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Electricity Market Modeling at the European Energy Exchange: Methods, Market Dynamics, and Renewable Impacts[#]

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ABSTRACT

The European Energy Exchange (EEX) is the leading electricity trading platform in Europe, covering spot, intraday, and futures markets. Owing to the non-storability of electricity, high renewable penetration, frequent price spikes, and evolving regulatory frameworks, EEX provides a representative setting for electricity market modeling. This paper reviews major modeling approaches applied to the EEX. For spot markets, econometric time-series models, jump-diffusion processes, regime-switching frameworks, and machine learning methods are compared in terms of their ability to capture seasonality, volatility, price spikes, and negative prices, while for futures markets, studies on forward pricing, risk premiums, and derivative valuation are examined. The impacts of renewable energy are highlighted, showing that wind and solar generation reduce average prices, increase volatility due to forecast uncertainty, and stimulate demand for renewable-linked products. Overall, the synthesis indicates that hybrid and policy-sensitive models are essential for forecasting, risk management, and policy evaluation in electricity markets under energy transition.

Keywords: European Energy Exchange (EEX), electricity market modeling, spot and futures prices, renewable energy impacts, risk premium, market volatility

NONMENCLATURE

Abbreviations	
EEX	European Energy Exchange
LPX	Leipzig Power Exchange
ECC	European Commodity Clearing
MCP	Market Clearing Price
MOE	Merit-Order Effect
MRS	Markov regime-switching

1. INTRODUCTION

The European Energy Exchange (EEX) is the central marketplace for electricity trading in Europe, covering spot, intraday, and futures markets [1]. Electricity trading differs fundamentally from conventional commodity markets due to non-storability, real-time balancing requirements, and the increasing role of intermittent renewable generation, making EEX a representative setting for electricity market modeling.

Over the past two decades, EEX has developed into an integrated European market infrastructure. Through EPEX SPOT and the European Commodity Clearing (ECC), it offers a transparent and liquid trading environment across more than 30 bidding zones [2]. Its market design comprises day-ahead auctions, intraday trading, and futures markets, supporting price discovery, risk management, and investment planning during Europe's energy transition.

Modeling electricity prices in this environment is analytically challenging and practically important. EEX price series exhibit strong volatility, frequent price spikes, and negative prices, which violate standard time-series assumptions. Regulatory reforms and rising wind and solar penetration further introduce structural breaks and shifting market fundamentals, requiring flexible and policy-aware modeling approaches [3]. Accordingly, diverse methods have been proposed, including econometric time-series models, jump-diffusion processes, regime-switching frameworks, and machine learning hybrids.

Despite extensive research, a systematic synthesis linking modeling approaches to the institutional structure and renewable-driven dynamics of the EEX remains limited. This paper reviews price formation mechanisms, compares spot and futures price modeling approaches, and examines the impacts of renewable

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energy, providing a concise framework for forecasting, risk management, and policy evaluation.

2. THE EEX ELECTRICITY MARKET

2.1 Market design and structure

2.1.1 Spot Market

The EEX spot market is structured around two segments: the day-ahead auction and the intraday market. The day-ahead market is conducted at 12:00 CET on D−1 and sets hourly clearing prices for the following 24 hours under a uniform marginal pricing rule. Through market coupling, clearing is performed simultaneously across major European bidding zones, including Germany/Luxembourg, France, Austria, Belgium, the Netherlands, and the Nordic countries. As illustrated in Fig. 1, traded volumes in the EPEX day-ahead market increased steadily from about 460TWh in 2017 to over 650TWh in 2024, and the resulting prices serve as a benchmark for short-term system operation and hedging.

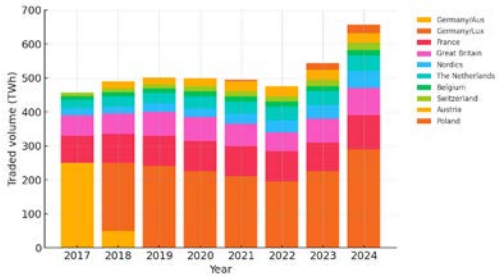

Fig. 1 Traded volume trends in the EPEX day-ahead market

The intraday market complements the day-ahead auction by addressing forecast errors and unexpected imbalances. It combines continuous trading until five minutes before delivery with three pan-European intraday auctions (IDA1–3). Traded volumes rose from 65TWh in 2017 to more than 215TWh in 2024, reflecting the growing need for short-term flexibility in power system balancing (Fig. 2).

