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USING SIMULATED ANNEALING ALGORITHM FOR OPTIMAL BIDDING STRATEGY IN ELECTRIC MARKETS

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Abstract- This study represents an optimal strategy for bidding in power markets which includes Environmental Penalties using agent-based modeling. Environmental penalties are considered for fossil-fueled power plants due to CO_2, NO_2, … emissions. The total emission of these pollutants can be expressed as sum of a quadratic and an exponential function. It has been assumed demand is inelastic, and then the reward of each player (Gen-Co) is optimized. Each player has three decision variables and bids to market through gaming them. The method used for optimize is Simulated Annealing (SA) that applies to optimization the multi variable functions. The results obtained through SA, are compared with results of Particle Swarm Optimization (PSO) Algorithm and represented 14.6% and 34.4% improvement in total reward of the market and emission, respectively.

Keywords: Simulated Annealing (SA) Algorithm, Power Market, Bidding Strategy, Environmental Penalties, Emission, Agent-Based.

I. INTRODUCTION

In all liberalized electricity markets each player (Agent) tries to bid to ISO so as to maximize his reward. With this assumption that demand is inelastic, demand side only sends his consumption quantity to the ISO, thus only Generating Companies (Gen-Cos) are able to game with quantity and price and optimize their rewards. Work that has previously been done in this issue is briefly described in the following: In [1] Rajkumar and et al develop a two-stage model using a stochastic game approach: 1) a stochastic game with average reward for the wholesale energy market operation, and 2) a Non Linear Programming (NLP) model for the unit-commitment and the optimal power flow aspects. Vasileios and et al [2] present a methodology for the development of bidding strategies for electricity producers in a competitive electricity marketplace. Initially, the problem was modeled as a two level optimization problem; where, at the first level, a market participant tries to maximize his expected profit under the constraint that, at the second level, an independent system operator dispatches power solving an optimal power flow problem that minimizes the total system cost. Monte Carlo simulation was used to calculate the expected profit and Genetic Algorithms (GA) were employed to find the optimal strategy. In [3] GA and in [4] Nash Equilibrium model is used for optimal bidding.

Pollutants emission minimization has been considered in the environmental economic dispatch (EED) problem. In [5] The EED problem is formulated as a nonlinear constrained multiobjective optimization problem with both equality and inequality constraints. The generator cost curves are represented by quadratic functions with sine components to represent the valve loading effects and emission function expressed as a quadratic function with exponential component. A Niched Pareto Genetic Algorithm (NPGA) based approach is considered to solve the problem. [6] and [7] have modeled EED problem is the same way as [5] and solved it with nondominated sorting GA, GA and Hybrid GA-Simulated Annealing respectively.

This study presents an optimal bidding strategy considering power plants fuel cost and environmental penalties. The fuel cost and emission function model used in aforementioned references, is applied in this study. Wholesale power market is a nonlinear system and also the player must decide in a short time for participating in market. Since Simulated Annealing (SA) is amongst suitable methods for optimizing nonlinear functions and has high speed and also does not have local problem (unlike PSO). In this paper SA is used for optimizing the problem and results of this method are compared with the PSO algorithm. Accordingly, our study will include the following sections: In section II and III Agent-Based approach and market players' behavior modeling in market will be described. In section IV the network which is used for the simulation is presented and in section V Simulated Annealing algorithms will briefly introduced. The results of SA algorithm are compared with the PSO algorithm in section VI. The conclusions are discussed in section VII.

II. AGENT-BASED APPROACH

This approach is proposed as a numerical technique (computer intense) for analyzing the various complexities of a system. Reinforcement Learning (RL) is often considered for agents to interact with a dynamic environment (e.g. power market). Amongst advantages of this approach is high accuracy in estimation of variations in market price comparing to the Neural Networks and Genetic Algorithm. Agent-Based model is a computational model for simulation of actions and reactions of many agents and observing their effects on the whole system.

This approach includes game theory, complex systems, multi-agent systems and evolutional programming. Most of the Agent-Based models consist of the following components:

2-1 A number of agents with different size;
2-2 Decision ability;
2-3 Adaptive processes or learning rules;
2-4 Operating policy;
2-5 Dynamic environment.

