Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

A Bilevel Optimization Model and a PSO-based Algorithm in Day-ahead Electricity Markets

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***Abstract*—Strategic bidding problems are becoming key issues in competitive electricity markets. This paper applies bilevel optimization theory to deal with this issue. We first analyze generating company strategic bidding behaviors and build a bilevel optimization model for a day-ahead electricity market. In this bilevel optimization model, each generating company will choose their bids in order to maximize their individual profits. A market operator will determine the output power for each unit and uniform marginal price based on the minimization purchase electricity fare. For solving this competitive strategic bidding problem described by the bilevel optimization model, a particle swarm optimization (PSO)-based algorithm is. Experiment results have demonstrated the validity of the PSO-based algorithm in solving the competitive strategic bidding problems for a day-ahead electricity market.**

***Keywords*—bilevel programming, electricity market, optimization, particle swarm algorithm, strategic bidding**

I. INTRODUCTION

Many decision problems have hierarchical structures, for which bilevel programming techniques have been developed. In a bilevel decision problem, a decision maker at the upper level is known as the leader, and at the lower level, the follower [1]. Tremendous research has been done on bilevel problems and a lot of achievements have been obtained [2]-[4]. The investigation of bilevel problems is strongly motivated by real world applications, and bilevel programming techniques have been applied with remarkable success in different domains such as decentralized resource planning [5], electric power market [6], logistics [7], civil engineering [8], and road network management [9][10].

Throughout the world, electric power industries are undergoing enormous restructuring processes from nationalized monopolies to competitive market. Because of the significance and particularity of electricity energy to national economics and the society, electricity market must be operated under the conditions of absolute security and stabilization. The research of electricity market has concerned a lot of researchers, owners and managers from electricity entities and authorities. The competitive mechanism of day-ahead markets is one of very important issues in the electricity market study, which can be described as follows. Each generating company (GC) submits a set of hourly (or half-hourly) generation prices and the available capacities for the following day. According to these data and an hourly (or half-hourly) load forecast, a market operator (MO) allocates generation output for each unit. Many researches have been done on how to strategically bid prices for those GCs, and how to dispatch generation output for MOs to each of their units. David and Wen [11] gave a literature survey on strategic bidding problems in competitive electricity markets. References [12]-[14] used supply function equilibrium models to describe a day-ahead electricity market to maximize GCs' profits and get Nash equilibrium[17]. References [15]-[17] used game theory to build a strategic bidding model for generating companies, and reach a Nash equilibrium solution. However, these models did not include ramp rate constraints, which are very crucial to guarantee a real optimal solution that considers factors from the real world. In addition, because strategic bidding problems involve two hierarchical optimizations, and are different from a conventional game model, a new Nash equilibrium is needed as a solution. From literature, only Pang and Fukushima [17] gave a general Nash equilibrium concept. Reference [18] used a bilevel optimization method to build a generation output allocation model, but did not consider competitive bidding problem from GCs. Reference [19] built a competitive strategic bidding model using bilevel optimization by means of the Cournot and Bertrand model, but did not include ramp rate constraints in their model. Therefore, this paper addresses the competitive strategic bidding problem in electricity markets using bilevel optimization techniques. It will propose a set of theories including a new Nash equilibrium concept and related bilevel optimization model, and also provide a way, the PSO algorithm, to get solutions.

The rest of this paper is organized as follows: Section II presents a competitive strategic bidding model for GCs and a generation output dispatch model for a MO in a day-ahead electricity market. Based on the analysis of strategic bidding behaviors in Section II, Section III proposes a bilevel optimization model, which includes ramp rate constraints, for describing strategic bidding problems in competitive electricity markets. To solve the problems described by a bilevel optimization model, Section IV develops a particle swarm optimization (PSO) technique-based solution algorithm. A set of experiments have been organized to test the validity of the proposed bilevel optimization model and the PSO-based algorithm. Section V shows these experiment results which can effectively support obtaining a solution for the competitive

978-1-4244-2794-9/09/$25.00 ©2009 IEEE

strategic bidding problems in an electricity market. Finally, conclusions and further study are highlighted in Section VI.