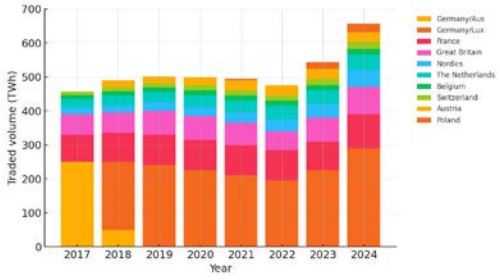

Fig. 2 Traded volume trends in the EPEX intraday market

2.1.2 Futures Market

The futures market is the most liquid segment of the EEX, covering more than 20 bidding zones and offering base- and peak-load contracts with delivery horizons from days to several years. Contracts may be cash-settled or physically delivered, although financial settlement dominates in practice. Trading volumes increased from 2,822TWh in 2017 to over 8,400TWh in 2024, accounting for more than 90% of total EEX electricity transactions. The futures market plays a central role in hedging price risk, valuing generation assets, and financing renewable projects. From a modeling perspective, its multi-maturity structure and pronounced risk premiums make it well suited for forward-curve construction and derivative pricing.

2.2 Price formation mechanism

2.2.1 Merit-order principle

Day-ahead prices at the EEX are determined by the merit-order principle, under which generation units are dispatched in ascending order of marginal cost until forecast demand is met. The marginal unit sets the Market Clearing Price (MCP), which is uniformly applied to all transactions. Zero-marginal-cost renewables, such as wind and solar, are dispatched first, followed by nuclear, hydro, coal, and gas-fired plants. Carbon costs under the EU Emissions Trading System (EU ETS) are reflected in bids, further strengthening the priority of renewable generation. This transparent pay-as-cleared mechanism provides a fundamental benchmark for price modeling and policy evaluation.

2.1.2 Negative Price

Negative prices are a distinctive feature of the EEX day-ahead market. First observed in 2008, negative Market Clearing Prices (MCPs) have become increasingly frequent as renewable penetration has exceeded 60%. They typically arise when inflexible baseload generation coincides with high wind or solar output during periods of low demand, and are amplified by subsidy schemes and limited cross-border transmission capacity. In 2024, negative prices occurred in 459 hours (5.2% of the year), posing challenges for classical linear models and motivating the use of jump-diffusion, regime-switching, and Bayesian change-point approaches.

3. REVIEW OF EEX SPOT MARKET MODELING

3.1 Time-series models

Classical time-series models, such as ARX, ARFIMA–GARCH, and CARMA, remain widely used for modeling

EEX prices. They are effective in capturing seasonality, volatility clustering, and long memory. Koopman et al. combined ARFIMA and GARCH to jointly model persistence and volatility in day-ahead prices, achieving lower forecast errors than ARMA benchmarks [4]. Benth et al. extended CARMA models to a continuous-time setting with GARCH volatility, successfully reproducing price dynamics and volatility clustering [5]. Steinert and Ziel incorporated futures prices and Lasso regularization into linear regression models, showing significant improvements in medium-term forecasts when financial information is included [6]. Despite their transparency and interpretability, time-series models are limited in handling price jumps, negative prices, and structural breaks.

3.2 Jump-diffusion and OU models

Jump-diffusion and Ornstein–Uhlenbeck (OU)–based models are widely used to describe the non-Gaussian behavior of EEX prices. They combine mean reversion with stochastic jumps to capture price spikes and heavy tails. Benth et al. applied Lévy-driven OU processes and demonstrated their ability to reproduce extreme price events [7]. Klüppelberg et al. proposed stable CARMA–Lévy models that capture multi-scale dynamics with infinite variance and improve model fit during turbulent periods [8]. Gonzalez et al. distinguished between positive and negative jumps, enhancing the representation of negative price events [9]. Despite their strengths in extreme-event modeling and derivative pricing, these models involve complex estimation and offer limited flexibility for incorporating fundamental drivers such as wind generation and demand.

