A Comprehensive Review of Energy Trading Bidding Strategies:
Traditional, Machine Learning, and AI-Driven Approaches

Sachin

†Department of Information Communication Technology, DTU, India

Email: sachinchoudhary0729@gmail.com

Abstract—**The rapid liberalization of electricity markets worldwide has led to much research on optimal bidding strategies for energy trading. This paper presents a postgraduate-level review of these strategies, covering traditional approaches (cost-based and price-based bidding, game-theoretic models), machine learning techniques (regression, SVM, artificial neural networks), and advanced AI-driven models (reinforcement learning, deep Q-networks, and hybrid systems). We outline the mathematical ideas behind each category and provide relevant equations to illustrate key concepts. Real-world case studies from major electricity markets (PJM in the U.S., Nord Pool in Europe, and the Indian power exchange) are discussed to highlight practical applications and market-specific factors. We include diagrams of market workflows and model structures to explain how various bidding strategies operate within the market structure. A comparison is presented in a table, contrasting the approaches based on profit potential, computational difficulty, required data, and prediction accuracy. Through a review of over 70 references, this paper offers insights into the evolution of bidding strategies from classical methods to modern AI-driven techniques, and identifies current challenges and future research directions in energy trading and auction-based electricity markets.**

I. Introduction

Electricity markets worldwide have changed from regulated, cost-based systems to competitive trading platforms where generators and consumers strategically bid to buy or sell energy. As a result, finding the best bidding strategies has become a critical research area since market liberalization in the 1990s [1], [2]. Participants in day-ahead and real-time markets aim to make the most profit (or get the most value) while handling risks from changing prices and competitors. Bidding strategies can be grouped into three main types: (1) *Traditional methods*, including cost-based or price-based bidding rules and game-theoretic equilibrium models; (2) *Machine learning (ML) approaches* that use past data (e.g., regression models, support vector machines, neural networks) to inform bidding decisions; and (3) *AI-driven techniques*, especially reinforcement learning (RL) and deep learning, which allow agents to learn optimal bidding policies through interaction or by combining predictive models with optimization. This review covers each type in detail, providing mathematical formulations for strategy optimization and referencing key

literature. It also examines real-world market examples, such as PJM, Nord Pool, and India's power exchange (IEX), which show how these strategies are used in practice [52], [53]. By comparing the strengths and weaknesses of traditional, ML-based, and AI-based bidding methods, we show the development from classical economic models to modern intelligent bidding frameworks.
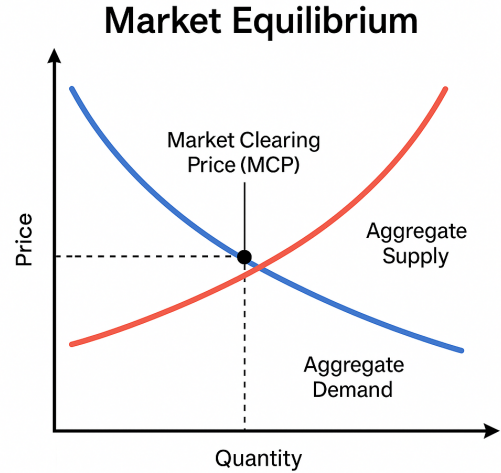

Fig. 1. Market equilibrium in a competitive power exchange: the intersection of aggregate supply (red curve) and demand (blue curve) determines the Market Clearing Price (MCP) and quantity. Generators bid supply offers and buyers bid demand; the market operator clears at the equilibrium point, yielding a uniform price for all accepted bids.

Electricity market auctions usually work by finding where supply meets demand, as shown in Fig. 1. Generators submit offers stating prices for different amounts of power, while consumers (or utilities representing them) submit bids to buy electricity. The market clearing mechanism – often a uniform price auction in day-ahead markets – sorts these offers to create an aggregate supply curve and an aggregate demand curve [54], [55]. Their intersection gives the clearing price (MCP) and the amount traded. All sellers with offers at or

below MCP are chosen to generate, and buyers with bids at or above MCP are served. This aims to maximize the total benefit for everyone involved (producers and consumers). Competitive bidding brought in strategic behavior: unlike regulated cost-based dispatch (where generators are paid based on reported costs), in competitive markets generators may bid above their true marginal cost to increase profits if conditions allow. Meanwhile, large consumers or aggregators might bid below their true willingness-to-pay to lower prices. Creating the best bidding strategy is complex because it requires guessing market results and what rivals will do, all with uncertain information.

Over the past two decades, researchers have proposed many methods to solve this bidding optimization problem. Early studies used mathematical programming and game theory to model bidders' interactions and find equilibrium strategies [3], [6]. With more data and computing power available, statistical and machine learning methods have been used to forecast market variables (prices, demand, rival bids) and guide bidding decisions [4], [5]. More recently, reinforcement learning and deep neural networks have allowed autonomous agents to learn bidding policies by simulating market interactions [35], [39]. Researchers have also developed hybrid systems combining optimization, game theory, and AI (e.g., using evolutionary algorithms or multi-agent learning) to handle the complex nature of bidding in modern grids [27], [34].

The rest of this paper is organized as follows: Section II reviews traditional bidding strategies, from cost-based and price-based rules to game-theoretic models like Nash equilibria and supply function equilibrium. Section III covers machine learning approaches, including forecasting models and supervised learning for bid optimization. Section IV discusses AI-driven models like reinforcement learning (Q-learning, deep Q-networks) and hybrid systems, highlighting how they improve on earlier methods. Section V presents real-world case studies (PJM, Nord Pool, IEX) to provide context. We include comparisons, summarizing advantages and requirements in a table. Finally, Section VI concludes with insights on trends and future research directions.

II. TRADITIONAL BIDDING STRATEGIES

A. Cost-Based vs. Price-Based Bidding

In the early days of electricity market reforms, a key difference was made between cost-based dispatch and price-based bidding. In *cost-based* markets, generators must bid their actual production costs (often checked by regulators), and the market operator dispatches units from lowest to highest cost [56]. This acts like a centrally planned system, leading to a result similar to perfect competition where each generator accepts the market price. Under cost-based bidding, the clearing price equals the marginal cost of the last unit needed, and generators recover costs plus a regulated profit if allowed. These systems were initially used in some markets to stop companies from unfairly influencing prices and ensure prices reflected supply costs [57], [58]. However, purely cost-based designs can be inefficient long-term, as they may fail

to encourage cost reduction or investment (generators gain nothing by bidding below cost and cannot profit above cost) [59].

