Electrical Power and Energy Systems xxx (2009) xxx–xxx

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A survey of critical research areas in the energy segment of restructured electric power markets

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ARTICLE INFO

Article history:
Received 4 September 2007
Received in revised form 25 October 2008
Accepted 28 January 2009
Available online xxxx

Keywords:
Deregulation
Electricity auctions
Market equilibrium
Market power

ABSTRACT

Availability of a large volume of recent literature on deregulated (a.k.a. restructured) electricity markets underscores the importance of the research needs to ensure proper design and functioning of the markets. Researchers have made significant contributions fueling the evolution of the fundamental market design changes that have taken place since the beginning of the restructuring process. Due to the vast scope, existing survey papers are focused on particular facets of deregulated electricity markets. We adopt a similar approach by focusing on the most important research areas related to the energy market. The contributions of the survey paper lie in the novel approach used in classifying the literature based on critical research areas. Some areas of research such as auction based pricing, bidding strategy formulation, market equilibria, and market power are reviewed in a different light than other existing survey papers. We conclude by providing some future research directions for the energy markets.

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1. Introduction

MOTIVATED by the success of deregulation in industries such as telecommunications, airlines, and transportation, electricity deregulation has been introduced in many parts of the US market as well as in many countries around the world. Electricity market deregulation has spurred a significant amount of research to model and subsequently, improve our understanding of how various segments of the market perform and interact with one other. Due to the interactions of political, socioeconomic, and technological forces, the deregulated electric power industries both in the United States and abroad have undergone many structural transformations. Though significant differences exist in the working of markets around the world, the commons goal of deregulation are the reduction of prices for the end-user and increase of social welfare.

Owing to the extremely complicated structure of a deregulated electricity market, the process of deregulation continues to face several challenges. Some of the challenges are:

- choice of appropriate electricity auction strategy,
- mitigating market power of the participants,
- alleviating transmission congestion and related locational price spikes,
- choice of AC-optimal power flow versus DC-optimal power flow to calculate nodal prices,
- maintaining system reliability,
- assessing market equilibrium and market efficiency.

Despite these challenges, successful operation of deregulated markets like in Pennsylvania–New Jersey–Maryland (PJM) interconnection and several markets around the world, has reinvigorated the policy makers. Currently, over a fourth of the states across the US, and several countries around the world, notably UK, Nordic countries, and Australia trade electricity in a deregulated environment.

Several insightful monographs ([1–3]) that deal with power system economics and operation of restructured markets exist in the literature. Recently, survey papers were presented to the power market literature by Ventosa et al. [4] and Day et al. [5], and Boucher and Smeers [6]. The survey in [4] consists of an excellent overview of recent market modeling trends, and Day et al. [5] and Boucher and Smeers [6] discuss market equilibrium formulations, respectively. However, the above monographs and survey papers do not shed light on the following: (1) modeling issues in key areas of the energy market and (2) model solution approaches. Also, some specific areas of recent research interest such as: (1) modeling issues in electricity auctions and (2) solution approaches used to obtain optimal bidding strategies and Nash equilibria; are not adequately addressed. The contributions of our survey paper lie in filling these voids. We believe that this survey paper will serve as a critical reference for new as well as experienced power market researchers.

Readers unfamiliar with the operations and economics of deregulated electricity markets can refer to the monograph by Stoft [1].

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0142-0615/$ - see front matter Published by Elsevier Ltd.
doi:10.1016/j.ijepes.2009.01.004

In the following sections we present a detailed review of five aspects of energy markets that have been the focus of recent literature.

(1) Price forecasting.
(2) Bilateral contracts.
(3) Auctions and bidding.
(4) Determination of optimal bidding strategy and determination of Nash equilibria.
(5) Market power mitigation.

2. Price forecasting

In restructured markets, price forecasting has become an increasingly important activity for both electricity producers and large consumers. Prices in an electricity market depend on various factors such as stochastic demand, competing bids of the market participants (generators and retailers), forward contracts, auction based pricing strategies, and network parameters including transmission constraints, reactive power limits, and commitment status of generators. One of the most important motivations for market participants to forecast electricity prices is to hedge themselves against the risk of profit volatilities. Using the price forecasts, generators as well as consumers can more accurately valuate their bilateral contracts. Also, companies with better forecasts can plan their production schedules in an economic manner. From a system operator standpoint, price forecasts can help identify trends of market power, transmission congestion, and even potential for investments in transmission. Common forecasting tools used are artificial neural network (ANN) models, time series models, and econometric models. These models derive predictions for short, medium, and long-term prices using historical data. However, variations in the large number of factors mentioned above, that affect the MCPs, make the formulation of accurate forecasting models a very challenging task. A good treatment of the existing price forecasting models in the form of a survey was presented to the literature by Li et al. [7], and hence we chose to provide in a tabular form a list of recent papers classified based on the forecasting method used (see Table 1).

3. Bilateral contracts and trading in bilateral markets

Bilateral transactions are contractual agreements for power supply between sellers (generation companies) and buyers (distribution companies). These transactions can be long-term or short term, for energy, instantaneous power, and reserves. The independent system operator (ISO) does not play any role in the contract process, however, both contracting parties are required to provide complete details of the contract to the ISO. Subsequently the ISO ensures that system security limitations are not violated by these contracts. According to [28], bilateral contracts are generally classified as:

- Physical bilateral contracts.
- Contracts for differences (CFDs).
- Future contracts with *call* and *put* options.

Physical bilateral contracts are signed by two parties that agree upon both price and quantity. Financial penalties are specified for reduced consumption and reduced supply. *Contracts for differences* are long-term two way hedge contracts in which a generator with CFDs pays the consumer if the spot price is above the strike price and vice versa. A future contract with *call options* consists of two main elements which are strike price and premium. The issuer of the call option is a generator and the buyer is a customer. The customers who hold the call option will generally exercise them when the spot prices are greater than the strike prices. The generator then pays the customer the difference between the spot price and the strike price, while the customer pays the generator the premium (difference between strike price and expected future spot price) for this benefit. A *put option* works in the opposite way, in that the issuer is a consumer and the buyer is a generator. The generators usually exercise their put options when the spot price is below the strike price.