3.3 Regime-switching models

Markov regime-switching (MRS) models capture structural transitions between normal, spike, and negative-price regimes. Bierbrauer et al. proposed two- and three-state MRS–OU models for EEX day-ahead prices, achieving a more realistic representation of observed dynamics [10]. Janczura and Weron formalized a three-state framework consisting of base, spike, and drop regimes, and demonstrated superior performance in modeling hourly price distributions [11,12]. Paraschiv et al. extended MRS models to ensure consistency between spot and forward prices, linking short-term volatility with long-term expectations [13]. Although effective in identifying structural regimes, MRS models are computationally demanding and can be difficult to interpret in economic terms.

3.4 Machine learning and hybrid models

The increasing availability of high-frequency data has accelerated the use of machine learning methods in EEX price modeling. These methods, including neural networks, random forests, gradient boosting, and hybrid approaches, offer strong flexibility in capturing nonlinear relationships. Cerjan et al. proposed a hybrid neural network that combines similar-day selection with spike correction and outperforms standard multilayer perceptrons [14]. Tschora et al. conducted a systematic evaluation of tree-based ensemble models and, using SHAP analysis, identified wind forecasts and demand as the most influential predictors [15]. Despite their strong predictive performance, machine learning models often suffer from limited economic interpretability and vulnerability to overfitting during regime changes.

4. REVIEW OF EEX FUTURES MARKET MODELING

4.1 Forward pricing and risk premiums

Forward prices are often viewed as conditional expectations of future spot prices. Empirical evidence for the EEX, however, consistently documents systematic deviations in the form of risk premiums. Several modeling approaches have been proposed to explain these deviations. Behavioral and structural models show that the sign of the premium depends on the distribution of market power between risk-averse producers and consumers. Reduced-form regression studies by Wilkens and Wimschulte find that short-term futures frequently trade at a discount, reflecting spike risk avoidance and volatility in carbon and fuel prices [16]. Information premium models proposed by Benth and Meyer-Brandis emphasize that forward prices embed expectations about future policy or capacity changes, a result supported by empirical evidence from the German nuclear phase-out [17]. Overall, these findings indicate that risk premiums in EEX futures are systematic and reflect risk aversion and asymmetric information rather than random noise, thereby challenging the naïve expectation hypothesis.

4.2 Forward curve construction and volatility modeling

Forward curve construction is essential for valuing structured products and long-term electricity contracts. A range of modeling approaches has been applied to EEX data. Broszkiewicz-Suwaj and Weron employed the Heath–Jarrow–Morton (HJM) framework to ensure arbitrage-free consistency across maturities, providing a structural foundation for forward price dynamics [18]. Caldana et al. further advanced curve construction by proposing high-performance forward curve (HPFC)

methods, which generate hourly forward curves from monthly contracts and allow integration with EPEX Spot data [19]. The literature has evolved from a primary focus on arbitrage-free stochastic dynamics toward practical curve-fitting techniques that support high-frequency and market-oriented applications.

4.3 Derivative pricing and structured products

Beyond standard futures contracts, the EEX offers a variety of derivatives, including options and renewable-linked products, whose valuation requires models capable of capturing jumps, spikes, and heavy tails. Piccirilli, Schmeck, and Vargiolu employed a two-factor Lévy process to reproduce volatility smiles in EEX power options, calibrating the model to overlapping futures and option chains [20]. These studies show that electricity derivatives require richer stochastic frameworks than conventional Black–Scholes-type models, particularly to account for negative prices and pronounced volatility smiles.