II. Bidding Strategy Analysis in Competitive Electricity Markets

In an auction-based day-ahead electricity market, each GC will try to maximize its own profit by strategic bidding. Generally speaking, each GC submits a set of hourly generation prices and available capacities for the following day. Based on these data and an hourly-load forecast, a MO will allocate generation output. This is a typical bilevel decision problem. GCs are leaders, and a MO is a follower. In this section, under the analysis of bidding strategy optimization problems, we build a competitive strategic bidding model for GCs and a generation output dispatch model for a MO in a day-ahead electricity market.

A. Generating Companies' Strategic Pricing Model

In the upper level, each GC (leader) concerns how to choose a bidding strategy, which includes generation price and available capacity. Many bidding functions have been proposed. For a power system, the generation cost function generally adopts a quadratic function of the generation output, i.e. the generation cost function can be represented as

$$C_j(P_j) = a_j P_j^2 + b_j P_j + c_j \tag{1}$$

where P_j is the generation output of generator j, and a_j, b_j, c_j are coefficients of generation cost function of generator j.

The marginal cost of generator j is calculated by

$$\lambda_j = 2a_j P_j + b_j \tag{2}$$

It is a linear function of its generation output P_j. The rule in a goods market may expect each GC to bid according to its own generation cost. Therefore we adopt this linear bid function. Suppose the bidding for *j*-th unit at time *t* is

$$R_{tj} = \alpha_{tj} + \beta_{tj} P_{tj} \tag{3}$$

where $t \in T$ is the time interval, T is time interval number, *j* represents the unit number, P_{tj} is the generation output of unit j at time t, and α_{tj} and β_{tj} are the bidding coefficients of unit j at time t.

According to the Justice Principle of "the same quality, the same network, and the same price", we adopt a uniform marginal price (UMP) as the market clearing price. Once the energy market is cleared, each unit will be paid according to its generation output and UMP. The payoff of GC_i is

$$F_i = \sum_{t=1}^{T} \left(\sum_{j \in G_i} UMP_t P_{tj} - \sum_{j \in G_i} (a_j P_{tj}^2 + b_{tj} P_{tj} + c_{tj}) \right) \tag{4}$$

where G_i is the suffix set of the units belonged to GC_i. Each GC wishes to maximize its own profit F_i. In fact, F_i is the function of P_{tj} and UMP_t, and UMP_t is the function of all units' bidding α_{tj}, β_{tj} and output power P_{tj}, which will impose impact to each other. Therefore, we can establish a strategic pricing model of these GCs as follows

$$\begin{aligned} &\max_{\alpha_{tj}, \beta_{tj}, j \in G_i} F_i = F_i(\alpha_{t1}, \beta_{t1}, \cdots, \alpha_{tN}, \beta_{tN}, P_{t1}, \cdots, P_{tN}) \\ &= \sum_{t=1}^{T} (UMP_t P_{ti} - \sum_{j \in G_i} (a_j P_{tj}^2 + b_j P_{tj} + c_j)) \\ &\qquad\qquad i = 1, 2, \cdots, L \end{aligned} \tag{5}$$

where L is GC number, $P_{ti} = \sum_{j \in G_i} P_{tj}$, $t = 1, 2, \cdots, T$.

The profit calculating for each GC will consider both P_{tj} and UMP_t, which can be computed by a MO according to the market clearing model.

B. A Market Operator's Generation Output Dispatch Model

A MO actually represents the consumer electricity purchase from GCs, under the conditions of security and stabilization. The objective of a MO is to minimize the total purchase fare while encouraging GCs to bid price as low as possible. It is reasonable that the lower the price, the more the output. Thus, the function value of a MO's objective will be calculated according to the bidding price. Most previous bidding strategic models do not include ramp rate constraints, without which, the solution for generating dispatch may not be a truly optimal one. We should consider the ramp rate constraints in the real world when modeling a generating dispatch. However, if a model includes ramp rate as constraints, the number of decision variables involved in the problem will increase dramatically, which imposes stronger request for a more powerful solution algorithm. Based on the analysis above, we build a MO's generation output dispatch model as follows:

$$\begin{cases} \min\limits_{P_{tj}} f = f(\alpha_{t1}, \beta_{t1}, \cdots, \alpha_{tN}, \beta_{tN}, P_{t1}, \cdots, P_{tN}) = \sum\limits_{t=1}^{T} \sum\limits_{j=1}^{N} R_{tj} P_{tj} \\ \sum\limits_{j=1}^{N} P_{tj} = P_{tD} \\ P_{j\min} \le P_{tj} \le P_{j\max} \\ -D_j \le P_{tj} - P_{t-1,j} \le U_j, t = 1, 2, \cdots, T \end{cases} \tag{6}$$

where $t \in T$ is the time interval, T is time interval number, *j* represents the unit number, P_{tj} is the generation output of unit j at time t, and α_{tj} and β_{tj} are the bidding coefficients of unit j at time t, P_{tD} is the load demand at time t, $P_{j\min}$ is the minimum output power of the *j*-th unit, $P_{j\max}$ is the maximum output power of the *j*-th unit, D_j is the maximum downwards ramp rate of the *j*-th unit, and U_j is the maximum upwards ramp rate of the *j*-th unit.

