants which change the velocity of a particle towards P_{best} and G_{best}. The random numbers, $rand_1$ and $rand_2$, are uniformly distributed numbers in [0, 1]. Finally, each particle's position X_i^k is updated by (12).

The main steps of the optimal bidding strategy algorithm based on the IWAPSO and the MC simulation are as follows.

Step 1: Read generator data, rivals' data and load data.

Step 2: Specify maximum iteration of updating, *iter_max*, and maximum number of the MC simulation, *mc_max*, and the risk tolerance parameter α.

Step 3: Randomize initial bid prices of Producer-A.

Step 4: Adjust the bid prices of Producer-A to satisfy the bid price limits in (5).

Step 5: Initialize *iter* = 1

Step 6: Execute the first MC simulation, *mc*=1, as

- 6.1: Generate rivals' bid prices based on their probability distribution function.
- 6.2: Arrange all offered bids.
- 6.3: Settle the market clearing price and quantity for all periods.
- 6.4: Check if *mc*<*mc_max*, *mc*=*mc*+1 and go to step 6.1; else, go to step 7.

Step 7: Evaluate the fitness function which consists of the objective function in (1) and the penalty function.

Step 8: Define local and global best particles.

Step 9: Provide the optimal bid prices of Producer-A by the IWAPSO in (10) to (12).

Step 10: Check if *iter*<*iter_max*, *iter*=*iter*+1 and go to step 6; else, stop.

The optimal bid price ($p_{i(t)}$) for *i*th unit of Producer-A at hour *t* with a fixed risk tolerance is provided by the above procedure. In addition, the risk tolerance parameter α is varied to examine the profit variance.

V. Numerical Example

In this section, a day-ahead market using a uniform price basis with step-wise bidding protocol is illustrated. A forecasted demand for 24 hours is shown in Fig. 1. The probability distribution parameters of rivals' unit bid prices are shown in Table I, and it will be performed by the normal probability density function [10]. The parameters of all units of Producer-A, the concerned producer, are shown in Table II.

For the IWAPSO, The maximum number of iteration is taken as 150 with the swarm size of 50 particles. The parameters associated with the IWAPSO are $a_1 = a_2 = 2$. The linearly decreasing inertia weight is from 0.9 to 0.4 with iteration cycle.

A 3 GHz Pentium IV personal computer with 1GB of RAM is performed under MATLAB software.

In this simulation, the minimum bid price is easily specified by using the marginal cost without the start-up cost, the shut-down cost and the valve point loading effect. Therefore, in this case, the minimum bid price of unit-1, unit-2 and unit-3 are limited at 9.89 \$/MWh, 17.40 \$/MWh and 34.79 \$/MWh, respectively.

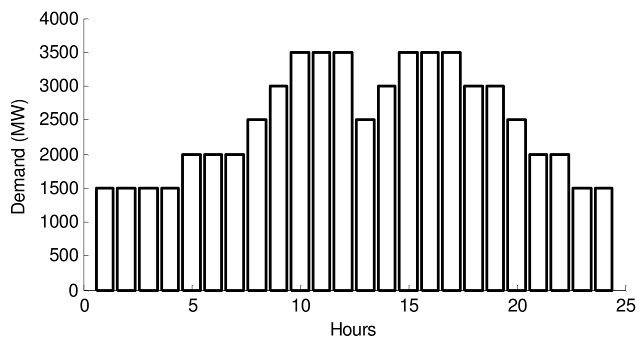

Fig. 1. Forecasted power demand by system operator.