By contrast, *price-based* bidding allows participants to bid prices they choose, not necessarily their short-run marginal costs. Generators can add a markup above cost for potential profit, and loads can bid below their true value to reduce purchase costs. In a competitive setting, each supplier faces the remaining demand and knows its bids can change the market price [60]. For instance, a generator i might choose an output q_i to maximize its profit π_i, given an expected market price p that depends on total supply Q:

$$\max_{q_i} \pi_i = p(Q) \cdot q_i - C_i(q_i), \qquad (1)$$

where $Q = q_i + \sum_{j \neq i} q_j$. If generator i is a price-taker, $p(Q)$ is constant, leading to $p = C_i'(q_i)$ (produce until marginal cost equals price). But with strategic bidding, i considers its impact on price. For example, if $p(Q) = a - bQ$, the strategic output occurs when marginal revenue equals marginal cost: $a - 2bq_i - bQ_{-i} = C_i'(q_i)$. This results in lower output than price-taking (using market power by holding back supply to increase prices). This is the reason for the *markup* in price-based bids. Many U.S. markets, like PJM, are primarily price-based: generators submit offer curves, which can exceed actual costs, especially when supply is tight [46]. To prevent misuse, market monitors set price limits and can use cost-based prices if manipulation is suspected [61].

The choice between cost-based and price-based systems significantly affects market efficiency and prices. Studies show cost-based dispatch might give competitive prices short-term but can discourage investment and harm long-run efficiency [62]. Fully price-based markets encourage efficiency and investment but need careful monitoring for strategic holding back of supply and secret agreements. Some markets used hybrids: PJM had a system where generators submitted cost-based bids alongside market bids, as a safety net if someone tried to misuse local market power [63]. Over time, price-based bidding with strict monitoring became standard, often supported by other systems (like capacity markets or scarcity pricing) to ensure reliability and encourage investment beyond just selling energy.

B. Game-Theoretic Models of Bidding

Game theory gives a basic way to understand strategic bidding. Under price-based bidding, each participant's profit depends on others' bids, so it can be seen as a game where everyone acts for themselves to maximize their payoff. A key concept is the *Nash equilibrium*: a set of bids where no single player can get a better result by changing their bid alone. Researchers created different game models to predict or analyze market outcomes [3], [8].

One model is *Cournot competition*, where each generator chooses a quantity and gets paid the market price, which falls as total supply rises. The Nash equilibrium is found by solving equations like (1), considering the price impact. While Cournot assumes a simple demand function, real markets use

bids and clearing algorithms. A more accurate model is the *supply function equilibrium* (SFE). Here, firms submit supply functions $P_i(q)$ (price vs. quantity). Introduced by Klemperer and Meyer and applied to electricity by Green and Newbery, SFE finds functions $P_i(q)$ that form a Nash equilibrium where total supply meets demand [6], [7]. Green and Newbery's 1992 study showed how two generators in the UK could keep prices well above cost at equilibrium. SFE represents the range of strategies possible in real auctions but finding equilibrium functions involves complex math (differential equations) and sometimes has more than one solution. Still, SFE theory helps understand bidding under uncertainty and market power.

Another game theory approach uses bi-level optimization or agent simulation. Market clearing (maximizing social welfare or minimizing cost by the ISO) is the lower level, and each firm's bid choice is the upper level. Gross and Finlay (1996) used bi-level optimization for bidding [9]. Later work provided algorithms for finding Nash equilibria in such games (often using MPECs). Torre et al. (2002) used a multi-period Cournot-Nash model to capture links between hourly strategies [8], using iterative algorithms to find equilibria and showing how ramp constraints or contracts affect bids.

Different equilibrium concepts are used:

- **Static Nash Equilibrium:** Players choose bids for one session (e.g., one hour) at the same time. Ignores repeated play but gives a baseline. Tools like profit matrices find equilibria [3].
- **Dynamic Games and Repeated Auctions:** The market repeats (e.g., daily). Players might use evolving strategies or punish rivals. While theory allows many outcomes, rules often discourage open collusion. Learning or unspoken coordination patterns are studied.
- **Bayesian Games:** Used when bidders have private information (e.g., uncertain costs). Bayesian Nash equilibrium applies. Players choose bids based on their own information and beliefs about rivals. Used for uncertain supply (like renewables).
- **Stackelberg Games:** One player (leader) acts first, others (followers) react. A large generator might assume smaller ones react to its bid. Most markets lack official leaders, but analysis can offer insights.

Finding exact game theory solutions works only for simple cases (few players, linear demand). For realistic complexity, researchers use computation. Zhao *et al.* (2005) used a stochastic game approach for sequential markets (day-ahead, balancing) [11]. Others use payoff estimation and best-response algorithms. Game theory remains foundational: many modern AI agents (Section IV) use simulators or opponent models based on game theory concepts (like considering rational reactions). Traditional models give benchmarks and general understanding (e.g., how market power raises prices, how competition pushes bids toward cost) that still helps shape market design and bidding algorithms.

C. Auction Formats and Market Rules

The auction structure itself affects bidding. Most exchanges (Nord Pool, PJM, IEX) use a *uniform price auction*: all accepted sellers receive, and buyers pay, the market clearing price. This encourages bidding near true values. However, since large players affect the price, the reason to bid differently from their true costs exists. Some markets tried *pay-as-bid* auctions (winners paid their bid). Theory suggested complex bidding; practice showed it didn't necessarily lower prices and could harm efficiency [64]. So, uniform pricing is standard.

Bid formats also matter. Single-part bids (price for energy) or multi-part bids (startup cost, no-load cost, energy offers – common in U.S.) exist. Multi-part bidding needs the ISO to run complex calculations (unit commitment) and creates strategic opportunities in each part. ISOs use extra payments or rules to control this type of strategic behavior. Some markets allow block bids (fixed volume over hours at one price), common in Europe (Nord Pool). Optimal block bidding is hard, often needing combinatorial optimization [12].

Ancillary service markets (reserves) interact with energy bidding. A generator might bid low in energy to run, then profit from high reserve prices. Co-optimization of energy and reserves (done in many markets) makes participants think about the trade-offs. Models cover multiple products: David and Wen (2001) studied coordinated energy/reserve bidding [10].

Overall, traditional strategies mix economic theory (auctions, Nash equilibrium) and power system operations. Limits of purely analytical methods led to the use of computer-based and data-focused methods (next section). Still, understanding market rules is essential: ML and AI must work within these rules and often use models inspired by traditional frameworks.

