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\*Corresponding author: Somendra P.S. Mathur, Electrical Engineering Department, Maulana Azad National Institute of Technology, Bhopal, India  
E-mail: [somendra.mathur0007@gmail.com](mailto:somendra.mathur0007@gmail.com)

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Gongnan Xie, Northwestern Polytechnical University, China

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## ELECTRICAL & ELECTRONIC ENGINEERING | RESEARCH ARTICLE

# Optimal bidding strategy for price takers and customers in a competitive electricity market

Somendra P.S. Mathur<sup>1\*</sup>, Anoop Arya<sup>1</sup> and Manisha Dubey<sup>1</sup>

**Abstract:** Bidding strategies are highly associated with the profit maximization and decreasing the risks for power utilities in a competitive market. For finding the optimal bidding strategies price takers need appropriate bidding structure. Thus, it is required to consider the model as a bi-level optimization problem. In the lower level price takers submit bid strategically to the ISO and in the upper level maximization of social welfare performed by solving the ISO Market clearing price (MCP). This paper aim to summarize the price taker's bidding strategy modeling methods for competitive market models on the state-of-the art. A new genetic algorithm approach in a day-ahead electricity market in sealed auction with a pay-as-bid MCP has been employed to solve the problem from two different viewpoints i.e. with symmetrical and unsymmetrical information. The efficiency of the proposed method has been tested on the IEEE-30 bus system.

**Subjects:** Power & Energy; Power Engineering; Engineering Economics

**Keywords:** bidding strategy; competitive electricity market; rival's behavior; genetic algorithm

## 1. Introduction

### 1.1. Background and motivation

Electricity market experienced major reforms all over the world and competition in power market increased greatly from monopoly power utilities to competitive market power. The liberalization in

## ABOUT THE AUTHOR

Somendra P.S. Mathur is a PhD research scholar in the Department of Electrical engineering at MANIT Bhopal. He received his BE from MITS Gwalior and Mtech from MANIT Bhopal in 2008 and 2011 respectively. His research interest includes Modern Power system, Deregulation, Power system economics and optimization techniques.

## PUBLIC INTEREST STATEMENT

In the competitive electricity market, dispatch of generation is based on bid and each price taker's company needs to compete with rivals via bidding to the market. Competition creates the opportunities for price taker's to get more profit. Therefore, in a competitive electricity market, each price takers will reasonably build strategic bidding to maximize its own profit. The bidding strategy problem was first introduced by David (1993) and has been afterward developed by many researchers. Also, there are several methods to find the optimal bidding strategy. GA are inspired by Darwin's evolutionary theory (Dahal, Galloway, Burt & McDonald, 2001; Ongsakal & Ruangpayoongsak, 2001; Zdansky & Pozivil, 2002) and it has been employed in many research works to solve different problem, but none of them has been considered practical limitations and rival's bid together. GA develop bidding price through crossover and mutation process.

the electricity market started in 1980's in the UK and some other countries which characterized by unbundling electricity services, open access to the network, open competitive energy markets etc. (Kirschen Daniel & Strbac, 2004). The proper operation and supervision of electric power supply bring out economical growth of the country. The innovation of new technologies and gaming on power market leads the restructured market in to the establishment of competitive market power. Reformation includes the thought of introduction of competitive energy market, unbundling of electricity services and opening access to the network. The aim of reformation is to change the economics of electricity from monopolies to oligopoly, increased fuel availability, develop new technologies in power generation and information technology with improved quality service and cost reduction (Liu & Wu, 2006). Since the mid-1980's a number of countries around the world have engaged in market reform initiatives including liberalization, privatization, and/or restructuring the electricity market. Chile is generally the first country to undertake a major market reform process in 1987 (Shukla & Thampy, 2011).

There are the three ways for developing the bidding models i.e. evaluation of market clearing price (MCP), gaming theory and bidding behavior of rival participants. The point of intersection between the aggregated supply for suppliers and a demand curve for consumers determines the market clearing prices (David & Wen, 2000). Theoretically, suppliers in a competitive electricity market to maximize profit should bid at very close to their marginal cost. However, the electricity market is not perfectly competitive due to limited number of producers. Therefore, the power companies bid their price slightly higher than the marginal production cost. When a suppliers bids other than the marginal cost, to take the advantage of imperfect market, this behavior is called strategic bidding (Wen & David, 2001).

### **1.2. Literature review**

According to different market designs and price components included in bid, addresses the problem of optimal bidding strategy selection various modeling techniques have been used it has been addressed in many research literatures. According to price taker's behavior, strategic bidding models for competitive electricity market can be classified into four groups i.e. Optimization models, Equilibrium models, agent-based models, and hybrid models. Market power indices's which were used in market power analysis and different market model methods on the state-of-art review are presented in (Mathur, Arya, & Dubey, 2017).

Optimization model consist of various mathematical programming methods such as mixed-integer programming (MIP), Non-linear programming (NLP), dynamic programming (DP) and Markov-decision process (MDP) etc. Saleh, Tsuji, and Oyama (2009) proposed a Lagrangian relaxation methodology for the optimal bidding strategy of a small genco where bilateral contract and unit commitment are taken in to account. In (Gutierrez, Quinonez, & Sheble, 2005) a MCP detection presented by using single and double side auction mechanism. The optimization problem is formulated as linear programming program. Yu, Nderitu, Sparrow, and Gotham (2000) have proposed a mixed integer non-linear programming mode for determining the quantities of real power, market clearing prices and ancillary services. In (Morales, Conejo, & Perez-Ruiz, 2010) the multi-stage stochastic integer linear programming problem is formulated as a LP model, and a case study for a wind price taker in Kansas is conducted as a linear programming model, which results in a higher profit and smaller risk. Boonchuay and Ongsakul (2011) proposed an optimal bidding strategy with considering risk management for a price takers by hierarchical particle swarm optimization combined with time-varying acceleration coefficients.

Equilibrium models also called Game theory models. Kian, Cruz, and Thomas (2005) described bidding strategies in competitive electricity with double-sided auctions as a dynamic system and use Nash-Cournot strategies for generating firms and load serving entities. In (Hu, Kapuscinski, & Lovejoy, 2010) a new version of Bertrand Edgeworth game described where the demand is inelastic and a price cap is set exogenously. In (Weglarz & Wylomanska, 2010) Stochastic asymmetric supply function equilibrium and Cournot models based on the assumption of the stochastic behavior of

electricity prices proposed to explore the price taker's performance on the energy market with derivatives such as contracts and Asian-type call options for power delivery. Day, Hobbs, and Pang (2002) presented a Conjectured supply function (CSF) model competition among power generators on a liberalized dc network. This application shows how transmission limits and strategic interactions affect equilibrium prices under forced divestment of generation.

