Journal of Applied Sciences and Modelling

https://journal.krrishpub.com/index.php/jasm/index

REVIEW ARTICLE

Intelligence and Digitalization in Energy Markets: A Comprehensive Review of Optimization, Risk Management, Blockchain Integration, and the Electric Vehicle Landscape

Mohammad Parhamfar [a], Milad Taheri [b,c,d,*], Yalda Ghorbani [e]

[a] *Independent Researcher and Entrepreneur, Isfahan, Iran.*
[b] *Dept. of Electrical Engineering, Na. C., Islamic Azad University, Najafabad, Iran.*
[c] *Smart Microgrid Research Center, Na. C., Islamic Azad University, Najafabad, Iran.*
[d] *Safahan Institute of Higher Education, Isfahan, Iran.*
[e] *Dept. of Electrical Engineering, Laser and Biophotonics in Biotechnologies Research Center, Isf.C. Islamic Azad University, Isfahan, Iran.*

Abstract

This paper analyzes the considerable impact of artificial intelligence (AI) and digitalization on energy markets and trading systems, as well as the expanding electric vehicle (EV) industry and its challenges. As the complexity of energy systems increases due to the incorporation of renewable energy, distributed generation (DG), and evolving regulations, traditional market models struggle to adapt. This evaluation examines how AI and digital technologies can enhance energy generation, distribution, and consumption across various applications, including improved forecasting, grid management, market organization, risk assessment, and automated trading. The research integrates findings related to AI-driven market improvement, risk evaluation, and relationships with blockchain, the Internet of Things (IoT), and smart grids. The analysis also explores the potential effects of cryptocurrency mining on the energy industry, in both beneficial and detrimental ways. It examines global innovations in this field and specifically addresses the impacts of Monte Carlo simulation (MCS). Charts and factual investigations are examined, indicating potential avenues for future investigation. It emphasizes the opportunities and challenges that AI and digitalization present for the energy industry, highlighting the need to address information security, regulatory compliance, and ethical issues to advance a sustainable and resilient energy future.

Keywords: Artificial Intelligence, Digitalization, Energy Markets, Energy Trading, Renewable Energy Systems, Risk and Uncertainty, Blockchain, Electric Vehicles, Smart Grids.

Article information:
ISSN: 3139-4337 (Online)
Published by: **Krrish Scientific Publications Pvt. Ltd.**
DOI: https://doi.org/10.71426/jasm.v2.i2.pp161-189
Received: *14 Aug. 2026* | Revised: *13 Sep. 2026* | Accepted: *30 Sep. 2026* | Published: *02 Nov. 2026*
Copyright ©2026 Author(s).
This is an open-access article distributed under the terms of the Creative Commons Attribution–NonCommercial 4.0 International License (CC BY-NC 4.0).

1. Introduction

The importance of this issue becomes clear when we examine the words of the US President. President Trump frequently emphasized the goal of American energy dominance. As he stated, "We are now an energy superpower." Even though he has not unequivocally referred to AI-driven energy trading models, his emphasis on improving American energy potential creates an environment in which these advancements can prosper, thereby improving the overall viability and resilience of the U.S. energy market. President Biden's 2025 Executive Order on AI Infrastructure highlights the significant impact of executive authority in directing technological advancement. It aims to harmonize AI's innovative possibilities with moral progress, emphasiz-

*Corresponding author
Email addresses: drparhamfar@gmail.com (Mohammad Parhamfar), milad.taheri@iau.ir, m.taheri@Safahan.ac.ir (Milad Taheri), Yalda_ieee19@yahoo.com (Yalda Ghorbani).

ing investment in computing infrastructure and information security. Moreover, the order implies a relationship between AI and energy, highlighting its potential impact on energy networks and renewable sources [1], [2]. The EU sees AI as significant for achieving its energy and climate goals, especially in connection with the European Green Deal (European Commission, 2019). AI will be utilized to upgrade energy networks, boost productivity, and strengthen cybersecurity (European Parliament, 2021). However, the EU recognizes issues concerning data protection, job loss, and ethical concerns (European Information Security Board, 2020). To address these issues, the EU is defining controls and financing research to ensure ethical AI implementation within the energy industry (European Commission, 2020) [3]. The objective is to harmonize innovation with the protection of rights and the fostering of a sustainable energy market. The REPowerEU Plan seeks to ensure that Europe is free from Russian fossil fuels by 2030 (European Commission, 2022). An essential element of the EU's approach to a robust energy sector is accelerating the implementation of RESs, especially by emphasizing solar PV capacity. The solar energy strategy of the EU intends to install more than 320 GW of new solar PV by 2025 and nearly 600 GW by 2030 [4]. The Carnegie Endowment report indicates that technological separation between the U.S. and China might disrupt the global energy market. This split could impede supply chains for essential technologies in renewable energy and electric vehicles, where China presently dominates. As a result, there could be higher costs and slower adoption of clean energy solutions, along with distinct regulatory environments that limit international cooperation on climate change and energy security. This could adversely impact the global energy transition and increase costs for developing nations in the Global South. Since the U.S. and China account for at least half of global renewable investments, this decoupling could obstruct their efforts to reduce carbon emissions [5].

This study commences with an examination of the energy market and its associated algorithms. To facilitate this, the earliest and most frequently cited articles are initially surveyed, serving as a basis for identifying further relevant references. Subsequently, the electricity market is explored, and pertinent statistics are presented.

2. Literature review

Energy ought to be both reasonable and accessible to everyone in our community. Not only must the cost of energy be prioritized, but consumers must also be empowered to control their energy consumption. Access to renewable resources, such as solar panels and batteries, is crucial for promoting sustainability and independence [178], [179]. Moreover, equipping people with the information and tools to navigate the energy market will certainly ensure that everyone can engage meaningfully with their energy choices. Together, let us create a future where energy is a right, not a privilege [6].

In 2025, the energy and utilities sector will grapple with both ongoing concerns and emerging challenges. The expected change in presidential administration could lead to new regulations impacting how infrastructure is built and how quickly the industry can reduce its carbon footprint. A major problem for the industry is the massive increase in electricity demand, fueled by the growing use of AI, data centers, and the transition to EVs and appliances. To cope, utility companies need to make the power grid more reliable, keep energy prices reasonable, and continue to promote cleaner energy sources [7].

MARKAL Global is a sophisticated multi-regional model designed to determine domestic prices within the dynamic electricity sector. It brings together five diverse global regions and encompasses a wide array of end-user sectors, including industrial, residential, and commercial segments, as well as transportation, non-commercial biomass use, and non-energy applications. The supply sector incorporates advanced technologies for generating electricity and heat, alongside a variety of end fuels such as petroleum products, alcohol, hydrogen, and natural gas, sourced from both fossil and renewable origins. This model also intricately integrates the essential systems for transmission and distribution, ensuring a comprehensive approach to energy management [8]. The MARKAL model has played a transformative role in UK energy and climate policy, evolving to support changing policy objectives and priorities, particularly the increasing focus on emissions reduction. The MARKAL model has served to connect and support a network of academic, consulting, and policy communities with shared interests in using technical and economic models to inform energy and climate policy. The changing use of the MARKAL model has been enabled by and has also helped to shape the evolving policy priorities and "images" around energy and climate policy in the UK [9].

Chen et al. examined carbon reduction strategies in China's energy system and analyzed their economic impacts using three models from the MARKAL family: MARKAL-ED, MARKAL, and MARKAL-MACRO [10]. Vaillancourt et al. analyzed the role of nuclear energy in long-term climate scenarios using the World-TIMES model [11]. In 2003, Dicorato et al. applied the EFOM model to evaluate the contributions of DG and energy efficiency measures. The presented methodology comprehensively describes the extraction of primary resources, as well as electricity and heat production, pollutant emissions, and end-user sectors [12].

Onat and Ersuz conducted a study on the wind conditions and wind energy potential in a specific region of Turkey [13]. They developed a model to analyze the wind characteristics of three regions in the country, focusing on

the relationship between wind speed and other climatic variables. To complete their analysis of wind energy potential, they used WASP software, which utilized wind speed data. Ultimately, they calculated the amount of electrical energy that could be technically generated and assessed the capacity utilization rate of installed turbines if wind farms were established in the selected regions. Chen et al. developed the China production planning model, which divides the production planning problem into a high-level power plant investment decision and a low-level operational planning issue. The Lagrangian method is used for the investment decision, while a probabilistic production simulation method addresses the operational planning [14]. Messner and Schrattenholze utilized the MESSAGE-MACRO model to develop and solve an energy supply model connected to a macroeconomic module. The reference energy system for the MESSAGE model encompasses coal, oil, gas, nuclear, and various RESs [15]. Rehman et al. examined the distribution of solar radiation and irradiance in Saudi Arabia using monthly continuity data [16]. This study explored the feasibility of the project with RETScreen software.

Shin et al. studied the impact of electricity generation from landfill gas on the electricity market, generation costs, and greenhouse gas emissions in Korea, utilizing the Environmental and Technology Database within the LEAP model [17]. Swala developed a coal mining and distribution planning model for Poland that is compatible with the ENPEP model [18]. Tomsik et al. developed a supply and demand model for Slovenia, focusing on energy planning through an integrated resource planning approach. This study utilizes the MESAP/PlaNet model, along with auxiliary models that analyze technology penetration and electricity demand. Additionally, planning for optimal expansion is conducted using the WASP software package. This comprehensive approach takes into account total energy consumption, as well as economic, environmental, and socio-political criteria [19]. Kydes examined the impact of renewable energy portfolio generation standards on the U.S. energy market. A 20% of renewable energy increase standard was first developed in the December 2001 version of the NEMS model [20]. Analysis of the economic impacts related to improving climate conditions can also be performed using the Energy 2020 model [21].

The power system is becoming more complex, leading to the need for new grid structures [224]. This approach aims to transfer the functions of transmission system operators (TSOs) to distribution system operators (DSOs) at medium- and low-voltage levels, where most RES-based DG systems are located. Liberalization of energy markets in Europe began with the monopolistic energy supply structure of the 20th-century and was initiated by the Directive 96/92/CE of the European electricity market [22]. The energy market is divided into two segments: the wholesale energy market (WEM) and the retail energy market (REM). The WEM involves large transactions between major generating companies and significant consumers, while the REM caters to smaller consumers at the distribution level. In the REM, consumers can choose their retail service provider, promoting competition in the market [23]. The movement to liberalize the energy market began in 1996 within the EU, spearheaded by Norway and Britain. Key discussions led to a significant agreement by the Council of Ministers to promote market liberalization. The goal was to enhance efficiency and reduce consumer prices through increased competition. While some countries have made progress, the results have often not met expectations, highlighting the ongoing need for commitment to this vital transformation [24].

Reforms in the electricity sector are crucial for the economy, with public interest focused on ensuring that they improve, rather than hinder, long-term performance. The restructuring aims to enhance competition in manufacturing and refine the regulation of transmission and distribution functions [25]. To effectively monitor the market, it is essential to consider the market structure, product innovation, pricing strategies, gross profit of electricity suppliers, and consumer behavior [26].

No central organization is responsible for supplying power in the wholesale electricity market. At the core of a restructured electricity market is a wholesale market where producers compete to meet demand. The prices of energy offered in the retail market are heavily influenced by wholesale market prices. By understanding how energy pricing operates in the wholesale market, one can gain insight into the movements of short-term and long-term prices, which can help optimize an energy management strategy [27]. The wholesale market on the energy exchange allows producers to participate in auctions, with winners announced by the market supervisor. This process facilitates the sale of electricity to retailers, who then supply consumers. Essentially, the market enables traders and intermediaries to manage short-term electricity supply and future deliveries [28]. The retail electricity market is a segment of the electricity and energy exchange markets, where retailers serve as intermediaries, purchasing and selling the electricity required by small consumers from the wholesale market [29].

The day-ahead market is a trading platform where electricity suppliers and consumers transact energy through daily auctions, primarily conducted one day before delivery [30]. Low prices in the balancing market result from expected surplus power, prompting producers with excess energy to participate in the intraday market. This helps them avoid the risk of low electricity prices in the balancing market during periods of stable demand. However, this may lead to decreased intraday prices. Therefore, factors such as forecast errors and flexibility indirectly influence

intraday prices as well [31].

Real-time pricing, combined with savings for subscribers, allows them to choose when to consume power based on their preferences. This program is tailored for commercial, agricultural, and pumping consumers who can shift or reduce their electricity usage during periods when prices are high [32]. A regulatory market is an exchange environment where governmental organizations, or occasionally industry or labor organizations, exercise oversight and control [33]. By employing careful design, the reserve market can effectively reduce power shortages and make strategic offerings to guarantee sufficient production at designated times and locations. Additionally, the system aims to generate more revenue for power generators, lower investment costs, and ultimately provide lower prices for consumers [34].

The integration of RESs, such as wind power, and the rising demand from uncertain loads, such as EVs, present challenges for system operators. The Flexible Ramping Product (FRP) helps manage uncertainties in energy demand and renewable output by offering additional upward and downward ramping flexibility. It is used in markets such as the California Independent System Operator (CAISO) and the Midwest Independent System Operator (MISO) [35]. This study investigates the impact of flexible resources, such as EVs, demand-side management, and bulk storage technologies, on the operation, spinning reserve, frequency response performance of plants, and overall system operation costs [36].

Basic statistical models that do not incorporate market principles and relevant factors often fall short as reliable forecasting tools. These models are typically restricted to factors such as past price patterns and external factors such as fuel costs and weather. These restrictions make them especially weak in emerging markets. Accurate electricity price forecasting requires accounting for plant characteristics, risk assessment, market design, agent learning, and strategic actions. Price formation depends on market structure; models must reflect the characteristics of the market, inferences, and price forecasts, even though this is not the case in many cases. Finally, relying solely on average daily prices ignores intraday specifics related to demand, supply, and operational limitations [176]. More frequent studies are needed to capture these details [37].

The goal is to create competitive energy markets through effective management by learning from the successes and failures of other nations and evaluating different market models. While distribution companies remain crucial, their roles are evolving with the rise of DG and storage solutions. The electricity industry continues to advance toward fully competitive global markets that enhance social well-being and tackle ongoing challenges [38].

AI is the most widely adopted emerging digital technology in the U.S. energy sector and contributes the highest wage premium and to energy firms' productivity compared to other emerging digital technologies. Among the emerging digital technologies (i.e., AI, Big Data, IoT, Robotics, Blockchain technology, and Cloud computing), AI is the most widely adopted in the energy sector [182], [186]. AI contributes the highest wage premium to the average wage of the adopted energy firm and the local labor market. Meanwhile, AI contributes the most to energy firms' performance [39]. Many articles discuss technology creation and productivity enhancement, but few address job loss and strategies for replacement. The energy market is undergoing a transformative phase, driven by the increasing integration of AI and digital technologies [40].

This evolution is fueled by the necessity to address complexities such as fluctuating prices, supply chain uncertainties, and the imperative shift towards RESs. At a pivotal juncture, the energy sector recognizes the potential of AI technologies to revolutionize the sector, offering new avenues for optimization and reliability [41], [42], [64], [217].

Digitalization and AI are increasingly intertwined with modern energy markets, driving significant transformations in how energy is produced, distributed, and traded. The traditional centralized energy system is evolving towards more flexible, decentralized structures through the emergence of energy communities (ECs), as described by López et al. [43]. These ECs, characterized by local energy transactions and active prosumer participation, are being significantly shaped by both AI and digital technologies. Specifically, studies suggest increased reliance on DER and local generation, with optimized management of transmission, generation, and energy systems all working in unison and being driven by AI [44]- [46]. Digital technologies and AI have been enabling components of local energy production and providing the means for local flexibility and better access to all sectors [47]. Their vital roles are mentioned below.

- Smart grids and IoT devices allow for real-time monitoring and control of energy resources, facilitating efficient distribution and management [45].
- AI-driven tools, such as ML models [48], [49], are used for predictive analytics to forecast demand and optimize trading strategies within ECs.
- These innovative tools are applied to load scheduling, smart contracts, and optimized trading to better benefit from energy costs.

There are many significant concerns regarding the implementation of AI technologies that have increased with their more widespread use [50]- [52]. The key points are outlined below.

- Cybersecurity threats
- Algorithmic bias
- The need for clear, consistent regulations for data sys-

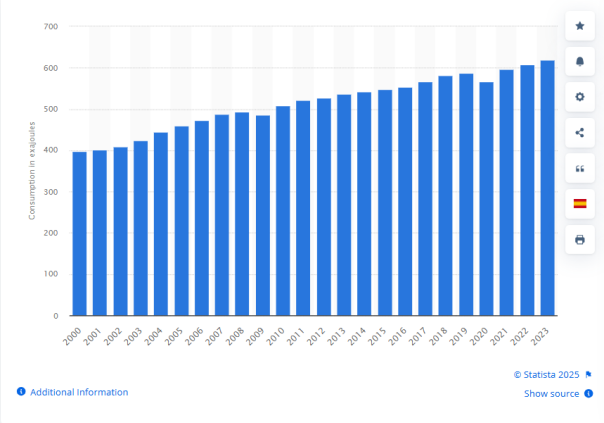


Figure 1: Global energy consumption [132].

tems and new processes

Thoughtful incorporation of AI-driven risk management during ERP projects can boost the effectiveness and precision of risk identification and mitigation [65]. While digital changes present obstacles such as cost, social issues, and skill gaps, greater AI use is still advised to improve existing operations [53]. This review examines the various ways AI and digitalization are transforming energy markets and trading frameworks, emphasizing AI-enhanced market optimization and risk assessment, along with the incorporation of AI into blockchain technology, the IoT, and smart grids. This review seeks to provide a thorough understanding of the present condition and future direction of AI-driven energy systems by integrating findings from recent studies. Table 1 presents key sources related to this subject, emphasizing their most important findings and insights.

3. Analyzing statistics and data

The year 2023 witnessed global primary energy consumption of approximately 620 exajoules, an increase of around two percent relative to 2022. This figure followed a period of disruption in 2020, during which the coronavirus pandemic and its associated impact on transportation fuel requirements and economic activity led to a decrease in primary energy consumption, returning it to the levels registered in 2016. However, forecasts suggest that global energy consumption is expected to expand over the next several decades [82]. Global energy consumption is shown in Figure 1.

According to Figure 2, in January 2024, energy prices in the Euro area rose to 151.16 points, up from 146.82 points in December 2023. From 1996 to 2025, energy prices in the Euro area averaged 91.38 points. The highest recorded price was 171.36 points in October 2022, while the lowest was 52.33 points in February 1999 [83].