TABLE I
DATA OF RIVAL'S BIDDING PARAMETERS

	Unit 1 (i = 1)			Unit 2 (i = 2)			Unit 3 (i = 3)		
	Q_i^n (MW)	μ_i^n (\$/MWh)	σ_i^n (\$/MWh)	Q_i^n (MW)	μ_i^n (\$/MWh)	σ_i^n (\$/MWh)	Q_i^n (MW)	μ_i^n (\$/MWh)	σ_i^n (\$/MWh)
Rival 1 (n=1)	200	10	2.5	300	20	3	400	30	3
Rival 2 (n=2)	300	15	3	400	30	2	500	50	4
Rival 3 (n=3)	250	10	2	300	15	2.5	300	20	2.5
Rival 4 (n=4)	300	20	4	350	25	5	450	40	5

TABLE II
PRODUCER-A DATA

	c_0 (\$/MW^{2}h)	c_1 (\$/MWh)	c_2 (\$/h)	c_3 (\$/h)	c_4 (rad./MW)	$\overline{q}$ (MW)	$\underline{q}$ (MW)	MUT (h)	MDT (h)	h (\$)	δ (\$)	τ (h)	c_i^d (\$)
Unit 1	0.00482	7.97	78	150	0.063	200	50	1	1	1000	1500	1	100
Unit 2	0.00194	15.85	310	200	0.042	400	100	2	1	1500	2500	1	200
Unit 3	0.001562	32.92	561	300	0.0315	600	100	4	2	2000	4000	8	400

A. Maximizing expected profit

In this part, the expected profit maximization is only concerned. The objective function in (1) is evaluated with the zero risk tolerance ($\alpha = 0$). The number of the MC simulation is taken as 10000 to provide the optimal bid prices of each unit of Producer-A.

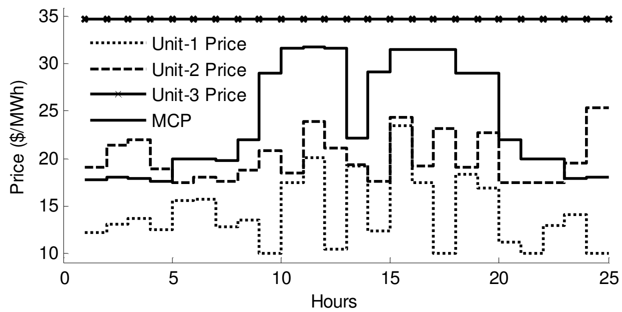

Fig. 2. Optimal bid prices of Producer-A and expected MCP.

In Fig. 2, the optimal bid prices of unit 1 to 3 of Producer-A and the expected MCP provided by the IWAPSO approach are shown. The optimal bid prices of unit-1 and unit-2 are higher than their marginal costs, while all bid prices of unit-3 are equal to its marginal cost that is the minimum bid price limit. The optimal bid prices of unit-2 during the peak demand periods are higher than the prices during the off-peak demand periods. Besides, during the less demand periods, the bid prices of unit-2 are higher than the expected MCP to prevent the negative profit.

In Table III, the expected power dispatch of Producer-A is shown. Unit-1 of Producer-A is expected to dispatch 200 MW for all trading periods. During hour 1 to 4 and 23 to 24, the bid prices of unit-2 are higher than the expected MCPs. This means that it may not be dispatched (ND). For unit-3, the bid prices are higher than the expected MCPs for all periods since the minimum bid price is limited by (5). Therefore, in this case, unit-3 is not dispatched during any trading periods.

TABLE III
EXPECTED POWER DISPATCH OF PRODUCER-A

Hour	Producer-A			Hour	Producer-A		
	Unit 1	Unit 2	Unit 3		Unit 1	Unit 2	Unit 3
1	200	ND	ND	13	200	391	ND
2	200	ND	ND	14	200	400	ND
3	200	ND	ND	15	200	400	ND
4	200	ND	ND	16	200	400	ND
5	200	381	ND	17	200	400	ND
6	200	362	ND	18	200	400	ND
7	200	373	ND	19	200	400	ND
8	200	394	ND	20	200	400	ND
9	200	400	ND	21	200	373	ND
10	200	400	ND	22	200	373	ND
11	200	400	ND	23	200	ND	ND
12	200	400	ND	24	200	ND	ND

In Table IV, the expected cumulative profit of Producer-A and the execution time are compared among different numbers of the MC simulation without the risk constraint. The 500-trial MC simulation provides the highest expected profit and the less execution time, $129846.46 and 9.47 min respectively, while the 10000 trials provide the lowest expected profit and the longest computation time, $129591.79 and 191.72 min respectively. The expected cumulative profits are a bit decreased with higher number of the simulation. On the other hand, the execution time is proportionally increased when increasing number of the MC simulation.