Power generators face the challenge of designing a trading portfolio of bilateral and spot market sales to maximize profit and minimize risk. Bilateral contracts provide a stable source of revenue to generators, but they may not be as profitable as sales in spot markets where the generators can take advantage of the price spikes. On the other hand, revenue from spot markets is not consistent across time, hence trade in spot markets is not preferred by risk averse generators. Therefore, the problem of developing the right proportion of trading in forward and spot markets is of great interest for generators (to maximize profits/minimize risk). Developing an optimal portfolio of bilateral contracts and spot transactions, is a challenging non-convex optimization problem due to operational constraints of the generators and other power market considerations.

According to Ref. [29], separate dispatch of bilateral contracts and pool-based markets may cause sub optimal social welfare solutions resulting in economic inefficiencies. To counter these inefficiencies the authors in [29] present an optimal power flow model that dispatches pool and bilateral markets together, while minimizing generation and transmission costs. Extensions to [29], are presented in [30,31], where the authors consider various types of bilateral contracts.

Bilateral transactions are sometimes blamed for system related insecurities, congestion, and losses, all of which are features that are continuously monitored and controlled by the system operator. Work that considers such system related insecurities can be found in [32,33]. Other recent literature from bilateral contract markets with the main focus area of the paper is listed in Table 2.

4. Auctions and bidding

Auction is defined as the method of allocating goods under competition. Auctions used in electricity markets are called multi-unit auctions since more than one unit of the same type is auctioned. Two forms of multi-unit auctions are commonly used in

Table 1
Electricity market price forecasting models.

Price forecasting method	References
Neural network	[8–13]
Fuzzy logic models	[14,15]
Time series and Bayesian theory	[13,16–25]
Econometric models	[26,27]

Table 2
Important Literature from Bilateral Contract (BC) Markets.

Primary focus of the paper	Reference
OPF models to counter economic inefficiencies due to BCs	[29,34]
OPF models incorporating different types of BCs	[30]
Performance analysis of markets with BCs	[31,35–37]
Allocating transmission losses to BCs	[38,39]
Multilateral contracts	[40]
Bilateral markets for ancillary services	[41]
Linear programming model for BCs in constrained networks	[42]

Please cite this article in press as: Nanduri V, Das TK. A survey of critical research areas in the energy segment of restructured … Int J Electr Power Energ Syst (2009), doi:10.1016/j.ijepes.2009.01.004

deregulated electricity markets: uniform price auction and discriminatory auction. In a uniform price auction, all selected suppliers are paid a uniform price, equal to the market clearing price. In a discriminatory auction, the suppliers are selected in a manner similar to the uniform auction, but are paid according to their own bids instead of the market clearing price. Important aspects of multi-unit electricity auctions such as appropriate choice of auction strategies, auction performance comparison, and strategic bidding behavior under different auctions are discussed in this section.

4.1. Choice of auction strategies and performance comparison

The design of an electricity auction is complicated by the fact that demand fluctuates from hour to hour, and it must be met in a least cost manner by coordinating suppliers with varied price structures. Electricity auctions differ in many dimensions in different parts of the world. For instance, the Spanish electricity market uses a single round auction with simple price quantity bids where as the New Zealand and Australian electricity markets use multi-round auctions with complex bids (bids that include ramping constraints, minimum units output etc.). In addition to structural complexities mentioned before, variations resulting from the use of different auction mechanisms have made its design a challenging task. Even though studies have been performed to identify the best auction format for electricity markets, conclusions as to the effectiveness of the auction formats are still unclear [43]. The fact that the results of the single unit auction studies cannot be directly applied to the multi-unit electricity auction scenario has proved to be a hurdle in understanding the effectiveness of various auction mechanisms [44]. Hence there is a critical need to assess the performance of auctions in electricity markets. Perceived poor performance of the uniform price auction led England and Wales markets to the shift to a discriminatory auction [45]. The decision by UK regulatory authorities to switch from uniform price auction to discriminatory auction in efforts to lower prices are justified by works of various researchers, in static settings [46,47].

A detailed evaluation of the design of two commonly used electricity market auctions; uniform price auction and discriminatory auction was undertaken by Fabra et al. [48]. A duopoly market model is constructed in [48] to analyze supplier bidding behavior and the resulting equilibrium. The paper also provides some extensions and variations of the duopoly model for conditions like price elastic demand, stochastic demand, and oligopolistic markets. Under a low demand realization, the equilibrium attained is shown to be unique and identical across both auction strategies. However, under high demand realizations, the equilibrium outcomes of the two auction mechanisms are very different. It is shown that for a discriminatory auction, only mixed strategy equilibria exist in high demand states. Also, in a price elastic demand setting and high demand conditions, bidding in discriminatory auction becomes more aggressive.

The choice of auction mechanism in electricity and other commodity markets [46,49]has been a topic of intense debate over the last decade. Elmaghraby and Oren study the efficiency of multi-unit auctions using a complete information game theoretic model [50]. The authors compare equilibrium attained using three different auction structures; daily supply curve vertical auction (DSCVA), hourly supply curve vertical auction (HSCVA), and horizontal auction (HA). In DSCVA and HSCVA, the demand is partitioned into daily and hourly markets, respectively and the generators submit supply curves for the corresponding markets. In a HA, demand is divided into distinct horizontal demand sets that are auctioned sequentially. A game theoretic model is then used to show that only a HA can result in a unique subgame perfect Nash equilibrium.

