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Generation bidding strategy in a pool based electricity market using Shuffled Frog Leaping Algorithm

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ABSTRACT

In an electricity market generation companies need suitable bidding models to maximize their profits. Therefore, each supplier will bid strategically for choosing the bidding coefficients to counter the competitors bidding strategy. In this paper optimal bidding strategy problem is solved using a novel algorithm based on Shuffled Frog Leaping Algorithm (SFLA). It is memetic meta-heuristic that is designed to seek a global optimal solution by performing a heuristic search. It combines the benefits of the Genetic-based Memetic Algorithm (MA) and the social behavior-based Particle Swarm Optimization (PSO). Due to this it has better precise search which avoids premature convergence and selection of operators. Therefore, the proposed method overcomes the short comings of selection of operators and premature convergence of Genetic Algorithm (GA) and PSO method. Important merit of the proposed SFALA is that faster convergence. The proposed method is numerically verified through computer simulations on IEEE 30-bus system consist of 6 suppliers and practical 75-bus Indian system consist of 15 suppliers. The result shows that SFLA takes less computational time and producing higher profits compared to Fuzzy Adaptive PSO (FAPSO), PSO and GA.

1. Introduction

Restructuring of the power industry mainly aims at abolishing the monopoly in the generation and trading sectors, thereby, introducing competition at various levels wherever it is possible. But the sudden changes in the electricity markets have a variety of new issues such as oligopolistic nature of the market, supplier's strategic bidding, market power misuse, price-demand elasticity and so on. Theoretically, in a perfectly competitive market, suppliers should bid at, or very near to the Market Clearing Price (MCP) to maximize profits [1]. However, practically the electricity markets are oligopolistic nature, and power suppliers may seek to increase their profit by bidding a price higher than MCP. Knowing their own costs, technical constraints and their expectation of rival and market behavior, suppliers face the problem of constructing the best optimal bid. This is known as a strategic bidding problem.

In general, there are three basic approaches to model the strategic bidding problem viz. (i) based on the estimation of Market Clearing Price, (ii) estimation of rival's bidding behavior and (iii) on game theory. David [2] developed a conceptual optimal bidding model for the first time in which a Dynamic Programming (DP) based approach has been used. Gross and Finaly adopted a Lagrangian relaxation-based approach for strategic bidding in England-Wales pool type electricity market [3]. Jainhui et al. [4] used evolutionary game approach to analyzing bidding strategies by considering elastic demand. Ebrahim and Galiana developed Nash equilibrium based bidding strategy in electricity markets [5]. David and Wen [6] proposed to develop an overall bidding strategy using two different bidding schemes for a day-ahead market using Genetic Algorithm (GA). The same methodology has been extended for spinning reserve market coordinated with energy market by David and Wen [7]. Ugedo et al. developed a stochastic-optimization approach for submitting the block bids in sequential energy and ancillary services markets and uncertainty in demand and rival's bidding behavior is estimated by stochastic residual demand curves based on decision trees [8]. To construct linear bid curves in the Nord-pool market stochastic programming model has been used by Fleten et al. [9]. The opponents' bidding behaviors are represented as a discrete probability distribution function solved using Monte Carlo method by David and Wen [10].

The deterministic approach based optimal bidding problem was solved by Hobbs et al. [11], but it is difficult to obtain the global solution of bi-level optimization problem because of non-convex objective functions and non-linear complementary conditions to represent market clearing. These difficulties are avoided by

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representing the residual demand function by Mixed Integer Linear Programming (MILP) model [12,13], in which unit commitment and uncertainties are also taken into account. The generators associated to the competitors' firms have been explicitly modeled as an alternative MILP formulation based on a binary expansion of the decision variables (price and quantity bids) by Pereira et al. [14]. Azadeh et al. formed optimal bidding problem for day-ahead market as multi objective problem and solved using GA [15]. Jain and Srivastava [16] considered risk constraint, for bidding single sided and double sided and solved using GA. Ahmet et al. used PSO to determine bid prices and quantities under the rules of a competitive power market [17]. Kanakasabhapathy and Swarup [18] developed strategic bidding for pumped-storage hydroelectric plant using evolutionary tristate PSO. Bajpai et al. developed blocked bid model bidding strategy in a uniform price spot market using Fuzzy Adaptive Particle Swarm Optimization (FAPSO) [19]. Venkaiah et al. used Fuzzy Adaptive Bacterial Foraging Algorithm (FABFA) for optimal rescheduling of active power of generators [20]. Recently the combination of PSO and Simulated Annealing (SA) is used to predict the bidding strategy of generation companies [21]. Fevrier et al. developed a new hybrid approach by combing the advantages of PSO and GA using fuzzy logic [22].

In general, strategic bidding is an optimization problem that can be solved by various conventional and non-conventional (heuristic) methods. Depending on the bidding models, objective function and constraints may not be differentiable, in that case conventional methods cannot be applied. Whereas, heuristic methods such as GA, Simulated Annealing (SA) and Evolutionary Programming (EP), Particle Swarm Optimization (PSO), etc., have main limitations of their sensitivity to the choice of parameters, such as the crossover and mutation probabilities in GA, temperature in SA, scaling factor in EP and inertia weight, learning factors in PSO and framing of rules in fuzzy adaptive Particle Swarm Optimization (FAPSO).