TABLE IV
EXPECTED PROFIT AND EXECUTION TIME COMPARED WITH DIFFERENT NUMBERS OF MONTE CARLO SIMULATION

Number of MC Simulation	Expected Profit ($)	Execution Time (Min.)
500	129846.46	9.47
1000	129666.19	18.93
5000	129622.84	94.34
10000	129591.79	191.72
Computer Configuration: 3GHz, PIV Processor, 1GB RAM		

In Fig. 3, the hourly expected profits of Producer-A without the risk constraint are shown. During the periods 10 to 13 h and 15 to 17 h, the expected profit is highest since it is during the peak demand periods. The expected profit of unit-3 is equal to zero since it has not been dispatched. In period 5, unit-2 provides the negative profit since the start up cost is taken.

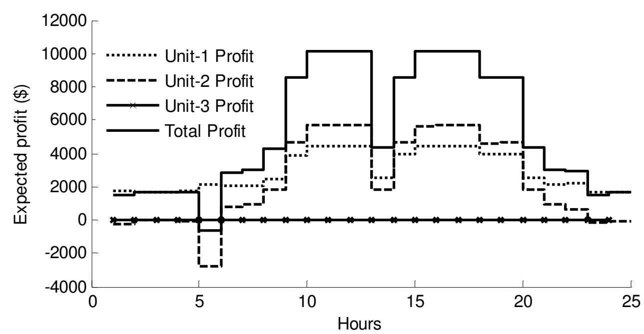

Fig. 3. Hourly expected profit curves of Producer-A.

B. Maximizing expected profit and minimizing risk

The 500-trial MC simulation is performed with the objective function in (1). The profit maximization and risk minimization are taken into account. The risk tolerant parameter α is varied between 0 to 0.01.

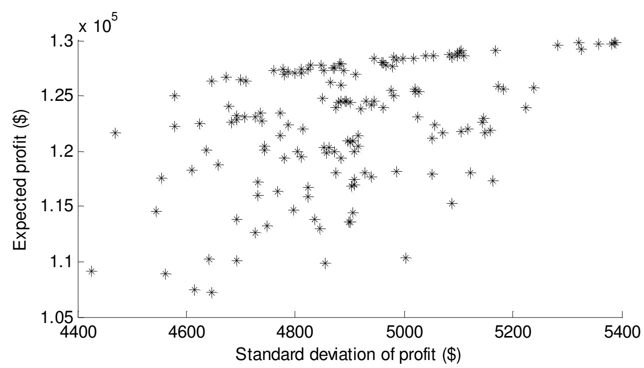

Fig. 4. Expected profit versus profit standard deviation of Producer-A.

In Fig. 4, the expected cumulative profit versus profit standard deviation of Producer-A is shown. Each scenario obtains bid prices of Producer-A with different expected profit and risk. The highest expected profit is $129846.46 with the profit standard deviation of $5390.18 while the lowest risk, the standard deviation of $4425.98, provides the expected profit of $109101.36.

In Fig. 5, the efficient scenarios for Producer-A are shown. These are the best combinations between expected profit and risk. In other words, efficient scenarios are non-dominated ones. Based on mean-variance (M-V) criterion [16], scenario-A (S_A) dominates scenario-B (S_B) if

$$\mathrm{E}[S_A] \geq \mathrm{E}[S_B] \quad (13)$$

and

$$\sigma_A \leq \sigma_B \quad (14)$$

and at least one inequality is strict. $\mathrm{E}[S_A]$ and σ_A are the expected profit and standard deviation of scenario-A, respectively. It is in the same way for scenario-B.

The dominated scenarios are eliminated by the M-V criterion in (13) and (14). The existing scenarios are the efficient set of bid prices, which is shown in Fig.5. In the next section, the method for selecting the optimal risky scenario for Producer-A will be described.