The alternative to equilibrium models are agent based simulation model when the bidding problem is too complex and it is bounded within a formal equilibrium frame work. In this model price takers followed some rules in the market and interacting with one another intelligently and dynamically that allow developing models to represent in more realistic way in the competitive electricity markets. But actual performance of the system is limited by mathematical or logical relationships foundation. Richter and Sheble (1998) presented a genetic algorithms based model to optimize the bidding strategies of genco and Transco trade power. This simulated electric commodity exchange can be used off-line to predict whether bid strategies will be profitable and successful. In (Azadeh, Ghaderi, Pourvalikhan Nokhandan, & Sheikhalishahi, 2012) genetic algorithm model employed to solve the problem of generation company when price takers submit its bids as a pair of magnitude and price, and the sealed auction with a pay-as-bid MCP. Bajpai, Punna, and Singh (2008) proposed the application of PSO method for strategic bidding of an electricity supplier in an oligopolistic power market with uncertain behavior of other competing suppliers. Search procedure of PSO is based on the concept of combined effect of cognitive and social learning of the members in a group. In (Ma, Jiang, Hou, & Wang, 2006) profit maximization considering network constraints is obtained by PSO with two level optimization problem proposed for a linear supply function equilibrium model. The parameterization techniques used in formulating the optimal supply function are analyzed based on the simulation results. In Srivastava and Arya (2016) and Arya, Kumar, and Dubey (2014) PSO and its various versions like non-dominated sorting PSO (nsPSO) has been implemented to solve service restoration and fault section estimation problems in distribution systems.

Addition the above three modeling approaches, some non-conventional methods and hybrid methods have also been proposed by various researchers for strategic bidding problems. In (Vahidinasab, Jadid, & Kazemi, 2008) An artificial neural network (ANN) with a modified Levenberg-Marquardt (LM) optimization algorithm are employed to estimate prices in PJM market and the results compared with the previous works that showed, results are reasonable and accurate. Soleymani (2011) proposes a new method that uses the combination of particle swarm optimization (PSO) and simulated annealing (SA) to predict the bidding strategy of Generating Companies (Gencos) in an electricity market where they have incomplete information about their opponents and market mechanism of payment is pay as bid. Areekul, Senjyu, Toyama, and Yona (2010) provides a hybrid methodology that combines both autoregressive integrated moving average (ARIMA) and ANN models for predicting short-term electricity prices. Empirical results indicate that a hybrid ARIMA-ANN model can improve the price forecasting accuracy.

In the price taker's optimization model the profit maximization problem of single participant are simplified while ignoring the behavior aspects of other participant. It means that the price-taker's generation company predicts the final bid of poolco according to worthily. In game theory approach profit maximization problem of price takers are simplified by taking in to account the strategic behavior of other player's interactions. The mutual interaction is represented by Game Theory. This model is developed with aim of improving economic efficiency. The alternative to equilibrium models are agent based simulation model when the bidding problem is too complex and it is bounded within a formal equilibrium frame work. In this model price takers followed some rules in the market and interacting with one another intelligently and dynamically that allow developing models to represent in more realistic way in the competitive electricity markets. But actual performance of the system is limited by mathematical or logical relationships foundation.

### 1.3. Contribution

The novelty of this paper is to employ a new GA approach for determining the optimal bidding strategy of a price taker's in a day-ahead market in sealed auction with a pay-as-bid MCP to solve the problem from two different viewpoints i.e. with symmetrical and unsymmetrical information. GA has been employed in many research works but practical limitation and rival's bid altogether are considered by none of them. In a day-ahead market, it is essential to consider fuel cost, start-up cost, generating limits and unit minimum up/down time to make sure that the price taker's are able to schedule the units needed to meet the demand.

### 1.4. Structure of paper

This paper organized as follows, Section 2 review the changing role of electricity systems modeling and response of modeling to change in market structure and to change in key policy areas in a strategic manner. Section 3 proposes a model structure of bidding strategy with the estimation of opponent's unknown information. Section 4 described new developed genetic algorithm technique. Section 5 illustrate the implementation of the proposed method. Finally Conclusive remarks as well as some possible directions for future research are presented in Section 6.

## 2. Competitive market structure and bidding protocols

There are two objectives for establishing an electricity market: ensuring a secure operation and facilitating an economical operation. Security could be facilitated by utilizing the diverse services available to the market and economical operation of the electricity market would reduce the cost of electricity utilization. The main components of electricity industry are generation, transmission owners and other market entities i.e. distribution companies, retailers, aggregators, brokers and customers (Shahidehpour, Yamin, & Li, 2002). A competitive electricity market would require an independent operational control of the grid. The ISO has the authority to commit and dispatch some or all system resources and to curtail loads for maintaining the system security (Shaidehpour & Almoush, 2001). The market power structure, auction rules, and bidding protocols are the main objectives in investigating bidding strategies. Market power can be defined as "The concentration of resources in the hands of a single producer or an insufficient numbers of producers". There are various measures for measuring competition and market power such as Concentration Ratio, Herfindahl-Hirschman index (HHI), Supply Margin Assessment (SMA), Residual Supply Index (RSI) and the lerner index (Chang, 2007).

There are three basic market power structure of the competitive electricity market. (a) Poolco model, (b) Bilateral contract model and (c) Hybrid model. In the electricity market PoolCo is a platform where electric power sellers/buyers submit bids to the trade of power. If the market participants bid is too high, it may not be selling and if the bid is too low then it may not be purchase. In this market, the winning bidders are paid the spot price that is equal to the highest bid of the winners (Yucekaya, Valenzuela, & Dozier, 2009). An auction is an efficient process of power market with specific set of laws to allocate demand for the market participants. The formation of resource allocation and setting prices for the bid in many countries is based on the auction (Singh, Hao, & Papalexopoulos, 1997). A bid consist of various energy price sections corresponding with the quantity of electricity. The pricing mechanisms for the suppliers are uniform pricing (UP) or pay-as-bid (PAB). In the uniform pricing all the winning market participants are paid at the same MCP. In the PAB all the winning market participants are paid at its bidding price of the committed amount of electricity (Ott, 2003). Auction methods can be classified whether the action is static or dynamic. Static auction can be categorized as discriminating and non-discriminating. In discriminating all winning bidders are paid according to differing prices while it paid according to uniform price in non-discriminating auctions, and in cases of multiple sellers or buyers, the non-discriminating auction is generally employed to promote the bidders to bid their marginal costs or benefits (Xiong, Okuma, & Fujita, 2004).