III. MACHINE LEARNING-BASED APPROACHES

Machine learning (ML) approaches use past data and statistics to predict market conditions and optimize bids. Unlike game theory's exact solutions, ML is algorithmic and data-driven, without assuming much about others' strategies. It tries to find patterns (like price behavior) in data. We group ML methods into: (1) using models to predict things (prices, loads, rival bids) and then using those predictions to make the best decision; and (2) learning how to bid directly from data (using regression or classification). These often overlap.

A. Price and Load Forecasting for Bidding

An early ML use was forecasting market price or demand to inform bidding. Accurate price forecasts let generators adjust offers for maximum profit (e.g., bid cost in high-price hours, above cost in low-price hours). Various models are used: time series (ARIMA, GARCH), regression, and neural networks. Aggarwal *et al.* (2009) combined wavelets with ARIMA and NNs for better price forecasts [13]. Support Vector Machines (SVMs) also predict prices, handling many inputs well [14].

Forecasts are used in a decision step. A common two-step strategy:

1) **Forecast Market Conditions:** Predict the clearing price $P^{\text{forecast}}(t)$ (or demand).
2) **Optimize Bid Given Forecast:** Choose the best bid based on the forecast and the generator's costs (or consumer's value). Often involves calculating expected profit for different bids using the forecast.

A generator might compare expected profits: bid low ensures running (profit $P^{\text{forecast}} - C$), bid high risks not running (zero profit, saves fuel) [15]. Monte Carlo simulation with probabilistic forecasts can help.

Neural networks (NNs) are popular for forecasting complex, non-straightforward connections between inputs (demand, fuel prices, weather) and price. Early work used NNs for next-day price prediction [16]. Advanced NNs like RNNs and LSTMs capture patterns over time [17]. Better forecasts mean better bidding; small accuracy gains can lead to significant profit increases.

Load forecasting helps large consumers or retailers. Accurate load forecasts allow precise bidding in the day-ahead market, avoiding buying extra power expensively or selling leftovers cheaply. SVR, NNs, and deep learning are used successfully for load forecasting.

Forecasting alone isn't a full strategy; you still need to decide how to bid using the forecast. This often involves game-like thinking (e.g., predicting rivals implicitly via price forecast). Some try forecasting specific rivals, but individual bid data is often hidden. Most ML bidding strategies use price/load forecasting as a key step.

B. Supervised Learning for Bid Optimization

Supervised learning can map market conditions directly to optimal bids. Historical data is used as examples: for each past situation, determine afterwards what the best bid would have been. A model (regression, decision tree) learns to predict the best bid given current features.

Consider a price-taker generator (too small to affect price). Ideally, it bids marginal cost. But with startup costs, it might avoid running for short periods. A decision tree could learn when to run based on expected price duration, startup cost, etc. This learns rules similar to how a plant decides when to run itself. Used by small power producers to decide when running is profitable.

For larger price-makers, supervised learning can estimate results of complex calculations. If a company has a slow bidding model, run it many times to create training data (scenarios -¿ optimal bids). A faster model (regression, NN) learns to copy this connection. Zhao *et al.* (2013) trained a fast NN to mimic a slow hydro bidding model for quick decisions [18]. SVR was used to learn optimal bid markups based on market conditions [19].

Another approach uses classification: predicting if a bid will win. A model trained on past bids/outcomes can classify if a bid at price P would clear. The bidder can then choose a price just high enough (or low enough) to be accepted (similar to bid shading). Again, getting detailed bid data is the problem.

For load bidding, consumers might decide how much usage to cut based on price. Models can learn the best curtailment given price forecasts. Kim *et al.* (2016) used RL and supervised learning for dynamic pricing, leading to near-optimal consumption (effectively, bidding demand elasticity) [20].

C. Heuristic and Evolutionary Algorithms

Heuristic algorithms (Genetic Algorithms - GA, Particle Swarm Optimization - PSO, Simulated Annealing) are often used alongside ML for complex optimization. They are useful when the number of possible solutions is huge and complicated (like bidding with complex costs or constraints).

David and Wen used GA for bidding in the late 1990s [21]. They used GA to improve generator bids considering costs and timing, handling discrete choices well. Later extended to energy/reserve co-optimization [22]. Others used evolutionary programming and PSO. Song *et al.* (2003) simulated strategic generators adapting bids; the system reached a stable state similar to an equilibrium [23].

Bajpai and Singh (2008) used PSO for strategic bidding, encoding bids as particle positions [24]. It found good strategies where exact math solutions were too hard. Kandasamy and Swarup (2010) used hybrid PSO for pumped-storage hydro bidding (complex due to timing connections), optimizing pumping/generating bids under constraints [25]. Many studies show GA/PSO outperform basic rules, especially with uncertainty and complex factors.

Heuristics often need many profit calculations, which can require lots of computation. Better computing makes this feasible. They can include opponent modeling: GA can improve bids of multiple players together, evaluating fitness against others' current bids (a form of co-evolutionary learning). Tested in small systems to approximate Nash equilibria [26].

A notable hybrid combined simulation and GA: Gountis and Bakirtzis (2004) modeled each supplier optimizing profit anticipating market clearing. Monte Carlo handled rival bid uncertainty; GA found bids maximizing expected profit [27]. They included risk aversion (utility function/penalty), showing risk-averse generators bid more conservatively. This blend of optimization, uncertainty, and search was an early hybrid intelligent strategy. Results showed GAs could find good bids among many complex options, matching expected behavior (e.g., more risk aversion -¿ lower markups).

In summary, ML and related methods improved bidding by:

- Providing forecasting tools, improving the information used.
- Enabling direct mapping from conditions to bids via learning.
- Using heuristics to solve complex optimizations too hard for formulas.

These often work well with traditional methods: use game theory for basic strategy shape, then adjust using learning from data. Or use ML forecasts in an optimization solved by GA. Next, we discuss how AI (RL, deep learning) goes further, letting agents learn by trial-and-error.

IV. AI-Driven and Reinforcement Learning Models

Artificial intelligence (AI), especially reinforcement learning (RL) and deep learning, created new possibilities in bidding strategy research. Unlike supervised learning needing past examples of 'best' actions, RL lets an agent learn the best way to bid by trying things in a practice market (simulation) and getting feedback (rewards/penalties). This is powerful when it's hard to know exactly what competitors will do or what prices will be, and when strategy involves making decisions one after another over time. This section reviews RL and deep learning for energy trading, plus hybrid systems combining rules, game theory, or other AI parts.