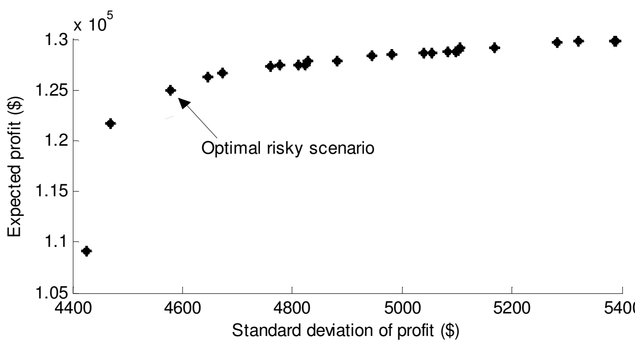

Fig. 5. Efficient scenario set of Producer-A.

C. Selecting the optimal risky scenario

Actually, efficient scenarios could be selected depending on the preference of the producer. However, in order to select the optimal risky scenarios, the index of the mean-standard deviation ratio (MSR) is performed in this problem. The MSR index which is the Sharpe index [17] without the risk-free asset is defined by

$$MSR_i = \frac{\mathrm{E}[S_i]}{\sigma_i}. \quad (15)$$

In (15), $\mathrm{E}[S_i]$ and σ_i are expected profit and standard deviation of ith scenario, respectively.

In Table V, the MSR values of selected efficient scenarios from Fig. 5 are compared. The scenario having the maximum MSR index implies the optimal risky scenario. In this case, scenario-8 has the highest MSR, 27.304, that obtains the expected profit of $124985.74 and the standard deviation of $4577.54.

TABLE V
MSR Comparison of Different Efficient Scenarios

Scenario	Expected Profit ($)	S.D. of Profit ($)	MSR
1	129846.46	5390.18	24.089
2	129148.57	5167.28	24.994
3	128765.41	5082.33	25.336
4	128363.43	4945.25	25.957
5	127882.37	4880.63	26.202
6	127395.13	4777.26	26.667
7	126640.42	4674.07	27.094
8	124985.74	4577.54	**27.304**
9	121701.57	4470.11	27.226
10	109101.36	4425.98	24.650

VI. Discussion

In this paper, a uniform price spot price is used to illustrate the multi-period treading. However, the proposed approach can be applied to provide the optimal bid prices in different market models such as pay-as-bid price and nodal price markets by modifying the market settlement process. In nodal price market, transmission constraints can be taken into account. Moreover, demand side bidding, reserve market and contract market can be integrated into this problem.

The IWAPSO based approach needs a few minutes to provide the optimal solution. In a simulation, the optimizer needs only 2.81sec. However, the MC method is performed to simulate the rivals' behavior, and many simulations are needed to provide the accurate solution, so a long execution time is required.

Although IWAPSO is an effective stochastic search approach to solve the non-convex optimization problem, it is very sensitive with their parameters such as the learning factors, a_1 and a_2, and the inertia weight ω. Therefore, it should be developed to be more suitable for this problem. In the future, the self-organizing hierarchical PSO [18] might be applied.

A profitable tool to provide the optimal bid price compromising between expected profit and risk (profit variance) has been developed. In the future, a decision making technique based on the modern portfolio theory [16] that includes degrees of risk aversion would be adopted into this problem.

VII. Conclusion

This paper provides the optimal bidding strategy for a generation company in a uniform price spot market. Maximizing expected cumulative profit with risk constraint is modeled as a stochastic optimization problem. The MC method has been used to deal with the uncertainty of the rivals' behavior in the market environment. The stochastic optimization problem has been solved by the IWAPSO. The proposed approach can provide the efficient scenario set of bid prices that optimally compromises between expected profit and risk (profit variance). The optimal risky scenario is selected by the highest MSR value. In a generation company's viewpoint, the proposed approach is a useful method for making a decision on multi-hourly trading to maximize their expected profit and also to minimize risk in spot market. This approach is easily applied into different market models including spinning reserve and contract markets. Moreover, transmission constraint and demand side bidding could be taken into consideration.