After receiving all GCs' bid data, MO determines the output power of each unit and UMP_t for all time slot *t*. UMP_t can be calculated according to the following steps:

Step1: calculate output power of each unit j for all time slot t using formula (6);

Step2: compute bidding R_{tj} corresponding to the generation output P_{tj};

Step3: account $UMP_t = \max_{j=1}^{N} R_{tj}$.

III. A BILEVEL OPTIMIZATION MODEL FOR COMPETITIVE ELECTRICITY MARKETS

From the analysis in Section II, we know that in an auction-based day-ahead electricity market, each GC tries to maximize its own profit by strategic bidding, and each MO tries to minimize its total electricity purchase fare. The decision from either of them will influence the other. This is a typical bilevel decision problem, which has multi-leaders and only one follower, with generating companies as leaders and a market operator as a follower.

By combining the strategic pricing model defined in (5) with the generation output dispatch model defined in (6), we establish a bilevel optimization model for competitive strategic bidding-generation output dispatch in an auction-based day-ahead electricity market as follows:

$$\begin{cases} \max\limits_{\alpha_{tj},\beta_{tj},j\in G_i} F_i = F_i(\alpha_{t1},\beta_{t1},\cdots,\alpha_{tN},\beta_{tN},P_{t1},\cdots,P_{tN}) \\ \qquad = \sum\limits_{t=1}^{T}(UMP_t P_{ti} - \sum\limits_{j\in G_i}(a_j P_{tj}^2 + b_j P_{tj} + c_j)), \\ \alpha_{t\min} \le \alpha_{tj} \le \alpha_{t\max}, \beta_{t\min} \le \beta_{tj} \le \beta_{t\max}, \\ t=1,2,\cdots,T; j=1,2,\cdots,N; i=1,2,\cdots,L \\ \min\limits_{P_{tj}} f = f(\alpha_{t1},\beta_{t1},\cdots,\alpha_{tN},\beta_{tN},P_{t1},\cdots,P_{tN}) \\ \qquad = \sum\limits_{t=1}^{T}\sum\limits_{j=1}^{N} R_{tj}P_{tj}, \\ \sum\limits_{j=1}^{N} P_{tj} = P_{tD}, \\ P_{j\min} \le P_{tj} \le P_{j\max}, \\ \text{-}D_j \le P_{tj} - P_{t-1,j} \le U_j, t=1,2,\cdots,T \end{cases} \quad (7)$$

where α_{tj} and β_{tj} are the bidding coefficients of unit j at time t, L is the number of generating companies, $P_{ti} = \sum_{j\in G_i} P_{tj}$, $P_{j\min}$ is the minimum output power of the j-th unit, $P_{j\max}$ is the maximum output power of the j-th unit, D_j is the maximum downwards ramp rate of the j-th unit, and U_j is the maximum upwards ramp rate of the j-th unit.

IV. A PARTICLE SWARM OPTIMIZATION-BASED ALGORITHM

In this section, we use the strategy adopted in PSO method [20] to develop a PSO-based algorithm to reach solutions for problems defined in (7).

Figure 1 outlines the structure and process of this algorithm. We first sample the leaders-controlled variables to get some candidate choices for leaders. Then, we use the PSO method together with Stretching technology [20] to get the follower's response for every leader's choice. Thus a pool of candidate solutions for both the leaders and the follower is formed. By pushing every solution pair moving towards current best ones, the whole solution pool is updated. Once a solution is reached for the leaders, we use Stretching technology [20] to escape local optimization. We repeat this procedure by a pre-defined count and reach a final solution.

