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A new genetic algorithm approach for optimizing bidding strategy viewpoint of profit maximization of a generation company

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ABSTRACT

This paper presents a new approach for bidding strategy in a day-ahead market from the viewpoint of a generation company (GENCO) in order to maximize its own profit as a participant in the market. It is assumed that each GENCO submits its own bid as pairs of price and quantity, and the sealed auction with a pay-as-bid market clearing price (MCP) is employed. The optimal bidding strategies are determined by solving an optimization problem with unit commitment constraints such as generating limitations. In this paper, the problem is solved from two different viewpoints including profit maximization of GENCO without considering rival's profit function, and profit maximization of GENCO by considering both rivals' bid and profit functions. Therefore, there is a multi-objective problem to be solved in this study. Since this problem is non-convex which is difficult to solve by traditional optimization techniques, hence, genetic algorithm (GA) has been employed to solve the problem. A simple test problem is designed to illustrate the efficiency of the proposed approach.

1. Introduction

In the competitive electricity market, dispatch of generation is based on bid and each generation company GENCO needs to compete with rivals via bidding to the market. Competition creates the opportunities for GENCOs to get more profit (Maa, Wena, Nia, & Liub, 2005). Therefore, in a restructured electricity market, each GENCO will reasonably build strategic bidding to maximize its own profit. Generally, three main approaches are used for GENCO strategic bidding. These are market clearing price (MCP) forecasting, rivals' bidding modeling, and game based rivals' strategic behavior simulating.

The bidding strategy problem was first introduced by David (1993) and has been afterward developed by many researchers (Attaviriyanupap, Kita, Tanaka, & Hasegawa, 2005; Bhattacharya, 2000; Gross & Finlay, 1996; Gross, Finlay, & Deltas, 1998; Guan, Ho, & Lai, 2001; Hao, 1999; Li, Svoboda, Guan, & Singh, 1999; Mielczarski et al.,1999; Ni & Luh, 2002; Richter & Sheble, 1998; Richter, Sheble, & Ashlock, 1999; Wen & David, 2000, 2001a, 2002; Xiong, Hashiyama, & Okuma, 2002; Zhang, Wang, & Luh, 2000). Sheble (2000) used GA to find the optimal bidding strategy in the auction market. In this study, the price that should be offered in next round of bidding by GENCO is encoded. GA develops this encoded bidding price through crossover and mutation process. To find fitness value and to calculate the price, the profit of all participants must be known. This fitness function is the flaw of this algorithm because each GENCO cannot know other profits. Attaviriyanupap et al. (2005) used GA to find the optimal bidding strategy in both day-ahead and reserved market with similar technique. However, GENCO need to forecast others market participants' bid before running that proposed algorithm.

A day-ahead market means a 24-h period, starting from hour 0, running through the hour 23 of a market day. Typically the market day is the next calendar's day from the day the assessments are done. In all markets that supply same commodity, the dispatch schedules for the day-ahead market are gathered hours ahead of the beginning of the operating day-ahead day. There are some of the rules of participating in day-ahead market for all GENCOs and loads willing to participate in the day-ahead market. They must submit their offers and bids to the market operator by a pre-determined deadline. In most markets, this time is set at 9 AM, which is 15 h ahead of starting market period. This lead time is allowed for solving the security-constrained economic dispatch and unit-commitment for the 24-h period; and for the market participants to accept or change their bid for the day-ahead market based on first published results. Once, these offers and bids are received by the market operators in deadline, they are considered as feasible, and will be take into the optimal security-constrained economic dispatch and unit- commitment considered. The market is considered continuously operates for the whole 24-h period transitioning smoothly from the previous day to the present market day, even though the load and GENCO's bids will be done as integrated hourly values for every hour of the day (Rodrigo, 2007).

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In this paper, a new approach is proposed for determining the optimal bidding strategy of GENCO in the day-ahead electricity market. This approach is developed from viewpoint of a GENCO that participates in a market and wish to maximize its own profit. It is assumed that the rivals' bidding information is known or can be estimated based on historical data. The proposed algorithm provides the optimal bidding for GENCO. Also, it is assumed that bids submitted as pairs of price and quantity, and bid segments are selected once only based on the forecasted load and price. In this case, GENCO tries to maximize its own profit without considering rival's bids and profit functions. Then, bid segments are selected based on the forecasted load, forecasted price and expectations concerning rival's bids and profit functions. Therefore, there is a multi-objective problem to be solved in the second case. By using GA, the constraints are treated and the optimal bidding is determined according to the maximization objective or objectives of a GENCO, simultaneously. Constraints such as generating limitations are considered that make the nature of the problem more difficult which cannot be solved with conventional methods. Therefore, the optimization problem is solved using GA.

GA has been employed in many research works to solve different problems, but to the best of our knowledge, none of them has been considered practical limitations and rival's bid altogether. In a day-ahead market, it is essential to consider constraints such as the fuel cost, start-up cost, generating limits, and unit minimum up/down time to make sure that the GENCOs are able to schedule the units needed to meet the demand (Attaviriyanupap et al., 2005).

This paper is the extension of the work presented by Ali Ali Azadeh and Behnaz Pourvalikhan Nokhandan (2009). This remainder of the paper is organized as follow: in Section 2 we review the relevant literature in this area. Section 3 presents mathematical modeling of profit maximization problem for optimizing bidding strategy. Section 4 gives an introduction to GA. Optimal bidding strategy using GA is shown by a simple example in Section 5 including problem description and GA-approach to solve it. Numerical results are presented in Section 6 and Conclusions are drawn in Section 7.

2. Literature review

The published articles relevant to this research area assumed several objectives and constrains to optimize bidding strategy and maximize the profit of a GENCO. Also, there are several methods to find the optimal bidding strategy. Weber and Overbye (1999) modeled the bidding problem as a bi-level problem by assuming complete information on a GENCO's rivals. The ISO's market clearing problem was modeled as a non-linear optimal power flow problem, and a Newton approach was employed to solve it. Wen and David (2001b) presented a method to predict the optimal energy production of a GENCO in an oligopoly energy market, but the model did not consider the technical constraints of the GENCOs. Wen and David (2001c) and Maa et al. (2005) used Monte Carlo simulation to find the optimal bidding strategy. Monte Carlo simulation repetitively computes the optimal bidding strategy for one player with randomly rival bidding. The average of bidding parameter was calculated to be the optimal strategy.

