2025 33rd Southern African Universities Power Engineering Conference (SAUPEC)

An Overview of Machine Learning Applications in Blockchain for Green Energy Exchanges

Pfano Nemakonde
Faculty Science, Engineering and Agriculture
Dept. of Physics
University of Venda
Thohoyandou, South Africa
18009737@mvula.univen.ac.za

Fhulufhelo Nemangwele
Faculty Science, Engineering and Agriculture
Dept. of Physics
University of Venda
Thohoyandou, South Africa
nemangwele@univen.ac.za

Mukovhe Ratshitanga
Dept. of Electrical, Electronic and Computer Engineering
Cape Peninsula University of Technology
Bellville, South Africa
ratshitangam@cput.ac.za

2025 33rd Southern African Universities Power Engineering Conference (SAUPEC) | 979-8-3315-3516-2/25/$31.00 ©2025 IEEE | DOI: 10.1109/SAUPEC65723.2025.10944462

***Abstract*—There is an increasing demand for affordable, decentralised and distributed electricity, which is one of the key motivating factors that has incentivised this review article's writing. Industrial 4.0 has been a conduit through which the conventional grids shift towards a self-autonomous system, and blockchain platforms are emerging as viable solutions to facilitate that paradigm. With the advent of peer-to-peer (P2P) energy trading, community-based energy exchanges have significantly contributed to reduced grid dependency. Machine learning (ML) is being implemented in predictive analytics for energy forecasting (EF), thereby aiding both distribution network operators (DNOs) and aggregators to precisely and predictably monitor, optimise and stabilise grid operations through smart agents. The main aim of this review paper is to provide a detailed analysis of the existing research and implementation approaches on blockchain-based P2P energy trading and a comparative overview of how ML applications aid predictive analytics in community-based energy exchanges.**

Keywords—blockchain-based energy trading, P2P energy trading, machine learning, predictive analytics, energy forecasting.

I. Introduction

The traditional grid is an electromechanically controlled distribution network and a conduit through which utilities transmit power from large-scale electric power stations into transmission grids through high-voltage transmission-lines. These grids then distribute the power to forefront customers in commercial settings i.e. large-scale businesses and industries. Which follows subsequent conversion into lower voltages, prio to being distributed to less energy intensive customers in localised grids [1]. Historically, when the energy demand outstripped the energy supply, fossil fuel energy producers, burned more fuel to meet that rising demand. The use of fossil fuel-based energy sources has led to severe environmental issues, including global warming and climate change [2]. This has spurred a significant transformation in the energy sector with the introduction of Renewable energy (RE) technologies such as photovoltaics, wind turbines, hydro, biomass etc [3].

Counterintuitively, integrating a bi-directional communications network with the traditional grid has given rise to the "Smart Grid (SG)" concept. This two-way dialogue, where electricity and information are shared between grid operators and consumers, is an evolving network of smart energy subsystem technologies (SESTs) working interoperably [4]. By utilising SESTs, the SG can monitor, control, and optimise the electricity demands of local areas cost-effectively and efficiently. For instance, it can predict peak demand periods and adjust energy production accordingly, or it can manage the flow of electricity to and from individual households based on their energy usage patterns [5]. In the endeavour for a decentralised, decarbonised, and digitised energy sector, the transition from the conventional grid to a smart grid network is met with a stagnant challenge. The emergence of distributed energy sources (DERs) has not only challenged the entire energy sector but also engaged it, since these innovations have not entirely matured and prone to economic and sociological factors [6]. This challenge necessitates the exploration of the most eligible control paradigm and distributed technologies for candidacy.

Technological innovations from Industry 4.0 have driven new regulatory frameworks supporting advanced solutions like ML, artificial intelligence (AI), IoT, cloud computing, fintech, and blockchain. These frameworks enable seamless technology integration across sectors. The rise of small-scale embedded generators (SSEGs) like rooftop solar and wind turbines empowers consumers as prosumers, fostering energy self-sufficiency and reducing reliance on centralised power systems [7]. Renewable energy (RE) offers a secondary income source by allowing consumers to sell surplus electricity back to the grid, enabling distributed P2P energy trading. Large industrial sites also benefit by selling excess capacity, reducing costs [8].

Transitioning to a smart grid requires reliable energy platforms, mathematical models, and control algorithms to maintain stability [9]. Blockchain technology (BT) has garnered attention for its secure Distributed Ledger Technology (DLT), ensuring tamper-proof transaction verification through consensus mechanisms. It fosters a self-sufficient sharing economy by allowing participants to choose market offerings. Innovations in smart meters enable energy trading via blockchain-based smart contracts (SMs) [10]. Globally, pilot projects and research focus on P2P energy trading, with four key approaches extensively studied: Game theory, Constrained optimisation, Simulation, and Algorithms. Considering the aforementioned approaches, the major contributions that can be attributed to this work are summarised as follows:

979-8-3315-3516-2/25/$31.00 ©2025 IEEE

Authorized licensed use limited to: Cape Peninsula University of Technology. Downloaded on November 25,2026 at 08:28:21 UTC from IEEE Xplore. Restrictions apply.