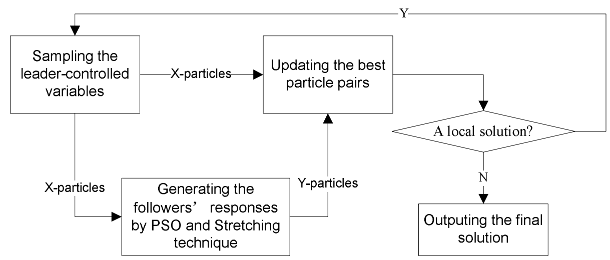

Figure 1. The outline of the PSO based algorithm

The detailed PSO-based algorithm has two parts, Algorithm 1, which is to generate the response from a follower, and Algorithm 2, which is to generate optimal strategies for all leaders. These two algorithms are specified as below.

Algorithm 1: Generate the response from a follower

Step 1: Input the values of x_{ij} from L leaders;

Step 2: Sample N_f candidates y_i and the corresponding velocities v_{y_i}, $i = 1,\ldots, N_f$;

Step 3: Initiate the follower's loop counter k_f =0;

Step 4: Record the best particles p_{y_i} and y^* from p_{y_i}, i = 1,…, N_f;

Step 5: Update velocities and positions using

$$v_{y_i}^{k+1} = w_f v_{y_i}^{K} + c_f r_{1l}^K (p_{y_i} - y_i^K) + c_f r_{2l}^K (y^{*K} - y_i^K)$$

$$y_i^{K+1} = y_i^K + v_{y_i}^{k+1}$$

Step 6: $k_f = k_f + 1$;

Step 7: If $k_f \geqslant MaxK_f$ or the solution changes for several consecutive generations are small enough, then we use Stretching technology to obtain the global solution and go to Step 8. Otherwise go to Step 5;

Step 8: Output y^* as the response from the follower.

Algorithm 2: Generate optimal strategies for leaders

Step 1: Sample N_l particles of x_{ij}, and the corresponding velocities $v_{x_{ij}}$;

Step 2: Initiate the leaders' loop counter $k_l = 0$;

Step 3: For the k-th particle, k =1,…, N_l, calculate the optimal response for each leader;

Step 3.1: Sample N_l particles x_{ij} within the constraints of x_{ij} ;

Step 3.2: By calling Algorithm 1, we calculate the rational response from the follower;

Step 3.3: Using PSO technique, we obtain the optimal response for each leader;

Step 4: Calculate the function value of every particle by Formula (7);

Step 5: Record $p_{x_{ij}}$, x_{ij}^*, j = 1,…, N_l for each x_{ij} , j = 1,…, N_l ;

Step 6: Update velocities and positions using

$$v_{x_{ij}}^{k+1} = w_l v_{x_{ij}}^{K} + c_l r_{1l}^K (p_{x_{ij}} - x_{ij}^K) + c_l r_{2l}^K (x_{ij}^{*K} - x_{ij}^K)$$

$$x_{ij}^{K+1} = x_{ij}^K + v_{x_{ij}}^{k+1}$$

Step 7: $k_l = k_l + 1$;

Step 8: If the sum of the differences between samples and optimal responses is smaller than ε or $k_l \geq MaxK_l$, then we use Stretching technology to current leaders' solutions to obtain the global solution.

Notations used in the algorithms are detailed in TABLE I.

TABLE I. EXPLANATION OF SOME NOTATIONS USED IN THE PSO-BASED ALGORITHM

N_l	the number of candidate solutions (particles) for leaders
N_f	the number of candidate solutions (particles) for the follower
x_{ij}	the j-th candidate solutions for the controlling variables from i-th leader
$p_{x_{ij}}$	the best previously visited position of x_{ij}
x_{ij}^*	current best one for particle x_{ij}
$v_{x_{ij}}$	the velocity of x_{ij}
k_l	current iteration number for the upper-level problem
y_i	the i-th candidate solution for the controlling variables from the follower
p_{y_i}	the best previously visited position of y_i
y^*	current best one for particle y
v_{y_i}	the velocity of y_i
k_f	current iteration number for the lower-level problem
$MaxK_l$	the predefined max iteration number for k_l
$MaxK_f$	the predefined max iteration number for k_f
w_l, w_f	inertia weights for leaders and follower respectively (coefficients for PSO)
c_l, c_f	acceleration constants for leaders and follower respectively (coefficients for PSO)
r_{1l}, r_{2l}, r_{1f}, r_{2f}	random numbers uniformly distributed in [0, 1] for leaders and follower respectively (coefficients for PSO)

V. EXPERIMENTS AND CASE STUDIES

In this section, we employ a real world strategic bidding problem in an electricity market to test the bilevel optimization model and the PSO-based algorithm developed in this study.