Ni and Luh (2002) investigated optimal bidding strategies for both energy and reserve markets with risk management by using a stochastic dynamic programming model. Song, Ni, Wen, Hou, and Wu (2003) introduced the concept of conjectural variation (CV) and its applications in electricity spot markets. The conjecture of a firm is defined as its belief or expectation of how its rivals will react to the change of its output. CV based bidding strategy (CVBS) method can help generation firms to improve their strategic bidding and maximize their profits in real electricity spot markets with imperfect information. In real applications, a firm using CVBS will integrate its rivals into one fictitious competitor and estimate its generation and reaction to the firm's change of output so that an optimal decision can be made accordingly. Al-Agtash and Yamin (2004) described a new approach for optimal supply curve bidding (OSCB) using Benders decomposition in competitive electricity markets. Supply curve bidding defined as better benefit of GENCOs compared to specific quantity-price bids. Then problem decomposed into base-case OSCB without constraint, and sub-problems for checking the feasibility of unit and network constraints.

Ragupathi and Tapas (2004) and Xiong, Okuma, and Fujita (2004) used reinforcement learning to find the optimal bidding strategy, in which, artificial agent decided about price which should be bidden in the next round of auction. The chosen price corresponded to load forecast and previous experience. If the agent has enough learning, decision of the agent is called the optimal bidding strategy. Kian and Cruz (2005) modeled oligopolistic electricity markets as non-linear dynamical systems and used discrete-time Nash bidding strategies. The optimal bidding strategies were developed mathematically using dynamic game theory. Then, they linearized non linear oligopolistic electricity multi-markets and used discrete-time Nash strategies for solving them. Kang, Kim, and Hur (2007) sought broach an optimal bidding strategy problem for power suppliers to benefit by bidding a price higher than the marginal production cost since the incumbent electricity market is not perfectly competitive. In other words, each GENCO will endeavor to maximize profits or payoffs by winning the bidding game given each player's strategic choice and the interactions of all players' strategies in the game.

Lee and Yang (2007) investigated the negotiation efficiency for the various bidding strategies that demander employed in different order conditions. The negotiation efficiency was assumed as the required negotiation times to achieve an agreement. Yin, Zhao, Saha, and Dong (2007) developed GENCO strategy bidding with incomplete information condition. The proposed method predicted the expected bidding productions of each rival generator in the market based on publicly available bidding data trough estimated from historical bidding and price data, using support vector machine. Tan, Shen, Lu, and Shen (2008) presented an alternative quantitative method for assisting a contractor to find out its own most competitive strategy in bidding for construction contracts by using goal programming. Wang, Yu, and Wen (2008) investigated the impacts of different numbers of bidding segments on the bidding strategies of GENCOs, then the optimal bidding strategy for a price-taker GENCO developed with a given number of bidding segments. Yucekaya, Valenzuela, and Dozier (2009) presented two particle swarm optimization (PSO) algorithms to determine bid prices and quantities. The first method used a conventional PSO technique to find solutions and the second method used a decomposition technique in conjunction with the PSO approach. They showed that for nonlinear cost functions PSO solutions provide higher expected profits than marginal cost-based bidding. Saleh, Tsuji, and Oyama (2009) proposed a methodology that employed an optimization method like Lagrange Relaxation to optimize the bidding problem. The problem of building optimal bidding strategies off small GENCO was proposed where both unit commitment and bilateral contract are taken into account.

Borghetti, Massuccob, and Silvestro (2009) presented an analysis of the possibility and the limits of taking into account the power plants technical constraints in the bidding strategy selection procedure of GENCO. The analysis carried out by using a computer procedure based both on a simple static game theory approach and cost-minimization unit-commitment algorithm. Lai, Tong, Yang, and Bing (2009) presented a dynamic bidding model of the power market based on the Nash equilibrium and a supply function with the following characteristics: first, it adopted a dynamic bid so that the bidding limit point was the Nash equilibrium point of the market. Second, it considered the system requirement and the market property such as involving the transmission constraints in the network, and using a supply function which was suitable for the oligopolistic competitive power market.

3. Mathematical modeling

In this paper, it is assumed that each GENCO in day-ahead electricity market submit its own bid as pairs of price and quantity. Suppose that there are K independent GENCOs participating in electricity market in which the sealed auction with a pay-as-bid MCP is employed. It is assumed that GENCOs have information about forecasted load, forecasted price and expectations of rival bids. Suppose jth GENCO wish to participate in this market. The objective of this GENCO is to maximize its own profit (i.e., revenue minus cost) subject to all prevailing constraints. For GENCO at the considered hour, the profit is given by (1):

$$\pi_j = RV_j - TC_j \tag{1}$$

π_j, RV_j, TC_j are profit, the total revenue and total production cost for jth GENCO, respectively. Total revenue and total production cost can be calculated at considered hour, from (2) and (3), respectively.

$$RV_j = \sum_{i=1}^{N_j} C_{ji} P_{ji} \tag{2}$$

$$TC_j = a_j + b_j P_j + c_j P_j^2 \tag{3}$$

where N_j is the number of bid segments for jth GENCO. C_{ji} and P_{ji} are offered price and quantity at segment i for jth GENCO, respectively. P_j is the total quantity produced by jth GENCO at considered time where

$$P_j = \sum_{i=1}^{N_j} P_{ji} \tag{4}$$

3.1. Objective function

In this paper, optimal bidding strategy is studied from two points of view. Once, jth GENCO do not consider rival's profit function for maximizing its own profit. In this case, objective function is considered only as profit function of considered GENCO. In this case the objective function is defined as follows:

$$Max \pi_j \tag{5}$$

In another point of view, it is assumed that GENCO wishing to maximize its own profit while consider rival's bid and their profit functions. In this case, Each GENCO knows that rivals try to maximize its own profits, too. Therefore, there is a multi objective function to be solved. In this case, GENCO maximize its own profit while maximizing rival's profits.

Most of the conventional algorithms reformulate a given multi-objective optimization problem into a single objective-function to be minimized or maximized. As an example, Huang and Song used the revised simplex linear programming algorithm to the problem considering constrains such as power, economical, dispatch and control. This algorithm is a good illustration of how reducing the given problem to a representative cost function forms a single objective-function. In this method a single objective-function is formed from combination of objectives to be optimized by determining appropriate weights to represent the importance of each of them. As said, this approach needs an *a priori* assumption of the relative importance of each objective that has to be incorporated. These forces the solution to be directed in a given direction based on the decision of the expert (Rodrigo, 2007). Therefore, in this study, following formulation is selected as objective function for case 2 based on two expert's idea.

$$\max \alpha_0 \left(\sum_{j=1}^{K} \pi_j \right) + \sum_{j=1}^{K} \alpha_j \pi_j \tag{6}$$

Objective function mentioned by (6) is a convex linear combination of GENCOs' profit functions where $\sum_{j=1}^{K} \alpha_j = 1$. α_0 is coefficient of sum of profits. In this way, coefficients can be determined by experts from before experiments.