III. MODELING THE BEHAVIOR OF MARKET PLAYERS

Each Gen-Co has a cost function for his generating units that can be shown as:

$$C_g(P) = aP^2 + bP + c + |d\sin(e(P_{\min} - P))| \tag{1}$$

where a, b, c, d and e are constant coefficients that have specified value for each unit. Sine term shows the valve loading effects. Another component of cost is related to emission. The total ton/h emission is expressed as:

$$E(P) = \alpha + \beta P + \gamma P^2 + \eta \exp(\delta P_{\min}) \tag{2}$$

where α, β, γ, η and δ are coefficients of the generator emission characteristics. Thus, the total cost of generation will be as follows:

$$C_T(P) = C_g(P) + \lambda E(P) \tag{3}$$

where λ is a constant coefficient [$/ton]. If the sine and exponential term were substituted with first and first to third term of Taylor series, the total cost will be:

$$C_T(P) = AP^2 + BP + C \tag{4}$$

In a competitive market, the players bid to the market according to their Marginal Cost (MC) in (5):

$$MC_g = \frac{\partial C_g}{\partial P} = 2AP + B \tag{5}$$

ISO receives bids and sorts them ascending, then settles the market with this consideration that the demand is constant. But, in fact the players bid different than the marginal cost to maximize their reward. For simulating this game, with this consideration that each player has three parameters a, b and S (the factor of offered generation: offered power is equal to $S \times P_{\max}$ that $P_{\max}$ is the maximum generation limit) for gaming, we consider a decision factor for each parameter that the parameter multiplied by this factor.

Factor k_1 for parameter a, k_2 for parameter b and k_3 for parameter S. Thus, the cost function will be as follow:

$$MC_g = k_1(2A)P + K_2 BP \tag{6}$$

and the offered generation quantity is:

$$q = k_3 P_{\max} \tag{7}$$

In fact each player games with this decision factors to optimize his reward. The reward function of player is shown in (5).

$$R_g = \pi P_g - C_g = \pi P_g - (AP_g^2 + BP_g + C) \tag{8}$$

where π is the market price and P_g is the generated power with which ISO runs the market and determines them. Thus, our optimization problem will be as follows:

$$\begin{aligned} &\max \quad R_{g_i},\ i = 1, 2, ..., n; \\ &s.t. \quad P_{i\min} < P_{g_i} < P_{i\max} \\ &\qquad \sum P_{g_i} = D \end{aligned} \tag{9}$$

where D is the total demand and $P_{i\min}$ and $P_{i\max}$ are lower and upper generation limits, respectively.

IV. SIMULATED ANNEALING (SA) METHOD

The simulated annealing (SA) is a generic probabilistic meta-heuristic for the global optimization problem of applied mathematics, namely locating a good approximation to the global minimum of a given function in a large search space. At each iteration, as SA goes toward better solution, it also stores solutions that their objective function values are not better than the previous iteration with a probability.

At first this probability is great and decreases while running algorithm with a positive parameter called Temperature (T). As algorithm progresses, T decreases in a specific way and inappropriate solutions have little chance to be accepted. The standard SA algorithm steps are as follow:

3-1 Initialize T;
3-2 Initialize cost function variables randomly at step t;
3-3 Calculate cost function with these initialized variables;
3-4 again initialize cost function variables randomly at step $t+1$;
3-5 Calculate cost function at step $t+1$;
3-6 if cost function at step $t+1$ is smaller than cost function at step t, then the solution at step $t+1$ is stored;
3-7 Else the solution at step $t+1$ is stored with this probability:

$$\exp\left[\left(\begin{array}{l}\left(3^{rd}\ stage\cos t\ function\right) \\ -\left(5^{th}\ stage\cos t\ function\right)\end{array}\right)/T\right] > \text{rand}$$

3-8 Decreases T;
3-9 Repeat 3rd stage to 8th stage until T reduces to a particular percentage of initial value assigned to T.

V. USED NETWORK AND REQUIREMENT DATA

Figure 1 shows the network used for simulation. The network includes 5 Gen-Cos located at bus 1, bus 3, bus 4 and buses 5 and 3 consumers located at bus 2, bus 3 and bus 4. The network, Gen-Cos and consumers data are brought in appendix.

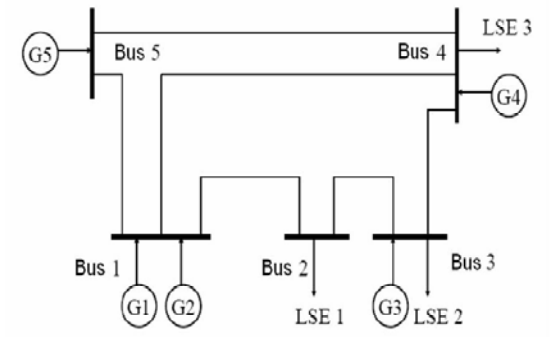

Figure 1. Used sample network for simulation [11]

VI. SIMULATION RESULTS

The results of simulation after 200 iterations are presented. Figures 2 and 3 show the load curves and LMP for each Gen-Co during a day. Since marginal cost of Gen-Co3 is greater than others, as Figure 3 shows, his LMP is higher than others. Price spike at hour 17 has been occurred due to peak load at this hour. Figure 4 illustrates factor k_1 at hour 17 that reaches to value 5 after 15 iterations. Finally, Figures 5 and 6 compares total reward of market (global welfare) and total emission obtained from PSO and SA algorithms.