A. Test Data

In order to test the effectiveness of the proposed bilevel optimization model and the algorithm in solving the model defined by (7), a typical competitive strategic bidding case consisting of 3 companies with 6 units and 24 time intervals is chosen. The generation cost function can be calculated by using formula (1), where the cost coefficients a_j, b_j, c_j of unit j and other techniques data are given in TABLE II, the load demands for each time interval t are given in TABLE III.

TABLE II. TECHNICAL DATA OF UNITS

Unit No.	a_j		$P_{\min}$ (MW)	$P_{\max}$ (MW)
1	0.00028		50	680
2	0.00312		30	150
3	0.00048		50	360
4	0.00324		60	240
5	0.00056		60	300
6	0.00334		40	160
Unit No.	b_j	c_j	D_j (MW/h)	U_j (MW/h)
1	8.10	550	110	165
2	8.50	180	35	30
3	8.10	309	50	40
4	7.74	250	45	35
5	7.82	290	50	40
6	7.78	200	40	30

In TABLE II, Unit1 and Unit 2 belong to GC1,Unit 3 and Unit 4 belong to GC2, Unit 5 and Unit 6 belong to GC3.

TABLE III. LOAD DEMANDS IN DIFFERENT TIME INTERVALS

t	1	2	3	4	5	6
P_{tD}	1033	1000	1013	1027	1066	1120
t	7	8	9	10	11	12
P_{tD}	1186	1253	1300	1340	1313	1313
t	13	14	15	16	17	18
P_{tD}	1273	1322	1233	1253	1280	1433
t	19	20	21	22	23	24
P_{tD}	1273	1580	1520	1420	1300	1193

To simplify computation, the limit of strategic bidding coefficients does not vary by different time slot, we suppose:

$$\alpha_{t\min} = 7, \alpha_{t\max} = 9, \beta_{t\min} = 0.0002, \beta_{t\max} = 0.007,$$
$$t = 1, 2, \cdots, T; \; j = 1, 2, \cdots, N$$

B. *Experiment Results*

This example is run by the PSO-based algorithm proposed in this paper, which was implemented by Visual Basic 6.0, and tested on a desktop computer with CPU Pentium 4, 2.8GHz, RAM 1G, Windows XP. running results for variables values are listed from TABLE IV to TABLE VIII.

TABLE IV. RUNNING RESULTS FOR α_{tj} FROM THE EXAMPLE

t \ j	1	2	3	4	5	6
1	8.40	8.64	8.35	8.06	8.30	8.01
2	7.80	8.77	7.74	8.19	7.16	8.14
3	8.21	7.92	7.63	7.87	7.58	7.29
4	8.39	7.37	8.34	8.79	7.76	8.74
5	8.13	7.84	7.55	7.79	7.50	7.21
6	7.62	8.60	7.04	8.02	8.99	7.97
7	8.15	8.39	8.09	7.80	8.04	7.75
8	8.96	7.93	8.91	7.88	8.86	7.83
9	7.33	7.03	8.74	8.98	8.69	8.40
10	7.45	8.43	8.87	7.85	8.82	7.80
11	8.61	8.32	8.56	8.27	7.97	8.21
12	8.05	7.03	8.00	8.44	7.42	8.39
13	8.52	8.23	8.47	8.18	7.89	8.13
14	7.28	8.26	8.70	7.68	8.65	7.62
15	7.07	8.78	8.49	8.73	8.44	8.15
16	8.62	7.59	8.56	7.54	8.51	8.96
17	7.72	7.96	7.67	7.38	7.09	7.33
18	7.11	8.09	8.53	7.50	8.48	7.45
19	9.00	7.24	8.95	8.66	8.90	8.61
20	7.71	8.68	7.66	8.10	7.08	8.05
21	8.91	7.15	8.86	8.57	8.81	8.52
22	8.94	7.92	8.36	7.33	8.31	7.28
23	7.46	7.70	7.41	7.12	8.83	7.07
24	8.27	7.25	8.22	7.20	8.17	8.62