VIII. Acknowledgment

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IX. References

[1] S. Hunt, *Making Competition Work in Electricity*. New York: Wiley, 2002.

[2] E. Bompard, Y. Ma, R. Napoli, and G. Abrate, “The demand elasticity impacts on the strategic bidding behavior of the electricity producers,” *IEEE Trans. Power Syst*., vol. 22, no. 1, pp. 188–197, Feb. 2007.

[3] A. G. Bakirtzis, N. P. Ziogos, A. C. Tellidou, and G. A. Bakirtzis, “Electricity producer offering strategies in day-ahead energy market with step-wise offers,” *IEEE Trans. Power Syst*., vol. 22, no. 4, pp. 1804–1818, Nov. 2007.

[4] A. K. David, “Competitive bidding in electricity supply,” *Proc. Inst. Elect. Eng., Gen., Transm., Distrib*., vol. 140, no. 5, pp. 421–426, Sep. 1993.

[5] R. W. Ferrero, S. M. Shahidehpour, and V. C. Ramesh, “Transaction analysis in deregulated power systems using game theory,” *IEEE Trans. Power Syst*., vol. 12, no. 3, pp. 1340–1347, Aug. 1997.

[6] R. W. Ferrero, J. F. Rivera, and S. M. Shahidehpour, “Application of games with incomplete information for pricing electricity in deregulated power pools,” *IEEE Trans. Power Syst*., vol. 13, no. 1, pp. 184–189, Feb. 1998.

[7] L. Ma, F. Wen, and A. K. David, “A preliminary study on strategic bidding in electricity market with step-wise bidding protocol,” *in Proc. IEEE/Power Eng. Soc. Transmission and Distribution Conf. Exhib. 2002: Asia Pacifi*c, Oct. 2002, pp. 1960–1965.

[8] F. S. Wen and A. K. David, “Strategic bidding for electricity supply in a day-ahead energy market,” *Elect. Power Syst. Res*., vol. 59, no. 3, pp. 197–206, Aug. 2001.

[9] F. Wen and A. K. David, “A genetic algorithm based method for bidding strategy coordination in energy and spinning reserve markets,” *Artificial Intel. in Eng*, vol. 15, no. 1, pp. 71–79, Jan. 2002.

[10] P. Bajpai and S. N. Singh, “Fuzzy adaptive particle swarm optimization for bidding strategy in uniform price spot market,” *IEEE Trans. Power Syst*., vol. 22, no. 4, pp. 2152–2160, Aug. 2007.

[11] H. M. Markowitz, “Portfolio selection,” *J. Finance*, vol. 8, pp. 77–91, 1952.

[12] R. Bjorgan, C. Liu, and J. Lawarrée, “Financial risk management in a competitive electricity market,” *IEEE Trans. Power Syst.*, vol. 14, no. 4, pp. 1285–1291, Nov. 1999.

[13] A. J. Conejo, F. J. Nogales, J. M. Arroyo, and R. García-Bertrand, “Risk constrained self scheduling of a thermal power producer,” *IEEE Trans. Power Syst.*, vol. 19, pp. 1569–1574, 2004.

[14] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proc. IEEE Int. Conf. Neural Networks*, Nov. 1995, vol. 4, pp. 1942–1948.

[15] Y. Shi and R. C. Eberhart, “A modified particle swarm optimizer,” in *Proc. IEEE Congr. Evolutionary Computation*, 1998, pp. 69–73.

[16] Z. Bodie, A. Kane, and A. J. Marcus, *Investments*, 4th ed. Chicago: Irwin/McGraw-Hill, 1999.

[17] R. A. Haugen, *Modern Investment Theory*, 5th ed. New Delhi: Pearson Education, 2001.

[18] K. T. Chaturvedi, M. Pandit, and L. Srivastava, “Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch,” *IEEE Trans. Power Syst*., vol. 23, no. 3, pp. 1079–1087, Nov. 2008.

X. Biographies

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