Son et al. [51] present a game theoretic model that is used to analyze two competing auction pricing mechanisms (uniform price auction and discriminatory auction). It is shown that the equilibrium revenues under uniform price auction and discriminatory auction are different, and that the revenue equivalence theorem put forth by classic auction theorists [52] does not hold even for simple cases of multi-unit auctions. It is demonstrated that expected total revenue of a network with market power is more under uniform price auction strategy when compared to discriminatory auction (pay-as-bid type). Due to lack of definitive conclusions about auction performance, it is still an area of open research. We believe that only a comprehensive study considering DA, real-time, FTR markets, AC–OPF with transmission constraints, and supply/demand side bidding, can result in definitive conclusions about auction performance.

Researchers use simulators as tools to perform offline studies of complex systems and apply the knowledge gained to real life systems. A few such simulators are presented in [53–55]. Zimmerman et al. [55,56], focus on designing a web based software package (called POWERWEB) that is used to simulate auction based electricity pricing. They use an internet based simulation environment where human subjects serve as market participants and submit price quantity bids. The auction pricing strategies and optimal power flow programs are implemented using an enhanced version of the MATPOWER software developed in their earlier work [57]. These simulators provide great insight into the competitive bidding behavior of market participants. They also guide ISOs in determining potential for market power misuse under different auction strategies.

4.2. Study of strategic bidding behavior

Under the influence of competition, market participants tend to bid strategically to make profits. Such strategic behavior results in varying prices under different auction mechanisms. Some of the noteworthy work examining bidding behavior were presented by Wolfram [58], Green and Newberry [59], von der Fehr and Harbord [60], and Kian et al. [61]. Wolfram performed empirical studies in the England and Wales markets based on strategic bidding behavior of two large generators [58]. She notes that due to high frequency of electricity auctions and large number of generator attributes, strategic bidding is a very common phenomenon. Some of the significant results from Wolfram's study are: (1) generators tend to increase their bids to get paid higher for their inframarginal units, (2) one can observe larger bid markups for units with higher marginal costs, and (3) reduced strategic bidding behavior under discriminatory auctions. Wolfram's work played a critical role in England and Wales electricity markets switch to discriminatory auction pricing from uniform auction pricing.

Another work that examines strategic bidding behavior under three different auction mechanisms is [62], where the authors develop two new market power indicators to measure strategic bidding behavior. The results of [62] indicate that discriminatory price auction presents more market power to participants under high load conditions, when compared to uniform or second price uniform auctions. This study also shows that a second price uniform auction can be used to attain close to marginal cost bidding.

5. Bidding strategy determination

Participants of the energy market attempt to maximize their benefits by seeking optimal bidding strategies. A generic version of the bidding strategy formulation problem in a power network can be given as follows. Let $\mathscr{B}$ denote the set of buses in the network, and $\mathscr{B}_s \subset \mathscr{B}$ denote the subset of supply buses (nodes). Let the number of generators at a supply bus $i \in \mathscr{B}_s$ be denoted by N_i, and M denote the number of loads in the network. Let

$\mathcal{G}_i = \{1, 2, \cdots, N_i\}$ and $\mathcal{L} = \{1, 2, \ldots, M\}$ denote the set of generators at a supply bus i and the set of loads in the network, respectively. Let $N = \sum N_i$, and $\mathcal{G} = \cup \mathcal{G}_i$. To keep the exposition simple, we consider only generator side bidding in the market.

Let the state of the network at time t (X_t) be the vector of realized loads (demands) q_t^s and prices p_t^s. Hence, $X_t = \{q_t^s, p_t^s\}$, where $q_t^s = (q_t^1, q_t^2, \ldots, q_t^{|\mathcal{B}|})$ and q_t^s denotes the realized hourly load quantity vector at the s^{th} bus, $s \in \mathcal{B}$. Also, $p_t^s = (p_t^1, p_t^2, \cdots, p_t^{|\mathcal{B}|})$, where p_t^s represents the realized hourly price vector at bus $s \in \mathcal{B}$.

Let the bid decision vector at the t^{th} time be given by $D_t = \{\mathcal{D}_t^l : l \in \mathcal{G}\}$, where $\mathcal{D}_t^l$ is the decision vector of generator l and $\mathcal{D}_t^l \in \{D^l\}$ and D^l denotes the set of all bid parameters vectors for generator l. These bid parameters depend on the nature of bids, for example, polynomial functions and piecewise linear functions, and determine the offer prices corresponding to the generation quantities. The bidding process involves selection of bid parameters by the generators, who seek to maximize their individual profits for the forecasted state of the network X_t. The profits corresponding to a set of bids submitted at any time t by the generators are obtained by solving the optimal power flow (OPF) model. The profit maximization problem for generator j, as commonly presented in the literature, can be stated as a bi-level problem as follows.

Choose $\mathcal{D}_t^j$ so as to:
Maximize profit $g(f_t^j, P_t^j)$
subject to:
Choice of other bidders $\mathcal{D}_t^l : l \in \mathcal{G} \setminus j$
and
The OPF problem

where, f_t^j and P_t^j are the nodal clearing price and quantity allocation for generator j as determined by the OPF model, which is provided next.

OPF models are formulated either to maximize social welfare or to minimize the total cost of meeting the power demand of a network. The OPF model simultaneously satisfies several system related constraints such as demand and supply constraints, voltage constraints, thermal limit constraints, and the constraints of power flow. Several papers presented to the literature utilize a DC version of the OPF model to curtail the computational complexity involved in solving an AC–OPF model. We however, provide here a generic mathematical formulation of the cost minimization version of the AC–OPF model. A linearized DC–OPF formulation can be found in [63].