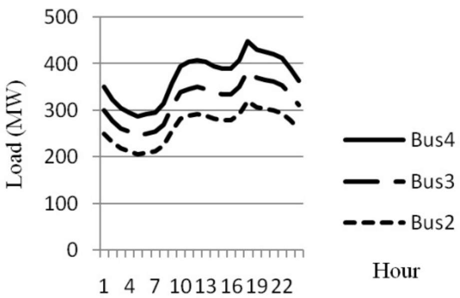

Figure 2. Load curves

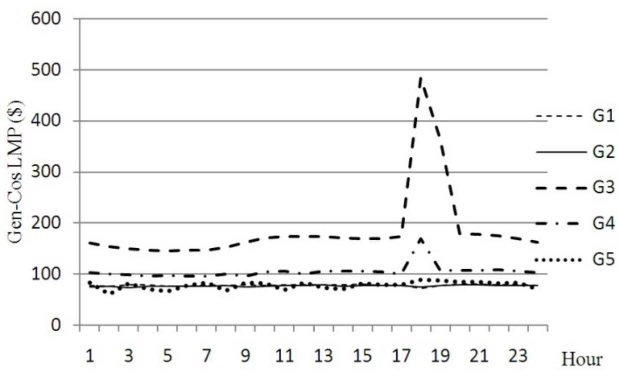

Figure 3. Gen-Cos LMP

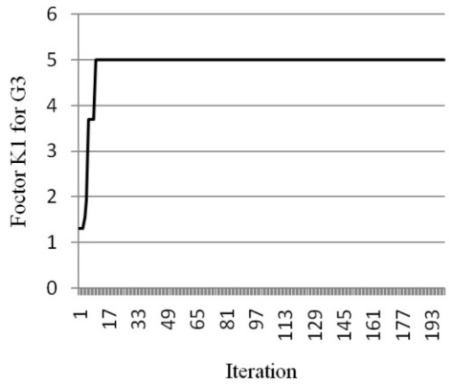

Figure 4. Factor k_1 for Gen-Co3 at hour 17

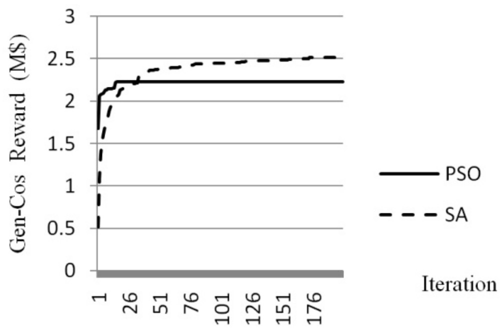

Figure 5. Global welfare obtained from SA and PSO

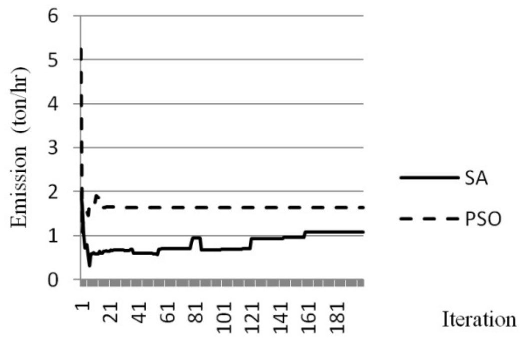

Figure 6. Total Emission obtained from SA and PSO

Table 1 presents the total reward of market and total emission to compare the results of SA and PSO algorithms. It is observed that SA method obtains 14.6% improvement in global welfare and 34.4% improvement in total emission comparing to PSO method. Table 1 presents the total reward of market and total emission to compare the results of SA and PSO algorithms. It is observed that SA method obtains 14.6% improvement in global welfare and 34.4% improvement in total emission comparing to PSO method.

Table 1. Comparison of SA and PSO Results

Methods	Total Reward of Market [M$]	Total Emission [ton/hr]
SA Method	2.55	1.078
PSO Method	2.225	1.643
Improvement (%)	14.6%	34.4%

VII. CONCLUSIONS

In this study we simulated market players using agent-based modeling and SA algorithm and compared its results with PSO algorithm results. The cost function of generators includes two terms: 1- fuel cost and 2- emission penalties. Three decision variables are considered for each Gen-Co, with which games to optimize his reward. The results showed improvements of 14.6% and 34.4% in total reward and total emission comparing PSO.

APPENDICES

Network and Generators Data

Tables 2, 3 and 4 show information of used network and generators fuel and emission cost characteristics, respectively.