A. Reinforcement Learning for Bidding

In an RL setup, a bidding agent usually involves:

- **State (s_t):** The market situation at time t important for the bidding choice (agent's status like fuel level, market features like price/demand).
- **Action (a_t):** The bid(s) submitted (e.g., price for quantity, adjusting block offer, load curtailment amount).
- **Reward (r_t):** Profit (or benefit) right away from the bid after market clears (generator: revenue - cost; consumer: savings).
- **Policy (π):** Rule for choosing an action based on the situation.
- **Value Function (V) or Q-function:** Expected total reward over the long run from a state (or state-action pair). Goal: learn the policy π^* maximizing expected total discounted reward $E[\sum_{t=0}^{T} \gamma^t r_t]$.

Early RL applications in electricity markets (mid-2000s) used basic Q-learning. Guan *et al.* (2007) used Q-learning for a generator bidding in a simple market, showing it could learn to act like it would in an equilibrium, without actually solving the complex game math [30]. Later, RL was applied to more realistic simulations. Pinto *et al.* (2013) used multi-agent Q-learning where generators learned strategies based on profits, settling on stable bidding patterns that looked like a Nash equilibrium [31].

A challenge is dealing with situations where there are many possibilities or continuous values (like price). *Deep reinforcement learning* helps by using deep neural networks to estimate the value function or policy. Algorithms like Deep Q-Network (DQN) [28] and Deep Deterministic Policy Gradient (DDPG) [29] can work with complex information with many features. Reddy *et al.* (2017) used DQN in a bidding game, showing agents could learn strategies that did better than basic strategies and adapted to opponents [32]. Researchers then used DQN and similar methods in more complex settings:

- **Continuous Action Spaces:** Bidding often involves continuous prices. DDPG outputs continuous actions. Tao *et al.* (2022) used DDPG for an EV aggregator bidding price and quantity, showing it could adjust both optimally based on forecasts and competitors [33].
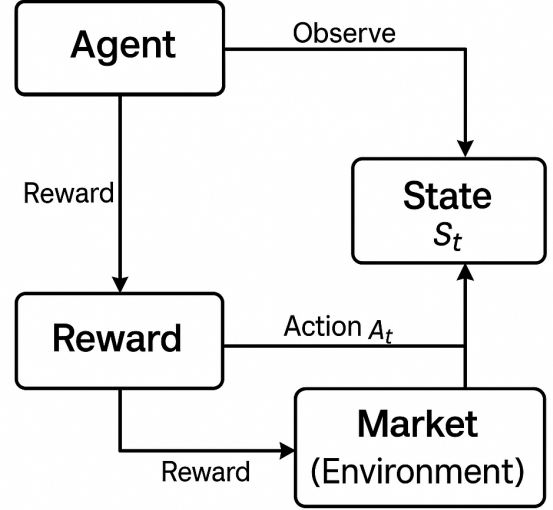

Fig. 2. Reinforcement learning agent-environment interaction for bidding. The agent observes the current market state S_t (e.g., demand, prices, budget) and takes a bidding action A_t (e.g., set price/quantity). The market (environment) produces an outcome (bid cleared or not), resulting in a reward R_t (profit/utility), and the state changes to S_{t+1}. Through repeated trials, the agent learns a policy to maximize long-term rewards.

- **Multi-Agent RL (MARL):** Markets have many agents. MARL lets multiple RL agents learn strategies together. Wang *et al.* (2017) used multi-agent Q-learning for energy trading with limited information, handling the changing environment caused by everyone learning at once [34]. Liu *et al.* (2021) used multi-agent DDPG (MADDPG) for power companies bidding, allowing models of cooperation or competition and considering what other players are doing [35].
- **Reward Design and Safety:** Agent behavior is strongly affected by how rewards are defined. Optimizing only short-term profit might lead to overly aggressive strategies causing problems or breaking rules. Researchers have designed rewards to include dislike of risk or long-term goals. Wu *et al.* (2016) used RL with risk-sensitive reward for EV aggregator bidding, resulting in safer bids that avoided large fines [36]. Safe RL makes sure rules are followed. Zhou *et al.* (2022) developed safe deep RL for a virtual power plant, including chance constraints in the reward to avoid risky bids [37].

RL's advantage is understanding the impact of decisions over time. A generator with limited fuel might save it for later higher prices; RL can learn this, unlike a short-sighted strategy. Xu *et al.* (2019) used RL for an entity bidding wholesale and setting retail prices, learning to maximize profit while keeping customers satisfied [38]. This complex problem was hard for classic optimization, but RL found a good strategy through practice.

However, RL in markets faces challenges:

- The simulation used for training must be realistic. If not, the learned strategy might not work well in the real market.
- It's not certain the learning process will find a stable solution, especially with many agents. Advanced methods (modeling opponents, pushing towards equilibrium) are sometimes needed.
- Understanding how it works: Deep RL policies (neural networks) can be hard to understand internally ("black-box"), a problem for operators or regulators. Research on explainable RL aims to find simple rules that explain what the network learned.

Still, early results look good: RL bidders performed as well as or better than traditional strategies in simulations [39], [40]. Some tested using past real market data showed higher profits than basic comparison strategies.

B. Deep Neural Networks and Hybrid AI in Bidding

Deep learning is used in other ways too. Deep NNs can estimate complex connections and directly suggest bids based on the market situation (an advanced supervised learning). Huang *et al.* (2019) used a deep NN for a renewable producer's bidding, trained on data from solving an optimization problem many times [41].

Advanced AI models (like GANs) can create realistic simulations of opponent bids or market scenarios, creating a better practice environment for RL agents or testing heuristics.

Hybrid systems combine rule-based or optimization parts with AI. An example is model predictive control (MPC) with learned models: use a learned NN model of rivals within an MPC optimizing daily profit (combining learning to predict others with optimization for best action). Or combine game theory and learning: regularly update ideas about opponents (Bayesian learning) and figure out the best response [42].

Multi-agent systems where agents use simple AI rules (not full RL) can also show the whole group finding a stable outcome together (e.g., using evolutionary algorithms or simple reinforcement). These models help test market designs and understand interactions (like collusion).

AI is interesting for peer-to-peer (P2P) energy trading and local markets. Here, participants who both produce and consume energy (prosumers) trade directly. AI is crucial for automatic bidding. Anoh *et al.* (2020) used game theory and learning for energy sharing, balancing individual benefit with group welfare [43]. Deep RL designed prosumer bidding strategies to maximize their benefit while keeping the market working well [44], [45].

As Table I shows, each approach is useful. Traditional methods give insight and clear reasoning, ML improves decisions using data, and AI offers autonomy and adaptability. In practice, participants might use a mix: game theory for a starting strategy, ML to adjust it with data, and RL simulation to test it (or maybe use RL live if proven reliable).