Shuffled Frog Leaping Algorithm (SFLA) overcomes the shortcomings of FAPSO, PSO and GA, because it is a memetic meta-heuristic that is based on evolution of memes carried by interactive individuals and a global exchange of information among the frog population. It combines the advantages of the Genetic-based Memetic Algorithm (MA) and social behavior-based PSO algorithm with such characteristics as simple concept, few parameter adjustment, prompt formation, great capability in global search and easy implementation.

The main contribution of this paper is, a new optimization paradigm based on Shuffled Frog Leaping Algorithm (SFLA) is introduced first time to solve optimal bidding strategy problem. The result shows that the proposed algorithm can generate better quality solution within shorter computation time and stable convergence characteristics compared to FAPSO, PSO and GA. The paper is organized as follows. Section 2 presents the mathematical formulation of optimal bidding problem. Section 3 contains a brief over view of the proposed SFLA method. Section 4 describes the application of SFLA for solving the optimal bidding problem. Section 5 reports the case studies solving optimal bidding problem for IEEE 30-bus system and practical 75-bus Indian system and Section 6 summed up the final outcome of the paper as Conclusion.

2. Problem formulation

Consider a system consist of 'm' suppliers participating in a pool-based single-buyer electricity market in which the sealed auction with a uniform Market Clearing Price (MCP) is employed. Assume that each supplier is required to bid a linear supply function to the pool. The jth supplier bid with linear supply curve denoted by $G_j(P_j) = a_j + b_jP_j$ for $j = 1, 2, \ldots, m$. Where P_j is the active power output, a_j and b_j are non-negative bidding coefficients of the jth supplier. After receiving bids from suppliers, the pool determines a set of generation outputs that meets the load demand and minimizes the total purchasing cost. It is clear that generation dispatching should satisfy the following Eqs. (1)–(3).

$$a_j + b_jP_j = R \quad j = 1, 2, \ldots, m \tag{1}$$

$$\sum_{j=1}^{m} P_j = Q(R) \tag{2}$$

$$P_{\min,j} \le P_j \le P_{\max,j} \quad j = 1, 2, \ldots, m \tag{3}$$

where R is the Market Clearing Price (MCP) of electricity to be determined, $Q(R)$ is the aggregate pool load forecast as follows

$$Q(R) = Q_o - KR \tag{4}$$

where Q_o is a constant number and K is a non-negative constant used to represent the load price elasticity. When the inequality constraint Eq. (3) is ignored, the solution to Eqs. (1) and (2) are,

$$R = \frac{Q_o + \sum_{j=1}^{m}(a_j/b_j)}{K + \sum_{j=1}^{m}(1/b_j)} \tag{5}$$

$$P_j = \frac{R - a_j}{b_j} \quad j = 1, 2, \ldots, m \tag{6}$$

$P_{\min,j}$ and $P_{\max,j}$ are the generation output limits of the jth supplier. If the solution of the Eq. (3) exceeds the maximum limit $P_{\max,j}$, P_j is set to $P_{\max,j}$. When P_j is less than $P_{\min,j}$, P_j is set to zero and relevant supplier is removed from the problem as a non-competitive participant for that hour. The jth supplier has the cost function denoted by $C_j(P_j) = e_jP_j + f_jP_j^2$, where e_j and f_j are the cost coefficients of the jth supplier. In a perfectly competitive market, $a_j = e_j$ and $b_j = f_j$.

The profit maximization objective of supplier j ($j = 1, 2, \ldots, m$) in a unit time for building bidding strategy can be described as:

$$\text{Maximize}: \quad F(a_j, b_j) = RP_j - C_j(P_j) \tag{7}$$

Subject to: Eqs. (5) and (6).

The objective is to determine bidding coefficients a_j and b_j so as to maximize $F(a_j, b_j)$ subject to the constraints Eqs. (5) and (6). Since the jth supplier does not know the bidding coefficients of rivals before the auction. But in sealed bid auction based electricity market, information for the next bidding period is confidential in which suppliers cannot solve optimization problem using Eq. (7) directly. However, bidding information of previous round will be disclosed after Independent System Operator (ISO) decide MCP and everyone can make use of this information to strategically bid for the next round of transaction between suppliers [10]. An immediate problem of each supplier is how to estimate the bidding coefficients of rivals.

Let, from the ith supplier's point of view, rival's jth ($j \neq i$) bidding coefficients, a_j and b_j obey a joint normal distribution with the following probability density function (*pdf*):

$$pdf_i(a_j, b_j) = \frac{1}{2\Pi\sigma_j^{(a)}\sigma_j^{(b)}\sqrt{1-\rho_j^2}} \times \exp\left\{-\frac{1}{2(1-\rho_j^2)}\left[\left(\frac{a_j-\mu_j^{(a)}}{\sigma_j^{(a)}}\right)^2 - \frac{2\rho_j(a_j-\mu_j^{(a)})(b_j-\mu_j^{(b)})}{\sigma_j^{(a)}\sigma_j^{(b)}} + \left(\frac{b_j-\mu_j^{(b)}}{\sigma_j^{(b)}}\right)^2\right]\right\} \tag{8}$$

where ρ_j is the correlation coefficient between a_j and b_j. $\mu_j^{(a)}$, $\mu_j^{(b)}$, $\sigma_j^{(a)}$ and $\sigma_j^{(b)}$ are the parameter of the joint distribution. The marginal distributions of a_j and b_j are both normal with mean values $\mu_j^{(a)}$ and $\mu_j^{(b)}$, and standard deviations $\sigma_j^{(a)}$ and $\sigma_j^{(b)}$ respectively.