3.2. Constraints

The following constraint (7) represent that offered price in each segment has to be lower than market price cap for all GENCOs.

$$C_{ji} \leq price\_cap \quad j = 1, \ldots, K, \; i = 1 \ldots N_j \tag{7}$$

The following constraint (8) represents GENCO's special requirements. A GENCO may have minimum and maximum generation requirements in order to participate in the market.

$$P_j^{\min} \leq P_j \leq P_j^{\max} \quad j = i, \ldots, K \tag{8}$$

Constraint (9) represent that total energy is supplied by market must meet demand, where P^f is the forecasted demand by jth GENCO.

$$\sum_{j=1}^{K} P_j = P^f \tag{9}$$

Also, the market clearing price at considered hour can be represented by (10):

$$C^P = C^f + \varepsilon \tag{10}$$

$$\varepsilon \approx N(\mu, \sigma^2) \tag{11}$$

where C^p is the actual price at considered hour, C^f is the forecasted price by jth GENCO; ε is a stochastic variable subject to the normal distribution with mean μ and variance δ^2, which are obtained from the historical forecasts. The players are willing to push prices up; hence have the motivation to offer a high price with an associated acceptable risk.

In addition, more constraint can be considered. Therefore, this problem is a non-convex and conventional optimization approach cannot solve this problem. Recently, evolutionary computation techniques are attractive for many researchers. Genetic algorithm is one of these techniques. In general, these techniques are different from conventional search in three key steps: a population of points is used in their search; calculated direct 'fitness' from the objective function, information instead of function derivatives or other related knowledge are used. Also, probabilistic rather than deterministic and transition rules are considered (Fogel, 1994; Back, 1996).

4. An overview of genetic algorithms

GAs are inspired by Darwin's evolutionary theory (Dahal, Galloway, Burt, & McDonald, 2001; Ongsakal & Ruangpayoongsak, 2001; Zdansky & Pozivil, 2002). Theory of genetics considers a cell as the fundamental element that builds every life organism. However, each cell in turn composes of blocks called *chromosomes*. Each chromosome is made up of strings of DNA. These strings serve as models for each organism. A *gene* is a combination of a block of DNA. A particular protein or a trait is encoded by a gene. The color of eyes of every human is an example of a *trait*. *Alleles* are the possible value settings in a gene to get up a given trait such as blue or brown in eyes. *Locus* is a position of a gene in the chromosome. *Genome* is a complete set of genetic material for all chromosomes in an organism. *Genotype* is a particular set of genes in a genome. The base for the organism's *phenotype*, its physical and mental characteristics, such as eye color, intelligence, etc is formed from genotype with later development after birth. The sexual reproduction (with parents) has two clearly defined steps: (a) duplication and separation of a reproductive cell, and (b) generation of a new offspring. To understand this process it is necessary to remember that a reproductive cell have two chromosome chains, one inherited from the father and other from the mother and, so, each element of the chromosome, the so called gene, have two alleles that define the genotype.

The duplication process occurs when a reproductive cell (with two chromosome chains) duplicates itself and separate forming 4 half of a cell (or in the father four spermatozoids). If this process of duplication and separation were uniform, then half from a generated cell (spermatozoid) will be the inherited information from the father or the mother. Meanwhile, the separation process happens when a recombination between the genetic materials inherited from the parents happens. Thus, one spermatozoid that is half from a cell is formed from inherited parts from father and mother for a recombination process that happens in the separation. This disorderly separation process is called Crossing-over. The crossover operator in GA tries to imitate that crossing-over process that happens when the spermatozoids are generated in the case of the father. The generation of a new offspring happens when half of a father cell (spermatozoid) joins other half from the mother (ovule) to form a new complete cell (zygote), this happens after the sexual process. In summary, the crossing-over happens when a cell generate other four half of a cell (duplications and separation) and the reproduction happens when two half of a cell join together to form a new cell. This last step happens in the reproduction.

Additionally, it is of special notice that the crossover genetic operator used in optimization do not work the same way that in genetics (the crossing over is the main source of genetic diversification among individuals). In the genetic crossing-over 4 half cell are generated from a reproductive cell, but in the optimization crossover operator two new offsprings are generated from two parents. But this issue is out of the scope of this discussion. In this process, new chromosomes are formed by genes from parents. Then, *mutation* carried out on new chromosomes. Elements of DNA are slightly modified by mutation process. Errors in copying from parents in the reproduction process cause modifications. Also, this creates offspring from both parents. Once, an offspring is created, its success in maintaining its presence in future generations will be determined by its ability to reproduce (Rodrigo, 2007).

The popular GA optimization techniques employ the basic biological principles described above. GA is known as a powerful non-deterministic method in problem solving and optimization. It is broadly used in finding the best possible solution in the complex problems, especially NP problems, which are considered with great dimensions and limits. GA is stochastic search method that mimics the metaphor of natural biological evolution. The algorithm operates on a population of potential solutions applying the principle of survival of the fittest to produce better and better approximations to best solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation. Algorithm is started with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness – the more suitable they are the more chances they have to reproduce. Fig. 1 shows the total structure of a simple GA (Davis, 1991; Goldberg, 1989; Orero & Irving, 1996).

GA is generally based on three modules, known as production module, evaluation module and reproduction module. (a) Production module: production module contains a set of operators and techniques for creating and manipulating population. The initialization operator is used to create the initial population by filling

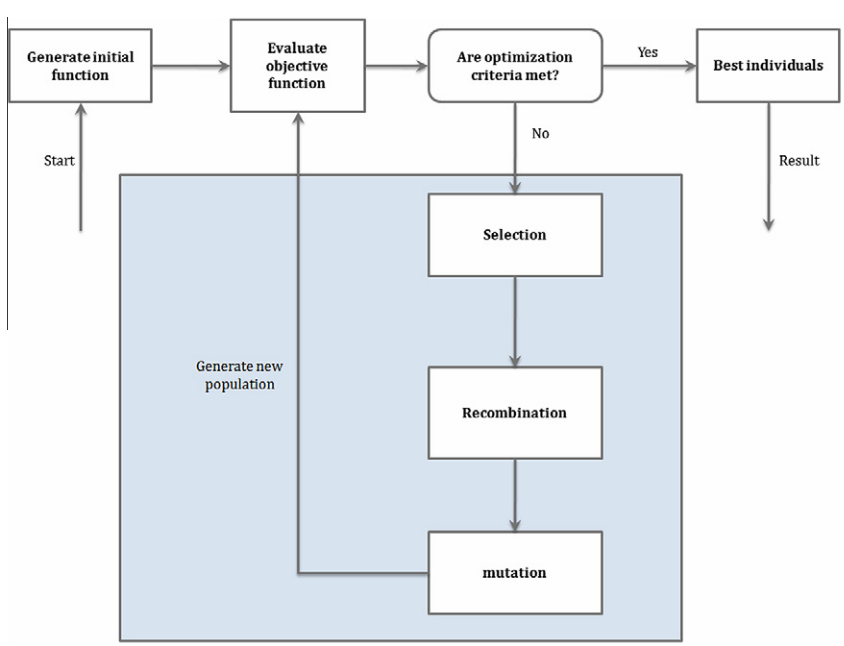


Fig. 1. Structure of a GA.