Let f_t^j denote the clearing price for the active power generation by supplier j at a decision epoch. Also, let P_t^j and Q_t^j denote the active and the reactive power generation quantities, respectively.

$$\min \sum_{j \in \mathcal{B}_s} f_t^j(P_t^j) \tag{1}$$

subject to

$$\sum_{j \in \mathcal{B}_s} P_t^j - l - l(V, \theta) = 0, \tag{2}$$

$$\sum_{j \in \mathcal{B}_s} Q_t^j - \tilde{l} - \tilde{l}(V, \theta) = 0, \tag{3}$$

$$S_{y,z} \leqslant S_{y,z}^{\max} \quad \forall y \neq z \in \{\mathcal{B}\} \tag{4}$$

$$V_w^{\min} \leqslant V_w \leqslant V_w^{\max}, \forall w \in \{\mathcal{B}\}, \mathcal{B} = \{\text{set of buses}\}. \tag{5}$$

$$P_{\min}^j \leqslant P_t^j \leqslant P_{\max}^j, \forall j \in \{\mathcal{B}_s\} \tag{6}$$

$$Q_{\min}^j \leqslant Q_t^j \leqslant Q_{\max}^j, \forall j \in \{\mathcal{B}_s\} \tag{7}$$

In the objective function equation, f_t^j denotes the auction based clearing price of active power at bus j, which serves as an input parameter to the optimization problem. Constraint (2) in the OPF model ensures that all the active demand (l) and the active transmission losses ($l(V, \theta)$) are met by the generators selected for dispatch at any given time (active power balance equation). The constraint (3) ensures that all the reactive demand ($\tilde{l}$) and the reactive transmission losses ($\tilde{l}(V, \theta)$) are met by generators selected for dispatch (reactive power balance equation). The term $S_{y,z}$ in (4) denotes the flow limit for the power transmitted from Bus y to Bus z. Constraint (4) ensures that the maximum flow limit constraints in both directions are not violated. The constraint (5) is used to maintain the voltage limits for each Bus. Constraints (6 and 7) are used to maintain active and reactive power generation limits.

(1) Solution strategies: Note that the bi-level bidding strategy problem is presented above from the perspective of profit maximization of generator j. But, the requirement of the knowledge of bid choices of the other players, as stated in the constraint set, makes the bi-level problem unsolvable in a deregulated market, where bid choices are not known a priori. Thus, the optimal generator bids should be derived from the Nash equilibrium strategies of the game. However, nonavailability of computationally viable tools to solve for Nash equilibria of multiplayer games had motivated researchers to look for alternative approaches to obtain optimal bidding strategies. For the purpose of examining the existing literature, we classify these contributions into two major categories: approaches that optimize individual strategies for given strategies of other players, and approaches that seek equilibrium strategies.

5.1. Optimization of individual bidding strategies

Several different optimization approaches have been used for this task including genetic algorithms [64–66], evolutionary programming [67], Monte Carlo simulation [68], dynamic programming [69,70], and mathematical program with equilibrium constraints [71,72]. In what follows, we review the key contributions and limitations of the above papers.

The work presented in [64] offers a *genetic algorithm* (GA) approach to optimizing profits of individual generators having multiple generating units. Solution of individual generator profits are obtained by assuming that the bids of other players are known in the form of probability distribution functions. GA is used as a means to navigate through the large actions spaces D_j of the individual generators $j \in \mathcal{G}$ while considering randomized bidding behavior of the other players. The solutions thus obtained do not have any equilibrium properties, since in a noncooperative bidding environment, no rational generator can be expected to behave randomly guided by a probability density function. As a result, the expected generator profits calculated by the algorithm are unlikely to be ever realized.

Attaviriyanapap et al. [67] present an *evolutionary programming* approach to finding bidding parameters that maximize individual generators profits. The authors attempt to obtain optimal bidding strategies of a supplier who owns multiple generating units. The clearing price f_j^t is obtained using a PX-type market settlement (simple matching of supply and demand curves) for 24 h of the day. The role of EP in this paper is to simply search through the decision space for profitable bids. EP-based search procedures have proven to be quite effective in navigating non-convex and non-differentiable spaces, where traditional optimization approaches may fail. However, due to lack of consideration of transmission, current, and voltage-related constraints (like the Eqs. (2)–(7)) the model as proposed in [67], is not readily applicable in realistic power market settings.

Wen and David use a Monte Carlo (MC) simulation method to obtain optimal generator bidding strategies in [68]. In [68], the authors consider rivals bids ($\mathcal{D}_l^t : l \in \{\mathcal{G} \setminus j\}$) to be available in the form of probability density functions and subsequently use MC simulation to obtain random samples from these bid pdf's. These samples are then considered to be fixed in the overall generator bidding strategy problem. Then, an elementary search technique known as *golden section* method used in finding the profit maximizing bid. However, it may be remarked here that the assumption of probabilistic estimation of rivals bids affects the ability of this approach to attain true optimality.

Rajaraman and Alvarado [69] present a deterministic nested dynamic programming (DP) approach of finding optimal bidding strategies for multi-period power market problems. DP-based approaches are suitable for small scale problems where decisions from one period affect the decisions and profits in subsequent periods (day ahead auction markets). The authors in [69] present several cases with consideration of hydro and thermal generators as well as cases with price making and price taking generators. However, their study does not consider multiple competing generators or transmission constraints. Also, the authors assume that the transition probability matrices (TPMs), or in other words, complete knowledge of the system, is readily available. However, it is well known that even for problems of relatively small sizes, determination of TPMs is almost impossible. As a result of such computational and modeling limitations, the approach presented in [69] cannot be applied to large transmission constrained networks having multiple competing generators. Nevertheless, the DP model may serve as a guidance tool for individual generators in determining profitable bidding strategies, for very small networks with limited state spaces.