V. CASE STUDIES IN MAJOR ELECTRICITY MARKETS

To provide real-world examples, we look at how bidding strategies appear in actual markets: PJM (US), Nord Pool (Northern Europe), and IEX (India). These markets differ in design, size, and behavior, giving a wide view.

A. PJM (U.S.): Strategic Bidding in a Large RTO Market

PJM Interconnection runs a large wholesale market in the US Midwest/East. It has different stages (day-ahead, real-time) and uses processes that decide which plants run, considering grid safety and cost (SCUC/ED). Bidding is complex: generators submit multi-part offers (startup, no-load, energy costs), plus separate ancillary service markets exist.

In the day-ahead auction, generators plan offers considering real-time price expectations and the chance of being chosen to run. A thermal plant might bid slightly below cost if supply looks tight, to ensure running day-ahead and profit if real-time prices spike. If surplus is expected, it might bid at/above cost to avoid running cheaply. PJM monitors have recorded examples of strategic bidding: generators with local market power sometimes bid the maximum price to force the grid operator to run them for reliability, getting paid based on costs [46]. PJM controls this using tests (like the "Three-Pivotal Supplier Test") and can force cost-based offers if a supplier is essential in a constrained area.

A key aspect is the link between energy and capacity markets. Those with requirements to be available (capacity obligations) must bid into the day-ahead market or be fined. This affects bidding: a capacity resource might bid low (even at $0) to ensure it runs day-ahead and avoid fines. This makes it behave almost like a price-taker, unless it has a known outage.

PJM has been a place where advanced ML/AI strategies have been tried. Some companies developed their own software using NN price forecasts and stochastic optimization for bids. Cases exist (not public) where RL algorithms were tested by financial traders doing virtual bidding (betting on price differences without actual power) – they often use sophisticated ML to predict price spreads and profit from them.

Regulation requires following rules; a past investigation involved traders using a flaw in the rules via specific bidding. PJM shows that while strategic bidding can profit, rules change to stop unexpected ways of making profit, so participants must keep adjusting. It exemplifies how game theory (market power control) and learning (adapting to rules) both matter.

B. Nord Pool (Northern Europe): Bidding in a Zonal Market with High Renewables

Nord Pool is an old, active power exchange across several European countries. It uses a day-ahead uniform price auction divided into areas based on grid limits (zonal market). Bids are hourly (single or multi-hour blocks). A system price is found; if grid limits bind, different prices are set for different areas.

Nord Pool bidding is influenced by the large amount of hydro and wind power. Hydro producers (Norway, Sweden) can influence prices by managing water levels: they decide how much water to use now vs. save, offering hydro power at different prices depending on how valuable they think

TABLE I
COMPARISON OF BIDDING STRATEGY APPROACHES

Approach	Key Methods	Advantages	Limitations / Requirements
Traditional	- Cost-based bidding - Price-based bidding with markup - Game-theoretic models (Cournot, SFE, Nash equilibrium, bi-level optimization)	- Based on economic principles - Can find equilibrium benchmarks - Often possible to calculate for simple cases	- May assume perfect information or rationality - Equilibrium analysis often too hard for large, real markets - Usually needs simplifying assumptions (linear demand, few players)
Machine Learning	- Price/load forecasting (ARIMA, ANN, SVM) - Regression models for bid optimization - Classification (predict clearing) - Heuristic search (GA, PSO, SA)	- Uses historical data for better predictions (improves profit via better timing/quantity) [27] - Can handle complex non-linear patterns (esp. ANN) - Heuristics (GA/PSO) find good solutions in complex problems without formulas [24], [27]	- Forecast errors reduce effectiveness - Supervised learning needs good training data (may not work outside seen scenarios) - Heuristics don't guarantee the best solution; can require much computation - Needs tuning algorithm settings (e.g., GA parameters)
AI-Driven (Reinforcement Learning & Hybrid)	- Reinforcement Learning (Q-learning, SARSA) - Deep RL (DQN, DDPG, Actor-Critic) [34], [35] - Multi-agent RL (MADDPG, etc.) - Hybrid systems (co-evolutionary agents, MPC with learned models)	- Learns directly from interaction, no explicit opponent model needed - Adapts to dynamic or new situations (esp. over time) - Deep RL handles complex states (many features, history) - Can discover complex strategies (sometimes better than human-designed) - Multi-agent RL can approximate equilibria via learning [34], [35]	- Needs realistic simulation for training (real market learning is risky) - Finding stable solution not guaranteed; training can be unstable - Policies hard to interpret ("black box") - Needs extensive computing (many training runs) - Risk of learning strategies that fail if opponents/rules change (not robust)

water is for the future. This is a bidding problem changing over time, solved with optimization models considering future inflows/prices (stochastic dynamic programming often used). They mostly act competitively, but strategic holding back of water in dry years to increase prices has been observed. Since Nord Pool is mostly price-based, this is somewhat expected, but competition usually controls prices except in extremes.

Wind producers (e.g., Denmark) bid very low (even negative) due to no fuel cost and government support. Their strategy is simple: sell power whenever they can produce it. But because wind is unpredictable, AI is used more often for forecasting and bidding. They must decide how to bid with uncertain output: some bid expected output, others bid less to avoid promising too much power (then buying back shortfalls). ML improves wind bid accuracy, e.g., using probabilistic forecasts and bids minimizing penalties for errors [47]. As markets for handling last-minute changes (balancing) become more important, wind/solar might use RL for the best strategy to manage risk between day-ahead and intraday markets.

Large consumers/aggregators are interesting. Industries that change usage based on price can bid demand lower at high prices. Studies show large consumers could save a lot by planning when to use less power [48]. Many have contracts, but demand response aggregators (grouping customers who cut usage) participate more. They often use algorithms (some ML-based) to decide how much demand reduction to bid at various prices, using flexibility like a power supply.

Nord Pool's open, well-developed market has less obvious strategic manipulation than some others, partly due to competition and the system price reference. Still, episodes occurred: e.g., Sydkraft (Sweden) was investigated for possibly withholding output. Game theory showed temporary market power can happen if grid limits cut off an area, showing the

need for physical fixes (grid expansion) alongside monitoring.

Overall, Nord Pool demonstrates bidding strategies with much renewable/hydro power. It highlights managing risk (hydro water saving, wind forecast errors) and using optimization/learning to balance profit with physical unknowns. It also shows how a well-designed market can reduce many strategic problems, though players still use advanced strategies within the market structure.