it with randomly generated individuals. Each individual is a representative of the problem solution identified by its digit string. The deletion operator deletes all old population which cannot contribute as influential parents in next generations when the reproduction has been occurred. (b) Evaluation module: this stage involves checking the individuals to see how good they are able to satisfy the objectives in the problem. The fitness operator quantifies the total characters of each chromosome (individual) in the population. The evaluating fitness operator assesses the value of fitness function of each chromosome in order to satisfy the objectives based on maximum or minimum level. (c) Reproduction module: this is really the most important stage in GA. The module includes three main operators. The selection operator is beneficially used to determine which individuals are chosen as parents for mating and how many offsprings from each selected individuals are produced. The recombination operator is used to produce new chromosomes in combining the information contained in the parents. After recombination, each offspring undergoes small perturbations (size of mutation step) with low probability by the mutation operator (Ebrahimipour, Azadeh, Rezaie, & Suzuki, 2007).

5. Optimal bidding strategy by GA

In general, prices and quantities of all GENCOs that should be offered in next round can be coded as a chromosome. Suppose maximum number of segment is L. so chromosome is an array combined by two rows and $L * K$ columns. First row show the offered quantity and second show the offered price (Fig. 2).

In the following, for representing the GA application in optimal bidding strategy, a simple problem is designed and solve by using of GA. Also, GA procedure is expressed step by step.

5.1. Test problem description

Suppose that there are two independent GENCOs participating in electricity market in which the sealed auction with a pay-as-bid MCP is employed. It is assumed that GENCOS have information about forecasted load, forecasted price and expectations of rival bids. Suppose first GENCO wish to participate at market and to maximize its own profit. Since, this problem is going to be solved from two points of view; therefore, it is needed to define different objective for each problem.

Case 1: In this case, the problem is going to be solved from GENCO's point of view that doesn't consider his rival's bid. This GENCO only wish to maximize his profit as objective function. Suppose player 1 wish to maximize his profit without considering rival's bid. So, following single objective is used:

$$\max \pi_1 \tag{12}$$

Case 2: In this case, the problem is going to be solved from GENCO's point of view considering his rival's bid. Therefore, there is a problem with multi objective function to solve. In this case, GENCO wish to maximize his profit while consider his rival wishing to maximize his profit, too. So, GENCO is going to solve two maximization problems. As mentioned before, one approach for solving such problems is transferring two objectives to a single objective by giving some coefficient to each objective based on its important.

P_{11}	P_{12}	...	$P_{1(L-1)}$	P_{1L}	...	P_{K1}	P_{K2}	...	$P_{K(L-1)}$	P_{KL}
C_{11}	C_{12}	...	$C_{1(L-1)}$	C_{1L}	...	C_{K1}	C_{K2}	...	$C_{K(L-1)}$	C_{KL}

Fig. 2. The general proposed chromosome.

Suppose player 1 wish to maximize his profit considering his rival bid wishing to maximize his profit, too. Thus, following proposed single objective based on an expert idea is used instead of two maximization objective.

$$\max 0.5^{*}(\pi_1 + \pi_2) + 0.3\pi_1 + 0.2\pi_2 \tag{13}$$

5.2. GA procedure

As said before, the evolutionary computation is appropriate to solve complex and non-convex bidding strategy problem. In this paper, GA is used as an important evolutionary computation to solve this optimization problem evolutionary computation. The proposed methodology consists of following components.

Population size: Here, the population represents a sample that is chosen to be representative of the whole solution set. Typically the population size of a GA is kept at a fraction of the whole solution set. The number of chromosomes in a generation will direct the time for result an optimal solution to a given problem. If there are too few chromosomes, there are few possibilities to carry out crossover and only a small part of the search space is explored. This may result in GA finish with a suboptimal solution. On the other side, if there are too many chromosomes, GA will slow down, outweighing the attractiveness of this algorithm over the conventional solution techniques. Researches show that populations with moderate-sized are best suited for many practical problems (Rodrigo, 2007).

Representation: The solution process begins with a set of identified chromosomes as the parents from a population. For this problem, the proper offered quantities for both GENCOs are selected as control variables in the problem. Each chromosome in this proposed GA-approach consists of these 6 variables and can be expressed as follows:

chromosome	q_{11}	q_{12}	q_{13}	q_{21}	q_{22}	q_{23}

$$\text{where } q_{ji} = P_{ji} + P_{j(i-1)} \quad j = 1, 2, \ldots,\ i = 1, \ldots, 3 \text{ and } P_{j0} = 0 \tag{14}$$

P_{ji} Show offered quantity of jth GENCO in ith segment. q_{ji} Show cumulative quantities for jth GENCO in ith segment.

Fitness function: In this study, the value of the objective function (profit) is used to designate the fitness of each chromosome.

Case 1: fitness function is considered as (12) for case 1-problem.
Case 2: fitness function is considered as (13) for case 2-problem.

Initialization: The population of chromosome is randomly initialized within the operating range of the control variables.

Reproduction: "Healthiest" chromosomes in a given generation are used to form the chromosomes of the new population in the next generation. The next population is selected by the hope it will be better than the old one. The members of the subsequent generation are called offspring. Competition method is used for chromosome selection in this approach. Selected chromosomes compose Matingpool. In fact, Reproduction operator select a set of the best chromosomes, but none of these are new. Crossover operators used to create new chromosome from randomly chromosome that are selected from matingpool. Here, offspring formulation will use heredity of each parent. The notion of using heredity is defined by two basic operations: mutation and crossover.

Crossover: In the biology analogy, an encoding methodology can represent each chromosome of a given (Rodrigo, 2007). Next, creation an offspring from its parents uses the principles of crossover. In the process, some genes are selected from one sub set of parents. These genes are mixed with different genes from other parents.

Mutation: Mutation process leads an offspring to have its own identity. Usually a very low mutation rate is selected to decrease the amount of randomness introduced into the solution. Selecting a proper level of mutation is the key to avoid a genetic algorithm from getting captured in local minima.