Table 2 shows the energy balances for the EU (27 countries). This picture provides detailed statistics on energy supply, consumption, and production across various fuel

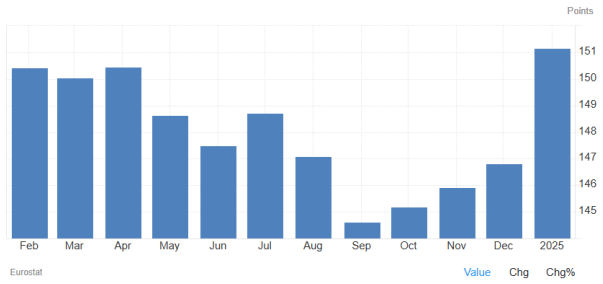


Figure 2: Global primary energy consumption, 2000-2003 [83].

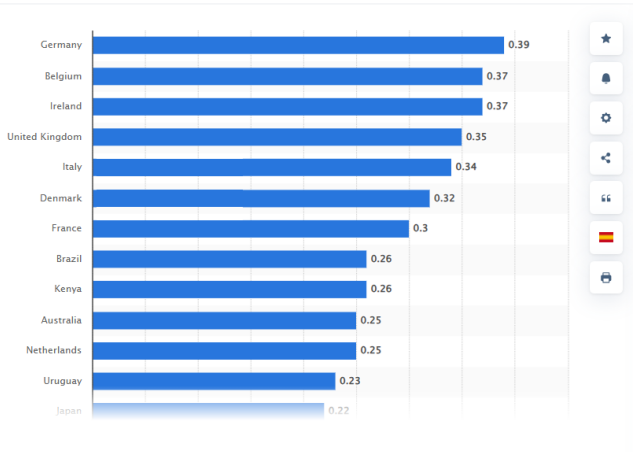


Figure 3: Household electricity prices worldwwide in june 2024, by country (in U.S. dollars per kilowatt-hour) [82].

families in the EU for 2024 [83].

According to Figure 3, Germany, Belgium, and Ireland had some of the most noteworthy household power costs around the world as of June 2024. At the time, German households were charged around 0.39 U.S. dollars per kilowatt-hour, whereas in Belgium, the cost stood at 0.37 U.S. dollars per kilowatt-hour. By comparison, in Qatar, inhabitants paid more than 10 times less [82].

4. Limitations of previous studies

After an examination of the conducted studies, a few essential restrictions and reactions have emerged:

- Narrow scope: Is the scope also restricted, centering only on particular advances (e.g., smart meters) or areas (e.g., grid operations) without considering broader systemic impacts?
- Need for interdisciplinarity: Do the papers address the complex socio-technical nature of energy markets by considering financial, social, policy, and technical dimensions, and engage with different important disciplines?
- Static view: Do the papers take a static approach, or do they analyze how energy markets and the role of AI and digitization evolve?
- Data constraints: Are the information sources reliable and representative? Are there any biases or limitations

Table 1: A thematic overview of energy market and trading models powered by AI and digitalization.

Subject	Specific area	Summary	References
Evolution of energy market structures	Energy market models	Decentralized, community-based energy markets utilizing technologies like blockchain are emerging to replace rigid, centralized systems, empowering prosumers and enabling more flexible, secure, and efficient local energy transactions.	[54]–[57]
AI as an enabler in energy transformation	Impact of AI and digitalization	This integration enhances energy efficiency, security, and sustainability, paving the way for smart grids and optimized resource allocation.	[58]–[61]
Optimizing markets through AI-powered tools	a. Energy market optimization with AI b. Energy market price prediction with AI	AI and ML are transforming the energy sector by providing predictive insights into energy prices, optimizing resource allocation, and improving customer engagement through adaptive distribution models.	[62]–[66], [118], [190]
Risk management & uncertainty mitigation with AI	a. AI-supported risk assessment in energy markets b. Uncertainty management using MCSs	AI-supported risk assessment and MCSs enhance decision-making in the energy sector by improving risk prediction, managing market uncertainties, and driving efficiency improvements.	[67]–[70]
Local energy markets and equitable distribution	a. Integration of AI and digitalization in LEMs b. Enhanced energy forecasting and grid management with IoT c. Equitable and sustainable energy future through AI in LEMs	The convergence of IoT, AI, and energy management enhances energy forecasting and grid management, enabling optimized resource allocation and supporting the transition to resilient and sustainable infrastructures.	[71]–[75]
Energy market and trading	a. Renewable-ready markets b. Storage and flexibility c. P2P energy trading d. Risk management e. AI and digitalization	More active prediction and better management can help achieve their desired goals.	[76]–[78], [189]
Ethics	Ethical implications	Lack of transparency, algorithm bias, and the need for AI implementations are key concerns.	[44]
Implementation concerns	Data quality and access	Access to quality, reliable data sources is crucial for effective AI systems and for delivering benefits.	[79]–[81]

within the data that seem to influence the results? (For example, dependence on particular datasets, restricted geographic scope, or brief time horizons.)

- Methodological meticulousness: Are the strategies utilized suitable for the research questions? Are the econometric models well-specified? Is there appropriate support for causal inferences?
- Lack of validation: Are the outcomes of the demonstration or investigation validated using independent information or real-world observations? Is an effect size analysis conducted to evaluate the strength of the findings?
- Transparency: Are the data and code utilized within the investigation readily accessible for verification and replication?
- Oversimplified connections: Are the connections between AI/digitization and energy market outcomes being distorted? Are the potential complex mechanisms adequately addressed?
- Neglect of unintended results: Do the papers take into consideration the potential negative results of AI /digitization, such as job displacement, increased inequality, or security risks?
- Limited policy relevance: Are the policy proposals practical and actionable? Do they sufficiently consider the feasibility, scalability, and political acceptability of the

Table 2: European Union (EU-27) energy balances by major fuel category in 2024 (ktoe)[223].

Energy balance flow	Total	Solid fossil	Manuf. gases	Peat	Oil shale	Natural gas	Oil prod.	Renewables	Non-ren. waste	Nuclear heat	Electricity	Heat
Total energy supply	1,250,653	112,229	0	663	2,201	273,096	423,989	269,725	14,181	154,856	-1,058	772
Transformation input	1,223,394	120,328	5,534	413	2,262	84,397	664,770	175,773	9,252	154,856	4,791	1,019
Transformation output	1,001,240	21,493	15,141	2	N/A	3,224	653,368	16,314	N/A	N/A	243,227	48,471
Energy sector use	59,321	317	4,817	1	0	9,189	25,755	636	53	N/A	15,856	2,696
Distribution losses	22,183	33	654	0	0	999	8	74	0	N/A	15,187	5,228
Available for final consumption	946,995	13,043	4,136	251	-61	181,734	386,824	109,555	4,876	0	206,336	40,300
Statistical differences	-9,102	-723	2	3	-134	-1,595	-7,546	413	-21	0	488	12
Final non-energy consumption	78,220	1,286	16	0	74	10,953	65,891	0	N/A	N/A	N/A	N/A
Final energy consumption	877,876	12,480	4,118	249	0	172,376	328,479	109,142	4,897	N/A	205,848	40,288
Gross electricity production	243,227	23,378	1,997	67	131	38,107	3,932	114,575	1,723	55,851	N/A	28
Gross heat production	48,471	7,197	544	259	25	15,760	1,169	16,844	3,391	99	330	N/A

Notes: Values are in thousand tonnes of oil equivalent (ktoe). "Manuf. gases" denotes manufactured gases; "Oil prod." denotes oil and petroleum products excluding the biofuel portion; "Non-ren. waste" denotes non-renewable waste. N/A indicates a value marked not applicable/available in the source export; – indicates an empty field (if any). Negative values are retained as reported. Gross electricity and heat production are balance entries and should not be added to final consumption. *Source:* Eurostat, Complete energy balances (dataset `nrg_bal_c`), EU-27, 2024; user-supplied CSV export. https://doi.org/10.2908/NRG_BAL_C.

proposed interventions?

- Ethical considerations: Do the papers address ethical issues related to the use of AI in energy markets, such as bias, fairness, transparency, and accountability?

Common impediments found in existing research:

- Data shortage and quality: Limited availability of high-quality, granular information on AI/digitization adoption and its impacts within the energy sector.
- Difficulty establishing causality: Challenges in isolating the causal impacts of AI/digitization from other factors affecting energy market outcomes.
- Short time horizons: Numerous studies are based on generally brief periods, making it difficult to assess long-term patterns and impacts.
- Geographic bias: Research is frequently concentrated in developed nations, with limited evidence from developing nations or emerging economies.
- Lack of standardization: The lack of standardized measurements and methodologies makes it difficult to compare results across different studies.
- Limited consideration of behavioral aspects: Disregard of the role of human behavior, organizational dynamics, and regulatory factors in shaping the adoption and impact of AI/digitization.
- Focus on optimization instead of transformation: Research often focuses on optimizing existing frameworks instead of investigating the potential for transformative changes enabled by AI/digitization.
- Ethical and social impacts are understudied: The social and ethical implications are typically not considered.

The limitations identified in existing research are shown in Figure 4.



Figure 4: Limitations found in existing research.

4.1. Traditional and modern energy trading

The energy trading market is undergoing significant expansion and transformation. Available data indicate that electricity trading in the spot market reached 880 terawatt-hours (TWh) in 2024, while forecasts suggest a substantial increase to 8,439 TWh. The European Energy Exchange (EEX) serves as a major trading platform for electricity, natural gas, coal, and carbon dioxide (CO_2) emission allowances across more than fifteen countries. Globally, electricity generation was projected to reach 28.81 trillion kWh in 2024, with an estimated annual growth rate of 2.52% through 2029. Within Europe, electricity generation is projected to reach 5.25 trillion kWh by 2025, with an anticipated annual growth rate of 1.60% between 2025 and 2029.

Alongside this growth, increasing emphasis has been placed on renewable energy investments, particularly within the European Union (EU-27) and Germany, reflecting a

strategic commitment to achieving carbon neutrality and enhancing energy security. Nevertheless, carbon emissions intensity remains a significant challenge, with Europe's electricity generation emissions intensity estimated at 285.75 gCO_2/kWh in 2025. Energy prices have also experienced considerable volatility due to several factors, including post-pandemic inflationary pressures, geopolitical instability, and supply chain vulnerabilities. Furthermore, projections indicate continued price fluctuations for natural gas, coal, and uranium, with uranium prices potentially doubling by 2025 [91].

Energy trading is progressively transitioning from traditional centralized structures to modern decentralized frameworks. This transformation is primarily driven by the increasing penetration of renewable energy sources and the adoption of emerging technologies such as blockchain. Wongthongtham et al. [92] highlighted that centralized energy trading systems often experience operational inefficiencies and limited adaptability to changing energy demands, particularly with the growing integration of renewable energy into power grids.

The emergence of peer-to-peer (P2P) energy trading represents a significant advancement in electricity market operations. Zhang et al. [93] discussed the concept of the "P2P energy trading trilemma," which refers to the challenges associated with simultaneously achieving computational efficiency, decentralized operation, and optimal trading solutions. Existing research suggests that P2P energy trading offers a promising alternative to conventional centralized trading mechanisms by improving scalability, flexibility, and efficiency in energy distribution.

Blockchain technology is further transforming energy trading by providing a secure, transparent, and reliable platform for energy transactions. Umar et al. investigated blockchain-based vehicle-to-vehicle (V2V) energy trading and demonstrated its potential to strengthen power grid operations through improved security, efficiency, and adaptability compared with conventional centralized approaches. In addition, researchers have explored the application of multi-agent reinforcement learning (MARL) to optimize decentralized energy trading systems. Further studies demonstrated that applying MARL to decentralized multi-energy trading can improve participants' economic benefits while preserving privacy and supporting system scalability [94].

The growing importance of integrating electricity and hydrogen markets has also accelerated the development of hybrid energy trading frameworks. Zhang et al. proposed a coordinated trading framework that enables renewable-to-hydrogen providers to participate strategically in multiple energy markets [95]. This approach aims to maximize economic benefits while promoting the efficient utilization of renewable energy sources.

The integration of AI and digital technologies offers substantial opportunities to improve the efficiency, security, and sustainability of modern energy systems. Cali et al. demonstrated that combining blockchain technology with ML enables secure communication and facilitates efficient decentralized energy trading between producers and consumers [96]. Similarly, Wang et al. [97] emphasized the importance of smart meters in collecting real-time energy consumption data to support improved demand-side management.

Despite these advantages, the increasing deployment of IoT devices introduces significant cybersecurity challenges. Although IoT-enabled devices improve grid responsiveness and facilitate real-time monitoring, they also increase exposure to cyberattacks, thereby requiring robust security mechanisms [98]. AI-based approaches contribute to power grid optimization and enhance the detection and mitigation of false data injection attacks. Recent developments in semi-supervised deep learning have further strengthened the ability of energy management systems to identify malicious activities and improve operational resilience.

Furthermore, Kwiliński et al. highlighted that changes in consumer behavior resulting from the COVID-19 pandemic necessitate a reassessment of existing energy consumption patterns and related energy management strategies [99].

5. Traditional and modern electricity markets

Energy markets are changing rapidly due to new technologies and updated regulations. Efficient energy movement and usage rely on energy systems and infrastructure acting as the link between those who need energy and those who provide it. Systems such as energy storage, digitalization, the connection of different energy sectors, demand management, and regional partnerships allow energy to be managed and moved effectively to where it is required [84], [85]. For a long time, electricity trading systems have used standard models such as zonal setups. However, these models no longer fit the modern energy market because they do not handle the intricate economic and environmental factors well enough. This research argues for moving to nodal models, which offer a more precise picture of electricity movement by considering price variations in different locations [86]. Unlike older methods, today's advanced models, particularly those using system dynamics, offer a more profound understanding of energy markets. For example, they developed a system dynamics model for nationwide electricity markets that relies on piecewise smooth differential equations. This model effectively simulates the intricate interplay of supply and demand, and it is designed to be adaptable to different investment situations. The use of non-smooth dynamics allows for a more accurate portrayal of real-world market actions, especially in investment decisions shaped by feedback loops within the flow of

energy systems [87]. Community energy markets are a new and exciting development in how energy is traded. Models are proposed for energy exchange within these communities, stressing the value of local trading among energy producers and consumers. By enabling local sales of extra energy, these models encourage energy independence and lower costs for community participants. The key to success for community models is understanding how different members of the community interact, which allows for better use of resources and greater overall benefit [88]. A key feature of today's energy markets is the incorporation of energy storage, which is crucial for dealing with inconsistent renewable energy supplies. Akram et al. suggest complex energy flow models that consider the unique operational details of different storage technologies. Their study shows that customized methods are needed to assess how ESSs engage in the market, rather than using simplified models that do not accurately reflect their performance [89].

P2P energy trading is another key innovation in today's energy markets. The P2P systems are explored that allow energy producers to share extra energy directly, cutting out traditional energy companies. These models create cooperative ways to distribute energy, giving consumers more control and challenging current regulations. Research suggests that P2P systems not only improve participants' finances but also encourage wider community involvement in sustainable energy practices. As energy markets change, the implications extend beyond just economic gains. The shift from traditional to modern models signifies a larger move toward more intricate, integrated methods that boost sustainability and efficiency [90].

5.1. Energy market optimization with AI

AI is becoming essential in the energy sector. Its capacity to analyze information and generate forecasts improves operations, asset management, and client relations. For example, AI is utilized to precisely anticipate energy utilization and optimize Battery Energy Storage Systems (BESS), reinforcing the control network and making it more eco-friendly. Research by Rocha et al. [100] suggests that AI-based coordination of solar and hydrogen energy can effectively balance supply and demand while improving energy efficiency. Synergistic partnerships between universities and businesses are driving progress in applying AI to energy storage, power grid management, and predicting renewable energy generation. To fully realize the potential of AI in the energy sector, it is crucial to tackle challenges related to managing complex datasets, integrating AI systems into existing infrastructure, and safeguarding against cybersecurity threats [101]. AI Applications in Energy Systems Management and Optimization are shown in Figure 5.

Key benefits of this approach yields several benefits, including a more efficient energy market that better handles the variability of RESs and leverages flexible energy

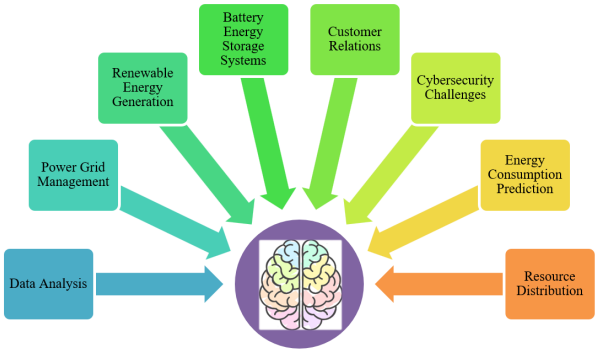


Figure 5: AI applications in energy systems management and optimization [217].

demand, thanks to the use of IoT technologies. These improvements translate into economic and social advantages such as reduced operational expenses and a more stable power grid, achieved by optimizing resource distribution and effectively managing energy demand from consumers [102].

5.2. Energy market prices and prediction using AI

AI is improving the accuracy of energy market price forecasts through several key strategies. These include decentralized AI models that improve data privacy and predictive power, hybrid forecasting approaches that combine ML with traditional data sources such as weather information for better renewable energy production estimates, and a collaborative approach that integrates human expertise to validate and refine AI-generated predictions. Furthermore, the critical role of human experts in ensuring the reliability of AI-driven decision support systems for energy markets is emphasized [103]. AI/ML algorithms for energy market price prediction are shown in Table 3.

(i) Potential for ML/AI in forecasting and analysis:

Research conducted by Mhlanga et al. [110] revealed that ML has a wide range of potential applications across various domains. These applications include assessing macroeconomic and energy trends, forecasting demand, managing risk, developing trading strategies, and processing data. For example, the prices of crude oil, natural gas, and electricity can be predicted using these techniques.

(b) The use of ML in energy systems shows great promise for both energy generation and consumption.

(c) Zhou et al. [111] state that improving the accuracy of power demand and price predictions is one of the most pressing issues in electrical engineering research.

(ii) Grid management and price prediction:

(a) The electricity industry has made great strides in adopting data analytics, largely due to the installation of smart meters and sensors that collect substantial amounts of data within the smart grid.

(b) Processing such a large volume of diverse data would be impossible without the support of big data analytics.