1. The main aim of this review paper is to provide a comprehensive overview of the technical perspective of blockchain platforms used in P2P community-based energy exchanges.
2. In addition, this article discusses various pilot projects that are being implemented as testbeds on the basis of existing approaches.
3. We also explore the use of various Machine-Learning-based energy forecasting models employed for predictive analytics.

This paper is organised as follows: Section II discusses the use of blockchain technology. Section III discusses blockchain technology in P2P energy trading. Section IV, focuses on ML applications in P2P energy trading. Section V presents the implications of blockchain in P2P energy trading. Section VI introduces the findings and recommendation. Lastly, Section VII provides the conclusion and future research outlook.

II. General Overview Of Blockchain Technology

BT only gained attraction in recent years with the advent of cryptocurrencies; this concept of "blockchain" was introduced as "chain of blocks" in the paper [11]. Blockchain is a P2P, distributed ledger that is cryptographically secure, append-only, immutable, and updatable only through peer consensus [12]. The layered architectural view of a generic blockchain is depicted in Table I [12].

TABLE I. The Architectural Layers in a Generic Blockchain

Applications	Smart contracts, Decentralised applications (DApps), Decentralised autonomous organisations (DAOs), & Autonomous agents
Executions	Virtual machines, Blocks, & Transactions
Consensus	State machine replication, Proof-based consensus, & Traditional Byzantine fault-tolerant protocols
Cryptography	Public key cryptography, Digital signatures, & Hash functions
P2P	Gossip protocols/Epidemic protocols, Routine protocols, & Flooding protocols
Network	The Internet, & TCP/IP

The 'Network layer' forms the foundation for blockchain communication via the Internet, with a 'P2P network' operating on top using various communication protocols. The 'Cryptography layer' ensures process integrity through security algorithms, while the 'Consensus layer' enables agreement among peers through mechanisms such as Proof of Work (PoW), Proof of Authority (PoA), and Practical Byzantine Fault Tolerance (PBFT) [13], [14]. The 'Execution layer' comprises virtual machines [15], transactions, smart contracts (SMs), and blocks, offering services such as value transfer, contract execution, and block generation. The 'Application layer' includes SMs, DApps, DAOs, and autonomous agents. For an in-depth description of the aforementioned concepts readers are directed to [12]. The chain's first block, called the '*Genesis block*,' is timestamped, hashed, and linked to subsequent blocks using the previous block's hash to ensure data integrity, as depicted in Fig. 1. This technique is one of the most secure options in the industry [16]. Blockchains differ in their permission models—private, public, or consortium—depending on user access. BT is often compared to shared database systems, where network information is stored in a master data centre accessible to all nodes.

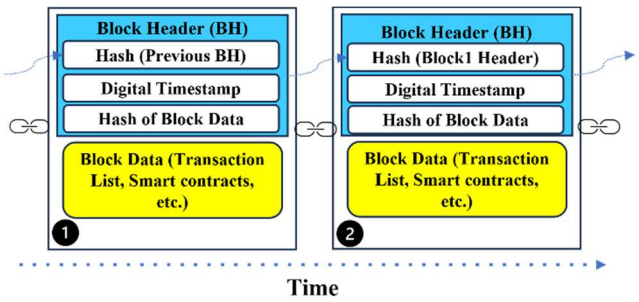

Fig. 1. A generic structure of a blockchain.

It is only when critical mass is achieved in the blockchain that it becomes genuinely decentralised and, therefore, immutable. This calls for community-wide or mass-scale market adoption, which rests on addressing technical, commercial, and public policy hurdles.

III. Blockchain in P2P Energy Trading

Consumers are increasingly becoming prosumers, generating energy from micro-sources like rooftop solar systems and wind turbines. These prosumers can sell surplus energy to consumers with insufficient supply, often under the supervision of arbiters [17]. P2P energy trading can be classified into three categories, notably, centralised [18], decentralised [19], and distributed [20], based on the market mechanism employed. The process typically involves steps such as registration, forecasting, bidding, market clearing, energy transactions, and subsidy settlements. To engage in P2P energy trading, peers should ideally have flexible loads, energy storage, and generation resources. Fig. 2 shows an architectural overview of an ideal peer. However, it is infeasible for the end-users through LV distribution networks to participate in the wholesale markets regulated by power distribution companies, because for trading to be effective, a P2P network is required [19]. Table II shows some of the literature which focuses on other approaches. Game theory has been used to analyse competition and cooperation between DERs, leading to stable and mutually conducive solutions among shareholders [21], [22]. Optimisation algorithms have also been utilised to improve the effectiveness of P2P energy trading [23]. Recent studies have demonstrated the effectiveness of BT in managing energy systems and facilitating efficient trading.

In [24], authors presented an optimisation model using blockchain architecture to manage crowdsourced energy systems for self-autonomous microgrids, employing a two-phase algorithm via the IBM Hyperledger Fabric. The model facilitated seamless energy trading at the distribution level but faced uncontrollable security risks. In [25], a cyber-enhanced transactive microgrid model utilising BT and optimised participant permissions was proposed to address peak demand management. Simulations highlighted improved transaction speed and demonstrated that node population impacted performance more significantly than block size. In [26], a blockchain-based energy framework

Authorized licensed use limited to: Cape Peninsula University of Technology. Downloaded on November 25,2026 at 08:28:21 UTC from IEEE Xplore. Restrictions apply.

was designed to decentralise energy supply and demand in prosumer communities. This GDPR-compliant Ethereum environment allowed SMs to operate in an energy-sharing market, validated using real industrial data and Peersim for scalability.