Hobbs et al. [72], present a mathematical program with equilibrium constraints (MPEC) approach to finding optimal bidding strategies of generators in a power network. The authors assume that while making their own bid all generators have complete information about rival players' bids. A bilevel optimization model is formulated, where a generator's profit maximization problem at the first level is subjected to the OPF constraints at the second level. As part of the MPEC procedure, the OPF constraints are then replaced with equivalent KKT conditions resulting in a linear complementarity problem framework (LCP). This 2-level problem, known as MPEC, has a maximization problem in the first level and equilibrium constraints in the second level. Such problem structures have been gaining significant attention lately due to their widespread applicability in a variety of fields such as chemical engineering, transportation science, and power system economics. For this reason, we chose to present a generic formulation of an MPEC problem based on [73].

$$\begin{aligned}
&\mathrm{Max}_{x,y,z}\Pi(x,y,z).\\
&\text{Subject to :}\\
&0 \leqslant F(x,y,z) \perp x \geqslant 0,\\
&G(x,y,z) = 0,\\
&z \in S, \mathit{and}\\
&x,y,z \in \Re,
\end{aligned}$$

where z represents first level variables and x and y represent second level variables, which must satisfy an LCP with fixed values of z from the first level. In general, $0 \leqslant x \perp y \geqslant 0$ is read as $x \geqslant 0, y \geqslant 0$, and $xy = 0$. In the power market context, the first level variables are generator bids (similar to $\mathscr{D}_t^l$) which serve as fixed parameters in the second level OPF problem. The above MPEC problem is a non-convex optimization problem, which has to be solved using special solution algorithms such as the penalty interior point (PIP) method. Details of the PIP algorithm can be found in [72]. Table 3 presents some important attributes of bidding strategy formulation problems available in literature.

Before we proceed to discuss the approaches that seek equilibrium bidding strategies, it is important to briefly highlight the role that risk plays in formulating bidding strategies. While risk is inherent in most physical power system operations, it plays an equally important role while making financial decisions in restructured markets. Generator profits are often affected by volatilities in power demands, fuel prices, and other network contingencies, thereby affecting bidding decisions. Lately, some power market researchers have begun to incorporate such risk in their models. The methodologies commonly used in insurance and finance industries (such as value-at-risk and conditional value-at-risk) are slowly gaining traction in traditional power market decision making. Rodriguez and Anders [15] use the Ontario electricity market as a test bed to examine how generators bid during high and low load periods, depending on varying attitudes of risk (risk prone or risk averse). As expected, they find that bidding behavior varies significantly with varying risk attitudes and demands. Recently, Carrión et al. [74] developed a risk constrained stochastic programming model (using a conditional value-at-risk measure) to examine how retailers could negotiate bilateral contracts to maximize profits. Other recent interesting works that examine risk involved in power system operation are [75,76].

5.2. Approaches seeking equilibrium strategies

In a competitive power network with multiple participants, NE is said to have been obtained if no market participant has the incentive to unilaterally deviate from his/her bids. This can be mathematically stated as:

$$g(x_j^*, x_{-j}^*) \geqslant g(x_j, x_{-j}^*) \quad \forall j$$

where x_j^* is the optimal bid of a participant j, and x_{-j}^* are the optimal bids for all other participants. As alluded to earlier, due to nonavailability of computationally viable approaches to find Nash equilibria (NE) strategies, many researchers have approached the problem from two different viewpoints: (1) individual generators' profit maximization perspective (explained above), and (2) methodologies that solve for equilibria of Nash games by making assumptions about the competitive bidding behavior of generators (explained next). Some of these assumptions are Nash–Cournot, Nash–Bertrand, and Nash-supply function. In Nash–Cournot, Nash–Bertrand, and Nash-supply function games, all players make their bids simultaneously.

5.3. Nash–Cournot competition

Under the Cournot assumption the generators compete only with quantities. Each generator assumes that the opponents quantity is fixed and then makes his/her own quantity decision. Then the game is solved for a Nash–Cournot equilibrium, where no generator gains by unilaterally deviating from his/her bid quantity.

5.4. Nash–Bertrand competition

Under the Bertrand assumption the generators compete with prices. Each generator assumes that the opponents price is fixed and then makes his/her own price bid. The NE obtained under such competition is termed as Bertrand–Nash equilibrium.

5.5. Nash-supply function competition

Supply functions are price-quantity curves submitted by generators to the ISO. Supply function competition is often argued to represent the working of ISO-type power markets more closely than Cournot and Bertrand type competitions. The resulting equilibria are known as Nash-supply function equilibria. Unlike in the above three Nash games, in certain oligopolistic situations, it is assumed that one of the players has more information than the rest.

Table 3
Some important modeling attributes from bidding strategy literature.

Solution methodology	Overall problem structure	# of buses	Market clearing	Type of bids
Genetic algorithms [64]	Two level optimization	9-Bus	DC–OPF	Linear supply functions
Genetic algorithms [65]	Traditional optimization	24-Bus	PX-type	Linear supply functions
MPEC [72]	Bi-level optimization	30-Bus	DC–OPF	Linear supply functions
Evolutionary programming [67]	Traditional optimization	10-Bus	PX-type	Linear supply functions
Monte Carlo simulation [68]	Stochastic optimization	6-Bus	DC–OPF	Linear supply functions
Dynamic programming [70]	Two level optimization	5-Bus	PX-type	Step function bid curve

Such an assumption leads to the so-called Stackelberg game. In a Stackelberg game, a "leader" makes a decision first, and then the "followers" make their decision knowing the leader's decision. Such competition has been shown to be useful in modeling oligopolistic markets with a large dominating firm and few smaller competing firms. Even though the above assumptions have been extensively used in bidding strategy literature, it may be noted that the premise of complete information about rivals bids before making one's own bidding decision is not representative of non-cooperative power market games.

In the remainder of this section, we briefly discuss three approaches to find NE bidding strategies of power market games. They are: (1) linear/nonlinear complementarity problems (LCP/NCP), (2) equilibrium problem with equilibrium constraints (EPEC) and (3) stochastic approximation based reinforcement learning (SARL). All these three solution approaches can consider Bertrand, Cournot, or supply function competitions. The EPEC method generally considers a Stackelberg framework, owing to its two-level structure.

5.6. Linear/nonlinear complementarity problems (LCP/NCP)

A general formulation for LCP problems from Ref. [77] is given here. The objective is to find variables w and z where $w = (w_1, \cdots, w_n)^T, z = (z_1, \cdots, z_n)^T$ satisfy $w - mz = q$, and $w \geqslant 0, z \geqslant 0$ and $w_i z_i = 0\ \forall i$. Hobbs [78] uses such a framework to identify market equilibria in a POOLCO setting. He defines market equilibrium as those set of prices, supply, demand, and line flows that simultaneously satisfy each market participants first order conditions for maximizing profit while matching network demand and supply.