Table 3: AI/ML Algorithms for energy market price prediction.

Algorithm Type	Specific Algorithm Examples	Application Area	Advantages	Disadvantages	Ref.
Time Series Analysis	ARIMA, SARIMA, Exponential Smoothing	Short-term and medium-term price forecasting (e.g., day-ahead, week-ahead)	Simple to implement, computationally efficient, and with well-established statistical properties.	May not capture complex non-linear relationships, requires stationary data, and has limited ability to incorporate external factors.	[104]
Regression-Based ML	Linear Regression, Support Vector Regression (SVR), Ridge Regression, Lasso Regression	Medium-term to long-term price forecasting, identifying key price drivers.	Can handle multiple input variables and is relatively easy to interpret.	Performance can be sensitive to feature selection; linear regression assumes linearity, and SVR can be computationally expensive.	[105]
Artificial Neural Networks (ANNs)	Feedforward Neural Networks, Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM)	Short-term, medium-term, and long-term price forecasting, capturing complex patterns.	Can model non-linear relationships, adaptive learning, is capable of handling noisy data, and can capture long-term dependencies (LSTMs).	Black box models (difficult to interpret), require large datasets for training, are prone to overfitting, are computationally intensive, and require hyperparameter tuning.	[106]
Tree-Based Methods	Decision Trees, Random Forests, Gradient Boosting Machines (GBM), XGBoost	Medium-term and long-term price forecasting, feature importance analysis.	Can leverage the strengths of different algorithms, often achieving superior performance compared to single models.	Increased complexity requires careful design and tuning.	[107]
Hybrid Models	Combination of different AI/ML techniques (e.g., ANN-ARIMA, Wavelet-ANN)	All forecasting horizons, improving accuracy and robustness.	Can leverage the strengths of different algorithms, often achieving superior performance compared to single models.	Increased complexity requires careful design and tuning.	[108]
Bayesian Methods	Gaussian Processes, Bayesian Neural Networks	Quantifying uncertainty in price predictions.	Provides probabilistic forecasts, captures uncertainty, and can be updated with new data.	Can be computationally expensive and sensitive to prior specification.	[109]

Both big data analytics and ML algorithms play crucial roles in electrical transmission and distribution networks [191]. They are necessary for data collection, storage, and analysis, as well as for forecasting and system maintenance [112].

(c) Individuals and businesses with their own energy generation systems can use this information to make strategic decisions about their energy usage. For example, the Adaptive Neural Fuzzy Inference System (ANFIS) has been implemented to predict short-term wind patterns that are essential for generating electrical power [113].

(d) Considering these developments, it is crucial for businesses and governments to invest in AI and ML. These technologies can enhance grid management and improve the accuracy of energy price estimates [114].

(iii) Forecasting for renewable energy:

Significance of short-term forecasting models for PV energy generation is discussed in [111], [215], [216]. The studies surveyed indicate that deep learning (DL)-based forecasting models in renewable energy can enhance accuracy, stability, and effectiveness, which are essential for energy system planning, scheduling, and management. Additionally, data preprocessing methods, such as Empirical Mode Decomposition (EMD) and Wavelet Decomposition (WD), along with post-correction techniques like Ensemble Methods and Rough Set Theory, are crucial for improving accuracy. Several articles have been reviewed to examine this issue, and the following aspects have been identified [115], [116]. A general deep learning-based point forecasting framework for renewable energy is shown in Figure 6.

(a) Overall architecture: The main components of the framework are data preprocessing, feature extraction, forecasting models, and error correction. Each of these components is interconnected, forming a cohesive system that enhances overall performance and accuracy.

(b) Specific techniques: What ML or statistical methods are applied in each component? (e.g., LSTM, CNN, wavelet transforms, Kalman filters, etc.)

(c) Data sources: What types of data are used (including historical generation data, weather data, and market data)?

(d) Framework performance evaluation: Which metrics are used to evaluate its effectiveness (e.g., RMSE, MAE, MAPE, and CRPS)?

(e) Strengths and weaknesses: What are the highlighted advantages and potential drawbacks of the framework?

(f) Novelty: What distinctive contribution does the framework offer?

(g) Commonalities: What elements or techniques are common across multiple frameworks?

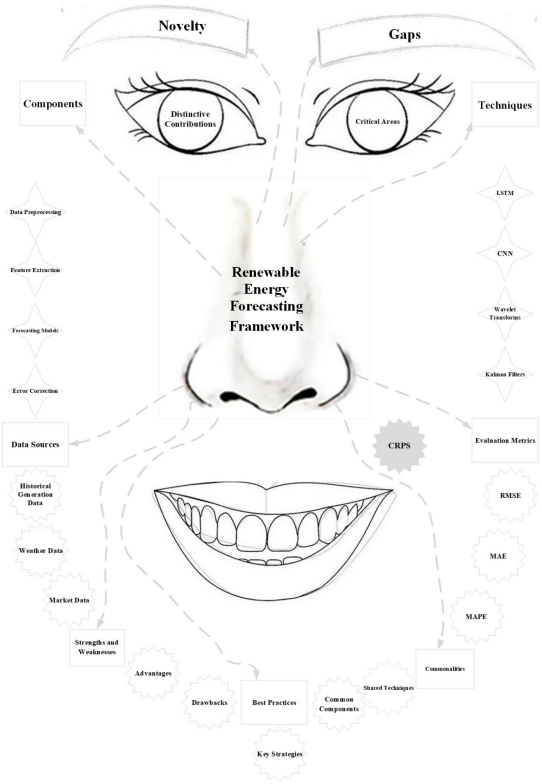


Figure 6: Forecasting framework of renewable energy.

(h) Commonalities: What elements or techniques are common across multiple frameworks?

(i) Gaps: Which critical areas remain unaddressed by current frameworks?

(j) Best practices: What are the key strategies for creating an effective renewable energy forecasting framework?

(k) Emerging trends: What new techniques or approaches are gaining popularity?

(l) Open challenges: What are the key challenges that researchers are still trying to address?

(m) Framework of understanding: The outcome is a comprehensive overview of existing frameworks, covering common components and variations, the strengths and weaknesses of different approaches, and key research directions in the field.

Based on a review of various articles, an algorithm for predicting prices in the renewable energy market has been proposed and is detailed below [117]- [119]. Figure 7 presents a summary of the contents.

5.3. Risk assessment models in the energy market

The energy industry is at a crucial juncture, requiring the development of sustainable, efficient, and secure energy systems. In this context, robust risk assessment models are crucial for managing market complexities. AI significantly enhances risk assessment capabilities in various fields, resulting in greater precision, efficiency, and flexibility. In particular, the nuclear energy industry relies heavily on probabilistic risk assessment (PRA) to ensure



Figure 7: Algorithm steps to improve renewable energy price prediction [117]- [119].

a thorough examination of potential hazards [120]. The Fuzzy Analytical Hierarchy Process (FAHP) is especially beneficial in scenarios with limited or ambiguous data, as it facilitates a deeper comprehension of risk by integrating the assessments of stakeholders. Additionally, the integration of environmental risk assessments into energy market evaluations has become increasingly popular [121]. This review paper addresses the growing complexities and uncertainties in modern electricity markets, highlighting the critical role of effective risk assessment and management for market participants and regulators. The authors analyze existing risk assessment and management methodologies applied to electricity markets, categorized into various risk types. The review identifies and examines key risks, including price volatility, operational risks, regulatory risks, and credit risks, and the models used to assess these risks. These include models such as Value-at-Risk (VaR), conditional Value-at-Risk (CVaR), and stochastic optimization techniques. Finally, the review outlines the limitations of the current risk management approach and provides suggestions for future research directions. These suggestions include data-driven methods that can improve risk assessment accuracy and adapt to the changing characteristics of electricity markets [122]. Another study presents an energy management system (EMS) for a microgrid participating in an electricity pool market, incorporating RESs, diesel generators, battery storage, and controllable loads. A key feature of the proposed EMS is a double-layer scenario-based stochastic programming approach, which addresses uncertainties related to renewable resources, customer loads, and electricity prices. To mitigate risks associated with these uncertainties, a risk management scheme employing CVaR is integrated into the objective function [123].

5.4. Risk identification in electrical energy markets

Effective risk assessment and management in energy markets offer several critical benefits, enabling market participants, regulators, and investors to make informed decisions and mitigate potential losses [124], [125]. These benefits are achieved through the application of various models and techniques, as outlined below:

(i) Improved decision-making:

- Benefit: Risk assessment models provide stakeholders with a clear understanding of the potential risks and uncertainties associated with energy market activities, enabling more informed and robust decision-making [126].

Solutions:

Price volatility modeling: Models like GARCH, stochastic volatility models, and jump-diffusion models can be used to quantify and forecast price volatility, enabling traders and portfolio managers to make better hedging and trading decisions [127].

Scenario analysis: Developing scenario-based simulations and risk assessments can also help improve investment decisions by understanding the effects on different outcomes.

(ii) Enhanced risk mitigation:

- Benefit: By identifying and quantifying risks, market participants can implement strategies to mitigate these risks, reducing the potential for financial losses and operational disruptions [128].

Solutions:

Hedging strategies: Using derivatives (e.g., futures, options, swaps) to hedge against price volatility and protect against adverse price movements.

Portfolio diversification: Diversifying energy portfolios across different assets, regions, or technologies to reduce overall risk exposure [129].

Insurance and risk transfer: Utilizing insurance products or risk transfer mechanisms to protect against specific operational risks (e.g., power plant outages, pipeline failures) [130].

Credit risk management: Implementing credit scoring models and collateral requirements to mitigate the risk of default by counterparties [131].

(iii) Optimized resource allocation:

- Benefit: Risk assessment models can help to optimize the allocation of resources, ensuring that capital is deployed efficiently and projects are selected based on their risk-adjusted returns [132].

Solutions:

Risk-adjusted return on capital (RAROC): Evaluating investment opportunities based on their RAROC, which takes into account the risk associated with the project [133].



Figure 8: Eight key benefits and solutions from risk assessment models in the energy market [217].

Stochastic Optimization: Using stochastic optimization techniques to optimize investment decisions under uncertainty, considering a range of possible scenarios [134].

(iv) Improved regulatory oversight:

- Benefit: Risk assessment models provide regulators with insights into the stability and resilience of the energy market, enabling them to implement policies and regulations that promote market efficiency and prevent systemic risk [135].

Solutions:

Stress testing: Conducting stress tests of energy market participants to assess their ability to withstand extreme events (e.g., price spikes, supply disruptions) [136].

Market surveillance: Monitoring market activity for signs of manipulation or excessive speculation [137].

Regulatory capital requirements: Setting capital requirements for energy market participants to ensure that they have sufficient resources to absorb potential losses [138].

(v) Attracting investment in renewable energy:

- Benefit: By quantifying and mitigating risks associated with renewable energy projects, risk assessment models can make these projects more attractive to investors, accelerating the transition to a cleaner energy future [139].

Solutions:

- Revenue stabilization mechanisms: Implementing feed-in tariffs, contracts for difference, or other mechanisms to stabilize revenues for renewable energy projects and reduce price risk [140].
- Credit guarantees and risk insurance: Providing credit guarantees or risk insurance to reduce the risk of default or project failure [141]. Eight key benefits and solutions associated with risk assessment models in the energy market are shown in Figure 8.

AI significantly impacts risk evaluation in the energy sector, marked by various opportunities and challenges. Its capacity to evaluate large datasets and offer predictive insights results in more informed decision-making processes

[142]. Ethical concerns and clarity enhance the incorporation of AI technologies. Yenduri et al. highlighted that AI tools such as GPT-4 significantly improve data analysis, allowing for the real-time detection of possible risks and opportunities [143].

5.5. MCS for energy market risk

To effectively manage uncertainty in the ever-changing and often unpredictable energy market, stakeholders can leverage MCSs. These valuable resources allow for the creation of models simulating a range of possible outcomes, supporting well-informed decisions within this complex industry. By incorporating dynamic financial modeling, project viability can be evaluated more comprehensively under varying market conditions, leading to a better understanding of potential risks and rewards [63], [68], [69]. Furthermore, fintech innovations are enhancing the precision of financial models, thereby improving financial forecasting and risk assessment [144]. This review paper addresses the increasing significance of uncertainty in modern power systems, arising from restructuring efforts and the integration of renewable energy resources. The authors systematically examine various uncertainty modeling techniques applicable to power system studies, categorizing them into probabilistic, possibilistic, hybrid possibilistic-probabilistic, information gap decision theory (IGDT), robust optimization, and interval analysis [145]. The uncertainty modeling approaches are explained in Table 4.

5.5.1. Modeling and the appropriate approach

Selecting an appropriate modeling approach is essential for improving decision-making, assessing potential risks, and optimizing energy management processes [146]. Data-driven strategies that integrate predictive analytics and AI can refine simulations and improve demand forecasting accuracy. The availability and quality of data are critical factors in selecting suitable modeling techniques. Probabilistic methods require sufficient historical data to reliably estimate probability density functions (PDFs) for uncertain variables and may become unreliable when data are scarce [147]. In contrast, possibilistic methods, particularly fuzzy logic, are useful when historical data are limited or imprecise, as expert knowledge and qualitative information can be employed to define membership functions [148]. Information-gap decision theory and robust optimization can support decision-making without requiring historical data, particularly under severe uncertainty [149]. The nature of uncertainty also influences model selection. Aleatory uncertainty represents inherent randomness, such as wind gusts and solar irradiance fluctuations, for which probabilistic methods are generally suitable [150]. Conversely, epistemic uncertainty arises from insufficient knowledge, such as future policy changes or technological costs, making possibilistic methods, IGDT, and robust optimization more appropriate. Model complexity and computational requirements must also be considered when selecting a suitable approach. Monte Carlo simulation can be computationally expensive, particularly for complex models involving numerous uncertain variables, although variance reduction techniques may improve computational efficiency [151]. Analytical approaches, including linearization and point estimate methods, offer computational efficiency but may compromise prediction accuracy [151].

The correlation among uncertain variables, desired outputs, risk preferences, model nonlinearity, and available computational resources are additional factors influencing the selection of uncertainty modeling techniques. When uncertain variables are correlated, the selected method should adequately represent their statistical dependencies. Copula functions provide an effective means of modeling dependencies among random variables [152], whereas simpler approaches, such as basic MCS implementations, may not adequately account for these correlations. The desired output of the uncertainty analysis also determines the modeling strategy. If the objective is to obtain the complete probability distribution of an output variable, MCS or analytical approaches, such as the cumulant method with appropriate series expansion, can be employed [145]. Sensitivity analysis can further identify the most influential uncertain variables affecting system performance [153]. The risk preferences of decision-makers should also be considered, as robust optimization and IGDT allow explicit consideration of risk aversion and facilitate the identification of solutions that remain effective under worst-case scenarios [154]. Furthermore, the degree of nonlinearity between input and output variables influences the suitability of analytical methods, since linearization techniques may produce inaccurate results for highly nonlinear systems [155]. Machine learning approaches, including deep convolutional neural networks (DCNNs) and deep recurrent neural networks (DRNNs), can support the modeling of complex systems under uncertainty [156]. Nevertheless, computational requirements vary considerably across modeling approaches, as methods such as MCS and deep learning may provide effective results while demanding substantial computational resources [115]. Therefore, selecting an appropriate modeling technique requires balancing data availability, uncertainty characteristics, computational efficiency, model accuracy, and decision-making objectives.

5.5.2. Monte Carlo Simulation (MCS)

MCS is a widely recognized and implemented numerical technique for uncertainty management in energy market modeling, particularly when addressing intricate, non-linear systems characterized by numerous uncertain variables. MCS leverages a computational, iterative approach to approximate the behavior of complex systems by simulating numerous scenarios based on probability distributions as-

Table 4: The uncertainty modeling approaches [144],[145]

S. No.	Uncertainty Modeling Criteria	Description
1	**Data availability**	The quality and amount of data are crucial for modeling.
2	**Type of uncertainty**	Understanding the nature of uncertainty is essential.
3	**Model complexity**	The computational cost of different modeling approaches must be considered.
4	**Correlation**	Methods should capture dependencies between uncertain variables.
5	**Desired output**	Identifying the needed information from uncertainty analysis is key.
6	**Risk aversion**	Decision-makers' risk preferences influence the method selection.
7	**Model non-linearity**	The relationship's linearity affects the choice of methods.
8	**Computational resources**	Different methods require varying levels of computational effort.

signed to uncertain input parameters. Within the energy market context, MCS finds applications in diverse areas, spanning risk assessment, investment planning, and operational optimization [157].

The MCS methodology typically involves the following sequential steps [158]:

- Input characterization:
  Defining the uncertain input parameters, such as fuel prices, electricity demand, renewable energy generation, and operational availability, and assigning appropriate PDFs to represent their variability. The selection of a PDF must rely on previous knowledge. It can also include normal, uniform, and lognormal distributions.
- Scenario generation:
  Generating a large number of scenarios by randomly sampling values from the defined PDFs for each uncertain input parameter. Latin hypercube sampling (LHS) or other variance reduction techniques may be employed to improve sampling efficiency. In this paper, a small-forward reduction, such as the General Algebraic Modeling System (GAMS)/Scenario Reduction (SCENRED), was implemented to reduce computation time and maintain the effectiveness of Monte Carlo.
- Model evaluation:
  Evaluating the deterministic energy market model for each generated scenario, calculating relevant output variables of interest, such as electricity prices, generation costs, and power flows.
- Statistical analysis:
  Aggregating the results from all simulated scenarios to derive statistical measures of the output variables, including mean, variance, percentiles, and confidence intervals. These statistical measures quantify the range of potential outcomes and the associated probabilities.
- Risk assessment:
  Calculating risk metrics based on the simulated output distributions, such as VaR and CVaR, to assess the potential for extreme losses. CVaR is an effective approach, helping with an appropriate trade-off in the model, but it might increase complexity.

Computationally intensive, MCS remains a vital tool for managing uncertainty in the energy market, providing a flexible, comprehensive framework for risk assessment, investment planning, and operational optimization. Ongoing research focuses on variance reduction techniques, hybrid approaches, and parallel computing to mitigate the computational limitations of MCS and extend its applicability to increasingly complex energy systems. A deep dive into MCS for uncertainty management in the energy market is shown in Table 5.

5.5.3. Risk assessment in the electricity market

Ahmad et al. examined a method for assessing the benefit of electric car charging piles based on the value at risk [42]. The invention assesses the investment benefit risk of EV charging piles using a VaR-based method and MCSs to obtain the probability distribution of charging amounts, then simulates the investment benefit model. This enables the benefit and risk assessment for EV charging piles through the VaR. The method supports investment from a technical and economic perspective and supports it. It reduces financial risk in investment and operation.