In the competitive electricity market the aim of price takers is to reduce costs of electrical energy for customers and this can be accomplished by removal of costly and inefficient units, implementation of new technologies and introduction of competition between producers and customers. Different competitive market models have been adopted by the various countries across the globe.

It can be classified in to two types; bilateral markets and mediated markets. In bilateral markets, power suppliers and customers submit a bid directly while in mediated markets an intermediary exists between suppliers and customers. Mediated market is of various types such as Dealer market, exchange and pool. An exchange is a centralized market power and it provides security and less flexibility for the traders. The poolco is also the main market competition structure and it characterized as no load costs and ancillary services (Prabavathi & Gnanadass, 2014).

The power pool acts, effectively, like a broker for managing energy suppliers' bids and large customer's offers, and establishes a MCP. Each participant submits a sealed bid close to the MCP. Otherwise, if the market participants bid is too high, it may not be selling and if the bid is too low then it may not be purchase. Theoretically, in perfect electricity markets, suppliers should bid at or very close to their marginal cost to maximize profit. However, the electricity market is not perfectly competitive due to limited number of producers; therefore, power suppliers may seek to benefit by bidding a price higher than the marginal production cost. When a supplier bids other than the marginal cost, to take advantages of imperfect market to increase their profit, this behavior is called strategic bidding (Wen & David, 2001).

Electricity market player determines the MCP by forming an aggregated supply curve for price takers and aggregated demand curve for customers. The point of intersection of the above two curves determines MCP. This point is called equilibrium point. At this point market is cleared (Shahidehpour et al., 2002). In Figure 1, MCP is the market clearing price and MCV is the market clearing volume. There are three ways to develop the bidding strategies i.e. based on the market structure, auction rules and bidding protocols. Different bidding protocols can be divided in to three main categories. First is based on estimation of market clearing price, the second one is based on gaming analysis and the third category is based on bidding behavior of rival participants (David & Wen, 2000).

### 3. Problem formulation for bidding strategy

Assume that a competitive power market consist of "m" independent power producers, an independent system operator (ISO), a market operator and a group of "n" customers (loads) who participate in the demand side bidding, in which a sealed auction with a pay-as-bid MCP is employed. Assume that each power producer and customer is required to bid a linear non-decreasing supply/ demand function to power exchange respectively denoted by  $G_i(P_i) = \alpha_i + \beta_i P_i / L_j (W_j) = \rho_j - \lambda_j W_j$  for  $i = 1, 2 \dots, m, j = 1, 2, \dots, n$ , where  $P_i$  is the active power output,  $W_j$  is the active power load and  $\alpha_i, \beta_i, \rho_j, \lambda_j$  are the non-negative bidding coefficients.

Now power exchange determine a set of generation outputs and a set load demand that minimize the total purchase cost and maximize the expected profit by solving the following Equations (1) to (5).

**Figure 1. Market clearing process.**

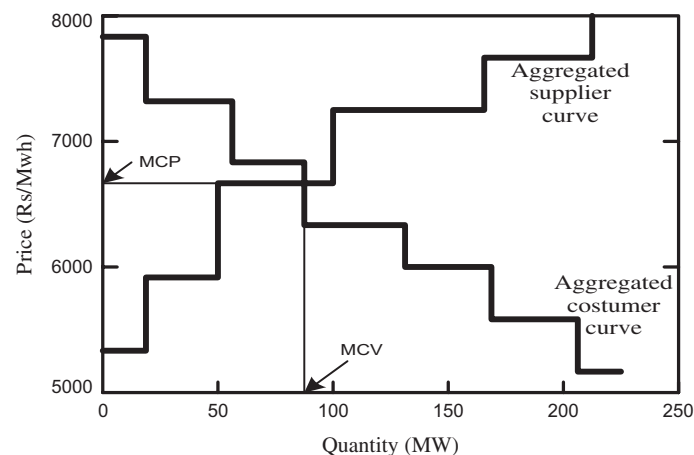
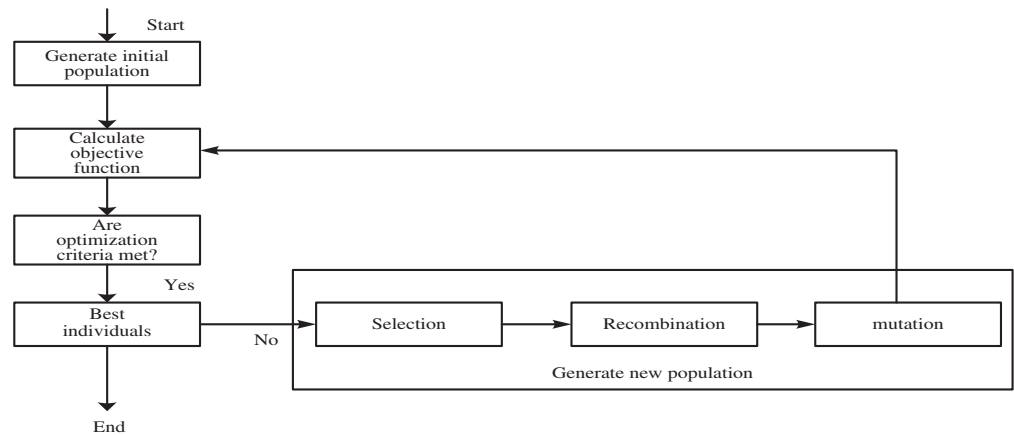


Figure 2. Structure of GA.