Termination criteria: There are various methods to end genetic algorithm running.

GA cods are presented by Appendix A.

6. Computational results

We considered an electricity market with two players for bidding. Suppose player 1 decides to submit his bidding by three segments. Suppose that forecasted demand and forecasted market clearing price by player 1 are 30 MVh and 7.5$, respectively. Also, price cap is equal to 8$. Suppose this player considers bidding caps for each segment's quantity equal to 5, 10, and 15 (MVh). Also, he determines his offered price for each segment based on historical data, price cap and forecasted price. For example, he select prices equal to 2, 5, 7 ($) for each segment, respectively. Also, suppose player 1 knows that his rival wishes to bid on three segments. Player 1 expect three bidding caps for quantity bidding of his rival equal to 6, 10, 20 (MVh) and three offered price equal to 2, 5, 7 ($). Suppose minimum and maximum generation for player 1 is equal to 11 and 15 (MVh), respectively. Also minimum and maximum generation for player 2 is equal to 16 and 20 (MVh), respectively. Total cost of player 1 and player 2 are considered fixed and are equal to 10 and 15, respectively. Therefore, profit functions of two players can be defined as follows:

$$\pi_j = \sum_{i=1}^{3} c_{ji} P_{ji}, \quad j = 1,2 \tag{15}$$

where c_{ji} is offered price by jth GENCO in ith segment. Also, P_{ji} show offered quantity of jth GENCO in ith segment. Based on this approach, profit functions for given players are obtained as follow:

$$\pi_1 = 2^* P_{11} + 3^* P_{12} + 7^* P_{13} - 10 \tag{16}$$

$$\pi_2 = 2^* P_{21} + 5^* P_{22} + 7^* P_{23} - 15 \tag{17}$$

Now, player 1 try to choose parameters based on constraints for maximizing own profits. The some unreality data were used to solve this example, because of simplifying problem to show efficiency of proposed GA solving such problems. In follow, a GA-approach is proposed for solving this problem. We considered an initial population composed of 17 chromosomes. Table 1, shows this population with fitness values of chromosomes.

It can be seen easily that all given constraints are certified by these chromosomes. First, given problem is solved from viewpoint of player 1 trying maximize its own profit without consider his rival's own profit. Therefore, column of profit-company 1 obtained based on Eq. (15) is the objective to maximize in this case. Competition method is used for chromosome selection in this problem. Selected chromosomes compose Matingpool shown by Table 2.

The crossover operator is carried out according to a rate of crossover. In this study crossover rate is defined as 0.7. Our crossover-approach is as follows. Two parents are selected from Matingpool as parents, randomly. A number is selected from interval (0, 1), randomly and uniformly. If random number is less than crossover rate then crossover operator create two new chromosomes as offspring from parents, else parents will be copied in offspring chromosomes cell by cell. Proposed crossover in this paper is described by an example as follows. First, two parents are selected.

Table 1
First population of chromosome in GA runs.

First population							Fitness values	
Ch. no.	Chromosomes						Profit-company1	Profit-company2
off-1	1	5	13	0	4	17	68	96
off-2	3	8	11	4	10	19	42	86
off-3	3	3	14	1	9	16	73	76
off-4	3	5	12	6	10	18	55	73
off-5	5	8	13	5	10	17	50	45
off-6	2	6	11	1	8	19	49	99
off-7	0	5	12	0	6	18	64	99
off-8	3	5	11	2	7	19	48	98
off-9	4	7	12	6	6	18	48	81
off-10	2	9	13	3	10	17	57	75
off-11	3	4	14	1	8	16	71	78
off-12	4	4	11	3	6	19	47	97
off-13	2	6	14	3	4	16	70	80
off-14	1	7	11	0	4	19	50	110
off-15	1	6	12	2	8	18	59	89
off-16	4	7	13	6	9	17	55	68
off-17	5	10	14	5	5	16	53	72

Table 2
Mating pool after first population created by competition method.

Matingpool							Fitness values	
No.	Chromosomes						Profit-com1	Profit-com2
off-1	1	5	13	0	4	17	68	96
off-3	3	3	14	1	9	16	73	76
off-3	3	3	14	1	9	16	73	76
off-4	3	5	12	6	10	18	55	73
off-5	5	8	13	5	10	17	50	45
off-6	2	6	11	1	8	19	49	99
off-7	0	5	12	0	6	18	64	99
off-11	3	4	14	1	8	16	71	78
off-9	4	7	12	6	6	18	48	81
off-10	2	9	13	3	10	17	57	75
off-11	3	4	14	1	8	16	71	78
off-3	3	3	14	1	9	16	73	76
off-13	2	6	14	3	4	16	70	80
off-14	1	7	11	0	4	19	50	110
off-15	1	6	12	2	8	18	59	89
off-16	4	7	13	6	9	17	55	68
off-17	5	10	14	5	5	16	53	72

parent 1	1	5	13	0	4	17
parent 2	3	3	14	1	9	16

Then, parents are encoded as on the base of scale of four. For example, 5 is a decimal number. Based on definition of numbers in scale of four, 11 show 5. Four scale-based coding is selected because selected quantity values are small in this paper. Although, binary cods is not proper because the size of chromosomes would be large.

parent1_1	0	0	1	0	1	1	0	3	1	0	0	0	0	1	0	1	0	1
parent1_2	0	0	3	0	0	3	0	3	2	0	0	1	0	2	1	1	0	0

After that, two random integer array between [0,1] called mask are produced as follows:

mask1	1	1	1	1	1	0	0	0	0	1	1	1	1	0	1	1	1	0
mask2	0	1	0	0	1	1	0	0	1	1	1	0	1	0	0	1	1	1

Then, if *j*th cell content of mask *i* is equal to 1, copy *j*th cell content of parent1_1 into *j*th cell of offspring *i*. Else, copy *j*th cell content of parent1_2 into *j*th cell of offspring *i*.

Offspring 1	0	0	1	0	1	3	0	3	2	0	0	0	0	2	0	1	0	0
Offspring 2	0	0	3	0	1	1	0	2	1	0	0	1	0	2	1	1	0	1

Table 3
First population of chromosome after first GA run.

Second population							Fitness values	
No.	Chromosomes						Profit-com1	Profit-com2
off-1	1	5	13	0	4	17	68	96
off-3	3	3	14	1	9	16	73	76
off-3	3	3	14	1	9	16	73	76
off-4	3	5	12	6	10	18	55	73
off-11	3	4	14	1	8	16	71	78
off-15	1	6	12	2	8	18	59	89
off-7	0	5	12	0	6	18	64	99
off-11	3	4	14	1	8	16	71	78
off-9	4	7	12	6	6	18	48	81
off-10	2	9	13	3	10	17	57	75
off-11	3	4	14	1	8	16	71	78
off-3	3	3	14	1	9	16	73	76
off-13	2	6	14	3	4	16	70	80
off-4	3	5	12	6	10	18	55	73
off-15	1	6	12	2	8	18	59	89
off-16	4	7	13	6	9	17	55	68
off-18	6	10	14	5	6	16	50	70

Table 4
Offspring of chromosomes after last GA run.