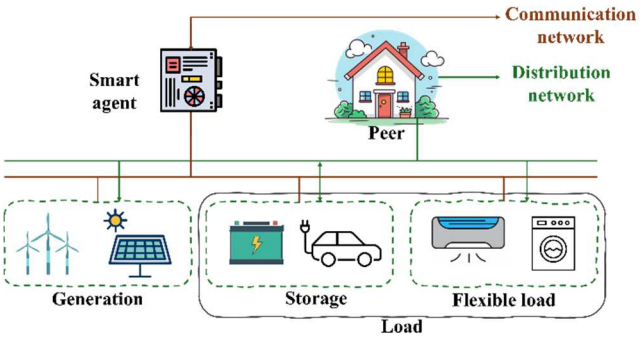

Fig. 2. Pictorial representation of a generic peer. Adapted from [27].

Authors in [28] explored integrating blockchain and IoT to enable green energy trading on existing grid infrastructure, reducing grid dependency and promoting renewable energy adoption, albeit incentivised by temporary cost benefits. The authors in [9], proposed an ML-driven P2P energy trading platform built on a permissioned blockchain via Hyperledger Caliper and SMs, leveraging short-term demand response (DR) for effective energy crowdsourcing. In [29], a DR bidding mechanism within a centralised blockchain model was introduced, employing hash encryption and robust verification protocols for high-elastic power systems using Remix IDE. This ensured secure and credible DR bidding transactions. In [30], authors proposed a decentralized energy transaction system architecture tailored for microgrids. They connected a double auction mechanism to insure that each participant's interest is met based on BT and the current status of China's green power trade. They asserted that their real and operational energy trading platform demonstrated dependability and efficacy, however this was based on simulations. While their model ensured centralised and effective monitoring, however the number of dispersed participants on the network had an upper limit.

TABLE II. IMPLEMENTATION APPROACHES IN P2P ENERGY TRADING

Implementation approaches	*Types*	*Ref.*
Game Theory	Non-cooperative games	[31], [32], [33], [34], [35], [36]
	Cooperative games	[37], [38], [39], [40], [41]
Double Auction	-	[42], [43], [44], [45], [46], [47]
Optimisation	-	[48], [49], [50], [51], [52]

According to the aforementioned literature, it is evident that BT is suitable for this paradigm shift from the traditional grid to a fully realised smart grid. In this regard, the smart agent illustrated in Fig. 2 enables aggregators to extract valuable insights for efficient elecricity management in real-time. This component uses historical power consumption data and AI to enable precise and predictable management of electricity generation/consumption plus viable DR protocols to be implemented; this significantly reduces the need to replace traditional energy meters.

IV. MACHINE LEARNING APPLICATIONS IN P2P ENERGY TRADING

Predictive analytics employs historical data and advanced statistical techniques to forecast future outcomes, providing organisations with critical insights for strategic decision-making [53]. The ability to extract actionable intelligence through predictive analytics is proportional to data volumes and becomes increasingly vital for organisational success [54]. Regression models are traditionally used for energy forecasting [55], primarily when dealing with structured data which does not require complex temporal dependencies. The models, as shown in Table III [56] are invoked in the smart agent depicted in Fig. 2. Precise energy forecasting (EF) is ideal for guaranteed assurance of efficiency in energy management, dynamically augmented supply-demand equilibrium, maximised resource usage and strengthed power system resilience [57].

The authors in [58], used a regression model to analyse the energy supply and demand in Germany to describe energy consumption in each sector, whilst considering the energy balance sheet data, correlation between energy consumption and some basic parameters such as GDP, population growth, and industrial growth rate. They reported an R^2 of 0.83, showing a highly correlated relationship between energy consumption and predictors. However, the energy consumption is predicted on a yearly basis and can't be used in short-term energy forecasting. In [59], authors proposed an Artificial-neural-network (ANN)-based model that was trained and validated using real-world data collected from a PV installation and smart buildings' electrical appliances. They deployed their model in CompactRIO by integrating Python with LabView through a Virtual Instrument. However, their model was not that accurate, which they attributed to the small size of the dataset used for training and validation. Furthermore, their approach excluded contextual data (i.e. Weather data).

In [60], authors proposed regularised ML models to forecast Brazilian power electricity consumption for short and medium terms, using Random Walk and Autoregressive-Integrated-Moving-Average to benchmark specifications. Their results showed that Random Forest and Lasso Lars were the most accurate when considering forecasts for all horizons. They further asserted that preserving the hidden state significantly increases the model's accuracy for very short-term forecasting. They also reported that more contextual parameters are better suited for long-term forecasting. In [61], authors proposed a Gradient-Boosting-Machine model to forecast short-term demand for an energy distribution company with various customers, seven Italian electricity markets were aggregated relative to each zone. They asserted that their model performed significantly better than conventional statistical models for time-series applications. The criteria used to evaluate the model's performance was Mean-Absolute-Percentage-Error with reported ranges of 5-10%; this choice was due to its biases towards penalising overestimations

Authorized licensed use limited to: Cape Peninsula University of Technology. Downloaded on November 25,2026 at 08:28:21 UTC from IEEE Xplore. Restrictions apply.

rather than underestimations; the training dataset was two-year-long.