$$\alpha_i + \beta_i P_i = R \quad i = 1, 2, \dots, m \tag{1}$$

$$\rho_j - \lambda_j W_j = R \quad j = 1, 2, \dots, n \tag{2}$$

Power balance equation and generation/load inequality constraints are as follows

$$\sum_{i=1}^m P_i = Q(R) + \sum_{j=1}^n W_j \tag{3}$$

$$P_{i,min} \leq P_i \leq P_{i,max} \tag{4}$$

$$W_{j,min} \leq W_j \leq W_{j,max} \tag{5}$$

where,  $R$  is the market clearing price (MCP) of the electricity to be determined,  $Q(R)$  is the aggregate pool load forecast by power exchange and is dependent on the price of elasticity of the aggregate demand.  $P_{i,min}$ ,  $P_{i,max}$ ,  $W_{i,min}$  and  $W_{j,max}$  are the generation output limits and customers demand limits of  $i$ th power producer and  $j$ th customer respectively. Suppose the aggregate pool load  $Q(R)$  takes the following linear form:

$$Q(R) = Q_0 - KR \tag{6}$$

where  $Q_0$  is a constant number and  $K$  is a coefficient of price elasticity, if aggregate pool demand is largely inelastic, then  $K = 0$ . The solutions of Equations (1) to (3) are, while generator and load inequality constraints are neglected –

$$R = \frac{Q_0 + \sum_{i=1}^m \frac{\alpha_i}{\beta_i} + \sum_{j=1}^n \frac{\rho_j}{\lambda_j}}{K + \sum_{i=1}^m \frac{1}{\beta_i} + \sum_{j=1}^n \frac{1}{\lambda_j}} \tag{7}$$

$$P_i = \frac{R - \alpha_i}{\beta_i} \quad i = 1, 2, \dots, m \tag{8}$$

$$W_j = \frac{\rho_j - R}{\lambda_j} \quad j = 1, 2, \dots, n \tag{9}$$

If the solution of Equation (8)/(9) violates generation output limits/customer demand limits (4)/(5), then it must be modified i.e. if  $P_i$  is larger than  $P_{i,max}$ ,  $P_i$  is set to  $P_{i,max}$  and if  $P_i$  is minimum than  $P_{i,min}$ ,  $P_i$  is set to be zero and the power producer removed from the problem, similar treatment is applicable to  $W_j$ .



For  $i$ th power producer/ $j$ th large customer at the considered hour, profit maximization objective function is expressed as:

$$\max \pi_i(\alpha_i, \beta_i) = R \times P_i - C_i(P_i) \tag{10}$$

$$\max \pi_j(\rho_j, \lambda_j) = B_j(W_j) - R \times W_j \tag{11}$$

where,  $C_i(P_i) = a_i + b_i P_i + c_i P_i^2$ , is the  $i$ th producer production cost function and  $B_j(W_j) = d_j + e_j W_j + f_j W_j^2$  is the  $j$ th customer demand function. This is to determine  $\alpha_i/\rho_j$ , and  $\beta_i/\lambda_j$  so as to maximize Equations (10) and (11) subject to constraints (1)–(5).

In sealed bid auction-based competitive market to solve the Equations (10) and (11), participants need bidding coefficients data of rivals. As bidding data of rivals is confidential, participants could be estimated based on historical data. So it is necessary to estimate opponent’s unknown information. Suppose  $p$  ( $p = 1, 2 \dots m + n$ ) identify all participants and  $p = 1, 2 \dots m$  represents the  $m$  power producers and  $p = m + 1, m + 2 \dots m + n$  represents the  $n$  large customers, respectively. So from the  $p$ th participants point of view, the bidding coefficients of  $i$ th power producers ( $i \neq j$ ),  $\alpha_i$  and  $\beta_i$ , obey a joint normal distribution with the following probability density function (pdf).

$$\text{pdf}(\alpha_i, \beta_i) = \frac{1}{2\pi\sigma_i^{(\alpha)}\sigma_i^{(\beta)}} \sqrt{1 - \zeta_i^2} \times \exp \left\{ -\frac{1}{2(1 - \zeta_i^2)} \left[ \left( \frac{\alpha_i - \mu_i^{(\alpha)}}{\sigma_i^{(\alpha)}} \right)^2 - \frac{2\zeta_i(\alpha_i - \mu_i^{(\alpha)})(\beta_i - \mu_i^{(\beta)})}{\sigma_i^{(\alpha)}\sigma_i^{(\beta)}} + \left( \frac{\beta_i - \mu_i^{(\beta)}}{\sigma_i^{(\beta)}} \right)^2 \right] \right\} \tag{12}$$

This can be expressed in the compressed form as:

$$(\alpha_i, \beta_i) \approx N \left\{ \begin{bmatrix} \mu_i^{(\alpha)} \\ \mu_i^{(\beta)} \end{bmatrix}, \begin{bmatrix} (\sigma_i^{(\alpha)})^2 & \zeta_i \sigma_i^{(\alpha)} \sigma_i^{(\beta)} \\ \zeta_i \sigma_i^{(\alpha)} \sigma_i^{(\beta)} & (\sigma_i^{(\beta)})^2 \end{bmatrix} \right\} \tag{13}$$

where,

$\zeta_i$  - correlation coefficient between  $\alpha_i$  and  $\beta_i$ .

$\mu_i^{(\alpha)}, \mu_i^{(\beta)}, \sigma_i^{(\alpha)}$  and  $\sigma_i^{(\beta)}$  - Mean and standard deviation value of  $\alpha_i$  and  $\beta_i$ .

Similarly, the bidding coefficients of the  $l$ th large consumer ( $l = 1, 2 \dots n$ , and  $l + m \neq p$ ) from the  $p$ th participants point of view, obey a joint normal distribution with the following probability density function (pdf):

$$(\rho_l, \lambda_l) \approx N \left\{ \begin{bmatrix} \mu_l^{(\rho)} \\ \mu_l^{(\lambda)} \end{bmatrix}, \begin{bmatrix} (\sigma_l^{(\rho)})^2 & \gamma_l \sigma_l^{(\rho)} \sigma_l^{(\lambda)} \\ \gamma_l \sigma_l^{(\rho)} \sigma_l^{(\lambda)} & (\sigma_l^{(\lambda)})^2 \end{bmatrix} \right\} \tag{14}$$

The meaning of  $\mu_l^{(\rho)}, \mu_l^{(\lambda)}, \sigma_l^{(\rho)}, \sigma_l^{(\lambda)}$  and  $\gamma_l$  are basically similar to  $\mu_i^{(\alpha)}, \mu_i^{(\beta)}, \sigma_i^{(\alpha)}, \sigma_i^{(\beta)}$  and  $\zeta_i$ . based on the historical bidding data, these parameters can be determined using mathematical methods such as the presented in (Bialek, Callan, & Strong, 1996).