Last population							Fitness values	
No.	Chromosomes						Profit-com1	Profit-com2
off-1	1	5	13	0	4	17	68	96
off-3	3	3	14	1	9	16	73	76
off-3	3	3	14	1	9	16	73	76
off-11	3	4	14	1	8	16	71	78
off-11	3	4	14	1	8	16	71	78
off-15	1	6	12	2	8	18	59	89
off-7	0	5	12	0	6	18	64	99
off-11	3	4	14	1	8	16	71	78
off-11	3	4	14	1	8	16	71	78
off-1	1	5	13	0	4	17	68	96
off-11	3	4	14	1	8	16	71	78
off-3	3	3	14	1	9	16	73	76
off-13	2	6	14	3	4	16	70	80
off-3	3	3	14	1	9	16	73	76
off-15	1	6	12	2	8	18	59	89
off-3	3	3	14	1	9	16	73	76
off-11	3	4	14	1	8	16	71	78

Table 5
GA results for case 1.

Run number	First run	Second run	···	Last run
Average fitness values of profit-company1 for each run	56.41176	63.05882	···	69.35294

As mentioned, the mutation operator is carried out according to the rate of mutation. In this study, mutation rate is considered as 0.02. Offsprings will be copied in an array as future parents, so it must return to first step for fitness calculating. Mutation operator changes two cell contents of offsprings if random number be lower than mutation-rate. In this step, offsprings are transferred to origin decimal numbers.

Offspring 1	1	7	14	0	8	16
Offspring 2	3	5	13	1	9	17

Here, algorithm will be completed by the determined number of repetitions equal to 20 runs. Tables 3 and 4 show the second population and last population, respectively.

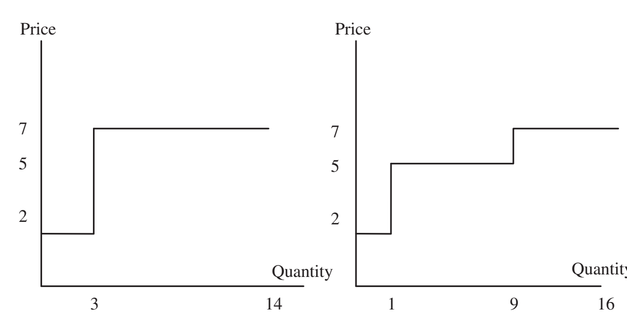
Also, the results of GA convergence for the first case are shown in Table 5.

It can be seen that average fitness values of profit-company 1 would become better by each run. In the last run this value is more than fitness values of pervious runs. After comparisons between chromosomes of the last population based on considered fitness function for this case (first defined case of problem), the optimal solution is shown in Table 6.

Also, optimal bidding strategy based on the above optimal solution is shown for both players by Fig. 3.

Table 6
The optimal solution.

No.	Chromosomes						Profit-company 1	Profit-company 2
off-3	3	3	14	1	9	16	73	76



a. optimal bid for player 1
Profit =73

b. optimal bid for player 1
Profit =76

Fig. 3. Optimal bidding strategy from viewpoint of player 1 without considering his rival's profit function.

Table 7
GA results for case 2.

No.	Chromosomes						Profit-company 1	Profit-company 2
off-3	1	7	11	0	4	19	50	110

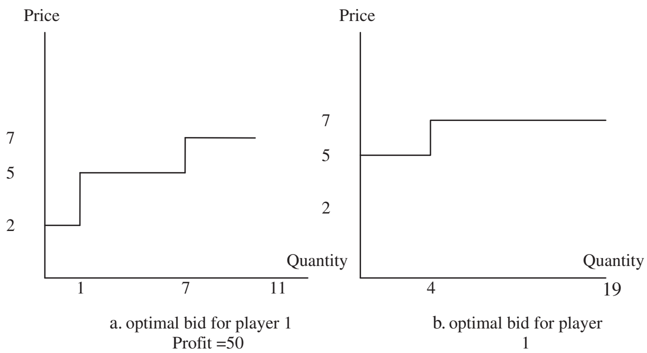


Fig. 4. Optimal bidding strategy from viewpoint of player 2 without considering his rival's profit function (case1).

Table 8
Optimal solution for the second case – viewpoint of profit maximization from of player 1 with considering player 2 profit maximization.

Chromosomes						Profit-company 1	Profit-company 2
1	5	13	0	4	17	68	96

Table 9
Optimal solution for the second case – viewpoint of profit maximization from of player 2 with considering player 1 profit maximization.

Chromosomes						Profit-company 1	Profit-company 2
1	5	13	0	4	17	68	96

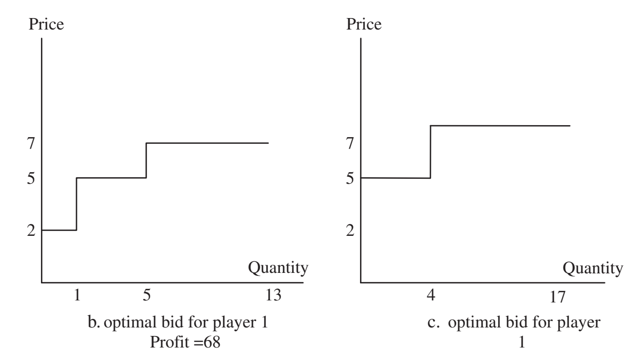


Fig. 5. Optimal bidding strategy from viewpoint of player 1 (also player 2) considering rival's profit function (case 2).

In the following, given problem is solved from viewpoint of player 2 without consider its own rival's profit function. Optimal solution is given by Table 7.

Also, optimal bidding based on above optimal solution is shown for both players by Fig. 4, as follow.

At the end, the given problem is solved while both players consider his rival's own profit function for bidding (case 2). This case is solved once from viewpoint of player 1 considering its own profit and its rival's profit, then from viewpoint of player 2 considering its own profit and its rival's profit. It is interested because both players got the same solution for bidding. These results are shown as Tables 8 and 9.

Table 8 shows optimal solution for second case of problem from viewpoint of profit maximization of player1 with considering player2 profits maximization.

Table 9 shows optimal solution for second case of problem from viewpoint of profit maximization of player2 with considering player1 profit maximization. Also, optimal bidding players based on above optimal solutions is shown for both players by Fig. 5 as follow.