In recent years, there has been a rise in digital start-up activity within the energy sector. Although there were predictions of a decrease in VC funding amid the COVID-19 pandemic, initial investments in clean energy start-ups increased in 2020. This trend emphasizes sustained enthusiasm for creative digital solutions and adaptability amid economic instability [194]. The energy industry has experienced a rise in digital start-up initiatives in recent years. Unexpectedly, early-stage investments in clean energy start-ups saw growth in 2020, despite forecasts of decreased VC financing due to the COVID-19 pandemic. This trend suggests a sustained interest in innovative digital solutions within the energy domain and resilience in the face of global economic uncertainty [195].

Table 5: Deep dive into MCS for uncertainty management in the energy market.

Subject	Descriptions	References
Core principle	Uses repeated random sampling to obtain numerical results. Simulates numerous scenarios based on probability distributions assigned to uncertain input parameters, then analyzes the results statistically.	[159]
Key advantages	Handles complex, non-linear systems effectively. Adaptable to various uncertainty types (continuous, discrete, qualitative). Conceptually straightforward and easy to implement. Provides comprehensive output (full probability distributions, risk metrics).	[145]
Input Characterization	1. Identify uncertain input parameters (fuel prices, demand, renewable generation, etc.). 2. Assign appropriate PDFs to each parameter. Consider historical data, weather conditions, trends, and patterns. Normal, uniform, lognormal, Weibull.	[145]
Scenario generation	**1-1.** Generate numerous scenarios by randomly sampling values from the PDFs: Latin Hypercube Sampling, Importance Sampling, and Markov Chain Monte Carlo. 2-2. Implement model fast-forward reduction to reduce computational burden.	[160]
Model evaluation	Evaluate the deterministic energy market model for each scenario to determine output variables (electricity prices, generation costs, power flows, reliability metrics).	[161]
Statistical analysis	Analyze results across all scenarios to obtain statistical measures (mean, variance, standard deviation, percentiles, confidence intervals).	[162]
Risk assessment	Calculate risk metrics (VaR, CVaR, Expected Shortfall, etc.).	[163]
Variance reduction techniques	Stratified sampling from PDFs for uniform representation. Importance Sampling: Sample more frequently from scenarios with high impact on results (rare event simulation). Control Variates: Use a correlated variable with a known expectation to reduce estimator variance.	[145]
Investment planning	Evaluating the economic viability of energy projects and optimizing investment decisions.	[164]
Microgrid energy management	An EMS helps the system make smarter decisions with a full range of information by utilizing both probability methods and distributions.	[80], [165]
Operational optimization	Generating electricity, managing transmissions, and designing DR.	[145]
Key challenges	1. High computational burden, especially with growing dimensions. 2. Accurate PDF. 3. Time-consuming as the model scales.	[145]

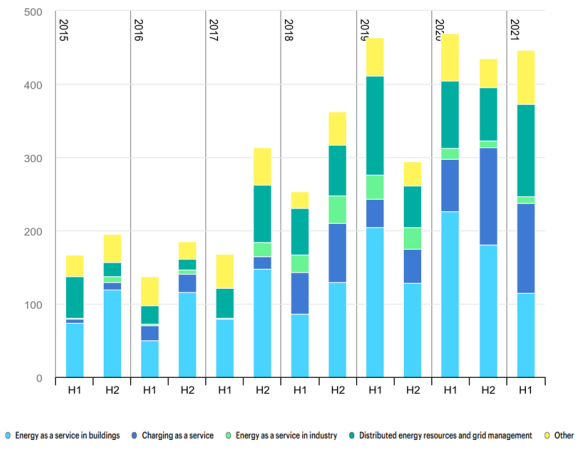


Figure 9: Global early-stage VC investments in digital energy-efficiency and demand-side flexibility Start-Ups, by Type of New Business Model, 2015–2021 [195].

According to the picture, digital start-ups analyzed for investment focus on developing energy technologies, services, and end-user solutions that include both hardware and software. Purely hardware manufacturing and distribution ventures are excluded. Key areas include energy-as-a-service for buildings (smart HVAC and management systems) and distributed energy resource/grid management (virtual power plants and energy trading). This analysis includes companies from seed through Series B funding, excluding outlier investments over USD 150 million, which totaled approximately USD 350 million in 2020 [195]. Global early-stage VC investments in digital energy-efficiency and demand-side flexibility start-ups, by type of new business model, 2015–2021, are shown in Figure 9.

5.6. Electricity and bitcoin

The connection between cryptocurrencies, especially those utilizing Proof-of-Work (PoW), and the energy market is intricate, encompassing significant negative effects as well as possible positive outcomes [204], [205]. "The Tragedy of the Energy Commons" suggests that uncontrolled cryptocurrency mining may result in serious environmental and public health issues because of its excessive

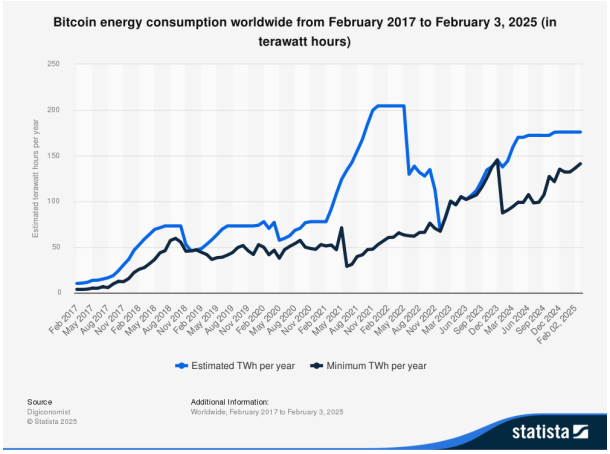


Figure 10: Bitcoin energy consumption [219].

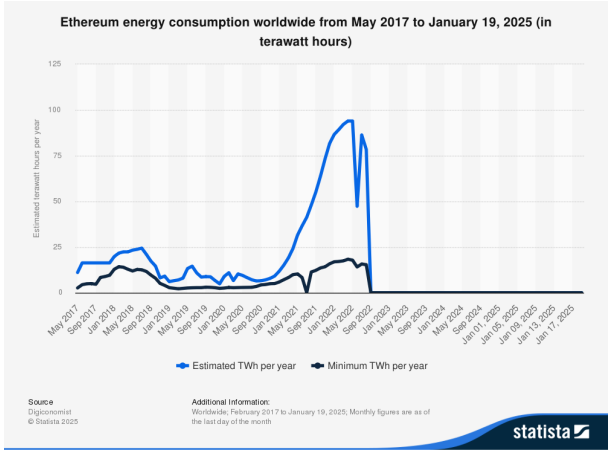


Figure 11: Ethereum's energy consumption [220].

energy use, resembling a "tragedy of the commons" situation. The book argues that governmental oversight is essential to alleviate these adverse externalities by promoting sustainable practices, minimizing pollution, and safeguarding public health, thus averting the excessive use of communal energy resources [196]. The average energy consumption for a single Bitcoin transaction in 2025 could be equivalent to hundreds of thousands of Visa card transactions. This estimate comes from a source attempting to assess Bitcoin's energy consumption over time. The calculation is based on the estimated amount miners spend on electricity, as there is no official tracking of the cryptocurrency's energy use. Additionally, the estimation of which countries mine the most Bitcoin is determined by cross-referencing IP addresses. According to the figure, the effect of cryptocurrencies on the electricity grid has been noteworthy, with Bitcoin alone consuming an estimated 175.87 terawatt-hours (TWh) per year as of February 2025. This is often comparable to the energy consumption of a small nation, with Bitcoin's electrical footprint around 17 percent of Russia's total energy generation. Cryptocurrency mining, especially for Bitcoin, is highly energy-intensive due to its PoW framework. A single Bitcoin transaction in 2025 consumes 1,171.95 kilowatt-hours, comparable to the energy utilized by 100,000 VISA transactions. This high energy demand has led to concerns about the environmental impact of cryptocurrencies [195].

The natural effect of cryptocurrencies. Ethereum, another major cryptocurrency, altogether diminished its energy consumption after transitioning from PoW to proof-of-stake in September 2022. By 2025, Ethereum's energy consumption had become insignificant compared to its past levels. The growing demand for power from cryptocurrencies, besides data centers and AI, is anticipated to account for a bigger share of global power utilization. Estimates recommend that by 2026, these advances may consume between 620 and 1,050 TWh yearly, up from 460 TWh in 2022 [181]. Bitcoin energy utilization is shown in Figure 10.

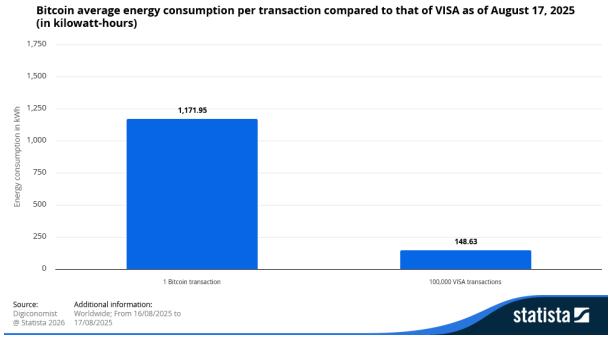


Figure 12: Bitcoin average energy consumption per transaction compared to that of visa as of august 17, 2025 (in Kilowatt-Hours) [221].

Ethereum's energy utilization is shown in Figure 11. Bitcoin average energy consumption per transaction compared to that of VISA as of August 17, 2025 (in kilowatt-hours), is shown in Figure 12.

5.6.1. Energy use and environmental pollution

- Demand:
- The essential concern with respect to Proof of Work (PoW) cryptocurrencies, such as Bitcoin, is their energy-intensive nature. Mining these cryptocurrencies requires solving complex computational issues to approve transactions and secure the blockchain. This process depends on specialized equipment, known as ASICs, and consumes endless amounts of power [197].
- Carbon footprint:
  The carbon footprint of cryptocurrency mining essentially depends on the energy sources utilized. When mining is fueled by fossil fuels like coal or natural gas, it significantly contributes to greenhouse gas emissions and climate change [198].
- Grid instability:
  Large-scale mining operations can put a strain on local and regional electricity grids, causing voltage fluctuations, blackouts, and higher costs for other consumers

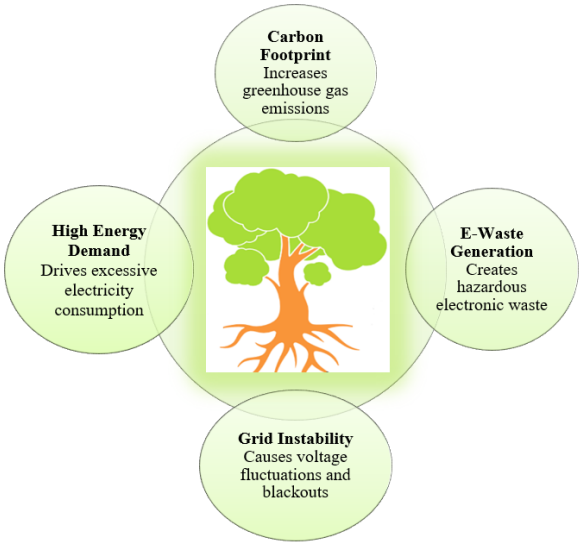


Figure 13: Negative impacts: energy consumption and environmental concerns [197]- [200].

[199].

- Waste:
  The equipment utilized for cryptocurrency mining rapidly becomes obsolete, resulting in a huge amount of electronic waste. This e-waste contains hazardous materials and poses critical environmental dangers [200]. The negative impacts - energy consumption and environmental concerns- are shown in Figure 13.

5.6.2. Potential positive impacts and opportunities

- DR and grid balancing:
  Cryptocurrency mining can serve as a flexible load on the electricity grid, offering DR services to help balance supply and demand. Miners can decrease or shift their electricity consumption during times of high demand or grid stress [201].
- Incentivizing renewable energy development:
  Cryptocurrency mining can increase the demand for renewable energy in remote or underserved areas, encouraging the development of new solar, wind, and hydropower projects [202].
- Blockchain for energy trading:
  Blockchain technology, which underlies cryptocurrencies, can create more efficient and transparent platforms for energy trading. This facilitates P2P energy trading, smart grids, and the integration of DERs [203]. Potential positive impacts and opportunities are shown in Figure 14.

5.7. Electric vehicles and the global energy transformation

The EV market is experiencing rapid global expansion, significantly impacting the energy sector. Projections show that the US EV market might reach a valuation of $104.72 billion by 2025, with an expected annual growth rate of

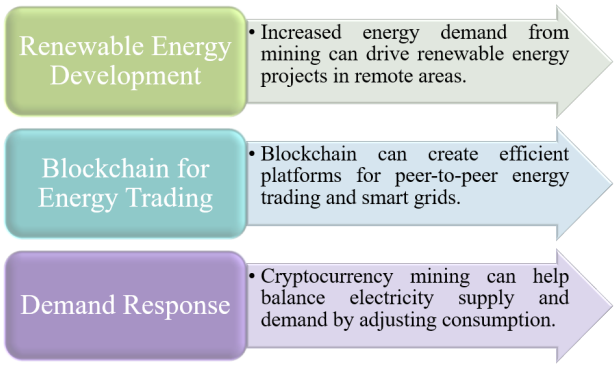


Figure 14: Potential positive impacts and opportunities [203].

10.53%. By that same year, the market is anticipated to reach $377.89 billion. This growing adoption of EVs is driving the demand for expanded charging infrastructure. As of 2023, the United States has roughly 168,400 public EV chargers distributed over 64,600 locations. However, the current charging network struggles to meet this rising demand, with 42% of US consumers citing limited availability of public charging facilities as a major deterrent. Estimates foresee a significant increase in energy demand for EV charging by 2030, with China anticipated to consume over 300 terawatt-hours. This shift in energy utilization is likely to have considerable impacts on the broader energy market, possibly accelerating the move away from conventional fossil fuel sources. To address these infrastructural challenges, government bodies are implementing initiatives such as the US National Electric Vehicle Infrastructure (NEVI) Formula Program. Furthermore, ongoing advancements within the industry, including the adoption of the North American Charging Standard (NACS) by major car manufacturers, are anticipated to improve charging availability and advance market development [206].

In smaller EV markets, sales growth in early 2024 was exceptionally high, beginning from a low base. In January and February, electric car sales quadrupled in Brazil and expanded more than sevenfold in Vietnam, whereas India saw sales rise by over 50%. First-quarter electric car sales have consistently accounted for 15–20% of total annual sales since 2021. Based on this trend and future advancements, we estimate that worldwide electric car sales may reach around 17 million in 2024, reflecting over 20% growth from 2023 and making EVs account for more than one-fifth of total car sales. Electric car sales neared 14 million in 2023, 95% of which were in China, Europe, and the United States [207]. The trend for EVs is shown in Figure 15.

By 2035, the number of public charging stations could expand sixfold, making it easier and more appealing for everyday consumers to embrace the shift to EVs. This refers to charging points that are neither publicly accessible nor located at private residences. The estimated home charging stock for 2023 is based on the electric light-duty vehicle stock and regional assumptions regarding the ratios of

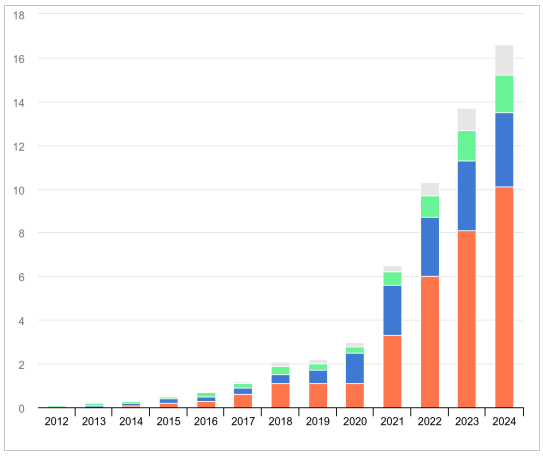


Figure 15: Trend of electric car sales, 2012-2024 [207].

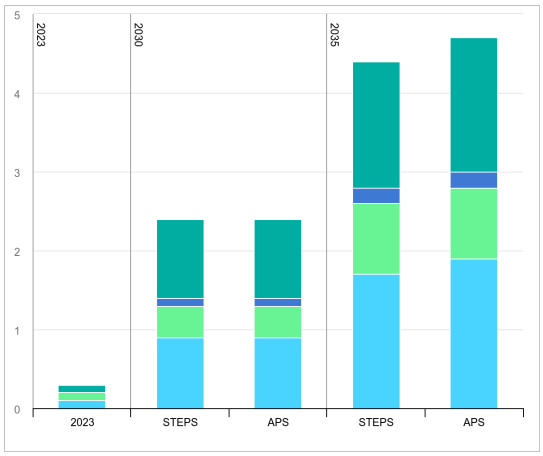


Figure 16: Light-duty vehicle charger capacity, 2023–2035, stated policies scenario, APS [218].

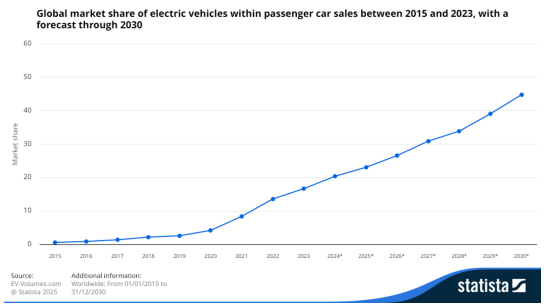


Figure 17: Global Market share of electric vehicles within passenger car sales between 2015 and 2023, with a forecast through 2030 [219].

electric vehicle supply equipment (EVSE) to EVs. You can explore regional projected EVSE stock data through the interactive Global EV Data Explorer [141]. The light-duty vehicle charger capacity for 2023–2035 under the Stated Policies Scenario (STEPS) and Announced Pledges Scenario (APS) is shown in Figure 16.

The EV market is experiencing rapid growth, with its global market share reaching 16.7% of passenger car sales in 2023, and it is also projected to reach 44.8% by 2030 [222]. The global market share of electric vehicles within passenger car sales between 2015 and 2023, with a forecast through 2030, is shown in Figure 17.