The LCP framework from Ref. [78] is presented here for exposition. For a constrained optimization problem, as the one given below

$$\begin{aligned}
&\mathrm{Max} F(x,y),\\
&\text{Subject to}:\\
&G(x,y) = 0,\\
&H(x,y) \leqslant 0,\\
&x \geqslant 0,
\end{aligned}$$

the KKT conditions can be written as follows:

$$\begin{aligned}
&x : \partial F/\partial x - \lambda \partial G/\partial x - \mu \partial H/\partial x \leqslant 0; x \geqslant 0,\\
&x(\partial F/\partial x - \lambda \partial G/\partial x - \mu \partial H/\partial x) = 0,\\
&y : \partial F/\partial y - \lambda \partial G/\partial y - \mu \partial H/\partial y \leqslant 0,\\
&\lambda : G(x,y) = 0,\\
&\mu : H(x,y) \leqslant 0, \mu \geqslant 0,\ \mathit{and}\ \mu H(x,y) = 0.
\end{aligned}$$

The equations associated with the non-negative variables are known as *complementarity conditions*, and λ and μ are the dual variables pertaining to the constraints G and H [78]. Hobbs develops such KKT conditions and combines them with the market clearing conditions. The first order KKT optimality conditions together with the market clearing conditions form the LCP. An equivalent quadratic program can then be written for the LCP and solved using standard solvers available in GAMS software. Another paper which discusses power market games [79], utilizes the well established Lemke–Howson algorithm of solving LCPs. In Ref. [79], the LCP is formulated from a bimatrix power market game. It may be noted that, while LCP's have been shown (both theoretically and computationally) to obtain NE of 2-player games, NCP frameworks have only been theoretically presented to solve games with more than two players. The proposed approaches of solving multiplayer games, such as [80,81], still have unresolved computational challenges. In the existing power market literature very few papers have attempted to solve multiplayer non-cooperative power market games. Most authors utilize an iterative approach for solving for equilibrium, wherein they fix rival players' parameters and essentially solve a large, but, single player optimization problem. Equilibrium is said to have been attained when no player can increase their profits further.

5.7. Equilibrium problem with equilibrium constraints (EPEC)

The MPEC optimization approach presented earlier can be extended to a game theoretic setting with multiple competing players, known as EPEC. In EPEC, each player is solving an MPEC problem subject to a set of common OPF constraints. We adopt the same notation used in the MPEC problem discussed earlier. Let all K players have the first level decision variables $z_k, k = 1 \cdots K$. The EPEC problem can now be stated as follows [73]:

$$\begin{aligned}
&z_k^*\ \mathit{solves}\ \mathit{Max}_{x,y,z_k} \Pi^k(x, y, z_k, z_{-k}^*)\\
&\text{Subject to}:\\
&0 \leqslant F(x, y, z_k, z_{-k}^*) \perp x \geqslant 0,\\
&G(x, y, z_k, z_{-k}^*) = 0,\\
&z_k \in S_k, \text{and}\\
&x, y, z \in \Re.
\end{aligned}$$

The variables z_{-k}^* represent optimal and fixed values of opponents. According to [82], there are two general methods to solve the EPEC problem: (1) obtain the optimality conditions (KKTs) for all the MPEC problems and solve them together as a complementarity problem, or (2) iteratively solve each of the MPECs using standard MPEC algorithms (like PIP) until the equilibrium solution of the EPEC game is obtained. The EPEC problem is extremely complicated and moreover does not guarantee an NE solution. If a solution does exit, it is called a subgame perfect Nash equilibrium. Some good applications of EPEC models have been presented in Refs. [83–86].

5.8. Stochastic approximation based reinforcement learning (SARL)

Stochastic approximation based reinforcement learning (RL) approach to finding NE differs significantly from the mathematical programming approaches like EPEC, NCP, and LCP. Unlike in the mathematical programming approaches, where one assumes complete knowledge of rivals bids, in SARL, all players compete simultaneously without knowledge of other players actions. Such a framework represents the true noncooperative game amongst

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power market participants. In [87], the authors use the well established value approximation mechanism which was previously successfully employed in solving large-scale, Markov and semi-Markov decision process problems with a single player [88] to develop a SARL algorithm that solves for NE of multiplayer noncooperative games. They first develop payoff matrices of the players and then employ the learning algorithm, which goes through a long cycle of exploration (attempting other strategies that may be profitable in the long run) and exploitation (selecting greedy strategies) before converging to the equilibrium solution. They present results from several games where their algorithm successfully yielded pure and mixed strategy NE. Though Nanduri and Das [87] presents promising numerical results, some theoretical convergence results are required to fully establish the algorithm.

6. Market power

The objectives of this section are three fold: (1) to define market power that arises in deregulated electricity markets, (2) to identify some of the commonly used market power indices and (3) to highlight possible approaches of market power mitigation.

6.1. What is market power?

Three types of market structures are often examined in microeconomic literature. They are monopoly, oligopoly, and perfectly competitive markets. Monopolistic and perfectly competitive markets are diametrical cases with a single seller and many competing sellers, respectively. Oligopoly is a market scenario with a few sellers in the market. Social welfare increases as the market moves from monopoly to perfect competition. The increase in social welfare was a principal motivator behind electricity industry restructuring. Even though the idealistic setting of perfect competition has not yet been attained, in general, most deregulated electricity markets converged towards an oligopolistic setting. These oligopolistic settings are often prone to market power misuse by large dominant firms. Microeconomic literature defines Market power (MP) as the ability of a seller to maintain prices above competitive levels for a sustained period of time.

6.2. MP indices

Market power indices have played a major role in shaping the restructuring process, by identifying the cause and/or the level of MP. Indicators like HHI and LI have been traditionally used by policy makers to assess the MP that could be exercised by dominant players. In this section we present some of the most commonly used MP indices, as well as shed light on some relatively new MP indices. Some of the most commonly used market power indices are:

(1) Herfindahl–Hirschman index (HHI).
(2) Lerner index (LI).
(3) Must-run ratio (MRR).
(4) Residual supplier index (RSI).