TABLE III. OVERVIEW OF TECHNIQUES EMPLOYED IN ENERGY FORECASTING.

	Applicable Techniques	
Forecasting Horizon	***Energy Load Forecasting (ELF)***	***Energy Generation Forecasting (EGF)***
Very Short-Term	ARIMA, ETS, ANN, SVR, RNN, LSTM	TBMs, XGBR, LGBMR, HGBR, GEM, Stacking
Short-Term	ARIMA, ETS, ANN, DBN, RNN, LSTM, GRU	TBMs, RF, GBR, Extra Trees, ANN, GEM, Voting, Bagging
Medium-Term	SARIMA, ARIMA, SVR, RNN, Bi-RNN, LSTM	TBMs, ZIC, ZIR, ABR, RNN, DBN, Constant Weighting, Dynamic Weighting
Long-Term	ARMA, SAR, Logistic Regression, DBN, LSTM, CNN	TBMs, RF, GBR, Stacking, GEM, Voting, Boosting

In [62], the authors proposed an Incremental Support Vector Machine (ISVM) combined with a Boosted Multi-Verse Optimiser (BMVO) to better capture complex nonlinearities in energy demand and contextual features. Their results showed a 53.73% reduction in MAPE and a 55.22% reduction in RMSE compared to the ANN approach reported in prior studies. However, the sample size significantly impacted the BMVO's alignment with ISVM prediction outcomes. The analysis suggests that practical implementation varies widely based on context, dataset features, and application domains, asserting the need for further research in this area.

V. IMPLICATIONS OF BLOCKCHAIN IN P2P ENERGY TRADING

P2P energy faces challenges best addressed through pilot projects. Globally, several initiatives are underway, including those discussed in [1], [63], [64], [65]. Power Ledger employs BT to enable market trading and clearing mechanisms [66]. Its primary goal is to realise a democratised and transparent energy trading platform, allowing consumers and communities to optimise their enegry supplier choices. The platform promotes RESs in residential units and incorporates models like asset ownership and dual tokens to facilitate energy exchanges [67]. Vattenfall Powerpeers is a digital marketplace designed to balance supply and demand in localised power generation [1]. Like Power Ledger, it supports P2P energy exchanges but offers participants the flexibility to choose their energy suppliers, with real-time supply-demand matching for each kWh. TransActive Grid is a Tendermint protocol, supports residential and commercial users in Brooklyn [68]. Its focus is on reducing dependency by incentivising community-driven solar power generation [69], [70]. However, its approach may lean toward centralisation due to privacy constraints [71]. SunContract, a live blockchain-based framework in Slovenia, provides nationwide access without monthly subscriptions [1]. It offers dynamic pricing and connects autonomous supply and demand through an energy pool underpinned by smart meters, eliminating intermediaries.

Although economically incentivised, balancing these incentives with environmental considerations presents significant challenges. Most pilot projects remain in early development stages, facing numerous obstacles beyond ‘proof-of-concept, particularly during industry-wide adoption. BTs must demonstrate scalability, speed, and security for complex distribution networks. Despite ongoing research into critical architectural designs like distributed consensus [13], [14], [72], [73], [74], [75] achieving a solution that integrates all desired characteristics without trade-offs remains elusive. Immature technology increases the likelihood of security breaches [76], [77], [78], risking bad publicity and consumer acceptance delays due to reliance on emerging algorithms. Another key challenge lies in integrating SETs and micro-sources into blockchain frameworks. Current smart meters lack computational capabilities and adapting existing grid infrastructure to support DLTs involves substantial costs. While blockchain systems enable low-cost information transfers, data validation and verification demand significant hardware and energy investments. Furthermore, expanding ledgers escalate storage costs, although sidechains have shown promise for mitigating these issues [78].

VI. FINDINGS AND RECOMMENDATIONS

The integration of machine/deep learning with blockchain for intelligent community-based. Green energy exchanges remains constrained by persistent security risks and underperforming EF models. Advancing distributed consensus protocols and enhancing predictive analytics with contextual features are critical areas for further research. Despite the challenges, democratised energy sharing holds immense potential to accelerate the transition to smarter grid management. However, strategies to address lessons from research and pilot projects require validation and refinement to drive adoption effectively.

VII. CONCLUSION

Blockchain-enabled P2P energy trading offers a novel approach to facilitating community-based energy exchanges. This paper reviewed recent advancements in P2P energy trading, presented a generic architecture for green trading platforms, and highlighted the role of predictive analytics in stabilising grid operations via smart agents. Comparative analyses of blockchain-based P2P platforms revealed contextual challenges in each use case. While BTs show promise for driving the paradigm shift towards energy democratisation, sociological and economic barriers remain significant obstacles.