Due to the inherent variability of the load demanded by the users, complexity in the modern power companies operation arises. Because of these load fluctuations and nature of participants, each GENCO is subjected to market risk. So, while making bidding strategies these risk factors also are considered to maximize the profit of market participants. The variance of the potential profit could be used to evaluate the risk of an investment. Based on this methodology, the proposed optimal bidding strategy for the  $i$ th GENCO with its operational risk may be formulated as

$$\text{Maximize } \psi(\alpha_i, \beta_i) = (1 - \chi)E(\pi_i) - \chi D(\pi_i) \tag{15}$$

$$\text{Subject to } P_{i,\min} \leq (E(R) - \alpha_i)/\beta_i \leq P_{i,\max}$$

where

$E(\pi_i)$  – Expected value of the profit

$D(\pi_i)$  – Standard deviation of the profit

$E(R)$  – Expected value of market clearing price

$\chi$  – Risk factor

Risk factor represents the degree of risk averseness of the  $i$ th supplier, if  $\chi = 0$ , the supplier's objective is to maximize the profit without considering the risk. If  $\chi = 1$ , it represents the extreme condition where the risk minimization is the unique objective as described in (Azadeh et al., 2012). Hence, the problem of building an optimal bidding strategy for the  $i$ th price takers with risk management can be described as: for a given Risk factor  $\chi$ , determine bidding coefficients  $\alpha_p, \beta_i/\rho_p, \lambda_j$  so as to maximize  $\psi_i(\alpha_p, \beta_i)/\psi_j(\rho_p, \lambda_j)$  subject to equation (15).

For maximizing  $\pi_i(\alpha_p, \beta_i)/\pi_j(\rho_p, \lambda_j)$  with the constraints (4) and (5), the bidding coefficients  $\alpha_p, \beta_i/\rho_p, \lambda_j$  cannot be selected independently. So in this paper Genco/Demand customers specified one coefficient i.e.  $\alpha_i/\rho_j$  and determine other coefficient  $\beta_i/\lambda_j$  using an optimization procedure. The optimum value of  $\beta_i$  are searched for in the interval between  $[\beta_i, M \times \beta_i]$ . The optimum value of  $M$  is set to 5 by trial and error in all of the simulation. Since this problem is non-convex which is difficult to solve by traditional optimization technique, hence, GA has been employed to solve the problem. Proposed algorithm has been tested on IEEE -30 bus system and Indian utility practical system.

#### 4. Optimal bidding strategy by GA

The genetic algorithm optimization technique, known as powerful non-deterministic method that is used in finding the best possible solution of the complex problems. The total structure of a simple GA is shown in Figure 2.

It is a stochastic search method and is generally based on three module, known as production module, evaluation module and reproduction module. (a) Production module – It is consist of initialization operator, which is used to create the initial population by filling it with randomly generated individuals and deletion operator, which is delete all old population when reproduction has been occurred.

(b) Evaluation module – In this stage the fitness operator quantifies the total characters of each chromosome in order to satisfy the objective based on maximum or minimum level. (c) Reproduction module – This module consists of three main operator i.e. selection, recombination and mutation. Selection operator is used to determine the mating pool and offspring's from the each selected individuals. Recombination operator is used to produce new chromosomes in combing the information contained in the parents. After recombination, each offspring undergoes small size of mutation step by the mutation operator (Berry & Hobbs, 1999). The flow chart of the proposed algorithm for optimal bidding strategy is shown in Figure 3.

##### 4.1. GA procedure

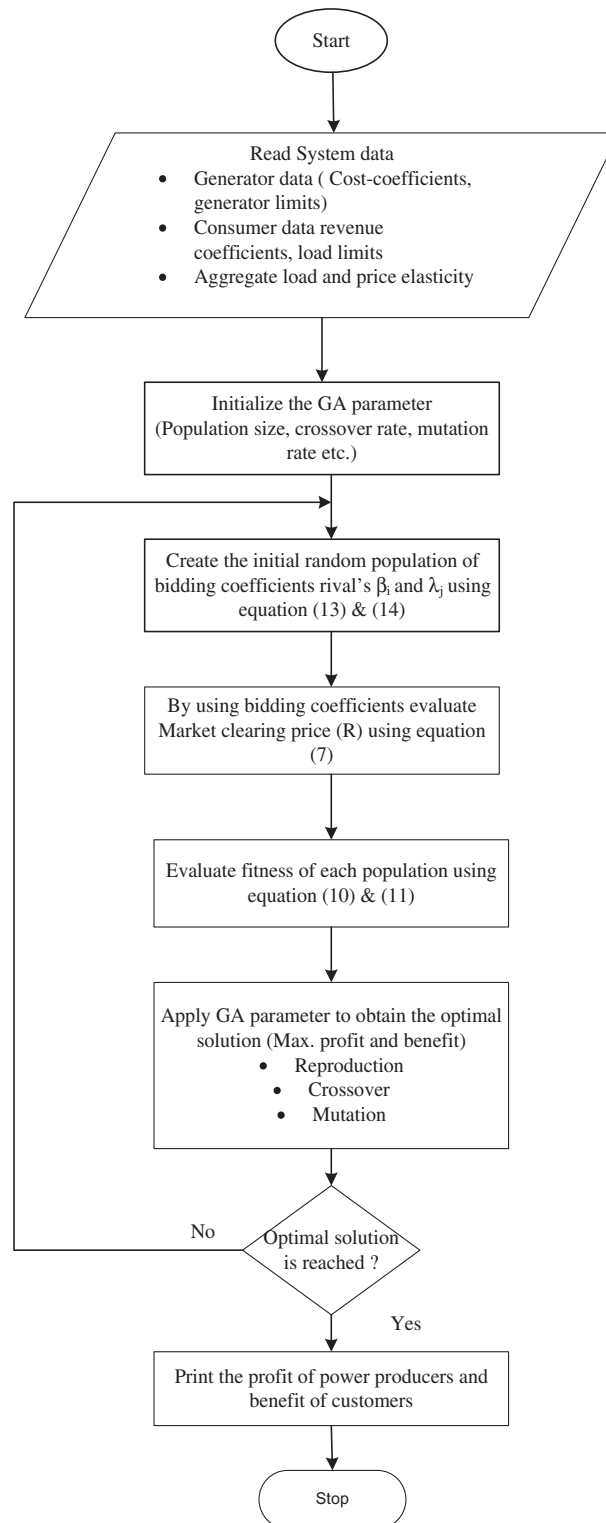
The proposed methodology consists of following components.

Population size: It represents a fraction of the whole solution set.

Representation: The solution process begins with a set of identified chromosomes as the parents from a population.



Figure 3. Flowchart of proposed GA.



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

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. Selected chromosomes compose mating pool.

Crossover: creation an offspring from its parents uses the principles of crossover.

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.