Some of the recently developed indices are:

(1) Quantity Modulated Price Index (QMPI).
(2) Revenue based market power index (RMPI).

6.3. Herfindahl–Hirschman index (HHI)

HHI, an index based on installed capacities, is defined as

$$\mathrm{HHI} = \sum_{j=1}^{N}\left(\frac{P^j_{\max}}{\sum_{j=1}^{N} P^j_{\max}} \times 100\right)^2,$$

where N is the total number of generators, $P^j_{\max}$ is the installed capacity of generator j, and the expression within the parenthesis is the percentage of market capacity owned by generator j. Clearly, the HHI of a monopoly would be 10,000, while the index value would be smaller for a larger number of market participants. Under Department of Justice/Federal Trade Commission (DOJ/ FTC) standards, a market with HHI value less than 1000 is considered to be free of market concentration. Markets with HHI values between 1000 and 1800 are considered moderately concentrated, and values greater than 1800 indicate high market concentration. Some of the earliest market power studies conducted by Borenstein et al. [89], presented the shortcomings of common market power indicators such as HHI.

HHI, as defined above, is an ex-ante index, which is static and thus differs from the actual market concentration that corresponds to the dynamic bid based supply allocations. Hence, such a market performance based HHI (referred hereafter as HHI*) could be obtained by simply replacing the installed capacities in the HHI expression by the generator supply quantities (P^j) resulting from the bid-based settlement. Nanduri and Das [62] note that:

$$\sum_{j=1}^{N}\left(\frac{P^j_{\max}}{\sum_{j=1}^{N} P^j_{\max}} \times 100\right)^2 \leqslant \sum_{j=1}^{N}\left(\frac{P^j}{\sum_{j=1}^{N} P^j} \times 100\right)^2.$$

That is, the ex-ante HHI value serves as the lower bound for the possible HHI* values in markets with strategic bidding.

6.4. Lerner index (LI)

LI, a price based MP index, at an individual generator's level can be calculated as the ratio of incremental margin to the price. At a network level it can be calculated as an average over all generators as

$$LI = \frac{1}{N}\sum_{j=1}^{N}\frac{f^j_1 - f^j_m}{f^j_1},$$

where f^j_1 denotes the price received for active power and f^j_m is the marginal cost of generator j. In a perfectly competitive market, where the demand curve is perfectly elastic, the Lerner index equals zero. In a monopolistic market, the generator will use its market power to set its profit-maximizing output in the inelastic portion of the demand curve and charge a price greater than the marginal cost. In that case, the Lerner index is greater than zero. In essence, inelastic demand implies large market power or vice versa. It may be noted that LI could be extremely difficult to estimate for industries like electricity and telecommunications, since producers may not divulge their marginal cost information [90]. Furthermore, calculating LI may be quite challenging for dynamic markets like electricity, where producer cost functions may also vary over time, due to fuel price and other volatilities.

6.5. Must-run ratio

HHI and LI do not consider transmission constraints across various zones in the electricity market. Transmission constraints play a significant role in impeding a suppliers ability to import or export power. One such index that considers transmission constraints is MRR. This index is discussed in detail in [91,92], and we present a short description below.

MRR for a supplier can be defined as:

$$\frac{P_d - P_l - \left(\sum_{j=1}^{N_g} P_{gj,\max} - \sum_{j=1}^{N_gA} P_{gj,\max}\right)}{\sum_{j=1}^{N_gA} P_{gj,\max}}$$

where, P_d is the total load of the zone, P_l is the import limit of the zone, $P_{gj,\max}$ is the output limit of generator j in zone, N_g is the number of generators in the zone, and N_gA is the number of generators owned by supplier A in the zone. This index calculates the locational market power of a supplier. Higher the MRR, higher the potential for locational market power for a generator.

6.6. Residual supplier index (RSI)

RSI is a market power index that helps in identifying those suppliers that are indispensable to the safe operation of a power network. It is defined as:

$$\mathrm{RSI}_i = \sum_{j=1,j\neq i}^{N} Q_j/D$$

where, $\sum_{j=1,j\neq i}^{N} Q_j$ is the quantity supplied by generators j excluding generator i, and D is the total demand of the network. If the ratio is less than 1 then, supplier i is said to have some market power. Lower the ratio, higher the market power of the supplier i. This indicator can be used in both ex-ante and ex-post situations by simply replacing Q_j with the installed capacity. An indispensable supplier is also known as a *pivotal supplier*.

6.7. Quantity modulated price index (QMPI)

It may be noted that using average price of a generator to calculate MP could be misleading, since in an auction based market settlement a generator may get a high price at the cost of reduced quantity. As in LI, where average price is considered in the MP calculations, due to average of prices over the length of the study, several high entries for price could raise the average price value. Use of such an average measure to assess MP could lead to wrong conclusions since it may not be appropriately reflected in the revenue earned by the generators. Hence, an average quantity weighted price (AQWP) is presented in [62] as a substitute for average price, which is defined as

$$\text{AQWP of Generator } j = \sum_{i=1}^{D} f_1^j(i)\,\frac{P^j(i)}{\sum_{i=1}^{D} P^j(i)},$$

where D is the total number of days in the study, $f_1^j(i)$ and $P^j(i)$ denote the price received and quantity supplied, respectively by generator j on day i.

QMPI was proposed in [62], and is defined as,

$$\mathrm{QMPI} = \frac{1}{N}\sum_{j=1}^{N}\frac{\mathrm{AQWP}^j - f_m^j}{\mathrm{AQWP}^j},$$

where N is the number of generators in the network. QMPI, though still a price based index, indirectly also considers the quantity allocation. Thus, QMPI is not undesirably impacted by scenarios where generators receive high prices without a significant supply allocation. This is in contrast to purely quantity based HHI and purely price based LI. Therefore, QMPI has the ability to capture the true MP exercised by a player. Even though the QMPI presented above considers the entire network, it can be easily modified to address MP of individual generators as well.