7. Conclusion

In this paper, a new GA-approach was presented for bidding strategy in a day-ahead market from the viewpoint of a GENCO for maximizing its own profit as a participant in the market. Two approaches were considered based on two different GENCO's point of view: as a supplier wishing to maximize the profit without considering rival's profit function, and as a supplier wishing to maximize the profit considering rival's bidding and profit functions. Therefore, in the second case, GENCO has a multi objective profit maximization problem to solve. Also, constraints such as generation limitations were considered. Therefore, the optimal bidding strategies were determined by solving an optimization problem that takes unit commitment constraints such as generating limits into account. This is a non-convex problem which is difficult to solve by conventional optimization techniques. Therefore, a GA was used to solve the problem. A simple test problem was defined and illustrated how this approach could tackle this problem efficiently by assuming a day-ahead market with two players concern to participate in market. Therefore, the optimal bidding strategy was developed using GA based on the forecasted load, forecasted market clearing price (MCP) and expectations concerning rival bids and profit functions. Numerical results represented that two players in case 2 achieve a common solution to submit bid by using the proposed approach. Also, the proposed algorithm showed that average fitness value of profit becomes better after each iteration. The obtained results show that the best strategy for each rivals are

Table 10
The features of this research versus other methods.

Method	Feature				
	Capable of handling unit commitment constraints	Incorporation of concurrent rivals' bid and profit functions	Handling multi-objective problems	Bids consider price and quantity concurrently	Models non-convex problems
The proposed GA-approach					
The proposed GA-approach					
Wen and David (2001)	√		√		√
Yucekaya et al. (2009)	√			√	
Attaviriyanupap et al. (2005)	√		√		√
Tan et al. (2008)	√		√		√
Wu, Gu, Turner, Wu, and Zhou (2004)					√
Xiong et al. (2004)			√		

same. Table 10 represents the related features of the proposed approach in this paper in comparison with some articles in this area. As shown in Table 10, there are a few research works that considered bids as pairs of quantity and price and, to the best of our knowledge, none of them considered rivals' bid and profit functions simultaneously.

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Appendix A

```
% Enter crossover_rate and mutation-rate
% determine size of population and size of chromosome
% first population and offspring are array by dimension
  (population size*number of chromosome cells)
% parent and offspring are a array by dimension (2*number of
  chromosome cells)
% coding(No) is a function that code the numbers based on a
  No.
% parent_cod and offspring_cod are transferred parent and
  offspring by selected coding
% in this case study, four-based coding is selected. Also,
  following assumption is considered:
crossover_rate=0.7;
mutation_rate=0.02;
population_size=20;
  chromosome_cell_No=6;
****
% Crossover process
rand_num=rand;
if rand_num<crossover_rate %if 1
parent_cod=coding(4);
rand;
mask=randint(2,18);
for j=1:2 %for1
for i=1:18 %for 2
if mask(j,i)==1 %if 2
offspring_cod(j,i)=parent_cod(1,i);
else
offspring_cod(j,i)=parent_cod(2,i);
end% end if 2
end% end for 2
end% end for 1
else
offspring_cod=parent_cod;
end% end if 1
% mutation process
mutation_rate=0.02;
for i=1:2
rand;
rand_num=rand;
if rand_num<mutation_rate
l1=randsrc(1,1,[1:18]);
l2= randsrc(1,1,[1:18]);
t=offspring_cod(i,l1);
offspring_cod(i,l1)= offspring_cod(i,l2);
offspring_cod(i,l2)=t;
  end%end if
end%end for
% after these process offspring must be checked to satisfy in
  constraint of problem
```

References

Al-Agtash, S., & Yamin, H. Y. (2004). Optimal supply curve bidding using Benders decomposition in competitive electricity markets. *Electric Power Systems Research, 71*(3), 245–255.

Attaviriyanupap, P., Kita, H., Tanaka, E., & Hasegawa, J. (2005). New bidding strategy formulation for day-ahead energy and reserve markets based on evolutionary programming. *Electrical Power and Energy Systems, 27*(3), 157–167.

Azadeh, A., Ghaderi, F., & Pourvalikhan Nokhandan, B. (2009). A new GA-approach for optimizing bidding strategy viewpoint of profit maximization of a GENCO. In *IEEE symposium series on computational intelligence, Nashville, USA*.

Back, T. (1996). *Evolutionary algorithm in theory and practice*. Oxford: Oxford University Press.

Bhattacharya, K. (2000). Strategic bidding and generation scheduling in electricity spot-markets. In *International conference on electricity utility deregular restrict power technology* (pp. 108–113).

Borghetti, A., Massuccob, S., & Silvestro, F. (2009). Influence of feasibility constrains on the bidding strategy selection in a day-ahead electricity market session. *Electric Power Systems Research, 79*(12), 1727–1737.

Dahal, K. P., Galloway, S. J., Burt, G. M., & McDonald J. R. (2001). Generation scheduling using genetic algorithm based hybrid techniques. In *LESCOPE '01, conference on 107 large engineering systems in power engineering* (pp. 74–78).

David, A. K. (1993). Competitive bidding in electricity supply. *IEE Proceedings Generation, Transmission and Distribution, 140(5)*, 421–426.

Davis, L. (1991). *Hand book of genetic algorithms*. New York: Van Nostrand Reinhold.

Ebrahimipour, V., Azadeh, A., Rezaie, K., & Suzuki, K. (2007). A GA–PCA approach for power sector performance ranking based on machine productivity. *Applied Mathematics and Computation, 186*(2), 1205–1215.

Fogel, D. B. (1994). An introduction to simulated evolutionary optimization. *IEEE Transactions on Neural Networks, 3*(2), 3–14.

Goldberg, D. E. (1989). *Genetic algorithm in search and optimization*. New York: Addison-Wesley.

Gross, G., & Finlay, D. J. (1996). Optimal bidding strategies in competitive electricity markets. In *Proceedings of 12th power system computer conference, PSCC* (pp. 815–822).

Gross, G., Finlay, D. J., & Deltas, G. (1998). Strategic bidding in electricity generation supply markets. In *Proceedings of IEEE power engineering society winter meeting* (pp. 309–315).

Guan, X., Ho, Y. C., & Lai, F. (2001). An ordinal optimization based bidding strategy for electric power suppliers in the daily energy market. *IEEE Transactions on Power Systems, 16*(4), 788–797.

Hao, S. (1999). A study of basic bidding strategy in clearing pricing auctions. In *Proceedings of the 21st international conference on power industry computer applications, PICA* (pp. 55–60).