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

### 5. Computational results

In order to estimate the performance of the GA algorithm for solving the bidding strategy problem of competitive electricity market, an IEEE 30 bus system with six power producers and two load customers and a practical 75-bus Uttar Pradesh State Electricity Board (UPSEB) Indian Utility system with fifteen generating units are considered. The simulations are carried out on Intel(R) core(TM) i7-3770 CPU @ 3.40 GHz processor with 4-GB RAM and MATLAB version (2013a) is used. During execution of the proposed GA algorithm, the numerical values of various control parameters are Population size = 200, No. of generations = 1000, Crossover rate = 0.7, Mutation rate = 0.02.

#### 5.1. IEEE-30 bus system

The production cost coefficients (cost function  $C_i(P_i) = a_i + b_i P_i + c_i P_i^2$ ), and generator output limits of the six power producers are listed in Table 1. The demand function coefficients (demand function  $B_j(W_j) = d_j + e_j W_j + f_j W_j^2$ ) and demand limits are listed in Table 2.

The parameter associated with the load characteristic as described in (6) are  $Q_0 = 450$  and  $K = 20$ . When the load is inelastic [ $K = 0$  in equation (6)]. Suppose producers/load customers decides to fix  $\alpha_i = b_i/\rho_j = e_j$  and employs the Monte Carlo simulation based approach to determine  $\beta_i/\lambda_j$ . The optimum value of  $\beta_i$  are searched for in the interval between  $[\beta_i, M \times \beta_i]$ . The optimum value of  $M$  is set to 10 by trial and error in all of the simulation.

**Table 1. The production cost coefficients and generator output limits**

Generator no.	<i>a</i>	<i>b</i>	<i>c</i>	<i>P</i> <sub>min</sub> (MW)	<i>P</i> <sub>max</sub> (MW)
1	0	2.0	0.00875	50	160
2	0	1.75	0.035	50	100
3	0	1.0	0.0625	30	80
4	0	3.15	0.00334	30	80
5	0	3.0	0.015	10	60
6	0	3.0	0.015	10	60

**Table 2 The demand function coefficients and demand limits**

Customer no.	<i>d</i>	<i>e</i>	<i>f</i>	<i>W</i> <sub>min</sub> (MW)	<i>W</i> <sub>max</sub> (MW)
1	0	30	0.04	0	200
2	0	25	0.03	0	150

**Table 3. Estimation of the rival's parameter**

	$\mu_i^{(a)}$	$\mu_i^{(b)}$	$\sigma_i^{(a)}$	$\sigma_i^{(b)}$	$\zeta_i$
With symmetrical information	$1.2 \times b_i$	$1.2 \times c_i$	$0.0375 \times b_i$	$0.0375 \times c_i$	-0.1
With unsymmetrical information	$1.1 \times b_i$	$1.1 \times c_i$	$0.0375 \times b_i$	$0.0375 \times c_i$	-0.1

Assume each rival supplier obey a joint normal distribution for the two bidding coefficients. The estimated parameters in the joint normal distribution for the rival's as described in Equation (12) are shown in Table 3 with symmetrical and without symmetrical information of the historical bidding data. These parameter can be estimated using mathematical methods described in (Berry & Hobbs, 1999), (Wen & David, 2001). The detail explanations of the estimated parameter are described in (Ma, Wen, Ni, & Liu, 2005).

The bidding parameter, Market clearing price, generation output/load demand and expected profit of power producers and load customers by using Monte Carlo method and proposed GA method are presented in Tables 4 and 5.

From the above results it is clear shown that GA gives lesser values of the bidding coefficients than Monte Carlo, thereby increasing the dispatched power, market clearing price, expected profit and the actual profit. Hence the power output of power producers using GA are more than Monte Carlo approach. The time taken by proposed method for 1,000 generations is 4.50 s, which is less than the Monte Carlo method.

The variation of profit of the supplier is analyzed by changing the value of risk factor and it varies from 0 to 1. For different  $\chi$ , simulation results are listed in Table 6, including optimal bidding coefficient  $\beta_2$ , expected dispatched level  $P_2$ , expected market clearing price  $R$ , as well as the expected value and variance of the profit. When  $\chi$  increases from 0.9 to 0.9335, the dispatched generation level of a rival is beyond its lower limit and hence the rival quits from the competition.

**Table 4. Monte Carlo method**

	Unit	$\alpha_i$	$\beta_i$	$\rho_j$	$\lambda_j$	MCP (R)	P, W (Megawatts)	Expected profit (\$)	
With symmetrical information	Generators	1	6.0	0.02927	-	16.35	160.00	1,368.0	
		2	5.25	0.12420	-		89.40	572.7	
		3	3.0	0.29231	-		45.70	322.9	
		4	9.75	0.07433	-		88.80	386.4	
		5	9.0	0.17058	-		43.10	177.5	
		6	9.0	0.17058	-		43.10	177.5	
	Consumers	1	-	-	30		0.09771	139.7	1,126.3
		2	-	-	25		0.07719	112.1	592.6
With unsymmetrical information	Generators	1	6.0	0.02927	-	16.72	160.00	1,420	
		2	5.25	0.15366	-		74.21	585.6	
		3	3.0	0.29231	-		47.45	342.2	
		4	9.75	0.07433	-		93.50	420.5	
		5	9.0	0.17058	-		45.8	192	
		6	9.0	0.17058	-		45.8	192	
	Consumers	1	-	-	30		0.09771	137.5	1,125.5
		2	-	-	25		0.07719	109.2	564.4

**Table 5. Proposed GA method**

	Unit	$\alpha_i$	$\beta_i$	$\rho_j$	$\lambda_j$	MCP (R)	P, W (Megawatts)	Expected profit (\$)	
With symmetrical information	Generators	1	6.0	0.0647	-	-	16.37	160.00	1,372
		2	5.25	0.1052	-	-		105.91	592.6
		3	3.0	0.2753	-	-		49.23	326.4
		4	9.75	0.0554	-	-		120.00	429
		5	9.0	0.1508	-	-		50.11	181
		6	9.0	0.1508	-	-		50.11	181
	Consumers	1	-	-	30	0.0806		171.23	1,165
		2	-	-	25	0.0596		145.86	623
With unsymmetrical information	Generators	1	6.0	0.0647	-	-	17.85	160	1,592.5
		2	5.25	0.1642	-	-		36.2	184.2
		3	3.0	0.2753	-	-		55.4	396.4
		4	9.75	0.0554	-	-		120.0	596.5
		5	9.0	0.1508	-	-		59.5	256.4
		6	9.0	0.1508	-	-		59.5	256.4
	Consumers	1	-	-	30	0.0806		155.2	942.6
		2	-	-	25	0.0596		122.5	442.4