AI essentially improves the productivity and flexibility of energy networks. Predictive analytics fueled by AI can forecast energy demand more accurately, leading to optimized asset allocation and reduced waste [208]. This can be particularly critical given the growing number of intermittent RESs, including wind and solar, which require complex balancing frameworks to keep the grid stable. Furthermore, AI algorithms can identify and respond to system abnormalities, improving cybersecurity and reducing the impacts of intrusions [209]. This is especially critical due to the expanding number of distributed RESs, such as wind and solar, which require modern balancing frameworks to preserve network stability. Also, AI algorithms can identify and respond to network abnormalities, improving cybersecurity and minimizing the impact of intrusions [210]. Integrating AI into energy markets and the EV ecosystem poses challenges such as information protection, algorithmic bias, and the need for solid regulations. However, the potential benefits are significant, offering a pathway to a cleaner and more efficient energy future. Ongoing research and thoughtful policy decisions are essential for maximizing AI's impact in these areas [211].

6. Discussion

The energy market has experienced significant changes driven by the increasing integration of renewable energy sources (RESs), the decentralization of energy generation, and the development of smart energy systems. Conventional market models have struggled to accommodate this growing complexity, necessitating innovative approaches that utilize artificial intelligence (AI) and digitalization. This study provides a comprehensive overview of energy markets and trading models, focusing on the integration of AI and advanced technologies to improve efficiency, reliability, and sustainability. Different AI techniques, including machine learning (ML), deep learning, and reinforcement learning, have been investigated in relation to their applications in forecasting, optimization, risk management, and energy market planning [173], [175]. Moreover, the role of digitalization in enabling real-time data exchange, information security, improved communication, and smart

trading platforms has been discussed [177], [187]. The challenges and opportunities associated with adopting AI and digital technologies in the energy sector have also been addressed, highlighting potential barriers and future research directions.

The energy sector is facing significant challenges and opportunities. The global transition toward decarbonization requires a shift from fossil fuels to RESs, particularly solar and wind energy [188]. Traditional energy market models, primarily designed for centralized generation and predictable electricity demand, may not adequately address these evolving operational requirements. Consequently, innovative approaches based on AI, digitalization, and intelligent energy management are essential for optimizing energy generation, distribution, and utilization [173], [187]. AI and digitalization offer considerable opportunities to improve energy market operations in several key areas.

(a) Enhanced forecasting:

Accurate forecasting of renewable energy generation and electricity demand is essential for effective grid management. AI-based algorithms can analyze large volumes of historical and real-time data to identify complex consumption patterns and improve forecasting performance. The integration of smart meter measurements and socioeconomic information can further support the identification of residential electricity consumption patterns [170], [171].

(b) Optimized grid management:

AI-based optimization techniques can improve resource allocation, manage network congestion, and support system stability under fluctuating renewable energy generation. Advanced digital technologies also enable improved monitoring and coordination of distributed energy resources (DERs), thereby enhancing the efficiency and reliability of smart grids and microgrids [173], [177], [187].

(c) Improved market planning:

AI can support the development of more efficient and dynamic energy market mechanisms that encourage DER participation and promote effective resource allocation. Demand bidding optimization and decentralized microgrid market designs offer opportunities to improve market participation and facilitate more efficient energy transactions [166], [183].

(d) Risk management:

AI-supported risk assessment and optimization techniques can assist utilities, market operators, and energy traders in managing uncertainties associated with electricity prices, renewable energy generation, and energy demand. Stochastic approaches, including Monte Carlo simulation (MCS), can support microgrid dispatch planning and risk assessment under uncertain operating conditions [167], [168], [169].

(e) Automated energy trading:

AI-powered trading algorithms can automate energy trading decisions, optimize bidding strategies, and improve market efficiency. The integration of blockchain and ML provides opportunities for decentralized peer-to-peer (P2P) energy trading, while blockchain-based smart trading mechanisms can support renewable energy transactions and green certificate management [55], [180], [184].

Several companies and organizations have implemented AI and digitalization solutions within the energy sector. These initiatives demonstrate the practical potential of advanced technologies and provide useful insights into their applications. Some notable examples are discussed below.

(a) Google's DeepMind:

DeepMind developed AI algorithms to optimize cooling systems in Google's data centers. This application reportedly reduced the energy required for cooling by up to 40% [212].

(b) Siemens:

Siemens has developed smart grid solutions that incorporate digitalization and AI-based technologies to improve grid efficiency, reliability, and security. Such solutions support utilities in monitoring, managing, and optimizing increasingly complex electricity networks.

(c) IBM:

IBM's Watson AI platform has been applied to data-driven decision support, with potential applications in forecasting, infrastructure management, and customer services. AI-based energy platforms can assist utilities in analyzing large datasets, identifying operational patterns, and improving energy management decisions [175].

(d) Grid Singularity:

Grid Singularity has developed blockchain-based approaches for decentralized energy trading. Such technologies are relevant to the development of P2P electricity markets, where producers and consumers can participate in local energy transactions. Blockchain-based energy trading mechanisms and microgrid market designs demonstrate the potential of decentralized approaches to improve transparency and market participation [51], [56], [180], [183].

The implications of cryptocurrency mining and its influence on energy markets have also been examined. Cryptocurrency mining, particularly Bitcoin mining, is associated with substantial electricity consumption, raising concerns regarding energy demand and carbon emissions. The increasing energy requirements of mining activities may create opportunities for renewable energy utilization while introducing additional challenges for electricity network stability. Blockchain-based smart contracts can facilitate P2P energy trading, strengthen consumer participation, and support decentralized electricity markets [180], [183], [184]. Furthermore, the tokenization of energy resources may provide opportunities for developing alternative financing and trading mechanisms for renewable energy projects. However, regulatory uncertainty, cybersecurity risks, and

the volatility of cryptocurrency markets remain important concerns for broader adoption. Blockchain infrastructure security is also an essential consideration when implementing decentralized energy trading platforms [172], [174]. The environmental implications of cryptocurrency mining therefore require further investigation to determine its long-term compatibility with sustainable energy development.

6.1. Future Research Directions

Future research should focus on addressing the technological, operational, and regulatory challenges associated with the increasing adoption of AI and digitalization in modern energy markets [192]. The following research directions are recommended.

- Development of more accurate and robust forecasting models:
  Further research is required to develop forecasting techniques capable of handling the increasing variability and uncertainty associated with renewable energy generation and electricity demand. The integration of advanced AI models with historical consumption data, smart meter measurements, and external variables may improve forecasting reliability and support energy management decisions [170], [173].
- Development of explainable artificial intelligence (XAI) algorithms:
  Research should focus on developing transparent and interpretable AI models that enable users, utilities, and system operators to understand the reasoning behind automated predictions and decisions. Improving model explainability can strengthen confidence in AI-supported energy management and facilitate the practical implementation of intelligent energy platforms [173], [175].
- Development of secure and resilient smart grid architectures:
  Future smart grids should incorporate advanced cybersecurity mechanisms to protect communication networks, metering infrastructure, and distributed energy resources against cyberattacks [74]. Research is also needed to improve fault tolerance, system recovery, and secure data exchange in IoT-enabled smart energy networks [174], [177], [193], [213], [214].
- Development of advanced control algorithms for ESSs and microgrids:
  Advanced control and optimization techniques are required to improve the coordinated operation of energy storage systems, distributed generation units, and microgrids. Stochastic optimization and AI-based control approaches can support efficient energy scheduling, improve system reliability, and address uncertainties associated with renewable energy generation [167], [168], [173].
- Exploration of federated learning for training AI models on distributed data:
  Federated learning offers opportunities for training AI models using datasets distributed across multiple locations without directly exchanging the underlying data. Future research should investigate its applicability to smart meters, distributed energy resources, and decentralized electricity markets, particularly in relation to data privacy, scalability, and model performance [72], [73], [77]. Secure communication and data management remain important considerations in the development of these frameworks [174], [177].
- Development of novel market mechanisms that encourage DER participation:
  Further research should investigate market mechanisms that provide fair compensation for the services offered by distributed energy resources. Demand bidding optimization, decentralized microgrid market structures, and blockchain-based P2P trading mechanisms can contribute to improved market efficiency, transparency, and renewable energy integration [166], [180], [183], [185].

7. Conclusion

The collaboration of AI and digitalization presents a significant opportunity to reshape energy markets and revolutionize built-up trading models. This audit highlights how the integration of AI enables decentralized energy frameworks, reinforces energy productivity, and cultivates the broader adoption of renewable energy and EVs. While these innovative progressions guarantee critical gains, it is essential to recognize and address potential challenges. Concerns encompassing information security, administrative systems, algorithmic bias, and the security scene require cautious thought, guaranteeing that the arrangement of AI is both inventive and morally capable. Looking forward, it is imperative to prioritize the advancement of adaptable and versatile AI-driven arrangements, especially within the setting of LEMs, to successfully oversee the developing complexity of the energy sector. A sustained focus on improving information quality and access, advancing straightforward AI calculations, actualizing vigorous security protocols, and planning inventive market instruments will be vital for realizing a sustainable and impartial energy future. Besides, cultivating industry-specific arrangements for interoperability and a comprehensive understanding of the more extensive natural and societal implications of AI and digitalization are fundamental for capably exploring this transformative scene. By tending to these multifaceted concerns, the total potential of AI and digitalization can be harnessed to construct an energetic future.

Declarations and ethical statements

Conflict of interest: The authors declare that they have no conflicts of interest.

Funding statement: The authors declare that no specific funding was received for this research.

Artificial Intelligence usage statement: During the preparation of this manuscript, the authors used ChatGPT solely for language refinement and grammatical correction. The authors reviewed and revised all generated content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.

Ethical consideration: All data utilized in this study came from publicly available documents and/or materi- als (official metric releases, published scholarly articles, publicly accessible institutional framework documentation).

Availability of data and materials: The paper uses secondary data and the same has been produced by form of tables in the paper.

CRediT authorship contribution statement

Mohammad Parhamfar: Conceptualization, Methodology, Writing- review & editing. **Milad Taheri**: Conceptualization, Methodology, Writing - original draft, review & editing. **Yalda Ghorbani**: Methodology & Visualization.

Publisher's note

Krrish Scientific Publications Pvt. Ltd. and the ***Journal of Applied Sciences and Modelling*** remain neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

[1] Lee C, Diamond D. Trump Signs Executive Order to Undo Obama Climate Policies. CNN. 2017 Mar. 28. Available from: https://www.nytimes.com/2017/03/28/climate/trump-executive-order-climate-change.html

[2] The White House. Statement by President Biden on the executive order on advancing U.S. leadership in artificial intelligence infrastructure. 2025 Jan. 14. Available from: https://bidenwhitehouse.archives.gov/briefing-room/statements-releases/2025/01/14/statement-by-president-biden-on-the-executive-order-on-advancing-u-s-leadership-in-artificial-intelligence-infrastructure/

[3] Gailhofer, P, Herold, A, Schemmel, J. P., Scherf, C. S, de Stebelski, C. U., Köhler, A. R, & Braungardt, S. The role of artificial intelligence in the European green deal (p. 30). Luxembourg, Belgium: *European Parliament*. 2021. Available from: https://www.europarl.europa.eu/thinktank/en/document/IPOL_STU(2021)662906

[4] Hinrichs-Rahlwes, R. Rethinking the European Green Deal: Accelerating the Transformation Toward Energy Independence Based on 100% Renewable Energy In *Mediterranean Architecture and the Green-Digital Transition: Selected Papers from the World Renewable Energy Congress Med Green Forum 2022* 2023 Sep 8 (pp. 389-402). Cham: Springer International Publishing. Available from: https://doi.org/10.1007/978-3-031-33148-0_31

[5] Bateman J. U.S.-China Technological "Decoupling": A Strategy and Policy Framework. Available from: https://carnegieendowment.org/research/2022/04/us-china-technological-decoupling-a-strategy-and-policy-framework

[6] IEA P. World Energy Outlook 2022. *Paris, France: International Energy Agency (IEA)*. 2022 Oct 13;17. IEA, P. Available from: https://www.iea.org/reports/world-energy-outlook-2022

[7] Omotoye GB, Bello BG, Tula ST, Kess-Momoh AJ, Daraojimba AI, Adefemi A. Navigating global energy markets: A review of economic and policy impacts. *International Journal of Science and Research Archive*. 2024 Jan;11(1):195-203. Available from: https://doi.org/10.30574/ijsra.2024.11.1.0029

[8] Capros P, Tasios N, De Vita A, Mantzos L, Paroussos L. Model-based analysis of decarbonising the EU economy in the time horizon to 2050. *Energy Strategy Reviews*. 2012 Sep 1;1(2):76-84. Available from: https://doi.org/10.1016/j.esr.2012.06.003

[9] Chen W, Wu Z, He J, Gao P, Xu S. Carbon emission control strategies for China: a comparative study with partial and general equilibrium versions of the China MARKAL model. *Energy*. 2007;32(1):59-72. Available from: https://doi.org/10.1016/j.energy.2006.01.018

[10] Chen W. The costs of mitigating carbon emissions in China: Findings from China MARKAL-MACRO modeling. *Energy Policy*. 2005 May 1;33(7):885-96. Available from: https://doi.org/10.1016/j.enpol.2003.10.012

[11] Vaillancourt K, Labriet M, Loulou R, Waaub JP. The role of nuclear energy in long-term climate scenarios: An analysis with the World-TIMES model. *Energy Policy*. 2008 Jul 1;36(7):2296-307. Available from: https://doi.org/10.1016/j.enpol.2008.01.015

[12] Dicorato M, L'Abbate A, Minoia A, Trovato M. Pricing criterions in presence of intra-and inter-zonal constraints. *Electric Power Systems Research*. 2003;66(2):179-186. Available from: https://doi.org/10.1016/S0378-7796(03)00044-0

[13] Onat N, Ersoz S. Analysis of wind climate and wind energy potential of regions in Turkey. *Energy*. 2011 Jan 1;36(1):148-56. Available from: https://doi.org/10.1016/j.energy.2010.10.059

[14] Chen H, Wang X, Zhao X. Generation planning using Lagrangian relaxation and probabilistic production simulation. *International Journal of Electrical Power & Energy Systems*. 2004 Oct 1;26(8):597-605. Available from: https://doi.org/10.1016/j.ijepes.2004.04.001

[15] Messner S, Schrattenholzer L. MESSAGE–MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. *Energy*. 2000 Mar 1;25(3):267-82. Available from: https://doi.org/10.1016/S0360-5442(99)00063-8

[16] Rehman S, Bader MA, Al-Moallem SA. Cost of solar energy generated using PV panels. *Renewable and Sustainable Energy Reviews*. 2007 Oct 1;11(8):1843-57. Available from: https://doi.org/10.1016/j.rser.2006.03.005

[17] Shin HC, Park JW, Kim HS, Shin ES. Environmental and economic assessment of landfill gas electricity generation in Korea using LEAP model. *Energy Policy*. 2005 Jul 1;33(10):1261-70. Available from: https://doi.org/10.1016/j.enpol.2003.12.002

[18] Suwala W. Coal sector model: Source data on coal for the energy and power evaluation program (ENPEP). In*Energy and Nuclear Power Planning using the IAEA's ENPEP Computer Package*. Proceedings of a workshop 1997 (No. IAEA-TECDOC–963, pp. 125-136). Available from: https://inis.iaea.org/re

cords/513wv-6pa59

[19] Tomsic M, Urbancic A, Al Mansour F, Merse S. Energy Supply and Demand Planning Aspects in Slovenia. In *Proceedings of the Sixth Forum: Energy day in Croatia* 1997 (No. INIS-HR–98-004, pp. 71-82). Available from: https://inis.iaea.org/records/96dwv-gc581

[20] Kydes AS. Impacts of a renewable portfolio generation standard on US energy markets. *Energy Policy*. 2007 Feb 1;35(2):809-14. Available from: https://doi.org/10.1016/j.enpol.2006.03.002

[21] Trutnevyte E, Hirt LF, Bauer N, Cherp A, Hawkes A, Edelenbosch OY, Pedde S, Van Vuuren DP. Societal Transformations in Models for Energy and Climate Policy: The Ambitious Next Step. *One Earth* . 2019 Dec 20;1(4):423-33. Available from: https://doi.org/10.1016/j.oneear.2019.12.002

[22] Holtschulte D, Erlangga AS, Ortjohann E, Kortenbruck J, Leksawat S, Schmelter A, Premgamone T, Morton D. Local energy markets in Clustering Power System Approach for smart prosumers. In *2017 6th International Conference on Clean Electrical Power (ICCEP)* 2017 Jun 27 (pp. 215-222). IEEE. Available from: https://doi.org/10.1109/ICCEP.2017.8004818

[23] Teotia F, Bhakar R. Local energy markets: Concept, design and operation. In *2016 national power systems conference (NPSC)* 2016 Dec 19 (pp. 1-6). IEEE. Available from: https://doi.org/10.1109/NPSC.2016.7858975

[24] Zhao XS, Wen FS, Gan DQ, Huang MX, Yu CW, Chung CY. Determination of AGC capacity requirement and dispatch considering performance penalties. *Electric Power Systems Research*. 2004 Jul 1;70(2):93-8. Available from: https://doi.org/10.1016/j.epsr.2003.11.004

[25] Joskow PL. Restructuring, Competition and Regulatory Reform in the U.S. Electricity Sector. *Journal of Economic Perspectives*. 1997 Aug 1;11(3):119-38. Available from: https://doi.org/10.1257/jep.11.3.119

[26] Mulder M, Willems B. The Dutch retail electricity market. *Energy Policy*. 2019 Apr 1;127:228-39. Available from: https://doi.org/10.1016/j.enpol.2018.12.010

[27] Sumper A, editor. Local and Micro Power Markets. *John Wiley & Sons* 2019 May 29. Available from: https://doi.org/10.1002/9781119434573.ch2

[28] Cramton P. Electricity market design. *Oxford Review of Economic Policy*. 2017 Dec 1;33(4):589-612. Available from: https://doi.org/10.1093/oxrep/grx041

[29] Luke M. The Disruptive Potential on Electricity Markets of Blockchains. In *World Scientific Encyclopedia of Climate Change: Case Studies of Climate Risk, Action, and Opportunity* Volume 3 2021 (pp. 319-324). Available from: https://doi.org/10.1142/9789811213960_0036

[30] Xu Z, Hu Z, Song Y, Wang J. Risk-Averse Optimal Bidding Strategy for Demand-Side Resource Aggregators in Day-Ahead Electricity Markets Under Uncertainty. *IEEE Transactions on Smart Grid*. 2015 Sep 24;8(1):96-105.. Available from: https://doi.org/10.1109/TSG.2015.2477101