Kang, D. J., Kim, B. H., & Hur, D. (2007). Supplier bidding strategy based on non-cooperative game theory concepts in single auction power pools. *Electric Power Systems Research, 77*(5–6), 630–636.

Kian, A. R., & Cruz, J. B. (2005). Bidding strategies in dynamic electricity markets. *Decision Support Systems, 40*(3–4), 543–551.

Lai, M., Tong, T., Yang, H., & Bing, P. (2009). Dynamic bidding analysis in power market based on the supply function. *Computers and Mathematics with Applications, 58*(1), 25–38.

Lee, C. C., & Yang, C. O. (2007). Development and evaluation of the interactive bidding strategies for a demander and its supplier's in supplier selection auction market. *International Journal of Production Research, 46*(17), 4827–4848.

Li, C. A., Svoboda, A. J., Guan, X. H., & Singh, H. (1999). Revenue adequate bidding strategies in competitive electricity markets. *IEEE Transactions on Power Systems, 14*(2), 492–497.

Maa, X., Wena, F., Nia, Y., & Liub, J. (2005). Towards the development of risk-constrained optimal bidding strategies for generation companies in electricity markets. *Electric Power Systems Research, 73*(3), 305–312.

Mielczarski, W., Michalik, G., & Widjaja, M. (1999). Bidding strategies in electricity markets. In *Proceedings of 21st international conference on power industry computer applications, PICA* (pp. 71–76).

Ni, E., & Luh, P. B. (2002). Optimal integrated generation bidding and scheduling with risk management under a deregulated daily power market. In *Proceedings of IEEE power engineering society winter meeting* (Vol. 1, pp. 70–76).

Ongsakal, W., & Ruangpayoongsak, N. (2001). Constrained dynamic economic dispatch by simulated annealing/genetic algorithms. In *22nd IEEE power engineering society international conference on power industry computer applications* (pp. 207–212).

Orero, S. O., & Irving, M. R. (1996). A genetic algorithm for generator scheduling in power system. *Journal of Electrical Power and Energy System, 18*(1), 19–26.

Ragupathi, R., & Tapas, K. (2004). A stochastic game approach for modeling wholesale energy bidding in deregulated power markets. *IEEE Transactions on Power Systems, 19*(2), 849–856.

Richter, J. R., & Sheble, G. B. (1998). Genetic algorithm evolution of utility bidding strategies for the competitive marketplace. *IEEE Transactions on Power System, 13*(1), 256–261.

Richter, J. R., Sheble, G. B., & Ashlock, D. (1999). Comprehensive bidding strategies with genetic programming/finite state automata. *IEEE Transactions on Power Systems, 14*(4), 1207–1212.

Rodrigo, D. (2007). *Optimal operational strategies for a day-ahead electricity market in the presence of market power using multi-objective evolutionary algorithm*. An abstract of a dissertation submitted in partial fulfillment of the requirements for the degree doctor of philosophy, Department of Electrical and Computer Engineering College of Engineering Kansas State University, Manhattan, Kansas.

Saleh, A., Tsuji, T., & Oyama, T. (2009). Optimal bidding strategies for a small generation company in a day-ahead electricity market with bilateral contracts taken into account. *American Journal of Engineering and Applied Sciences, 2*(1), 176–183.

Sheble, G. B. (2000). Agent based economics. In I. Marija, G. Francisco, & F. Lester (Eds.), *Power systems restructuring* (pp. 187–242). Kluwer Academic Publishers.

Song, Y., Ni, Y., Wen, F., Hou, Z., & Wu, F. F. (2003). Conjectural variation based bidding strategy in spot markets: Fundamentals and comparison with classical game theoretical bidding strategies. *Electric Power Systems Research, 67*(1), 45–51.

Tan, Y., Shen, L., Lu, W., & Shen, Q. (2008). Multiple-objective bidding strategy using goal programming technique. *Management Decision, 46*(4), 656–672.

Wang, L., Yu, C. W., & Wen, F. S. (2008). The impacts of different bidding segment numbers on bidding strategies of generation companies. *Electric Power Systems Research, 78*(3), 458–463.

Weber, J., & Overbye, T. (1999). A two-level optimization problem for analysis of market bidding strategies. In *IEEE PES summer meeting* (Vol. 2, pp. 682–687).

Wen, F. S., & David, A. K. (2000). Strategic bidding in reserve market. In *Proceedings of fifth international conference on advanced power system control, operation and management, APSCOM* (pp. 80–85).

Wen, F. S., & David, A. K. (2001a). Oligopoly electricity production under incomplete information. *IEEE Power Engineering Review*, 58–61.

Wen, F. S., & David, A. K. (2001b). Strategic bidding for electricity supply in a day-ahead energy market. *Electric Power Systems Research, 59*(3), 197–206.

Wen, F. S., & David, A. K. (2001c). Optimal bidding strategies and modeling of imperfect information among competitive generators. *IEEE Transactions on Power Systems, 16*(1), 15–21.

Wen, F. S., & David, A. K. (2002). Coordination of bidding strategies in day-ahead energy and spinning reserve markets. *Electrical Power and Energy Systems, 24*(5), 251–261.

Wu, Q. H., Gu, o J., Turner, D. R., Wu, Z. X., & Zhou, X. X. (2004). Optimal bidding strategies in electricity markets using reinforcement learning. *Electric Power Components and Systems, 32*(2), 175–192.

Xiong, G., Hashiyama, T., & Okuma, S. (2002). An evolutionary computation for supplier bidding strategy in electricity auction market. In *Proceedings of IEEE power engineering society winter meeting* (pp. 83–89).

Xiong, G., Okuma, S., & Fujita, H. (2004). Multi-agent based experiments on uniform price and pay-as-bid electricity auction markets. In *Proceeding of conference on electricity utility deregulation, restructuring and power technologies, Hong Kong* (pp. 72–76).

Yin, X., Zhao, J., Saha, T. K., & Dong, Z. J. (2007). *Developing GENCO's strategic bidding in an electricity market with incomplete information. Power engineering society general meeting*. IEEE.

Yucekaya, A. D., Valenzuela, J., & Dozier, G. (2009). Strategic bidding in electricity markets using particle swarm optimization. *Electric Power Systems Research, 79*(2), 335–345.

Zdansky, M., & Pozivil, J. (2002). Combination genetic/tabu search algorithm for hybrid flew shop optimization. In *Proceedings of algoritmy, 16th conference on scientific computing, Vysoke Tatry – Podbanske, Sloakia* (pp. 230–236).

Zhang, D., Wang, Y., & Luh, PB. (2000). Optimization based bidding strategies in the deregulated market. *IEEE Transactions on Power Systems, 15*(3), 981–986.