**Table 6. Profit of suppliers by considering risk factor**

Risk factor	$E(\pi_i)$	$D(\pi_i)$	Profit
0	589.76	40.35	589.76
0.3	588.02	40.01	397.99
0.5	582.14	39.20	268.77
0.7	489.06	33.63	119.40
0.9	477.29	27.02	18.56
0.9335	469.67	23.37	4.95

**Table 7. The production cost coefficients and generator output limits**

Generator no.	a	b	c	$P_{min}$ (MW)	$P_{max}$ (MW)
1	0	0.8140	0.0008	100	1,500
2	0	1.3804	0.0014	100	300
3	0	1.5662	0.0016	40	200
4	0	1.6069	0.0016	40	170
5	0	1.5662	0.0016	2	240
6	0	1.7422	0.0018	1	120
7	0	1.7755	0.0018	1	100
8	0	1.7422	0.0018	20	100
9	0	1.1792	0.0012	60	570
10	0	1.6947	0.0017	30	250
11	0	1.6208	0.0016	40	200
12	0	0.4091	0.0004	80	1,300
13	0	0.6770	0.0007	50	900
14	0	1.4910	0.0015	10	150
15	0	1.0025	0.0010	20	454

**Table 8. Bidding coefficients, generator output, MCP, and profit using proposed GA**

Generator	$\alpha_i$	$\beta_i$	MCP (R)	P (MW)	Profit (Rs)
1	0.8140	0.0029	7.56	171.7	119.7
2	1.3804	0.0048		56.6	23
3	1.5662	0.0040		62.6	23
4	1.6069	0.0028		100	100
5	1.5662	0.1970		3.4	3.5
6	1.7422	0.0054		52.7	22.5
7	1.7755	0.0121		80	150
8	1.7422	0.0050		73.5	40.2
9	1.1792	0.0042		74.3	34.5
10	1.6947	0.0032		90	57
11	1.6208	0.0032		104.5	73
12	0.4091	0.0031		225.4	233
13	0.6770	0.0030		202.6	182
14	1.4910	0.0027		125	189
15	1.0025	0.0036		77.0	33
Total profit					1,284

### 5.2. Practical 75-bus Indian system

The production cost coefficients (cost function  $C_i(P_i) = a_i + b_i P_i + c_i P_i^2$ ), and generator output limits of 75-bus Uttar Pradesh State Electricity Board (UPSEB) Indian Utility system with fifteen generating units are listed in Table 7 (Raglend & Padhy, 2006). The bidding coefficients, generator output, MCP, and profit of the power producer are calculated using the proposed GA method shown in Table 8.

The percentage deviation of the profit of the power producer computed as follows

$$PD = \frac{(\text{Best} - \text{Worst})}{\text{Best}} \times 100\%$$

#### Total profit

Best	Worst	Average	PD%
1,283	1,093	1,188	0.15

### 6. Conclusion

In this paper a modified GA approach has been implemented for the optimal bidding of power producer and customer with risk management in the competitive electricity market. In this approach each participants tries to maximize their profit with symmetrical and with unsymmetrical information of rivals. The algorithm can be easily used to develop the bidding strategy in different market rules, different fixed load, different capacity of buyers and sellers. The results obtained from the proposed method confirm the feasibility and reliability of GA algorithm as an efficient methodology in analyzing the optimal bidding strategy of market participants. The effectiveness of the proposed GA method has been tested on an IEEE 30-bus system and a practical 75-bus Indian system. Several factors such as transmission capacity, unit commitment and ramp rate constraints over a series of trading period (hours) can be considered for the further research work.

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#### Author details

Somendra P.S. Mathur<sup>1</sup>

E-mail: [somendra.mathur0007@gmail.com](mailto:somendra.mathur0007@gmail.com)

ORCID ID: <http://orcid.org/0000-0003-1861-4011>

Anoop Arya<sup>1</sup>

E-mail: [anooparya.nitb@gmail.com](mailto:anooparya.nitb@gmail.com)

ORCID ID: <http://orcid.org/0000-0002-9735-511X>

Manisha Dubey<sup>1</sup>

E-mail: [manishadubey6@gmail.com](mailto:manishadubey6@gmail.com)

<sup>1</sup> Electrical Engineering Department, Maulana Azad National Institute of Technology, Bhopal, India.