6.8. Revenue based market power indicator (RMPI)

RMPI is a measure of network profit (net revenue minus net marginal cost), which is defined as

$$\mathrm{RMPI} = \sum_{j=1}^{N} \bar{f}_1^j \bar{P}^j - \sum_{j=1}^{N} \left(f_m^j P^j\right),$$

where $\bar{f}_1^j$ denote the average price of active power received by generator j over the period of the study, and f_m^j denotes the marginal cost of generator j. The term $\bar{P}^j$ denotes the average active power quantity allocation [62]. For a market to be competitive, a lower value of RMPI is desirable. It is evident that the lowest possible value of RMPI is zero, which is attainable only in a perfectly competitive market. Such indicators can be used to study the effect of excessive market power on the network as a whole. Once high levels of RMPI are observed in a power network, market designers can focus on individual MPs of generators using QMPI or other equivalent indicators.

Some important MP based literature along with the main focus of the papers, the market studied, and the indicators or the methodology used to study MP, are presented in Table 4.

6.9. Market power mitigation

Market power mitigation is among the prime concerns of designers and policy makers. MP offers perverse incentives to dominant firms leading them to act in anti-competitive ways resulting in reduced social welfare (causing higher end-user prices). Some of the approaches mentioned below, which have been often discussed in literature, may be adopted by regulators to mitigate market power misuse.

- Encouraging investment in generation by removal of artificial barriers such as regulatory uncertainty and harsh environmental policies. The current level of regulatory uncertainty may deter new investors from entering the market. The recent case of deregulation policy reversals, akin to those in Virginia and Arkansas, send the wrong investment signals to independent power generators, driving them to invest elsewhere. Extremely harsh environmental and emissions regulations may also serve as a deterrent for new investors.

Table 4
Some important attributes of market power literature

Paper	Main focus of the paper	Intended market/network studied	Methodology used/MP indicator proposed
[91]	MP in congested networks	IEEE 39-bus	MRR
[92]	nodal MP assessment	IEEE RTS 24-bus	Nodal must run share (NMRS)
[93]	MP in generation sector	Queensland market	Optimization model
[62]	MP under various auctions	IEEE 7-bus	Game theoretic model (QMPI/RMPI)
[94]	MP under various auctions	Australia/UK	Analytical computation
[95]	MP in PX type environment	England and Wales	Agent based simulation
[96]	MP under discriminatory double-auctions	6-Generators 3 buyers	Agent based simulation
[97]	MP in PX type environment	California	Cournot equilibrium model
[98]	MP assessment and sensitivity analyses of simulation models of CA and NEPOOL	California & NEPOOL	Simulation models
[99]	MP under transmission constraints and demand side bidding	4-Bus	Internet based market simulation

- Introducing bid price caps to prevent generators from abusing MP.
- Prevent capacity withholding by dominant firms during peak load periods (capacity withholding was observed during California energy crisis).
- Introducing efficient capacity markets, with stringent market monitoring, to spur capacity investment by existing and new generators, subsequently leading to more competitive markets.
- Older generating technologies should be upgraded to be on par with current technological standards. At the same time new entrants should be required to adopt efficient technologies. This reduces the cost of power production and subsequently limits the costs that generators often pass on to consumers.
- Transmission congestion presents strategically located generators with the ability to sell electricity at higher prices. Hence, adequate transmission investment is vital to mitigation of MP.
- Consumer education about deregulation (the ability to choose between suppliers) is important in controlling the MP of monopolistic utilities. In Texas, a recently concluded survey shed light on the issue of lack of consumer awareness of deregulation. A majority of the surveyed group were not aware that they had a choice of suppliers [100].

7. Concluding remarks

This paper presents a survey of some critical research areas in the energy market. Barring a couple of existing survey papers, most others focus on very specific areas of energy markets. We however adopt a more broader approach by reviewing some of the most commonly researched topics in the energy sector. We bring to light some relatively new areas of research such as auction based price settlement, price forecasting, and bilateral contracts. At the same time, we also devote significant attention to the commonly studied critical issues such as bidding strategy formulation, market equilibria, and market power. Some widely used solution approaches such as MPEC, EPEC, and LCP are discussed as well.

Even though deregulated electricity market has been a widely researched topic for several years, the deficiency of a unified formula for electricity deregulation, signals the need for even more research. Though the current deregulation efforts appear to have benefited the producers more than the consumers, unlike airline and telecommunication sectors, it is incorrect to conclude that deregulation is not suitable for electricity markets. We firmly believe that it is the responsibility of the research and academic communities to address the challenge by developing models to establish a competitive structure for deregulated electricity markets and expose its true societal benefits. Without a wholehearted effort to address this challenge, we face the real possibility of going back to regulation and not realize the benefits of deregulation in a vital sector of our economy.

Due to recent events such as:

(1) california energy crisis,
(2) northeast blackouts,
(3) environmental threats (greenhouse gas emissions and resultant global warming),
(4) skyrocketing fuel prices,
(5) post 9/11 security issues,

the development of a risk constrained economic and physical power system reliability model has become imperative.

Such comprehensive multiobjective models can be developed by considering the following factors in concert.

- risk management and risk mitigation with respect to electricity market operation,
- capacity expansion planning,
- energy market operations,
- transmission market operations,
- emissions regulations
- ancillary market operations.

With peta-scale computing capabilities in the near horizon, development of such large-scale multiobjective power market optimization problems will become feasible. Consequently, such large-scale models (which are lacking in literature) will become amenable to detailed analysis and aid in better market design and assessment.

Acknowledgement

This work was funded in part by National Science Foundation Grant # ECS 0400268.

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Please cite this article in press as: Nanduri V, Das TK. A survey of critical research areas in the energy segment of restructured ... Int J Electr Power Energ Syst (2009), doi:10.1016/j.ijepes.2009.01.004