TABLE V. RUNNING RESULTS FOR β_{tj} FROM THE EXAMPLE

t \ j	1	2	3	4	5	6
1	0.000496	0.000247	0.000298	0.000349	0.000401	0.000452
2	0.000328	0.000489	0.000430	0.000292	0.000233	0.000394
3	0.000439	0.000490	0.000321	0.000373	0.000424	0.000475
4	0.000279	0.000220	0.000381	0.000322	0.000484	0.000425
5	0.000478	0.000308	0.000360	0.000411	0.000462	0.000214
6	0.000405	0.000266	0.000207	0.000369	0.000310	0.000471
7	0.000311	0.000362	0.000413	0.000465	0.000296	0.000347
8	0.000246	0.000407	0.000348	0.000210	0.000451	0.000392
9	0.000239	0.000290	0.000342	0.000393	0.000444	0.000496
10	0.000481	0.000343	0.000284	0.000445	0.000387	0.000328
11	0.000483	0.000234	0.000285	0.000337	0.000388	0.000439
12	0.000433	0.000374	0.000315	0.000476	0.000417	0.000279
13	0.000221	0.000272	0.000324	0.000375	0.000426	0.000478
14	0.000258	0.000420	0.000361	0.000302	0.000463	0.000405
15	0.000355	0.000406	0.000457	0.000208	0.000260	0.000311
16	0.000399	0.000340	0.000202	0.000443	0.000304	0.000246
17	0.000203	0.000334	0.000385	0.000437	0.000488	0.000239
18	0.000335	0.000497	0.000438	0.000379	0.000240	0.000481
19	0.000226	0.000278	0.000329	0.000380	0.000431	0.000483
20	0.000366	0.000228	0.000469	0.000330	0.000271	0.000433
21	0.000265	0.000316	0.000367	0.000419	0.000470	0.000221
22	0.000412	0.000353	0.000215	0.000456	0.000317	0.000258
23	0.000398	0.000449	0.000201	0.000252	0.000303	0.000355
24	0.000253	0.000494	0.000356	0.000297	0.000458	0.000399

TABLE VI. RUNNING RESULTS FOR UMP_t FROM THE EXAMPLE

$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$
1.67	6.16	12.70	18.39	1.33	1.89
$t=7$	$t=8$	$t=9$	$t=10$	$t=11$	$t=12$
5.52	14.62	12.62	3.94	4.66	17.19
$t=13$	$t=14$	$t=15$	$t=16$	$t=17$	$t=18$
19.62	7.01	10.14	6.08	18.25	16.41
$t=19$	$t=20$	$t=21$	$t=22$	$t=23$	$t=24$
16.63	15.98	17.91	12.14	14.75	17.53

TABLE VII. RUNNING RESULTS FOR P_{tj} FROM THE EXAMPLE

t \ j	1	2	3	4	5	6
1	138	35	349	61	290	160
2	155	40	336	64	250	155
3	213	45	323	72	210	150
4	272	50	310	80	170	145
5	379	55	297	90	130	115
6	455	60	284	96	90	135
7	556	65	271	104	60	130
8	603	70	258	112	85	125
9	620	75	245	120	120	120
10	630	80	232	128	155	115
11	573	85	219	136	190	110
12	543	90	206	144	225	105
13	483	85	193	152	260	100
14	517	80	180	160	290	95
15	448	75	167	168	285	90
16	488	70	154	176	265	100
17	515	65	141	184	245	130
18	626	60	155	210	225	157
19	517	30	130	196	250	150
20	680	60	160	230	290	160
21	642	90	180	238	240	130
22	561	120	215	224	200	100
23	458	130	250	232	160	70
24	414	140	240	239	120	40

Under these solutions, the objective values for both the leaders and the follower are listed in TABLE VIII

TABLE VIII. OBJECTIVE VALUES FOR THE DECISION MAKERS

The 1st GC	The 2nd GC	The 3rd GC	MO
29952	15605	15217	203866

VI. CONCLUSIONS

Based on the analysis on the competitive strategic model for day-ahead electricity market, this paper presents a bilevel optimization model for bidding problems in electricity markets. The proposed PSO-based algorithm can obtain solutions for the competitive strategic bidding problems by providing GCs a competitive strategic bidding within network security constraints. The algorithm has been implemented in a bilevel decision support system software.

Considering the cost with uncertainty, building fuzzy optimal strategic bidding model for day-ahead electricity market will be our next research issue. We will also develop more applications to test and improved the developed bilevel decision support system software.

ACKNOWLEDGMENT

The work presented in this paper was supported by Australian Research Council (ARC) under the discovery project DP0557154.