[31] De Vos, K. Negative Wholesale Electricity Prices in the German, French and Belgian Day-Ahead, Intra-Day and Real-Time Markets. *The Electricity Journal*. 2015;28(4):36-50. Available from: https://doi.org/10.1016/j.tej.2015.04.001

[32] Zeinal-Kheiri S, Ghassem-Zadeh S, Shotorbani AM, Mohammadi-Ivatloo B. Real-time energy management in a microgrid with renewable generation, energy storages, flexible loads and combined heat and power units using Lyapunov optimisation. *IET Renewable Power Generation*. 2020 Mar;14(4):526-38. Available from: https://doi.org/10.1049/iet-rpg.2019.0297

[33] Cabot C, Villavicencio M. The demand-side flexibility in liberalised power market: A review of current market design and objectives. *Renewable and Sustainable Energy Reviews*. 2024 Sep 1;201:114643. Available from: https://doi.org/10.1016/j.rser.2024.114643

[34] Habibian M, Downward A, Zakeri G. Multistage stochastic demand-side management for price-making major consumers of electricity in a co-optimized energy and reserve market. *European Journal of Operational Research*. 2020 Jan 16;280(2):671-88. Available from: https://doi.org/10.1016/j.ejor.2019.07.037

[35] Yurdakul O, Ela E, Billimoria F. Flexible Ramping Product Procurement in Day-Ahead Markets. *IEEE Transactions on Energy Markets, Policy and Regulation*. 2024 Sep 3;3(1):13-31. Available from: https://doi.org/10.1109/TEMPR.2024.3453907

[36] Kim HJ, Kim MK. Data-Driven Virtual Power Plant Bidding Strategy in Electricity Markets Integrating Hybrid Forecasting Model and Customized Incentive Demand Response. *IEEE Internet of Things Journal*. 2025 Jan 2;12(10):13851-69. Available from: https://doi.org/10.1109/JIOT.2024.3525060

[37] Castelli M, Groznik A, Popovič A. Forecasting Electricity Prices: A Machine Learning Approach. *Algorithms*. 2020 May 8;13(5):119. Available from: https://doi.org/10.3390/a13050119

[38] Estanqueiro A, Couto A. New electricity markets. The challenges of variable renewable energy. In *Local Electricity Markets* 2021 Jan 1 (pp. 3-20). Academic Press. Available from: https://doi.org/10.1016/B978-0-12-820074-2.00016-2

[39] Liu J, Qian Y, Yang Y, Yang Z.Can Artificial Intelligence Improve the Energy Efficiency of Manufacturing Companies? Evidence from China. *International Journal of Environmental Research and Public Health*. 2022 Feb 13;19(4):2091. Available from: https://doi.org/10.3390/ijerph19042091

[40] Alkkhayat AH, Jaisudha J, Nazira I, Misra N, Durgadevi G, Senthil Kumar R, Gadhave Subhash S. AI-Driven Energy Trading Platforms: Market Dynamics and Challenges. In *E3S Web of Conferences* 2024 Jun (Vol. 540, p. 07001). EDP Sciences. Available from: https://doi.org/10.1051/e3sconf/202454007001

[41] Rojek I, Mroziński A, Kotlarz P, Macko M, Mikołajewski D. AI-Based Computational Model in Sustainable Transformation of Energy Markets. *Energies*. 2023 Dec 14;16(24):8059. Available from: https://doi.org/10.3390/en16248059

[42] Ahmad T, Zhang D, Huang C, Zhang H, Dai N, Song Y, Chen H. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *Journal of Cleaner Production*. 2021 Mar 20;289:125834. Available from: https://doi.org/10.1016/j.jclepro.2021.125834

[43] López I, Goitia-Zabaleta N, Milo A, Gómez-Cornejo J, Aranzabal I, Gaztañaga H, Fernandez E. European energy communities: Characteristics, trends, business models and legal framework. *Renewable and Sustainable Energy Reviews*. 2024 Jun 1;197:114403. Available from: https://doi.org/10.1016/j.rser.2024.114403

[44] Adadi A, Berrada M. Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). *IEEE Access*. 2018 Sep 17;6:52138-60. Available from: https://doi.org/10.1109/

ACCESS.2018.2870052

[45] Adeyemi AB, Ohakawa TC, Okwandu AC, Iwuanyanwu O, Ifechukwu GO. Affordable housing and resilient design: Preparing low-income housing for climate change impacts. *Journal of Sustainable Architecture*. 2024;12(2):45-60. Available from: https://doi.org/10.51594/ijarss.v6i9.1585

[46] Di Vaio A, Palladino R, Hassan R, Escobar O. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research*. 2020 Dec 1;121:283-314. Available from: https://doi.org/10.1016/j.jbusres.2020.08.019

[47] Guo Z, Qin B, Guan Z, Wang Y, Zheng H, Wu Q. A High-Efficiency and Incentive-Compatible Peer-to-Peer Energy Trading Mechanism. *IEEE Transactions on Smart Grid*. 2023 Apr 13;15(1):1075-88. Available from: https://doi.org/10.1109/TSG.2023.3266809

[48] Balasubramaniyan S, Kumar PK, Vaigundamoorthi M, Rahuman AK, Solaimalai G, Sathish T, Vidhya RG. Deep Learning Method to Analyze the Bi-LSTM Model for Energy Consumption Forecasting in Smart Cities. In*2023 International Conference on Sustainable Communication Networks and Application (ICSCNA)* 2023 Nov 15 (pp. 870-876). IEEE. Available from: https://doi.org/10.1109/ICSCNA58489.2023.10370467

[49] Antal C, Cioara T, Antal M, Mihailescu V, Mitrea D, Anghel I, Salomie I, Raveduto G, Bertoncini M, Croce V, Bragatto T. Blockchain based decentralized local energy flexibility market. *Energy Reports*. 2021 Nov 1;7:5269-88. Available from: https://doi.org/10.1016/j.egyr.2021.08.118

[50] Heymann F, Marot A, Subramanian M, Galus M. Risk Evaluation of AI Systems in the Energy Sector - Three Case Studies from TSO Business. In *2024 IEEE 8th Forum on Research and Technologies for Society and Industry Innovation (RTSI)* 2024 Sep 18 (pp. 172-177). IEEE. Available from: https://doi.org/10.1109/RTSI61910.2024.10761769

[51] Parhamfar M, Zabihi A, Taheri M, Oyinna B. Enhancing Cyber Attack Detection in Microgrids for Resilient Energy Networks. *Journal of Modern Technology*. 2024 Nov 25;1(2):75-86. Available from: https://doi.org/10.71426/jmt.v1.i2.pp75-86

[52] Zabihi A, Parhamfar M, Khodadadi M. Strengthening Resilience: A Brief Review of Cybersecurity Challenges in IoT-Driven Smart Grids. *Journal of Modern Technology*. 2024 Nov 25;1(2):106-20. Available from: https://doi.org/10.71426/jmt.v1.i2.pp106-120

[53] Dey PK, Clegg B, Cheffi W. Risk management in enterprise resource planning implementation: a new risk assessment framework. *Production Planning & Control*. 2013 Jan 1;24(1):1-4. Available from: https://doi.org/10.1080/09537287.2011.597038

[54] Borowski PF. Zonal and Nodal Models of Energy Market in European Union. *Energies*. 2020 Aug 13;13(16):4182. Available from: https://doi.org/10.3390/en13164182

[55] Soto EA, Bosman LB, Wollega E, Leon-Salas WD. Peer-to-peer energy trading: A review of the literature. *Applied Energy*. 2021 Feb 1;283:116268. Available from: https://doi.org/10.1016/j.apenergy.2020.116268

[56] Salehi N, Martínez-García H, Velasco-Quesada G, Guerrero JM. A Comprehensive Review of Control Strategies and Optimization Methods for Individual and Community Microgrids. *IEEE Access*. 2022 Jan 13;10:15935-55. Available from: https://doi.org/10.1109/ACCESS.2022.3142810

[57] Arora M, Vishwanath GM, Sharma A, Chilamkurti N. Blockchain-enabled secure energy trading in smart home devices. *Electric Power Systems Research*. 2026 Sep 1;258:113113. Available from: https://doi.org/10.1016/j.epsr.2026.113113

[58] Mololoth VK, Saguna S, Åhlund C. Blockchain and Machine Learning for Future Smart Grids: A Review. *Energies*. 2023;16(1):528. Available from: https://doi.org/10.3390/en16010528

[59] Paul S, Rabbani MS, Kundu RK, Zaman SM. A review of smart technology (Smart Grid) and its features. In*2014 1st International Conference on Non Conventional Energy (ICONCE 2014)* 2014 Jan 16 (pp. 200-203). IEEE. Available from: https://doi.org/10.1109/ICONCE.2014.6808719

[60] Shaikh PH, Nor NB, Nallagownden P, Elamvazuthi I, Ibrahim T. A review on optimized control systems for building energy and comfort management of smart sustainable buildings. *Renewable and Sustainable Energy Reviews*. 2014 Jun 1;34:409-29. Available from: https://doi.org/10.1016/j.rser.2014.03.027

[61] AAli SS, Choi BJ. State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review. *Electronics*. 2020 Jun 22;9(6):1030. Available from: https://doi.org/10.3390/electronics9061030

[62] Hayati A, Gharehveran SS, Shirini K. Electricity price forecasting with ensemble meta-models and SHAP explainers: a PCA-driven approach. *Scientific Reports*. 2026 Jan 28;16(1):6466. Available from: https://doi.org/10.1038/s41598-026-35839-1

[63] Huang M, Ma J, Luo Y, Man KL, Guan SU, Zhang X, Zhu X, Lim EG. RIS-LLM: Reasoning-informed semantic modeling of electricity market price dynamics. *Advanced Engineering Informatics*. 2026 Nov 1;76:104949. Available from: https://doi.org/10.1016/j.aei.2026.104949

[64] Ogundiran J, Asadi E, Gameiro da Silva M. A Systematic Review on the Use of AI for Energy Efficiency and Indoor Environmental Quality in Buildings. *Sustainability*. 2024 Apr 26;16(9):3627. Available from: https://doi.org/10.3390/su16093627

[65] Lin K, Feng P. Machine learning-based price forecasting and risk management in renewable energy markets. *Sustainable Energy Research*. 2026 Dec;13(1):13. Available from: https://doi.org/10.1186/s40807-025-00234-3

[66] Chalal ML, Benachir M, White M, Shrahily R. Energy planning and forecasting approaches for supporting physical improvement strategies in the building sector: A review. *Renewable and Sustainable Energy Reviews*. 2016 Oct 1;64:761-76. Available from: https://doi.org/10.1016/j.rser.2016.06.040

[67] Yue X, Pye S, DeCarolis J, Li FG, Rogan F, Gallachóir BÓ. A review of approaches to uncertainty assessment in energy system optimization models. *Energy Strategy Reviews*. 2018 Aug 1;21:204-17. Available from: https://doi.org/10.1016/j.esr.2018.06.003

[68] Attah RU, Garba BM, Gil-Ozoudeh I, Iwuanyanwu O. Advanced Financial Modeling and Innovative Financial Products for Urban Development: Strategies for Economic Growth. *Int J Eng Res Dev*. 2024;20(11):1362-73. Available from: https://doi.org/10.13140/RG.2.2.15147.96805

[69] Shinde P, Hesamzadeh MR, Date P, Bunn DW. Optimal Dispatch in a Balancing Market With Intermittent Renewable Generation. *IEEE Transactions on Power Systems*. 2020 Aug 5;36(2):865-78. Available from: https://doi.org/10.1109/TPWRS.2020.3014515

[70] Schachter JA, Mancarella P. A critical review of Real Options

thinking for valuing investment flexibility in Smart Grids and low carbon energy systems. *Renewable and Sustainable Energy Reviews*. 2016;56:261-271. Available from: https://doi.org/10.1016/j.rser.2015.11.071

[71] Wu SR, Shirkey G, Celik I, Shao C, Chen J. A Review on the Adoption of AI, BC, and IoT in Sustainability Research. *Sustainability*. 2022 Jun 28;14(13):7851. Available from: https://doi.org/10.3390/su14137851

[72] Michael-Ahile T, Samuels JA, Booysen MJ. A simulation-based assessment of community-based energy trading for circular energy sharing in low-income communities. *Energy Conversion and Management: X*. 2026 May 1;30:101665. Available from: https://doi.org/10.1016/j.ecmx.2026.101665

[73] Huy TH, Maghami A, Papadimitriou C, Nguyen PH, Deconinck G, Tuan LA. DigiRES: Digital Integration of Multi-Energy Flexibility Assets in Regional Energy Systems. In *2025 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)* 2025 Oct 20 (pp. 1-5). IEEE. Available from: https://doi.org/10.1109/ISGTEurope64741.2025.11305282

[74] Rathor SK, Saxena D. Energy management system for smart grid: An overview and key issues. *International Journal of Energy Research*. 2020 May;44(6):4067-109. Available from: https://doi.org/10.1002/er.4883

[75] Jnr BA. Distributed energy prosumer communities and the application of emerging technologies: A systematic literature review. *Sustainable Futures*. 2025 Jun 1;9:100794. Available from: https://doi.org/10.1016/j.sftr.2025.100794

[76] Ahmadzadeh S, Parr G, Zhao W. A Review on Communication Aspects of Demand Response Management for Future 5G IoT-Based Smart Grids. *IEEE access*. 2021 May 20;9:77555-71. Available from: https://doi.org/10.1109/ACCESS.2021.3082430

[77] Kabalci Y, Kabalci E, Padmanaban S, Holm-Nielsen JB, Blaabjerg F.Internet of Things Applications as Energy Internet in Smart Grids and Smart Environments. *Electronics*. 2019 Aug 31;8(9):972. Available from: https://doi.org/10.3390/electronics8090972

[78] Yan Y, Qian Y, Sharif H, Tipper D. A Survey on Smart Grid Communication Infrastructures: Motivations, Requirements and Challenges. *IEEE communications surveys & tutorials*. 2012 Feb 24;15(1):5-20. Available from: https://doi.org/10.1109/SURV.2012.010912.00035

[79] Zhang D, Han X, Deng C. Review on the research and practice of deep learning and reinforcement learning in smart grids. *CSEE Journal of Power and Energy Systems*. 2018 Sep 23;4(3):362-70. Available from: https://doi.org/10.17775/CSEEJPES.2018.00520

[80] Sun Y, Haghighat F, Fung BC. A review of the-state-of-the-art in data-driven approaches for building energy prediction. *Energy and Buildings*. 2020 Aug 15;221:110022. Available from: https://doi.org/10.1016/j.enbuild.2020.110022

[81] Cheng L, Yu T. A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems. *International Journal of Energy Research*. 2019 May;43(6):1928-73. Available from: https://doi.org/10.1002/er.4333

[82] Statista. (n.d.). Energy supply worldwide from 2000 to 2025. Available from: https://www.statista.com/statistics/265598/consumption-of-primary-energy-worldwide/

[83] Trading Economics. (n.d.). Trading Economics. Available from: https://tradingeconomics.com/

[84] Alizadeh MI, Moghaddam MP, Amjady N, Siano P, Sheikh-El-Eslami MK. Flexibility in future power systems with high renewable penetration: A review. *Renewable and Sustainable Energy* . 2016 May 1;57:1186-93. Available from: https://doi.org/10.1016/j.rser.2015.12.200

[85] Zabihi A, Parhamfar M. Decentralized energy solutions: The impact of smart grid-enabled EV charging stations. *Heliyon*, 2025 Aug 1;11(13). Available from: https://doi.org/10.1016/j.heliyon.2025.e41815

[86] Tan Z, Cheng T, Liu Y, Zhong H. Extensions of the locational marginal price theory in evolving power systems: A review. *IET Generation, Transmission & Distribution*. 2022 Apr;16(7):1277-91. Available from: https://doi.org/10.1049/gtd2.12381

[87] Selvakkumaran S, Ahlgren EO. Review of the use of system dynamics (SD) in scrutinizing local energy transitions. *Journal of environmental management*. 2020 Oct 15;272:111053. Available from: https://doi.org/10.1016/j.jenvman.2020.111053

[88] Mendes G, Ioakimidis C, Ferrão P. On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools. *Renewable and Sustainable Energy Reviews*. 2011 Dec 1;15(9):4836-54. Available from: https://doi.org/10.1016/j.rser.2011.07.067

[89] Akram U, Nadarajah M, Shah R, Milano F. A review on rapid responsive energy storage technologies for frequency regulation in modern power systems. *Renewable and Sustainable Energy Reviews*. 2020 Mar 1;120:109626. Available from: https://doi.org/10.1016/j.rser.2019.109626

[90] Sen B, Kumar DS, Krishnan SB, Sharma A. A Review on Peer-to-Peer Energy Trading: Advancements, Challenges, and Future Prospects. In *2025 IEEE 5th International Conference on Sustainable Energy and Future Electric Transportation (SEFET)* 2025 Jul 9 (pp. 1-6). IEEE. Available from: https://doi.org/10.1109/SEFET65155.2025.11255600

[91] Raimi D, Zhu Y, Newell RG, Prest BC. Global Energy Outlook 2024: Peaks or Plateaus. *Resources for the future: Washington, DC, USA*. 2024 Apr 2. Available from: https://www.rff.org/publications/reports/global-energy-outlook-2024/

[92] Wongthongtham P, Marrable D, Abu-Salih B, Liu X, Morrison G. Blockchain-enabled Peer-to-Peer energy trading. *Computers & Electrical Engineering*. 2021 Sep 1;94:107299. Available from: https://doi.org/10.1016/j.compeleceng.2021.107299

[93] Zhang C, Wu J, Long C, Cheng M. Review of Existing Peer-to-Peer Energy Trading Projects. *Energy Procedia*. 2017 May 1;105:2563-8. Available from: https://doi.org/10.1016/j.egypro.2017.03.737

[94] Umar A, Kumar D, Ghose T. Blockchain-based decentralized energy intra-trading with battery storage flexibility in a community microgrid system. *Applied Energy*. 2022 Sep 15;322:119544. Available from: https://doi.org/10.1016/j.apenergy.2022.119544

[95] Zhang T, Hu Z. Optimal Scheduling Strategy of Virtual Power Plant With Power-to-Gas in Dual Energy Markets. *IEEE Transactions on Industry Applications*. 2021 Sep 14;58(2):2921-9. Available from: https://doi.org/10.1109/TIA.2021.3112641