Future research will explore the techno-economic feasibility of blockchain-enabled green energy exchanges, evaluating their readiness for adoption against the status quo of South Africa’s grid infrastructure.

REFERENCES

[1] S. Shan, S. Yang, V. Becerra, J. Deng, and H. Li, “A Case Study of Existing Peer-to-Peer Energy Trading Platforms: Calling for Integrated Platform Features,” *Sustainability (Switzerland)*, vol. 15, no. 23, Dec. 2023, doi: 10.3390/su152316284.

[2] E. Vine, “Breaking down the silos: The integration of energy efficiency, renewable energy, demand response and climate change,” Jan. 2008. doi: 10.1007/s12053-008-9004-z.

[3] A. Raheem *et al.*, “Renewable energy deployment to combat energy crisis in Pakistan,” Dec. 01, 2016, *Springer Verlag*. doi: 10.1186/s13705-016-0082-z.

Authorized licensed use limited to: Cape Peninsula University of Technology. Downloaded on November 25,2026 at 08:28:21 UTC from IEEE Xplore. Restrictions apply.

[4] S. Misra and S. Bera, "Introduction to Smart Grid," in *Smart Grid Technology: A Cloud Computing and Data Management Approach*, Cambridge: Cambridge University Press, 2018, pp. 3–17. doi: DOI: 10.1017/9781108566506.003.

[5] C. Liu, X. Zhang, K. K. Chai, J. Loo, and Y. Chen, "A survey on blockchain-enabled smart grids: Advances, applications and challenges," Jun. 01, 2021, *John Wiley and Sons Inc*. doi: 10.1049/smc2.12010.

[6] A. Borkovcová, M. Černá, and M. Sokolová, "Blockchain in the Energy Sector—Systematic Review," Nov. 01, 2022, *MDPI*. doi: 10.3390/su142214793.

[7] Y. Parag and B. K. Sovacool, "Electricity market design for the prosumer era," *Nat Energy*, vol. 1, no. 4, Mar. 2016, doi: 10.1038/NENERGY.2016.32.

[8] E. M. Gui and I. MacGill, "Typology of future clean energy communities: An exploratory structure, opportunities, and challenges," *Energy Res Soc Sci*, vol. 35, pp. 94–107, Jan. 2018, doi: 10.1016/j.erss.2017.10.019.

[9] F. Jamil, N. Iqbal, Imran, S. Ahmad, and D. Kim, "Peer-to-Peer Energy Trading Mechanism Based on Blockchain and Machine Learning for Sustainable Electrical Power Supply in Smart Grid," *IEEE Access*, vol. 9, pp. 39193–39217, 2021, doi: 10.1109/ACCESS.2021.3060457.

[10] C. Plaza, J. Gil, F. de Chezelles, and K. A. Strang, "Distributed Solar Self-Consumption and Blockchain Solar Energy Exchanges on the Public Grid Within an Energy Community," in *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, 2018, pp. 1–4. doi: 10.1109/EEEIC.2018.8494534.

[11] S. Nakamoto, "Bitcoin: A Peer-to-Peer Electronic Cash System," 2008. [Online]. Available: www.bitcoin.org

[12] Imran. Bashir, *Mastering Blockchain : Inner workings of blockchain, from cryptography and decentralized identities, to DeFi, NFTs and Web3*. Packt Publishing, 2023.

[13] D. Mingxiao, M. Xiaofeng, Z. Zhe, W. Xiangwei, and C. Qijun, "A review on consensus algorithm of blockchain," in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2017, pp. 2567–2572. doi: 10.1109/SMC.2017.8123011.

[14] V. Zhebka, S. Zhebka, T. Bazhan, P. Skladannyi, and V. Sokolov, "Methodology for Choosing a Consensus Algorithm for Blockchain Technology," 2024. [Online]. Available: https://www.researchgate.net/publication/379957938

[15] F. Ethereum, "Ethereum Virtual Machine (EVM)." [Online]. Available: https://ethereum.org/en/developers/docs/evm/

[16] G. Karame and S. Capkun, "Blockchain Security and Privacy," *IEEE Security & Privacy*, vol. 16, no. 04, pp. 11–12, 2018, doi: 10.1109/MSP.2018.3111241.

[17] N. Liu, X. Yu, C. Wang, and J. Wang, "Energy Sharing Management for Microgrids with PV Prosumers: A Stackelberg Game Approach," *IEEE Trans Industr Inform*, vol. 13, no. 3, pp. 1088–1098, Jun. 2017, doi: 10.1109/TII.2017.2654302.

[18] C. Long, J. Wu, Y. Zhou, and N. Jenkins, "Peer-to-peer energy sharing through a two-stage aggregated battery control in a community Microgrid," *Appl Energy*, vol. 226, pp. 261–276, Sep. 2018, doi: 10.1016/j.apenergy.2018.05.097.

[19] F. Luo, Z. Y. Dong, G. Liang, J. Murata, and Z. Xu, "A Distributed Electricity Trading System in Active Distribution Networks Based on Multi-Agent Coalition and Blockchain," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4097–4108, Sep. 2019, doi: 10.1109/TPWRS.2018.2876612.