REFERENCES

[1] G. Zhang, J. Lu, Y. Gao, "A Fuzzy Multi-objective Multi-follower Partial Cooperative Bilevel Programming Algorithm", International Journal of Intelligent & Fuzzy Systems, vol. 19, pp. 303-319, 2008.

[2] G. Zhang, J. Lu, Y. Gao, "Fuzzy bilevel programming: Multi-objective and multi-follower with shared variables", International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, vol. 16, pp. 105-133, 2008.

[3] M Sakawa and I. Nishizaki, "Interactive fuzzy programming for two-level nonconvex programming problems with fuzzy parameters through genetic algorithms, Fuzzy Sets and Systems", vol. 127, pp. 185-197, 2002.

[4] J. Lu, C. Shi, and G. Zhang, "An extended branch-and-bound algorithm for bilevel multi-follower decision making in a referential-uncooperative situation", International Journal of Information Technology and Decision Making, vol. 6, pp. 371-388, 2006.

[5] H. Yu, C. Dang, and S. Wang, "Game theoretical analysis of buy-it-now price auctions," International Journal of Information Technology and Decision Making, vol. 5, pp. 557–581, 2006.

[6] B. F. Hobbs, B. Metzler, and J. S. Pang, "Strategic gaming analysis for electric power system: an mpec approach," IEEE Transactions on Power System, vol. 15, pp. 637–645, 2000.

[7] G. Zhang and J. Lu, "Model and approach of fuzzy bilevel decision making for logistics planning problem," Journal of Enterprise Information Management, vol. 20, pp. 178–197, 2007.

[8] J. Amat and B. McCarl, "A representation and economic interpretation of a two-level programming problem," Journal of the Operational Research Society, vol. 32, pp. 783–792, 1981.

[9] C. Feng and C. Wen, "Bi-level and multi-objective model to control traffic flow into the disaster area post earthquake," Journal of the Eastern Asia Society for Transportation Studies, vol. 6, pp. 4253 – 4268, 2005.

[10] Y. Gao, G. Zhang, J. Lu, and S. Gao, "A bilevel model for railway train set organizing optimization," in 2007 International Conference on Intelligent Systems and Knowledge Engineering (ISKE2007). Atlantis Press, pp. 777–782, 2007.

[11] A.K. David and F. Wen**,** "Strategic bidding in competitive electricity markets: a literature survey", Power Engineering Society Summer Meeting, IEEE, vol. 4, pp. 2168 - 2173 2000.

[12] A. Rudkevich, "Supply Function Equilibrium: Theory and Applications, System Sciences", Proceedings of the 36th Annual Hawaii International Conference, 2003.

[13] T. Li and M. Shahidehpour, "Strategic bidding of transmission-constrained GENCOs with incomplete information", IEEE Transactions on Power Systems, Vol. 20, pp. 437 – 447, Februray 2005.

[14] H. Haghighat, Hossein Seifi, and R. Kian Ashkan, "Gaming Analysis in Joint Energy and Spinning Reserve Markets", IEEE Transactions on Power Systems, Vol. 22, pp. 2074 – 2085, November 2007.

[15] F. Wen and A. D. Kumar, "Optimal bidding strategies and modeling of imperfect information among competitive generators", IEEE Transactions on Power Systems, Vol. 16, pp. 15 – 21,Februry 2001.

[16] J. D. Weber, T. J. Overbye, J. D. Weber, and T. J. Overbye, "An Individual Welfare Maximization Algorithm for Electricity Markets", IEEE Transactions on Power Systems, Vol. 17, pp. 590-596, August 2002.

[17] J. Pang and M. Fukushima, "Quasi-variational inequalities, generalized Nash equilibria, and multi-leader-follower games, Computational Management Science", Vol. 2, pp. 21-56, January, 2005.

[18] M. BJØNDAL and K. JØRNSTEN, "The Deregulated Electricity Market Viewed as a Bilevel Programming Problem", Journal of Global Optimization, vol. 33, pp. 465–475,2005.

[19] M. Fampa, L.A. Barroso, D. Candal, and L. Simonetti, "Bilevel optimization applied to strategic pricing in competitive electricity markets", Comput Optim Appl,

[20] K. E. Parsopoulos and M. N. Vrahatis, "Recent approaches to global optimization problems through particle swarm optimization", Natural Computing, vol. 1, pp. 235–306, 2002.