[96] Cali U, Halden U, Andoni M, Catak FO, Chen S, Couraud B, Kantar E, Knapper S, Kucukdemiral I, Kusetogullari H, Kuzlu M. Generative AI and LLM applications in renewable energy and smart grids: a systematic review for the sustainable energy transition. *Artificial Intelligence Review*. 2026 Apr 7. Available from: https://doi.org/10.1007/s10462-026-11545-2

[97] Wang Y, Chen Q, Hong T, Kang C. Review of Smart Meter

Data Analytics: Applications, Methodologies, and Challenges. *IEEE Transactions on smart Grid*. 2018 Mar 22;10(3):3125-48. Available from: https://doi.org/10.1109/TSG.2018.2818167

[98] Ustun TS, Hussain SS. A Review of Cybersecurity Issues in Smartgrid Communication Networks. In*2019 International Conference on Power Electronics, Control and Automation (ICPECA)* 2019 Nov 16 (pp. 1-6). IEEE. Available from: https://doi.org/10.1109/ICPECA47973.2019.8975629

[99] Kwilinski A, Rebilas R, Lazarenko D, Stezhko N, Dzwigol H. The Impact of the COVID-19 Pandemic on the Evolution of Investment Markets in Central and Eastern Europe. /emphForum Scientiae Oeconomia. 2023 Dec. 31;11(4):157-86. Available from: https://doi.org/10.23762/FSO_VOL11_NO4_8

[100] Rocha HR, Honorato IH, Fiorotti R, Celeste WC, Silvestre LJ, Silva JA. An Artificial Intelligence based scheduling algorithm for demand-side energy management in Smart Homes. *Applied Energy*. 2021 Jan 15;282:116145. Available from: https://doi.org/10.1016/j.apenergy.2020.116145

[101] El Mrabet Z, Kaabouch N, El Ghazi H, El Ghazi H. Cybersecurity in smart grid: Survey and challenges. *Computers & Electrical Engineering*. 2018 Apr 1;67:469-82. Available from: https://doi.org/10.1016/j.compeleceng.2018.01.015

[102] Goudarzi A, Ghayoor F, Waseem M, Fahad S, Traore I. A Survey on IoT-Enabled Smart Grids: Emerging, Applications, Challenges, and Outlook. *Energies*. 2022 Sep 23;15(19):6984. Available from: https://doi.org/10.3390/en15196984

[103] Zhang R, Li G, Ma Z. A Deep Learning Based Hybrid Framework for Day-Ahead Electricity Price Forecasting. *IEEE Access*. 2020 Aug 4;8:143423-36. Available from: https://doi.org/10.1109/ACCESS.2020.3014241

[104] Mystakidis A, Koukaras P, Tsalikidis N, Ioannidis D, Tjortjis C. Energy Forecasting: A Comprehensive Review of Techniques and Technologies. *Energies*. 2024 Mar 30;17(7):1662. Available from: https://doi.org/10.3390/en17071662

[105] Zhao C. Can industrial structure optimization and industrial structure transition both lead to carbon lock-in mitigation? The case of China. *Environmental Science and Pollution Research*. 2024 Mar;31(15):23247-61. Available from: https://doi.org/10.1007/s11356-024-32609-2

[106] Hernández Rodríguez M, Baca Ruiz LG, Criado Ramón D, Pegalajar Jiménez MD. Artificial Intelligence-Based Prediction of Spanish Energy Pricing and Its Impact on Electric Consumption. *Machine Learning and Knowledge Extraction*. 2023 May 2;5(2):431-47. Available from: https://doi.org/10.3390/make5020026

[107] Ahmad MW, Mourshed M, Rezgui Y. Tree-based ensemble methods for predicting PV power generation and their comparison with support vector regression. *Energy*. 2018 Dec 1;164:465-74. Available from: https://doi.org/10.1016/j.energy.2018.08.207

[108] Osório GJ, Lotfi M, Shafie-Khah M, Campos VM, Catalão JP. Hybrid Forecasting Model for Short-Term Electricity Market Prices with Renewable Integration. *Sustainability*. 2018 Dec 22;11(1):57. Available from: https://doi.org/10.3390/su11010057

[109] Williams CK, Rasmussen CE. Gaussian Processes for Machine Learning, vol. 2, no. 3. Available from: https://pdfs.semanticscholar.org/6a52/87336aa1a2a653d6df95fac402612fd20772.pdf

[110] Mhlanga D. Artificial Intelligence and Machine Learning for Energy Consumption and Production in Emerging Markets: A Review. *Energies*. 2023 Jan 9;16(2):745. Available from: https://doi.org/10.3390/en16020745

[111] Zhou H, Liu Q, Yan K, Du Y. Deep Learning Enhanced Solar Energy Forecasting with AI-Driven IoT. *Wireless Communications and Mobile Computing*. 2021;2021(1):9249387. Available from: https://doi.org/10.1155/2021/9249387

[112] Dhupia B, Usha Rani M, Alameen A. The Role of Big Data Analytics in Smart Grid Management. *Emerging Research in Data Engineering Systems and Computer Communications: Proceedings of CCODE 2019*. 2020 Feb 11:403-12. Available from: https://doi.org/10.1007/978-981-15-0135-7_38

[113] Liu J, Wang X, Lu Y. A novel hybrid methodology for short-term wind power forecasting based on adaptive neuro-fuzzy inference system. *Renewable Energy*. 2017 Apr 1;103:620-9. Available from: https://doi.org/10.1016/j.renene.2016.10.074

[114] Jędrzejewski A, Lago J, Marcjasz G, Weron R. Electricity Price Forecasting: The Dawn of Machine Learning. *IEEE Power and Energy Magazine*. 2022 Apr 21;20(3):24-31. Available from: https://doi.org/10.1109/MPE.2022.3150809

[115] Wang H, Lei Z, Zhang X, Zhou B, Peng J. A review of deep learning for renewable energy forecasting. *Energy Conversion and Management*. 2019 Oct 15;198:111799. Available from: https://doi.org/10.1016/j.enconman.2019.111799

[116] Notton G, Nivet ML, Voyant C, Paoli C, Darras C, Motte F, Fouilloy A. Intermittent and stochastic character of renewable energy sources: Consequences, cost of intermittence and benefit of forecasting. *Renewable and Sustainable Energy Reviews*. 2018 May 1;87:96-105. Available from: https://doi.org/10.1016/j.rser.2018.02.007

[117] Vrahatis AG, Lazaros K, Kotsiantis S. Graph Attention Networks: A Comprehensive Review of Methods and Applications. 2024 Sep 3;16(9):318. Available from: https://doi.org/10.3390/fi16090318

[118] Aslam S, Herodotou H, Mohsin SM, Javaid N, Ashraf N, Aslam S. A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. *Renewable and Sustainable Energy Reviews*. 2021 Jul 1;144:110992. Available from: https://doi.org/10.1016/j.rser.2021.110992

[119] Haque AU, Nehrir MH, Mandal P. A Hybrid Intelligent Model for Deterministic and Quantile Regression Approach for Probabilistic Wind Power Forecasting. *IEEE Transactions on Power Systems*. 2014 Jan 28;29(4):1663-72. Available from: https://doi.org/10.1109/TPWRS.2014.2299801

[120] Kyriakarakos G. Artificial Intelligence and the Energy Transition. *Sustainability*. 2025 Jan 30;17(3):1140. Available from: https://doi.org/10.3390/su17031140

[121] Heo E, Kim J, Boo KJ. Analysis of the assessment factors for renewable energy dissemination program evaluation using fuzzy AHP. *Renewable and Sustainable Energy Reviews*. 2010 Oct 1;14(8):2214-20. Available from: https://doi.org/10.1016/j.rser.2010.01.020

[122] Bao M, Ding Y, Zhou X, Guo C, Shao C. Risk assessment and management of electricity markets: A review with suggestions. *CSEE Journal of Power and Energy Systems*. 2021 Sep 10;7(6):1322-33. Available from: https://doi.org/10.17775/CSEEJPES.2020.04250

[123] Shen J, Jiang C, Liu Y, Wang X. A Microgrid Energy Management System and Risk Management Under an Electricity Market Environment. *IEEE Access*. 2016 Apr 25;4:2349-56. Available from: https://doi.org/10.1109/ACCESS.2016.2555926

[124] Xie S, Zhang X, Luo J, Wu G, Dong S. Uncertainty management in oil depot risk assessment: Current approaches, challenges, and future directions. *Journal of Loss Prevention in the Process Industries*. 2025 Oct 1;97:105711. Available from: https://doi.org/10.1016/j.jlp.2025.105711

[125] Syntetos AA, Babai Z, Boylan JE, Kolassa S, Nikolopoulos K. Supply chain forecasting: Theory, practice, their gap and the future. *European Journal of Operational Research*. 2016 Jul 1;252(1):1-26. Available from: https://doi.org/10.1016/j.ejor.2015.11.010

[126] Eydeland A, Wolyniec K. Energy and power risk management: New developments in modeling, pricing, and hedging. *John Wiley & Sons* 2002 Dec 30. Available from: https://www.wiley.com/en-br/shop/general-finance-investments/energy-and-power-risk-management-new-developments-in-modeling-pricing-and-hedging-p-9780471104001

[127] Fernandes MJ. Three Essays on Modeling Energy Prices with Time-Varying Volatility and Jumps *(Doctoral dissertation, ISCTE-Instituto Universitario de Lisboa (Portugal))*. Available from: http://hdl.handle.net/10071/22640

[128] Geman H. Commodities and Commodity Derivatives: Modeling and Pricing for Agriculturals, Metals and Energy. BIROn (Birkbeck, University of London). 2009. Available from: https://eprints.bbk.ac.uk/id/eprint/8303/

[129] Gollier C. The Economics of Optimal Insurance Design. In*Handbook of Insurance* 2013 Jul 31 (pp. 107-122). New York, NY: Springer New York. Available from: https://doi.org/10.1007/978-1-4614-0155-1

[130] Saunders A. Credit risk measurement: new approaches to value-at-risk and other paradigms. *John Wiley & Sons;* 1999 Jul 2. Available from: https://www.researchgate.net/publication/239487772_Credit_Risk_Measurement-New_Approaches_to_Value_at_Risk_and_Other_Paradigms

[131] Collier BL, Ellis CM, Keys BJ. The Cost of Consumer Collateral: Evidence From Bunching. *Econometrica*. 2025 May;93(3):779-819. Available from: https://doi.org/10.3982/ECTA22303

[132] Crouhy M, Galai D, Mark R. The essentials of risk management. *New York: McGraw-Hill*; 2006. Available from: https://www.mheducation.com/highered/mhp/product/essentials-risk-management-third-edition.html?viewOption=student

[133] Birge JR, Louveaux F. Basic Properties and Theory. In*Introduction to Stochastic Programming* 2011 May 27 (pp. 103-161). New York, NY: Springer New York. Available from: https://doi.org/10.1007/0-387-22618-4_3

[134] Consigli G, Campos BV, Liu J. Multiperiod interval-based stochastic dominance with application to dynamic portfolios. *Quantitative Finance*. 2025 Apr 3;25(4):543-75. Available from: https://doi.org/10.1080/14697688.2025.2476080

[135] Correa SB, Mosquera-López S, Uribe JM. Time-varying systemic risk in electricity markets using generative adversarial networks: Market resilience and policy. *Energy Policy*. 2026 Mar 1;210:115034. Available from: https://doi.org/10.1016/j.enpol.2025.115034

[136] Westgaard S, Fleten SE, Negash A, Botterud A, Bogaard K, Verling TH. Performing price scenario analysis and stress testing using quantile regression: A case study of the Californian electricity market. *Energy*. 2021 Jan 1;214:118796. Available from: https://doi.org/10.1016/j.energy.2020.118796

[137] Joskow PL. Incentive Regulation in Theory and Practice Electricity Distribution and Transmission Networks. *Book: Economic Regulation and Its Reform: What Have We Learned?*. 2014 Jun 17:291-344. Available from: https://www.nber.org/books-and-chapters/economic-regulation-and-its-reform-what-have-we-learned/incentive-regulation-theory-and-practice-electricity-distribution-and-transmission-networks

[138] Hull J, Hull JC. Risk Management and Financial Institutions. Available from: https://www.wiley.com/en-dk/shop/general-finance-investments/risk-management-and-financial-institutions-5th-edition-p-9781119448099

[139] Penttinen SL. Regulatory and policy instruments to promote decarbonization in the energy sector. In *Research Handbook on Climate Change Mitigation Law* 2022 Sep 8 (pp. 338-362). Edward Elgar Publishing. Available from: https://doi.org/10.4337/9781839101595.00022

[140] Mitchell C, Connor P. Renewable energy policy in the UK 1990–2003. *Energy Policy*. 2004 Nov 1;32(17):1935-47. Available from: https://doi.org/10.1016/j.enpol.2004.03.016

[141] Heydari M, Lai KK, Xiaohu Z. Risk Management in Public-Private Partnerships. *Routledge;* 2020 Dec 28. Available from: https://doi.org/10.4324/9781003112051

[142] Pimenow S, Pimenowa O, Prus P. Challenges of Artificial Intelligence Development in the Context of Energy Consumption and Impact on Climate Change. *Energies*. 2024 Nov 27;17(23):5965. Available from: https://doi.org/10.3390/en17235965

[143] Yenduri G, Ramalingam M, Selvi GC, Supriya Y, Srivastava G, Maddikunta PK, Raj GD, Jhaveri RH, Prabadevi B, Wang W, Vasilakos AV. GPT (Generative Pre-Trained Transformer)—A Comprehensive Review on Enabling Technologies, Potential Applications, Emerging Challenges, and Future Directions. *IEEE Access*. 2024 Apr 15;12:54608-49. Available from: https://doi.org/10.1109/ACCESS.2024.3389497

[144] Liu X, Zeng M. Renewable energy investment risk evaluation model based on system dynamics. *Renewable and Sustainable Energy Reviews*. 2017 Jun 1;73:782-8. Available from: https://doi.org/10.1016/j.rser.2017.02.019

[145] Aien M, Hajebrahimi A, Fotuhi-Firuzabad M. A comprehensive review on uncertainty modeling techniques in power system studies. *Renewable and Sustainable Energy Reviews*. 2016 May 1;57:1077-89. Available from: https://doi.org/10.1016/j.rser.2015.12.070

[146] Alekperov R, Salahli V, Imamguluyev R. Decision Making Under Uncertainty: A Z-Number-Based Regret Principle. *Mathematics*. 2025 Nov 7;13(22):3579. Available from: https://doi.org/10.3390/math13223579

[147] Şen Z. Uncertainty and Modeling Principles. In *Shallow and Deep Learning Principles: Scientific, Philosophical, and Logical Perspectives* 2023 Jun 2 (pp. 141-243). Cham: Springer International Publishing. Available from: https://doi.org/10.1007/978-3-031-29555-3_4

[148] Rahim S, Siano P. A survey and comparison of leading-edge uncertainty handling methods for power grid modernization. *Expert Systems with Applications*. 2022 Oct 15;204:117590. Available from: https://doi.org/10.1016/j.eswa.2022.117590

[149] Ben-Haim Y. Info-Gap Decision Theory Decisions Under Severe Uncertainty 2nd Edition. *Elsevier;* 2006 Oct 11. Available from: https://shop.elsevier.com/books/info-gap-decision-theory/ben-haim/978-0-12-373552-2

[150] Piironen A. Migratory behaviour and year-round distribution of two goose species. Available from: https://urn.fi/URN:

ISBN:978-951-29-9201-0

[151] Reza MS, Hannan MA, Ker PJ, Mansor M, Lipu MH, Hossain MJ, Mahlia TI. Uncertainty parameters of battery energy storage integrated grid and their modeling approaches: A review and future research directions. *Journal of Energy Storage*. 2023 Sep 15;68:107698. Available from: https://doi.org/10.1016/j.est.2023.107698

[152] Liu X, Jiang C. Multi-scale features of volatility spillover networks: A case study of China's energy stock market. *Chaos: An Interdisciplinary Journal of Nonlinear Science*. 2020 Mar 1;30(3). Available from: https://doi.org/10.1063/1.5131066

[153] Brailsford SC, Eldabi T, Kunc M, Mustafee N, Osorio AF. Hybrid simulation modelling in operational research: A state-of-the-art review. *European Journal of Operational Research*. 2019 Nov 1;278(3):721-37. Available from: https://doi.org/10.1016/j.ejor.2018.10.025

[154] Hildebrandt P, Knoke T. Investment decisions under uncertainty—a methodological review on forest science studies. *Forest Policy and Economics*. 2011 Jan 1;13(1):1-5. Available from: https://doi.org/10.1016/j.forpol.2010.09.001

[155] García-Marín S, González-Vanegas W, Murillo-Sánchez CE. MPNG: A MATPOWER-Based Tool for Optimal Power and Natural Gas Flow Analyses. *IEEE Transactions on Power Systems*. 2022 Aug 1;39(4):5455-64. Available from: https://doi.org/10.1109/TPWRS.2022.3195684

[156] Gecgel S, Goztepe C, Kurt GK. Jammer Detection based on Artificial Neural Networks: A Measurement Study. In*Proceedings of the ACM Workshop on Wireless Security and Machine Learning* 2019 May 15 (pp. 43-48). Available from: https://doi.org/10.1145/3324921.3328788

[157] Aminizade F, Zadeh MM, Mohammadi F, Alizadeh MH, Bathaee SM. Scenario generation techniques: From Monte Carlo, Latin hypercube, and beyond. In*Stochastic Planning and Modeling for Energy Systems* 2026 Jan 1 (pp. 25-48). Elsevier. Available from: https://doi.org/10.1016/B978-0-443-45298-7.00007-0

[158] Vose D. Risk analysis: a quantitative guide. *John Wiley & Sons;* 2008 May 5. Available from: https://www.wiley.com/en-be/shop/general-introductory-business-management/risk-analysis-a-quantitative-guide-3rd-edition-p-9780470512845

[159] Díaz H, Teixeira AP, Soares CG. Application of Monte Carlo and Fuzzy Analytic Hierarchy Processes for ranking floating wind farm locations. *Ocean Engineering*. 2022 Feb 1;245:110453. Available from: https://doi.org/10.1016/j.oceaneng.2021.110453

[160] Schuster I, Klebanov I. Markov Chain Importance Sampling—A Highly Efficient Estimator for MCMC. *Journal of Computational and Graphical Statistics*. 2020 Dec 23;30(2):260-8. Available from: https://doi.org/10.1080/10618600.2020.1826953