[20] M. R. Alam, M. St-Hilaire, and T. Kunz, "Peer-to-peer energy trading among smart homes," *Appl Energy*, vol. 238, pp. 1434–1443, Mar. 2019, doi: 10.1016/j.apenergy.2019.01.091.

[21] F. Wei, Z. X. Jing, P. Z. Wu, and Q. H. Wu, "A Stackelberg game approach for multiple energies trading in integrated energy systems," *Appl Energy*, vol. 200, pp. 315–329, 2017, doi: 10.1016/j.apenergy.2017.05.001.

[22] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model," *IEEE Transactions on Industrial electronics*, vol. 66, no. 8, pp. 6087–6097, 2018.

[23] M. R. Alam, M. St-Hilaire, and T. Kunz, "Peer-to-peer energy trading among smart homes," *Appl Energy*, vol. 238, pp. 1434–1443, 2019.

[24] S. Wang, A. F. Taha, J. Wang, K. Kvaternik, and A. Hahn, "Energy Crowdsourcing and Peer-to-Peer Energy Trading in Blockchain-Enabled Smart Grids," Jan. 2019, [Online]. Available: http://arxiv.org/abs/1901.02390

[25] M. Onyeka Okoye *et al.*, "A Blockchain-Enhanced Transaction Model for Microgrid Energy Trading," *IEEE Access*, vol. 8, pp. 143777–143786, 2020, doi: 10.1109/ACCESS.2020.3012389.

[26] I. Petri, M. Barati, Y. Rezgui, and O. F. Rana, "Blockchain for energy sharing and trading in distributed prosumer communities," *Comput Ind*, vol. 123, Dec. 2020, doi: 10.1016/j.compind.2020.103282.

[27] M. K. AlAshery *et al.*, "A Blockchain-Enabled Multi-Settlement Quasi-Ideal Peer-to-Peer Trading Framework," *IEEE Trans Smart Grid*, vol. 12, no. 1, pp. 885–896, 2021, doi: 10.1109/TSG.2020.3022601.

[28] K. Victor Sam Moses Babu *et al.*, "Energy Highway: A Community-Centric Approach for Decentralized Green Energy Exchange and Self-Sufficiency," in *2024 3rd International Conference on Power, Control and Computing Technologies, ICPC2T 2024*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 104–109. doi: 10.1109/ICPC2T60072.2024.10474948.

[29] X. Mao *et al.*, "Centralized bidding mechanism of demand response based on blockchain," *Energy Reports*, vol. 8, pp. 111–117, Aug. 2022, doi: 10.1016/j.egyr.2022.02.145.

[30] W. Zhao, S. Zhang, L. Xue, T. Chang, and L. Wang, "Research on Model of Micro-grid Green Power Transaction Based on Blockchain Technology and Double Auction Mechanism," *Journal of Electrical ==Engineering and Technology*, vol. 19, no. 1, pp. 133–145, Jan. 2024, doi: 10.1007/s42835-023-01541-9.

[31] C. Zhang, J. Wu, Y. Zhou, M. Cheng, and C. Long, "Peer-to-Peer energy trading in a Microgrid," *Appl Energy*, vol. 220, pp. 1–12, Jun. 2018, doi: 10.1016/j.apenergy.2018.03.010.

[32] H. Liu, J. Li, S. Ge, X. He, F. Li, and C. Gu, "Distributed day-ahead peer-to-peer trading for multi-microgrid systems in active distribution networks," *IEEE Access*, vol. 8, pp. 66961–66976, 2020.

[33] S. Cui, Y.-W. Wang, and J.-W. Xiao, "Peer-to-peer energy sharing among smart energy buildings by distributed transaction," *IEEE Trans Smart Grid*, vol. 10, no. 6, pp. 6491–6501, 2019.

[34] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model," *IEEE Transactions on Industrial electronics*, vol. 66, no. 8, pp. 6087–6097, 2018.

[35] S. W. Park, Z. Zhang, F. Li, and S. Y. Son, "Peer-to-peer trading-based efficient flexibility securing mechanism to support distribution system stability," *Appl Energy*, vol. 285, Mar. 2021, doi: 10.1016/j.apenergy.2020.116403.

[36] Y. Jin, J. Choi, and D. Won, "Pricing and operation strategy for peer-to-peer energy trading using distribution system usage charge and game theoretic model," *Ieee Access*, vol. 8, pp. 137720–137730, 2020.

[37] W. Zhong, S. Xie, K. Xie, Q. Yang, and L. Xie, "Cooperative P2P energy trading in active distribution networks: An MILP-based Nash bargaining solution," *IEEE Trans Smart Grid*, vol. 12, no. 2, pp. 1264–1276, 2020.

[38] W. Tushar *et al.*, "A coalition formation game framework for peer-to-peer energy trading," *Appl Energy*, vol. 261, p. 114436, 2020.

[39] J. Li, Y. Ye, D. Papadaskalopoulos, and G. Strbac, "Computationally efficient pricing and benefit distribution mechanisms for incentivizing stable peer-to-peer energy trading," *IEEE Internet Things J*, vol. 8, no. 2, pp. 734–749, 2020.