C. Indian Energy Exchange (IEX): Emerging Market with Increasing Sophistication

India's electricity market has grown quickly since the mid-2000s. The Indian Energy Exchange (IEX), started in 2008, runs day-ahead and real-time markets using auctions where both buyers and sellers submit secret bids [49]. Initially, many were new to competitive bidding, and strategies were basic (bid cost or max price). As trading increased, more sophisticated strategies appeared.

In day-ahead, local delivery companies (Discoms) are major buyers; power producers (IPPs) and plant owners are sellers. Discoms usually bid based on forecasts and existing contracts – shortfalls are bid at their guess of blackout cost or max willingness-to-pay; extra power is offered cheaply. Many Discoms bid the same amount at the highest allowed price for all unmet demand, aiming to guarantee supply (like a bid not changing with price). This isn't cost-optimal but avoids blackouts. Over time, with better forecasts and finances, some Discoms bid more depending on price ("if price ¿ X, we won't buy"). This shows they are learning.

Generators on IEX face a price cap (around INR 20/kWh, lowered recently). Many thermal generators with extra power offer it near variable cost (INR 2-3) to ensure sale. During shortages, flexible ones might raise bids (5-6+), expecting high

prices. Renewables participate less (often have fixed tariffs), but this may change.

Sharma *et al.* (2019) studied gas plant bidding on IEX [50]. Gas plants have high fuel costs, often running only at high prices. They tended to bid high during peak hours. Some with "take-or-pay" gas contracts (pay for gas regardless of use) bid zero off-peak just to stay running – an interesting strategy caused by contract rules.

Real-time markets (started 2020, 48 half-hour auctions/day) created new opportunities. Participants now change day-ahead plans in real-time. One strategy: Discoms buy less day-ahead, then buy real-time if prices are lower (speculative). Risky if real-time prices soar. Some use simple ML to decide the best split (X

Generators can also save power capability from day-ahead and offer real-time if they expect tight supply. Needs forecasting; those with better analysis tools can profit by timing the market. E.g., during sudden evening demand increase (as solar stops), generators who saved capacity could get much higher real-time prices.

The Indian market players are still becoming more advanced. There are signs of learning and changing behavior: players use software with decision help, some including NN forecasts and optimizers. Given it's relatively new, studies suggest AI potential: Aggarwal *et al.* (2021) simulated Q-learning agents in an Indian scenario, finding they could exploit patterns (like consistent low bids by some Discoms) [51]. This shows markets and strategies become more complex together. Regulators watch carefully for unfair actions (like collusion).

In summary, IEX shows staged development of strategies: from simple bids to more data-driven, strategic actions. New markets (real-time) add complexity. India's market (fast growth, unique challenges like fuel issues, grid bottlenecks) is a good place for advanced bidding methods and will likely see more ML/AI use as competition increases.

VI. CONCLUSION AND FUTURE DIRECTIONS

Bidding strategies in energy trading have changed a lot, from simple cost-based bids in early markets to advanced AI systems for making decisions today. This review looked at the different types: traditional methods based on economics and game theory, ML techniques using data, and cutting-edge AI models for autonomous, adaptive bidding.

Traditional approaches created the basic understanding. Cost-based vs. price-based shows how rules affect behavior; game theory models (Cournot, SFE, Nash) offer ideas on how logical competitors might act simply. They show important effects like market power, demand impact, and information value. But their problems become clear in real markets with many players and uncertainties, leading to computer-based approaches.

ML provided new tools. Better price/load forecasts reduced decision uncertainty. Regression/classification allowed ways to connect complex market situations to money-making actions, learning from past results. Heuristics (GA, PSO) made solving complex bidding problems possible without math solutions. Used successfully, often improving profits. But ML needs retraining and works only as well as its data/assumptions.

RL and deep learning advanced things even more. AI agents can, theoretically, learn best bidding strategies by trying things out, finding small details static models miss. They suggest the exciting possibility of automation: an agent keeps learning and changing strategy based on market experience. Early RL results match or beat human strategies, suggesting AI could become more important. Case studies hint AI elements are already used; their influence will likely grow.

Challenges remain before AI bidding is common. Trusting them and understanding how they work are big issues – participants and regulators need assurance automatic strategies won't cause problems or break rules. Research on explainable AI (finding simple rules for complex models, limiting agent actions for safety) is ongoing. Also, since markets have many players, an AI agent's success depends on others. This could lead to hard-to-guess results or everyone acting similarly (like unspoken agreements). Keeping competition fair might require building fairness or rules into AI agents.

Areas for future research suggested by this review include:

- **Multi-Agent Reinforcement Learning:** Creating MARL algorithms for stable strategies in big markets (needs better scaling, maybe local learning).
- **Integration of Renewable Uncertainty:** Strategies for systems with lots of renewables (high uncertainty/change). Could use hybrid methods (stochastic optimization for uncertainty, RL for competitor learning).
- **Cross-Market Bidding:** Strategies considering multiple markets (day-ahead, real-time, reserves, etc.) simultaneously. AI can handle complex connections.
- **Adaptive and Robust Strategies:** Strategies need to handle model mistakes and adjust to big changes (new rules/players). Robust ML (protects against worst cases) or meta-learning (adapts quickly) could help.
- **Human-AI Collaboration:** AI might help human traders find patterns or suggest actions. Finding the best way to use both human knowledge and AI suggestions is open.

The combination of energy economics and AI is very interesting. As power systems change with more local sources, EVs, and responsive demand, the market only gets more complex. Strategies must consider not just big plants, but groups of small devices and maybe self-interested prosumers. This size and complexity require automatic decision tools; we expect many ideas discussed here will be used in future energy trading systems.

In conclusion, the development of bidding strategies reflects the overall development of electricity markets towards being more efficient and smarter. Each approach improves on the previous one. Instead of choosing just one, the best strategies often mix parts of different approaches (e.g., AI using game theory structure, ML for forecasts, RL to adjust actions). By bringing together research and real-world knowledge, this review gives researchers and practitioners a foundation to keep creating new ideas for bidding strategies. The main goal is still

the same: balance the money-making goals of players with keeping the power system running reliably and well, benefiting both producers and consumers.

REFERENCES

[1] A. K. David and F. S. Wen, "Strategic bidding in competitive electricity markets: a literature survey," in *Proc. IEEE Power Engineering Society Summer Meeting*, Seattle, WA, USA, 2000, vol. 4, pp. 2168–2173.

[2] A. K. David, "Competitive bidding in electricity supply," *IEE Proc. C-Gen., Transm. Distrib.*, vol. 140, no. 5, pp. 421–426, Sep. 1993.