[161] Zugno M, Conejo AJ. A robust optimization approach to energy and reserve dispatch in electricity markets. *European Journal of Operational Research*. 2015 Dec 1;247(2):659-71. Available from: https://doi.org/10.1016/j.ejor.2015.05.081

[162] Cullen AC, Frey HC. Probabilistic techniques in exposure assessment: a handbook for dealing with variability and uncertainty in models and inputs. *Springer Science & Business;* 1999 Jul 31. Available from: https://link.springer.com/book/9780306459566

[163] Hong LJ, Hu Z, Liu G. Monte Carlo Methods for Value-at-Risk and Conditional Value-at-Risk: A Review. *ACM Transactions on Modeling and Computer Simulation (TOMACS)*. 2014 Nov 18;24(4):1-37. Available from: https://doi.org/10.1145/2661631

[164] de Oliveira S. Economic Feasibility Applied to Wwind Energy Projects. *International Journal of Emerging Sciences*. 2011 Dec 1;1(4):659. Available from: https://www.researchgate.net/profile/Wagner-Sousa-De-Oliveira/publication/224047590_Economic_Feasibility_Applied_to_Wind_Energy_Projects/links/555b325a08ae6fd2d829a96c/Economic-Feasibility-Applied-to-Wind-Energy-Projects.pdf

[165] Sarker IH. Data Science and Analytics: An Overview from Data-Driven Smart Computing, Decision-Making and Applications Perspective. *SN computer science*. 2021 Sep;2(5):377. Available from: https://doi.org/10.1007/s42979-021-00765-8?urlappend=%3Futm_source%3Dresearchgate.net%26utm_medium%3Darticle

[166] Yao L, Lim WH, Tiang SS, Tan TH, Wong CH, Pang JY. Demand Bidding Optimization for an Aggregator with a Genetic Algorithm. *Energies*. 2018 Sep 20;11(10):2498. Available from: https://doi.org/10.3390/en11102498

[167] Fioriti D, Poli D. A novel stochastic method to dispatch microgrids using Monte Carlo scenarios. *Electric Power Systems Research*. 2019 Oct 1;175:105896. Available from: https://doi.org/10.1016/j.epsr.2019.105896

[168] Mokryani G, Siano P. Combined Monte Carlo simulation and OPF for wind turbines integration into distribution networks. *Electric Power Systems Research*. 2013 Oct 1;103:37-48. Available from: https://doi.org/10.1016/j.epsr.2013.05.003

[169] Turner-Bandele N, Pandey A, Pileggi L. A Risk-Managed Steady-State Analysis to Assess the Impact of Power Grid Uncertainties. *arXiv preprint* arXiv:2111.10290. 2021 Nov 19. Available from: https://doi.org/10.48550/arXiv.2111.10290

[170] Tang W, Wang H, Lee XL, Yang HT. Machine learning approach to uncovering residential energy consumption patterns based on socioeconomic and smart meter data. *Energy*. 2022 Feb 1;240:122500. Available from: https://doi.org/10.1016/j.energy.2021.122500

[171] Nuthakki S. Role of AI Enabled Smart Meters to Enhance Customer Satisfaction . *International Journal of Computer Science and Mobile Computing*. 2022 Dec 30. Available from: https://doi.org/10.47760/ijcsmc.2022.v11i12.010

[172] Blossey G, Eisenhardt J, Hahn G. Blockchain Technology in Supply Chain Management: An Application Perspective. 2019. Available from: https://aisel.aisnet.org/hicss-52/os/impact_of_blockchain/6/

[173] Mohammadi E, Alizadeh M, Asgarimoghaddam M, Wang X, Simões MG. A Review on Application of Artificial Intelligence Techniques in Microgrids. *IEEE Journal of Emerging and Selected Topics in Industrial Electronics*. 2022 Aug 15;3(4):878-90. Available from: https://doi.org/10.1109/JESTIE.2022.3198504

[174] Hardjono T, Smith N. Decentralized Trusted Computing Base for Blockchain Infrastructure Security. *Frontiers in Blockchain*. 2019 Dec 6;2:24. Available from: https://doi.org/10.3389/fbloc.2019.00024

[175] Mishra N, Choubey S. Artificial Intelligence-Driven Energy Platforms: Applications and Challenges. In*E3S Web of Conferences* 2024 Jun (Vol. 540, p. 08012). EDP Sciences. Available from: https://doi.org/10.1051/e3sconf/202454008012

[176] Ben-Daya M, Hassini E, Bahroun Z. Internet of Things and

Supply Chain Management: A Literature Review. *International Journal of Production Research*. 2019 Aug 29;57(15-16):4719-42. Available from: https://doi.org/10.1080/00207543.2017.1402140

[177] Abir SA, Anwar A, Choi J, Kayes A. IoT-Enabled Smart Energy Grid: Applications and Challenges. *IEEE access*. 2021 Mar 19;9:50961-81. Available from: https://doi.org/10.1109/ACCESS.2021.3067331

[178] Zhu XX, Tuia D, Mou L, Xia GS, Zhang L, Xu F, Fraundorfer F. Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources. *IEEE Geoscience and Remote Sensing Magazine*. 2017 Dec 31;5(4):8-36. Available from: https://doi.org/10.1109/MGRS.2017.2762307

[179] Ball JE, Anderson DT, Chan CS. Comprehensive survey of deep learning in remote sensing: theories, tools, and challenges for the community. *Journal of Applied Remote Sensing*. 2017 Oct 1;11(4):042609-. Available from: https://doi.org/10.1117/1.JRS.11.042609

[180] Jamil F, Iqbal N, Ahmad S, Kim D. Peer-to-Peer Energy Trading Mechanism Based on Blockchain and Machine Learning for Sustainable Electrical Power Supply in Smart Grid. *IEEE Access*. 2021 Feb 19;9:39193-217. Available from: https://doi.org/10.1109/ACCESS.2021.3060457

[181] Chun J. New Roles for Intermediaries: The Case of Community-Owned Solar Energy Development. *Massachusetts Institute of Technology;* 2023. Available from: https://dspace.mit.edu/entities/publication/90071f91-a92d-4801-9097-d339f2457c8a

[182] Shukla S, Abiha U, Bhutani R, Kapoor N, Shukla SK. Blockchain technology for environmental conservation. In*Microbial biocontrol techniques: Importance in ensuring food security* 2025 Jan 21 (pp. 323-362). Singapore: Springer Nature Singapore. Available from: https://doi.org/10.1007/978-981-97-8739-5_17

[183] Mengelkamp E, Gärttner J, Rock K, Kessler S, Orsini L, Weinhardt C. Designing microgrid energy markets: A case study: The Brooklyn Microgrid. *Applied Energy*. 2018 Jan 15;210:870-80. Available from: https://doi.org/10.1016/j.apenergy.2017.06.054

[184] Guo SM, Feng TT. Blockchain-based smart trading mechanism for renewable energy power consumption vouchers and green certificates: Platform design and simulation. *Applied Energy*. 2024 Sep 1;369:123351. Available from: https://doi.org/10.1016/j.apenergy.2024.123351

[185] Myoung N, Kwon Y, Park M, Eun C. Data Interworking Model and Analysis for Harmonization of Smart Metering Protocols in IoT-Based AMI System. *Sensors*. 2023 Mar 7;23(6):2903. Available from: https://doi.org/10.3390/s23062903

[186] Dragičević T, Siano P, Prabaharan SR. Future Generation 5G Wireless Networks for Smart Grid: A Comprehensive Review. *Energies*. 2019 Jan;12(11):2140. Available from: https://doi.org/10.3390/en12112140

[187] Ninomiya Y, Thomas S, Kolde L, Sasakawa A. Digitalization and the Energy Transition: Use of digitalization to optimize grid operation utilizing AI and Big Data collected from DERs. *Tokyo* , Apr. 2021. Available from: https://gjetc.org/wp-content/uploads/2022/06/GJETC-Study_Digitalization_III_Grid_operation_AI_DERs_FINAL-20210428.pdf

[188] Lopes JP, Hatziargyriou N, Mutale J, Djapic P, Jenkins N. Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. *Electric power systems research*. 2007 Jul 1;77(9):1189-203. Available from: https://doi.org/10.1016/j.epsr.2006.08.016

[189] Meyer MH, DeTore A. Product development for services. *Academy of Management Perspectives*. 1999 Aug 1;13(3):64-76. Available from: https://doi.org/10.5465/ame.1999.2210315

[190] Stiglitz J. Towards a New Paradigm of Development. *Making Globalization Good: The Moral Challenges of Global Capitalism* Oxford University Press, New York, NY. 2003:76-107. Available from: https://doi.org/10.1093/0199257019.003.0005

[191] Shirazi F, Tajvidi M, Adegbite O, Hajli N, Powell P. Strategic integration of big data analytics in R&D: Impact on new product success in turbulent markets. *Industrial Marketing Management*. 2025 Feb 1;125:303-18. Available from: https://doi.org/10.1016/j.indmarman.2025.01.002

[192] Benga B, Elhamma A. Navigating The Digital Frontier: A Literature Review on Business Digitalization. *European Scientific Journal ESJ*. 2024;27. Available from: https://doi.org/10.19044/esj.2024.v20n10p107

[193] Geraci G, Garcia-Rodriguez A, Azari MM, Lozano A, Mezzavilla M, Chatzinotas S, Chen Y, Rangan S, Di Renzo M. What Will the Future of UAV Cellular Communications Be? A Flight From 5G to 6G. *IEEE Communications Surveys & Tutorials*. 2022 May 4;24(3):1304-35. Available from: https://doi.org/10.1109/COMST.2022.3171135

[194] Hiteva R, Foxon TJ. Beware the value gap: Creating value for users and for the system through innovation in digital energy services business models. *Technological Forecasting and Social Change*. 2021 May 1;166:120525. Available from: https://doi.org/10.1016/j.techfore.2020.120525

[195] IEA , Global early-stage venture capital investments in digital energy-efficiency and demand-side flexibility start-ups, by type of new business model, 2015-2021, IEA, Paris. 2022. Available from: https://www.iea.org/data-and-statistics/charts/global-early-stage-venture-capital-investments-in-digital-energy-efficiency-and-demand-side-flexibility-start-ups-by-type-of-new-business-model-2015-2021,

[196] Thomson JC. Tragedy of the Energy Commons: How Government Regulation Can Help Mitigate the Environmental and Public Health Consequences of Cryptocurrency Mining. *eattle Journal of Technology, Environmental, & Innovation Law*. 2020;11:77. Available from: https://digitalcommons.law.seattleu.edu/sjteil/vol11/iss1/4

[197] Koutra A, Tenentes V. Multi-Vt-based energy efficiency optimization for ASIC designs of the double secure hash algorithm toward a sustainable bitcoin network. *IEEE Transactions on Circuits and Systems II: Express Briefs*. 2024 Jan 4;71(3):1596-600. Available from: https://doi.org/10.1109/TCSII.2024.3350035

[198] Stoll C, Klaaßen L, Gallersdörfer U. The Carbon Footprint of Bitcoin. *Joule*. 2019 Jul 17;3(7):1647-61. Available from: https://doi.org/10.1016/j.joule.2019.05.012

[199] Hayes AS. Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and informatics*. 2017 Nov 1;34(7):1308-21. Available from: https://doi.org/10.1016/j.tele.2016.05.005

[200] BBadea L, Mungiu-Pupazan MC. The Economic and Environmental Impact of Bitcoin. *IEEE access*. 2021 Mar 24;9:48091-104. Available from: https://doi.org/10.1109/ACCESS.2021.3068636

[201] Ahl A, Yarime M, Tanaka K, Sagawa D. Review of blockchain-based distributed energy: Implications for institutional devel-

opment. *Renewable and Sustainable Energy Reviews*. 2019 Jun 1;107:200-11. Available from: https://doi.org/10.1016/j.rser.2019.03.002

[202] Küfeoğlu S, Özkuran M. Bitcoin mining: A global review of energy and power demand. *Energy Research & Social Science*. 2019 Dec 1;58:101273. Available from: https://doi.org/10.1016/j.erss.2019.101273

[203] Kirli D, Couraud B, Robu V, Salgado-Bravo M, Norbu S, Andoni M, Antonopoulos I, Negrete-Pincetic M, Flynn D, Kiprakis A. Smart contracts in energy systems: A systematic review of fundamental approaches and implementations. *Renewable and Sustainable Energy Reviews*. 2022 Apr 1;158:112013. Available from: https://doi.org/10.1016/j.rser.2021.112013

[204] De Vries A. BBitcoin's Growing Energy Problem. *Joule*. 2018 May 16;2(5):801-5. Available from: https://www.cell.com/joule/fulltext/S2542-4351(18)30177-6

[205] Wendl M, Doan MH, Sassen R. The environmental impact of cryptocurrencies using proof of work and proof of stake consensus algorithms: A systematic review. *Journal of Environmental Management*. 2023 Jan 15;326:116530. Available from: https://doi.org/10.1016/j.jenvman.2022.116530

[206] Keramidas K, Fosse F, Diaz Rincon A, Dowling P, Garaffa R, Ordonez J, Russ P, Schade B, Schmitz A, Soria Ramirez A, Van der Vorst C. Global Energy and Climate Outlook 2023. *EU JRC, Luxembourg*. 2023 Dec. Available from: https://cretanbusiness.gr/wp-content/uploads/2025/02/JRC139986_01.pdf

[207] IEA , Electric car sales, 2012-2024, IEA, Paris. 2024. Available from: https://www.iea.org/data-and-statistics/charts/electric-car-sales-2012-2024

[208] Xu G, Yang G, Bao J, Feng H, Zhang F, Zheng H. AI-enhanced multi-timescale optimization strategy for virtual power plants: Advancing losad forecasting and dynamic demand response integration. *Plos one*. 2026 Jan 23;21(1):e0339606. Available from: https://doi.org/10.1371/journal.pone.0339606

[209] Berghout T, Benbouzid M, Muyeen SM. Machine learning for cybersecurity in smart grids: A comprehensive review-based study on methods, solutions, and prospects. *International Journal of Critical Infrastructure Protection*. 2022 Sep 1;38:100547. Available from: https://doi.org/10.1016/j.ijcip.2022.100547

[210] Sadeghian O, Oshnoei A, Mohammadi-Ivatloo B, Vahidinasab V, Anvari-Moghaddam A. A comprehensive review on electric vehicles smart charging: Solutions, strategies, technologies, and challenges. *Journal of Energy Storage*. 2022 Oct 1;54:105241. Available from: https://doi.org/10.1016/j.est.2022.105241

[211] Mittelstadt BD, Allo P, Taddeo M, Wachter S, Floridi L. The ethics of algorithms: Mapping the debate. *Big data & society*. 2016 Nov;3(2):2053951716679679. Available from: https://doi.org/10.1177/2053951716679679

[212] IEA , Light-duty vehicle charger capacity, 2023-2035, IEA, Paris. 2024. Available from: https://www.iea.org/data-and-statistics/charts/light-duty-vehicle-charger-capacity-2023-2035-2,

[213] Taheri M, Shahgholian G, Fani B, Mosavi A, Fathollahi A. A Protection Methodology for Supporting Distributed Generations with Respect to Transient Instability. In*2023 IEEE 17th International Symposium on Applied Computational Intelligence and Informatics (SACI)* 2023 May 23 (pp. 000545-000550). IEEE.. Available from: https://doi.org/10.1109/SACI58269.2023.10158594

[214] Taheri M, Parhamfar M, Hajarkesht A, Soleimani A, Güven AF, PINNARELLI A. A Systematic Approach for Protective Relay Coordination and Transient Stability Examination in Energy Networks with Substantial DG Penetration. *Journal of Modern Technology*. 2025 May 5;2(1):264-82. Available from: https://doi.org/10.71426/jmt.v2.i1.pp264-282

[215] Rehman S, El-Amin I. Performance evaluation of an off-grid photovoltaic system in Saudi Arabia. *Energy*. 2012 Oct 1;46(1):451-8. Available from: https://jeip.x-press.org/article_244121.html

[216] Taheri M, Parhamfar M, Moazzami M. Enhancing Large-Scale Solar Power Plant Performance Through an EPC Framework: A 10 MW Grid-Connected Case Study. *Journal of Energy Innovation, Policy & Sustainable Solutions*. 2026 Jun 1;1(1):e244122. Available from: https://jeip.x-press.org/article_244122.html

[217] Basaran K, Chandrakala KV, Lazaroiu GC, Parhamfar M, Roscia M, Lazaroiu AC, Siano P. AI and digitalization in electricity markets with renewables and electric vehicles: A review of price volatility, forecasting, and stability approaches. *Energy*. 2026 Apr 21:141068. Available from: https://doi.org/10.1016/j.energy.2026.141068

[218] Light-duty vehicle charger capacity, 2023-2035. Available from: https://www.iea.org/data-and-statistics/charts/light-duty-vehicle-charger-capacity-2023-2035-2

[219] Statista. Bitcoin Energy Consumption Worldwide. 2025. Available from: https://www.statista.com/statistics/881472/worldwide-bitcoin-energy-consumption/

[220] Ethereum Energy Consumption Worldwide. Available from: https://electroiq.com/stats/ethereum-statistics/

[221] Bitcoin average energy consumption per transaction compared to that of VISA as of August 17, 2025(in kilowatt-hours). Available from: https://www.statista.com/statistics/881541/bitcoin-energy-consumption-transaction-comparison-visa/?srsltid=AfmBOorK-sfHZstf4amvbt8iojvAHfEvsQNy27iBfYKeZzO4C9Vbad5K

[222] Global market share of electric vehicles within passenger car sales between 2015 and 2023, with a forecast through 2030. Available from: https://search.eitaa.com/?url=https://www.statista.com/statistics/1371599/global-ev-market-share/?srsltid=AfmBOorPwDBswEb5_xhDKpXFo3-EN75XbqsI_W1ukNe_BvNdvoaoeqEi

[223] Energy Balances. Available from: https://ec.europa.eu/eurostat/cache/visualisations/energy-balances/enbal.html?geo=EU27_2020&unit=KTOE&language=EN&dataset=nrg_bal_c

[224] Hancock MA, Stanlake M, Cowan PC, Van Gorp JC, Kidd D, Lindsay HT, Toffler J, Gamroth C, Wu K, Marinakis D, inventors; Schneider Electric USA Inc, assignee. Method and system for managing an electrical distribution system in a facility. *United States Patent US* 10,025,337. 2018 Jul 17. Available from: https://patents.google.com/patent/US10025337B2/en