[40] J. Li, Y. Ye, and G. Strbac, "Stabilizing peer-to-peer energy trading in prosumer coalition through computational efficient pricing," *Electric Power Systems Research*, vol. 189, p. 106764, 2020.

[41] W. Tushar, T. K. Saha, C. Yuen, P. Liddell, R. Bean, and H. V. Poor, "Peer-to-peer energy trading with sustainable user participation: A game theoretic approach," *IEEE Access*, vol. 6, pp. 62932–62943, 2018.

[42] W. Liu, D. Qi, and F. Wen, "Intraday residential demand response scheme based on peer-to-peer energy trading," *IEEE Trans Industr Inform*, vol. 16, no. 3, pp. 1823–1835, 2019.

[43] W. Tushar, T. K. Saha, C. Yuen, T. Morstyn, H. V. Poor, and R. Bean, "Grid influenced peer-to-peer energy trading," *IEEE Trans Smart Grid*, vol. 11, no. 2, pp. 1407–1418, 2019.

Authorized licensed use limited to: Cape Peninsula University of Technology. Downloaded on November 25,2026 at 08:28:21 UTC from IEEE Xplore. Restrictions apply.

[44] S. Seven, G. Yao, A. Soran, A. Onen, and S. M. Muyeen, "Peer-to-peer energy trading in virtual power plant based on blockchain smart contracts," *Ieee Access*, vol. 8, pp. 175713–175726, 2020.

[45] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains," *IEEE Trans Industr Inform*, vol. 13, no. 6, pp. 3154–3164, 2017.

[46] B. P. Hayes, S. Thakur, and J. G. Breslin, "Co-simulation of electricity distribution networks and peer to peer energy trading platforms," *International Journal of Electrical Power & Energy Systems*, vol. 115, p. 105419, 2020.

[47] S.-V. Oprea, A. Bâra, and A. I. Andreescu, "Two novel blockchain-based market settlement mechanisms embedded into smart contracts for securely trading renewable energy," *IEEE access*, vol. 8, pp. 212548–212556, 2020.

[48] N. Uddin, Y. Wu, M. S. Islam, and K. M. Zakaria, "An optimized decentralized peer-to-peer energy trading system for smart grids incorporating uncertain renewable energy sources through fuzzy optimization," *Electric Power Systems Research*, vol. 238, p. 111154, Jan. 2025, doi: 10.1016/j.epsr.2024.111154.

[49] S. A. Ahmed *et al.*, "Optimization of social welfare and mitigating privacy risks in P2P energy trading: Differential privacy for secure data reporting," *Appl Energy*, vol. 356, p. 122403, 2024.

[50] J. Hussain *et al.*, "Optimization of social welfare in P2P community microgrid with efficient decentralized energy management and communication-efficient power trading," *J Energy Storage*, vol. 81, p. 110458, 2024.

[51] S. A. Ahmed *et al.*, "Optimization of social welfare and mitigating privacy risks in P2P energy trading: Differential privacy for secure data reporting," *Appl Energy*, vol. 356, p. 122403, 2024.

[52] S. Nguyen, W. Peng, P. Sokolowski, D. Alahakoon, and X. Yu, "Optimizing rooftop photovoltaic distributed generation with battery storage for peer-to-peer energy trading," *Appl Energy*, vol. 228, pp. 2567–2580, 2018.

[53] G. Shmueli and O. Koppius, "Predictive analytics in information systems research," 2011. [Online]. Available: http://hdl.handle.net/1765/87835

[54] D. Bertsimas and N. Kallus, "From Predictive to Prescriptive Analytics," *Manage Sci*, vol. 66, no. 3, pp. 1025–1044, 2020, [Online]. Available: https://EconPapers.repec.org/RePEc:inm:ormnsc:v:66:y:2020:i:3:p:1025-1044

[55] P. Pinson, L. Han, and J. Kazempour, "Regression markets and application to energy forecasting," *TOP*, vol. 30, no. 3, pp. 533–573, Oct. 2022, doi: 10.1007/s11750-022-00631-7.

[56] A. Mystakidis, P. Koukaras, N. Tsalikidis, D. Ioannidis, and C. Tjortjis, "Energy Forecasting: A Comprehensive Review of Techniques and Technologies," Apr. 01, 2024, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/en17071662.

[57] D. Coakley, P. Raftery, and M. Keane, "A review of methods to match building energy simulation models to measured data," 2014, *Elsevier Ltd*. doi: 10.1016/j.rser.2014.05.007.

[58] S. Tabasi, A. Aslani, and H. Forotan, "Prediction of Energy Consumption by Using Regression Model," *Computational Research Progress in Applied Science & Engineering ©PEARL publication*, vol. 02, no. 03, pp. 110–115, 2016.

[59] S. Bourhnane, M. R. Abid, R. Lghoul, K. Zine-Dine, N. Elkamoun, and D. Benhaddou, "Machine learning for energy consumption prediction and scheduling in smart buildings," *SN Appl Sci*, vol. 2, no. 2, Feb. 2020, doi: 10.1007/s42452-020-2024-9.