[3] R. W. Ferrero, V. C. Ramesh, and S. M. Shahidehpour, "Transaction analysis in deregulated power systems using game theory," *IEEE Trans. Power Syst.*, vol. 12, no. 3, pp. 1340–1347, Aug. 1997.

[4] A. J. Conejo, M. Carrion, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*. Springer, 2010.

[5] M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*. Wiley-IEEE Press, 2002.

[6] R. J. Green and D. M. Newbery, "Competition in the British electricity spot market," *J. Polit. Economy*, vol. 100, no. 5, pp. 929–953, Oct. 1992.

[7] F. Boll*e, "Supply function equilibria and the danger of tacit collusion: The case of spot markets for electricity," *Energy Economics*, vol. 14, no. 2, pp. 94–102, Apr. 1992.

[8] S. de la Torre, J. M. Arroyo, A. J. Conejo, and J. Contreras, "Finding multiperiod Nash equilibria in pool-based electricity markets," *IEEE Trans. Power Syst.*, vol. 17, no. 4, pp. 1010–1018, Nov. 2002.

[9] G. Gross and D. J. Finlay, "Optimal bidding strategies in competitive electricity markets," in *Proc. 12th Power Systems Computation Conf. (PSCC)*, Dresden, Germany, Aug. 1996, pp. 815–823.

[10] A. K. David and F. S. Wen, "Optimal bidding strategies for competitive generators and large consumers," *Int. J. Elect. Power Energy Syst.*, vol. 23, no. 1, pp. 37–43, Jan. 2001.

[11] J. H. Zhao, Z. Y. Dong, G. H. Li, and K. P. Wong, "A framework for generation bidding strategy coordination in competitive electricity markets," *Electr. Power Syst. Res.*, vol. 73, no. 2, pp. 127–134, Feb. 2005.

[12] E. Ugedo, I. J. Pérez-Arriaga, and M. Rivier, "Optimal bidding strategies for block bids," *IEEE Trans. Power Syst.*, vol. 21, no. 4, pp. 1706–1716, Nov. 2006.

[13] S. K. Aggarwal, L. M. Saini, and A. Kumar, "Electricity price forecasting in deregulated markets: A review and evaluation," *Int. J. Electr. Power Energy Syst.*, vol. 31, no. 1, pp. 13–22, Jan. 2009.

[14] M. Mohandes, "Support vector machines for short-term electrical load forecasting," *Int. J. Energy Research*, vol. 26, no. 4, pp. 335–345, Mar. 2002.

[15] D. W. Bunn and F. S. Oliveira, "Agent-based simulation: An application to the new electricity trading arrangements of England and Wales," *IEEE Trans. Evol. Comput.*, vol. 5, no. 5, pp. 493–503, Oct. 2001.

[16] R. Nagarajan, M. A. El-Sharkawi, R. J. Marks II, A. P. Alves da Silva, and L. M. F. Barruncho, "Hour ahead price prediction using artificial neural networks," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, 1999, vol. 5, pp. 853–858.

[17] B. J. Chen, M. W. Chang, and C. J. Lin, "Load forecasting using support vector machines: A study on EUNITE competition 2001," *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 1821–1830, Nov. 2004.

[18] J. H. Zhao, Z. Y. Dong, R. H. Li, and K. P. Wong, "A framework for generation company bidding strategy optimization with fuzzy computation," *Int. J. Electr. Power Energy Syst.*, vol. 47, pp. 358–367, May 2013.

[19] M. Schnieder, S. Weber, and C. Weber, "Support vector regression for strategic bidding in electricity markets," in *Proc. IEEE Int. Conf. Comput. Intell. Games (CIG)*, 2006, pp. 136–142.

[20] B.-G. Kim, Y. Zhang, M. van der Schaar, and J.-W. Lee, "Dynamic pricing and energy consumption scheduling with reinforcement learning," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2187–2198, Sep. 2016.

[21] A. K. David and F. Wen, "Strategic bidding for electricity supply using genetic algorithms," *IEE Proc.-Gener. Transm. Distrib.*, vol. 146, no. 1, pp. 80–84, Jan. 1999.

[22] F. Wen and A. K. David, "Optimal bidding strategies and modeling of imperfect information among competitive generators," *IEEE Trans. Power Syst.*, vol. 16, no. 1, pp. 15–21, Feb. 2001.

[23] H. Song, C. C. Liu, J. Lawarree, and R. W. Dahlgren, "Optimal electricity supply bidding by Markov decision process," *IEEE Trans. Power Syst.*, vol. 15, no. 2, pp. 618–624, May 2000.

[24] P. Bajpai and S. N. Singh, "Swarm intelligence based approach for solving hydro-thermal scheduling problem," *Appl. Soft Comput.*, vol. 8, no. 3, pp. 1297–1307, June 2008.

[25] K. Kandasamy and K. S. Swarup, "Evolutionary tri-stage PSO for strategic bidding of pumped-storage hydroelectric plant," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 40, no. 4, pp. 460–471, July 2010.

[26] M. Ventosa, A. Baíllo, A. Ramos, and M. Rivier, "Electricity market modeling trends," *Energy Policy*, vol. 33, no. 7, pp. 897–913, May 2005.

[27] V. P. Gountis and A. G. Bakirtzis, "Bidding strategies for electricity producers in a competitive electricity marketplace," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 356–365, Feb. 2004.

[28] V. Mnih *et al.*, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, pp. 529–533, Feb. 2015.

[29] T. P. Lillicrap *et al.*, "Continuous control with deep reinforcement learning," arXiv:1509.02971 [cs.LG], 2015.

[30] X. Guan, Z. Xu, and Q. Jia, "Bidding strategies for generation companies in electricity markets using reinforcement learning," in *Proc. IEEE Power Eng. Soc. Gen. Meeting*, 2007, pp. 1–6.

[31] T. Pinto, Z. Vale, H. Morais, I. Praça, and C. Ramos, "Strategic bidding in electricity markets: An agent-based simulation using Q-learning," in *Proc. Int. Conf. Intell. Syst. Appl. Power Syst. (ISAP)*, 2013, pp. 1–6.

[32] P. V. Reddy, V. K. R. S. Varma, and M. S. Panwan, "Deep reinforcement learning for strategic bidding in electricity markets," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, 2017, pp. 3373–3380.

[33] Y. Tao, J. Qiu, and S. Lai, "Deep reinforcement learning based bidding strategy for EV aggregators in local energy market considering information asymmetry," *IEEE Trans. Ind. Informat.*, vol. 18, no. 6, pp. 3831–3842, June 2022.