Table 2. Line information

From	to	Line Capacity [MW]	Line Reactance [ohm]
1	2	250	0.0281
1	4	150	0.0304
1	5	400	0.0064
2	3	350	0.0108
3	4	240	0.0297
4	5	240	0.0297

Table 3. Generators fuel cost coefficients

ID	Node	c	a	b	Lower Cap. [MW]	Upper Cap. [MW]
1	1	1600	14	0.005	0	110
2	1	1200	15	0.006	0	100
3	3	8500	25	0.010	0	520
4	4	1000	30	0.012	0	200
5	5	5400	10	0.007	0	600

Table4. Generators emission cost coefficients

α	β	γ	ξ	λ
200.4	-4.07	0.051	0.497	0.0202
53.4	-2.44	0.031	0.504	0.0207
150.0	-3.81	0.034	0.497	0.0200
53.4	-2.44	0.031	0.504	0.0207
220.0	-3.07	0.047	0.548	0.0234

NOMENCLATURES

$\alpha,\ \beta,\ \gamma,\ \eta,\ \delta$: fixed coefficients of emission function

π : market price [$/MW]

λ : Penalty factor [$/ton]

P : Generation [MW]

$P_{\min}$: Generation lower limit [MW]

$P_{\max}$: Generation upper limit [MW]

C_g : Generation cost [$]

E : Emission function [ton/hr]

C_T : Total generation cost [$]

MC_g : Generators' marginal cost [$/MW]

q : bided generation [MW]

P_g : Sold power [MW]

R_g : Generator reward [$]

D : Total demand for each hour [MW]

Δf : Change in cost function

T : Initial temperature

$k_1,\ k_2,\ k_3$: Decision making factors

$A,\ B,\ C$: Total cost function coefficients

$a,\ b,\ c,\ d,\ e$: Fixed coefficients of generation cost function

REFERENCES

[1] R. Ragupathi, T.K. Das, "A Stochastic Game Approach for Modeling Wholesale Energy Bidding in Deregulated Power Markets", IEEE Transactions on Power Systems, Vol. 19, No. 2, pp. 849-856, 2004.

[2] V.P. Gountis, A.G. Bakirtzis, "Bidding Strategies for Electricity Producers in a Competitive Electricity Marketplace", IEEE Transactions on Power Systems, Vol. 19, No. 1, February 2004.

[3] K. Japanya, W. Ongsakul, "Optimal Bidding Strategy in Competitive Market using Genetic Algorithm", Electric Power System Research, 2005.

[4] E.V. Beck, R. Cherkaoui, A. Germond, "Optimal Bidding in a Multi-Period Electricity Spot Market", Nanjing, China, April 2008.

[5] M.A. Abido, "A Niched Genetic Algorithm for Multi-Objective Environmental/Economic Dispatch", Electrical Power and Energy Systems, 2003.

[6] M. Basu, "Dynamic Economic Emission Dispatch using Nondominated Sorting Genetic Algorithm - II", Electrical Power and Energy Systems, 2008.

[7] E. Tsoi, K.P. Wong, C.C. Fung, "Hybrid GA/SA Algorithms for Evaluating Trade-off Between Economic Cost and Environmental Impact in Generation Dispatch", 1995.

[8] A.J. Bagnall, G.D. Smith, "A Multi-Agent Model of the UK Market in Electricity Generation", March 16, 2005.

[9] A. Somani, L. Tesfatsion, "An Agent-Based Test Bed Study of Wholesale Power Market Performance Measures", IEEE Computational Intelligence Magazine, Vol. 3, No. 4, pp. 56-72, November 2008.

[10] E.S. Gopi, "Algorithm Collections for Digital Signal Processing Applications using MATLAB", National Institute of Technology, Tiruchi, India.

[11] C. Goldman, B.C. Lesieutre, E. Bartholomew, "A Review of Market Monitoring Activities at US Independent System Operators", Energy Analysis Department, January 2004.

[12] M.M. Tripathi, K.G. Upadhyay, S.N. Singh, "Electricity Price Forecasting using Generalized Regression Neural Network (GRNN) for PJM Electricity Market", International Review on Modelling and Simulation, Vol. 1, No. 2, pp. 318-324, December 2008.

BIOGRAPHIES

Mojtaba Mahvy received his B.Sc. degree from Amirkabir University of Technology, Tehran, Iran, in 2008. He is currently the M.Sc. student of power electrical engineering in Amirkabir University of Technology. His research interests include the artificial intelligence to power system control design, operation and planning and electricity market.

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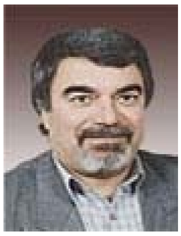

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