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#### References

- Areekul, P., Senjyu, T., Toyama, H., & Yona, A. (2010). A hybrid ARIMA and neural network model for short-term price forecasting in deregulated market. *IEEE Transactions on Power Systems*, 25, 0885–8950.
- Arya, A., Kumar, Y., & Dubey, M. (2014). Non-dominated sorting particle swarm optimization based fault section estimation in radial distribution systems. *Advances in Intelligent Systems and Computing*, Springer India, 259, 471–487.
- Azadeh, A., Ghaderi, S. F., Pourvalikhan Nokhandan, B., & Sheikhalshahi, M. (2012). A new genetic algorithm approach for optimizing bidding strategy viewpoint of profit maximization of a generation company. *Expert Systems with Applications*, 39, 1565–1574. <https://doi.org/10.1016/j.eswa.2011.05.015>
- Bajpai, P., Punna, S. K., & Singh, S. N. (2008). Swarm intelligence-based strategic bidding in competitive electricity markets. *IET Generation, Transmission & Distribution*, 2, 175–184. <https://doi.org/10.1049/iet-gtd:20070217>
- Berry, G. A., & Hobbs, B. F. (1999). Analyzing strategic bidding behavior in transmission networks. *IEEE tutorial on game theory applications in electric power markets*, IEEE PES, pp. 7–32.
- Bialek, W., Callan, C. G., & Strong, S. P. (1996). Field theories for learning probability distributions. *Physical Review Letters*, 77, 4693–4697. <https://doi.org/10.1103/PhysRevLett.77.4693>
- Boonchuay, C., & Ongsakul, W. (2011). Optimal risky bidding strategy for a generating company by self organizing hierarchical PSO. *Energy Conversion and Management*, 52, 1047–1053.
- Chang, Y. (2007). The new electricity market of Singapore: Regulatory framework, market power and competition. *Energy Policy*, 35, 403–412. <https://doi.org/10.1016/j.enpol.2005.11.036>
- Dahal, K. P., Galloway, S. J., Burt, G. M., & Macdonald, 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. *IEEE Proceedings Generation, Transmission and Distribution*, 140, 421–426.
- David, A. K., & Wen, F. (2000). Strategic bidding in competitive electricity markets: A literature survey. *Proceedings of IEEE Power Engineering Society Summer Meeting*, 4, 2168–2173.
- Day, C. J., Hobbs, B. F., & Pang, J. S. (2002). Oligopolistic competition in power networks: A conjectured supply function approach. *IEEE Transactions on Power Systems*, 17, 597–607. <https://doi.org/10.1109/TPWRS.2002.800900>
- Gutierrez, G., Quinonez, J., & Sheble, G. B. (2005). Market clearing price discovery in single and double-side auction market mechanisms: Linear programming solution. *IEEE conference on Power Technology, Russia, 2005*, 1–5. doi:10.1109/PTC.2005.4524694
- Hu, S., Kapuscinski, R., & Lovejoy W. S.. 2010. *Bertrand-Edgeworth auction with multiple asymmetric bidders*. Social Science research network working paper series. Retrieved from SSRN <https://ssrn.com/abstract=1659996>
- Kian, A. R., Cruz, J. B., & Thomas, R. J. (2005). Bidding strategies in oligopolistic dynamic electricity double-sided auctions. *IEEE Transactions on Power Systems*, 20, 50–58. <https://doi.org/10.1109/TPWRS.2004.840413>
- Kirschen, D. S., & Strbac G. (2004). *Fundamentals of power system economics*. England: John Wiley & Sons. <https://doi.org/10.1002/0470020598>
- Liu, Y., & Wu, F. F. (2006). Generator bidding in oligopolistic electricity markets using optimal control: Fundamentals and application. *IEEE Transactions on Power Systems*, 21, 1050–1061. <https://doi.org/10.1109/TPWRS.2006.876701>
- Ma, X., Wen, F., Ni, Y., & Liu, J. (2005). Towards the development of risk-constrained optimal bidding strategies for generation companies in electricity markets. *Electric Power Systems Research*, 73, 305–312. <https://doi.org/10.1016/j.epsr.2004.07.004>
- Ma, Y., Jiang, C., Hou, Z., & Wang, C. (2006). The formulation of the optimal strategies for the electricity producers based on the particle swarm optimization algorithm. *IEEE Transactions on Power Systems*, 21, 1663–1671. <https://doi.org/10.1109/TPWRS.2006.883676>
- Mathur, S., Arya, A., & Dubey, M. (2017). *A review on bidding strategies and market power in a competitive energy market*. IEEE international conference on Energy, communication, data analytics and soft computing.
- Morales, J. M., Conejo, A. J., & Perez-Ruiz, J. (2010). Short-term trading for a wind power producer. *IEEE Transactions on Power Systems*, 25, 554–564.
- Ongsakul, 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).
- Ott, A. L. (2003). Experience with PJM market operation, system design, and implementation. *IEEE Transactions on Power Systems*, 18, 528–534. <https://doi.org/10.1109/TPWRS.2003.810698>
- Prabavathi, M., & Gnanadass, R. (2014). Energy bidding strategies for restructured electricity market. *Electrical Power and Energy Systems*, 64, 956–966.
- Raglend, I. J., & Padhy, N. P. (2006). Solutions to practical unit commitment problems with operational power flow and environmental constraints. *IEEE Power Engineering Society General Meeting*, 1–6.
- Richter, C., & Sheble, G. (1998). Genetic algorithm evaluation of utility bidding strategies for the competitive marketplace. *IEEE Transactions on Power Systems*, 13, 256–261. <https://doi.org/10.1109/59.651644>
- 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, 176–183.
- Shahidehpour, M., & Almouh, M. (2001). *Restructured electrical power systems operation, Trading and Volatility*. New York, NY: Marcel Dekker Inc.
- Shahidehpour, M., Yamin, H., & Li, Z. (2002). *Market operations in electric power systems: Forecasting, scheduling, and risk management*. New York, NY: IEEE Wiley-Inter Science. <https://doi.org/10.1002/047122412X>
- Shukla, U. K., & Thampy, A. (2011). Analysis of competition and market power in the wholesale electricity market in India. *Energy Policy*, 39, 2699–2710. <https://doi.org/10.1016/j.enpol.2011.02.039>
- Singh, H., Hao, S., & Papalexopoulos, A. (1997). Power auctions and network constraints. In *Proceedings of the Thirtieth Hawaii International Conference on stem sciences* (Vol. 5, pp. 608–614).
- Soleymani, S. (2011). Bidding strategy of generation companies using PSO combined with SA method in the pay as bid markets. *International Journal of Electrical*



- Power & Energy Systems*, 33, 1272–1278.  
<https://doi.org/10.1016/j.jepes.2011.05.003>
- Srivastava, I., & Arya, A. (2016). An application of particle swarm optimization method for solving network reconfiguration problem in distribution system. *International Journal of Swarm Intelligence*, 2, 154–170.
- Vahidinasab, V., Jadid, S., & Kazemi, A. (2008). Day-ahead price forecasting in restructured power systems using artificial neural networks. *Electric Power Systems Research*, 78, 1332–1342. <https://doi.org/10.1016/j.epr.2007.12.001>
- Weglarz, M., & Wylomanska, A. (2010). *Optimal bidding strategies on the power market based on the stochastic models* (pp. 1–6). International Symposium on Modern Electric Power Systems, Wrocław, Poland.
- Wen, F. S., & David, A. K. (2001). Optimal bidding strategies for competitive generators and large consumers. *International Journal of Electrical Power & Energy Systems*, 23, 37–43.  
[https://doi.org/10.1016/S0142-0615\(00\)00032-6](https://doi.org/10.1016/S0142-0615(00)00032-6)
- Xiong, G., Okuma, S., & Fujita, H. (2004). Multi-agent based experiments on uniform price and pay-as-bid electricity auction markets. *IEEE international conference on electric utility deregulation, restructuring and power technologies*, 1, 72–76. <https://doi.org/10.1109/DRPT.2004.1338471>
- Yu, Z., Nderitu, D. G., Sparrow, F. T., & Gotham, D. J. (2000). Optimal and reliable dispatch of supply and demand bids for competitive electricity markets. *IEEE power engineering society summer meeting*, 4, 2138–2143.
- Yucekaya, A., Valenzuela, J., & Dozier, G. (2009). Strategic bidding in electricity markets using particle swarm optimization. *Electric Power Systems Research*, 79, 335–345. <https://doi.org/10.1016/j.epr.2008.07.006>
- Zdanský, M., & Pozivil, J. (2002). Combination genetic/tabu search algorithm for hybrid flow shop optimization. In *Proceedings of algorithmy, 16th conference on scientific computing, Vysoké Tatry - Podbanske, Slovakia* (pp. 230–236).



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