5. IMPACT OF RENEWABLE ENERGY ON EEX MAEKET

5.1 Effects on price levels

A key impact of renewable integration on electricity prices is the Merit-Order Effect (MOE). Under the MOE, low-marginal-cost renewable generation is dispatched first, displacing conventional plants and reducing market-clearing prices. Tveten et al. showed that photovoltaic generation reduces average day-ahead prices by around 7%, with midday peak prices declining by more than €9/MWh [21]. Ketterer found that a 1% increase in wind output lowers EEX prices by approximately 0.09–0.10% [22]. Paraschiv et al. demonstrated that the MOE is time-varying, with wind exerting stronger price effects at night and solar power primarily reducing midday peak prices [23]. These findings indicate persistent downward pressure on average prices and a higher incidence of negative price events.

5.2 Effects on price volatility

Renewable output uncertainty also influences price volatility. Ketterer et al. showed that wind generation significantly increases conditional variance in GARCH models, amplifying market risk during periods of low demand [22]. Rintamäki et al. found that the concentration of wind generation in Germany, particularly at night and under limited system flexibility, leads to higher volatility, whereas Denmark's integration with hydro resources in the Nordic system helps smooth price fluctuations [24]. These results indicate that while renewable integration reduces average price levels, it tends to increase short-term price volatility, especially in the presence of forecast errors.

5.3 Risk management

Renewable-linked futures have been introduced to manage revenue risks arising from volatile renewable generation. At the EEX, wind power futures provide hedging instruments tailored to production uncertainty. Gersema and Wozabal showed that producers are often willing to accept discounted wind futures prices in exchange for reducing exposure to output risk [25]. Hain et al. provided empirical evidence that wind futures can reduce portfolio risk by up to 90% in regions with strong correlation to the settlement index [26]. Härdle et al. identified pronounced seasonal patterns, with positive risk premiums in winter and negative premiums in summer, reflecting heterogeneous market preferences [27].

6. COMPARATIVE ANALYSIS AND CONCLUSIONS

6.1 Comparison of modeling frameworks

This review highlights that no single modeling framework dominates across all applications in the EEX. Econometric time-series models remain reliable for capturing seasonality and volatility, but they perform poorly in the presence of price jumps and negative prices. Jump-diffusion and OU processes are well suited to reproducing spikes and heavy tails and are therefore widely used in derivative pricing, although they typically require complex estimation procedures. Regime-switching models explicitly represent structural market states and improve the modeling of extreme events, but often do so at the expense of economic interpretability. Machine learning and hybrid approaches achieve high predictive accuracy and effectively capture nonlinear relationships, yet they face challenges related to transparency and robustness under regime changes. In addition, the emergence of renewable-linked products, such as wind futures, underscores the need to extend modeling frameworks beyond spot and futures markets toward derivative pricing under renewable uncertainty. This methodological diversity implies that model selection should be task-dependent, as forecasting, risk management, and policy evaluation place different and sometimes conflicting demands on modeling approaches.

6.2 Summary of empirical findings

Empirical evidence from the EEX highlights three recurring patterns. First, high penetration of wind and

solar power systematically depresses price levels through the merit-order effect. Second, price volatility is amplified by forecast errors and limited system flexibility, particularly under high shares of variable renewable generation. Third, renewable-related risks are increasingly financialized, as wind futures and other derivative instruments translate physical production variability into tradable contracts. These findings indicate that electricity markets undergoing energy transition cannot be adequately modeled using classical tools alone. Instead, they require modeling approaches that are sensitive to policy reforms, renewable-driven dynamics, and linkages across spot, futures, and derivative markets.

6.3 conclusions and future directions

This review examined electricity market modeling in the context of the European Energy Exchange (EEX) and shows that high renewable penetration, complex market design, and financial innovation jointly challenge conventional modeling approaches. Spot price models must address spikes, negative prices, and regulatory-driven structural breaks, while futures modeling requires an integrated treatment of risk premiums, forward curves, and derivative pricing. At the same time, renewable integration depresses average price levels, amplifies short-term volatility, and creates demand for renewable-linked hedging instruments.

Future progress in EEX modeling will depend on hybrid frameworks that combine econometric rigor, stochastic processes, and machine learning flexibility. Embedding policy interventions, high-frequency market data, and cross-border market coupling into adaptive modeling structures is essential for supporting forecasting, risk management, and policy evaluation in Europe's energy transition.

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