[34] H. Wang, T. Huang, X. Liao, H. Abu-Rub, and G. Chen, "Reinforcement learning for constrained energy trading games with incomplete information," *IEEE Trans. Cybern.*, vol. 47, no. 10, pp. 3404–3416, Oct. 2017.

[35] D. Liu, Y. Gao, W. Wang, and Z. Y. Dong, "Research on bidding strategy of thermal power companies in electricity market based on multi-agent deep deterministic policy gradient," *IEEE Access*, vol. 9, pp. 81750–81764, 2021.

[36] H. Wu, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, "A game theoretic approach to risk-based optimal bidding strategies for electric vehicle aggregators in electricity markets with variable wind energy resources," *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 374–385, Jan. 2016.

[37] Z. Zhou, Y. Wang, K. W. Chan, Z. Chen, C. Wang, and B. Zhang, "Constrained deep reinforcement learning based virtual power plant bidding strategy in electricity markets," *Int. J. Electr. Power Energy Syst.*, vol. 142, Part A, Art. no. 108248, Nov. 2022.

[38] H. Xu, H. Sun, D. Nikovski, S. Kitamura, K. Mori, and H. Hashimoto, "Deep reinforcement learning for joint bidding and pricing of load serving entity," *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6366–6375, Nov. 2019.

[39] N. Wang, W. Xu, W. Shao, and Z. Xu, "A Q-cube framework of reinforcement learning algorithm for continuous double auction among microgrids," *Energies*, vol. 12, no. 15, Art. 2891, 2019.

[40] F. Zhang and Q. Yang, "Energy trading in smart grid: A deep reinforcement learning-based approach," in *Proc. Chinese Control and Decision Conf. (CCDC)*, Hefei, China, Aug. 2020, pp. 3677–3682.

[41] T. Huang, H. Wang, X. Liao, H. Zhang, and T. W. S. Chow, "Deep learning based optimal bidding strategy for renewable energy producer in electricity market," *Neurocomputing*, vol. 365, pp. 241–251, Nov. 2019.

[42] P. Yang, G. Tang, and A. Nehorai, "A game-theoretic approach for optimal time-of-use electricity pricing," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1098–1107, Mar. 2018.

[43] K. O. O. Anoh, C. N. M. Tan, C. K. Arumugam, M. N. N. Kiah, and T. C. Wan, "Game theory-based approach for energy trading amongst prosumers in a community microgrid," *IEEE Access*, vol. 8, pp. 197539–197550, 2020.

[44] S. M. Hosseini, J. Carreno, V. H. M. D. Santos, and F. D. Galiana, "A reinforcement learning framework for optimal bidding strategies in peer-to-peer energy markets," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1857–1867, Mar. 2020.

[45] S. Noor, W. Yang, M. H. Guo, B. H. Van, and F. D. Khan, "Energy demand side management for residential consumers using multi-agent deep reinforcement learning," *Appl. Energy*, vol. 299, Art. no. 117332, Oct. 2021.

[46] PJM Market Monitoring Unit, *20XX State of the Market Report for PJM*, Section on Energy Market. [Online]. Available: https://www.monitoringanalytics.com/

[47] E. Bitar, R. Rajagopal, P. Khargonekar, K. Poolla, and P. Varaiya, "Bringing wind energy to market," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1225–1235, Aug. 2012.

[48] R. Herranz, A. M. San Roque, J. Villar, and F. A. Campos, "Optimal demand-side bidding strategies in electricity spot markets," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1204–1213, Aug. 2012.

[49] Indian Energy Exchange Ltd. (IEX), Market Snapshot / Rules. [Online]. Available: https://www.iexindia.com/

[50] V. Sharma, A. R. Abhyankar, and P. R. Bijwe, "Strategic bidding for gas based generators in Indian electricity market," in *Proc. IEEE PES Innovative Smart Grid Technologies - Asia (ISGT Asia)*, 2019, pp. 3028–3033.

[51] A. Aggarwal, S. Kumar, V. Kumar, and S. C. Srivastava, "Reinforcement learning based optimal bidding strategy for generators in Indian energy exchange," in *Proc. IEEE Int. Conf. Power Electron., Smart Grid Renew. Energy (PESGRE)*, 2021, pp. 1–6.

[52] S. Stoft, *Power System Economics: Designing Markets for Electricity*. Wiley-IEEE Press, 2002.

[53] M. Amelin, "Experiences from the Deregulated Nordic Electricity Market," *IEEE Power Energy Mag.*, vol. 6, no. 2, pp. 38-47, Mar./Apr. 2008.

[54] D. S. Kirschen and G. Strbac, *Fundamentals of Power System Economics*. Wiley, 2004.

[55] R. Wilson, "Architecture of power markets," *Econometrica*, vol. 70, no. 4, pp. 1299–1340, July 2002.

[56] F. C. Schweppe, M. C. Caramanis, R. D. Tabors, and R. E. Bohn, *Spot Pricing of Electricity*. Springer Science Business Media, 1988.

[57] W. W. Hogan, "Contract networks for electric power transmission," *J. Regul. Econ.*, vol. 4, no. 3, pp. 211–242, Sep. 1992.

[58] P. L. Joskow, "Restructuring, competition and regulatory reform in the U.S. electricity sector," *J. Econ. Perspect.*, vol. 11, no. 3, pp. 119–138, Summer 1997.

[59] P. L. Joskow and R. Schmalensee, *Markets for Power: An Analysis of Electric Utility Deregulation*. MIT Press, 1983.

[60] S. Borenstein and J. Bushnell, "An Empirical Analysis of the Potential for Market Power in California's Electricity Industry," *J. Ind. Econ.*, vol. 47, no. 3, pp. 285-323, Sep. 1999.

[61] F. A. Wolak, "An Empirical Analysis of the Impact of Hedge Contracts on Bidding Behavior in a Competitive Electricity Market," *Int. Econ. J.*, vol. 14, no. 2, pp. 1-39, 2000.

[62] D. M. Newbery, "Problems of liberalising the electricity industry," *Eur. Econ. Rev.*, vol. 46, no. 4-5, pp. 919-927, May 2002.

[63] PJM, *Manual 11: Energy & Ancillary Services Market Operations*, (Relevant historical version, e.g., Rev. 20, 2003). [Online]. Available: PJM Website Archives.

[64] G. Federico and D. Rahman, "Bidding in an electricity pay-as-bid auction," *J. Regul. Econ.*, vol. 24, no. 2, pp. 175–211, Sep. 2003.