[60] P. C. Albuquerque, D. O. Cajueiro, and M. D. C. Rossi, "Machine learning models for forecasting power electricity consumption using a high dimensional dataset," *Expert Syst Appl*, vol. 187, Jan. 2022, doi: 10.1016/j.eswa.2021.115917.

[61] L. Di Persio and N. Fraccarolo, "Energy Consumption Forecasts by Gradient Boosting Regression Trees," *Mathematics*, vol. 11, no. 5, Mar. 2023, doi: 10.3390/math11051068.

[62] A. Huang, Q. Bi, L. Dai, and H. Hosseinzadeh, "Developing a hybrid technique for energy demand forecasting based on optimized improved SVM by the boosted multi-verse optimizer: Investigation on affecting factors," *Heliyon*, vol. 10, no. 7, Apr. 2024, doi: 10.1016/j.heliyon.2024.e28717.

[63] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model," *IEEE Transactions on Industrial electronics*, vol. 66, no. 8, pp. 6087–6097, 2018.

[64] M. R. Alam, M. St-Hilaire, and T. Kunz, "Peer-to-peer energy trading among smart homes," *Appl Energy*, vol. 238, pp. 1434–1443, 2019.

[65] S. Suthar, S. H. C. Cherukuri, and N. M. Pindoriya, "Peer-to-peer energy trading in smart grid: Frameworks, implementation methodologies, and demonstration projects," Jan. 01, 2023, *Elsevier Ltd*. doi: 10.1016/j.epsr.2022.108907.

[66] L. Power, "Power Ledger," 2024, [Online]. Available: https://powerledger.io/

[67] A. Goranovic, M. Meisel, L. Fotiadis, S. Wilker, A. Treytl, and T. Sauter, "Blockchain applications in microgrids an overview of current projects and concepts," *IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society*, pp. 6153–6158, 2017, [Online]. Available: https://api.semanticscholar.org/CorpusID:40455946

[68] E. Brooklyn, "About Brooklyn Energy," 2024, [Online]. Available: https://www.brooklyn.energy/about

[69] J. Lee and Y. Cho, "Estimation of the usage fee for peer-to-peer electricity trading platform: The case of South Korea," *Energy Policy*, vol. 136, p. 111050, 2020, doi: https://doi.org/10.1016/j.enpol.2019.111050.

[70] M. F. Zia, M. Benbouzid, E. Elbouchikhi, S. M. Muyeen, K. Techato, and J. M. Guerrero, "Microgrid Transactive Energy: Review, Architectures, Distributed Ledger Technologies, and Market Analysis," *IEEE Access*, vol. 8, pp. 19410–19432, 2020, doi: 10.1109/ACCESS.2020.2968402.

[71] G. Kim, J. Park, and J. Ryou, "A Study on Utilization of Blockchain for Electricity Trading in Microgrid," *2018 IEEE International Conference on Big Data and Smart Computing (BigComp)*, pp. 743–746, 2018, [Online]. Available: https://api.semanticscholar.org/CorpusID:44082033

[72] B. Lucas and R. V. Paez, "Consensus algorithm for a private blockchain," in *ICEIEC 2019 - Proceedings of 2019 IEEE 9th International Conference on Electronics Information and Emergency Communication*, Institute of Electrical and Electronics Engineers Inc., Jul. 2019, pp. 264–271. doi: 10.1109/ICEIEC.2019.8784500.

[73] V. Zhebka, S. Zhebka, T. Bazhan, P. Skladannyi, and V. Sokolov, "Methodology for Choosing a Consensus Algorithm for Blockchain Technology." [Online]. Available: https://www.researchgate.net/publication/379957938

[74] T. Bhagawan *et al.*, "Proof of Stake with Casper the Friendly Finality Gadget Protocol for Fair Validation Consensus in Ethereum," 2018. [Online]. Available: https://www.researchgate.net/publication/362517846

[75] M. A. Alrowaily, M. Alghamdi, I. Alkhazi, A. B. Hassanat, M. M. S. Arbab, and C. Z. Liu, "Modeling and Analysis of Proof-Based Strategies for Distributed Consensus in Blockchain-Based Peer-to-Peer Networks," *Sustainability*, vol. 15, no. 2, p. 1478, Jan. 2023, doi: 10.3390/su15021478.

[76] C. Öztürk and A. Yildizbaşi, "Barriers to implementation of blockchain into supply chain management using an integrated multi-criteria decision-making method: a numerical example," *Soft comput*, vol. 24, no. 19, pp. 14771–14789, 2020.

[77] W. Mougayar, *The business blockchain: promise, practice, and application of the next Internet technology*. John Wiley & Sons, 2016.

[78] C. Worley and A. Skjellum, "Blockchain Tradeoffs and Challenges for Current and Emerging Applications: Generalization, Fragmentation, Sidechains, and Scalability," in *2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*, 2018, pp. 1582–1587. doi: 10.1109/Cybermatics_2018.2018.00265.

Authorized licensed use limited to: Cape Peninsula University of Technology. Downloaded on November 25,2026 at 08:28:21 UTC from IEEE Xplore. Restrictions apply.