Journal of Energy and Power Engineering 19 (2025) 74-83
doi: 10.17265/1934-8975/2025.02.004

Forecasting the Future: How Artificial Intelligence Is Revolutionizing Global Energy Demand Prediction

Farhang Mossavar-Rahmani[1] and Bahman Zohuri[2]

1. Finance School of Business, Technology, and Engineering, National University, San Diego 92110, California, USA

2. Ageno School of Business, Golden Gate University, San Francisco 94105, California, USA

Abstract: Accurate energy demand forecasting is crucial in today's rapidly electrifying world with decentralized systems and integrated renewables. Traditional models struggle with the dynamic complexities, but AI (artificial intelligence), particularly ML (machine learning) and DL (deep learning), offers transformative solutions. This article explores how AI enhances forecasting accuracy, enables real-time adaptability, and supports strategic energy management. It examines the synergy between AI, IoT (Internet of Things) devices, and smart grids in generating predictive and prescriptive insights. Through case studies, we analyze the benefits and challenges of deploying AI in this domain, including data quality, model explainability, and infrastructure needs. Ultimately, AI emerges as a key enabler for the resilient, data-driven energy systems required to meet modern society's evolving demands and achieve a sustainable future.

Key words: Energy demand forecasting, AI, ML, smart grid, time-series prediction, DL models, IoT, renewable energy integration, real-time energy analytics, sustainable energy planning.

1. Introduction

The global energy landscape is undergoing a profound transformation driven by technological, environmental, and socio-economic factors. As nations strive to meet ambitious climate targets and transition toward more sustainable energy systems, the ability to accurately forecast energy demand has never been more critical. Reliable demand forecasting is central to maintaining grid stability, optimizing energy production, integrating renewable resources, managing costs, and shaping energy policy [1].

Historically, energy demand forecasting has relied heavily on statistical models that use historical consumption patterns, demographic data, and macroeconomic indicators. While these traditional methods have provided a foundational framework, they are increasingly inadequate in the face of today's complex and rapidly evolving energy systems. Emerging trends such as the electrification of transportation, the proliferation of DERs (distributed energy resources), the growth of smart grids, and the volatility introduced by intermittent renewable sources like solar and wind, introduce dynamics that traditional statistical models struggle to capture accurately. This necessitates a more agile and intelligent approach, as illustrated in Fig. 1, which depicts the shift from traditional methods towards more advanced techniques (potentially mentioning AI (artificial intelligence) here in Fig. 1 specifically shows that).

AI is emerging as a game-changer in this context. Leveraging techniques such as ML (machine learning), DL (deep learning), and NNs (neural networks), AI systems can analyze vast volumes of structured and unstructured data to recognize patterns, detect anomalies, and make highly accurate, real-time forecasts. These models adapt to changing behaviors and climate patterns and learn and improve continuously, offering significant advantages over static models.

Corresponding author: Bahman Zohuri, Ph.D., adjunct professor, research fields: artificial intelligence and machine learning.

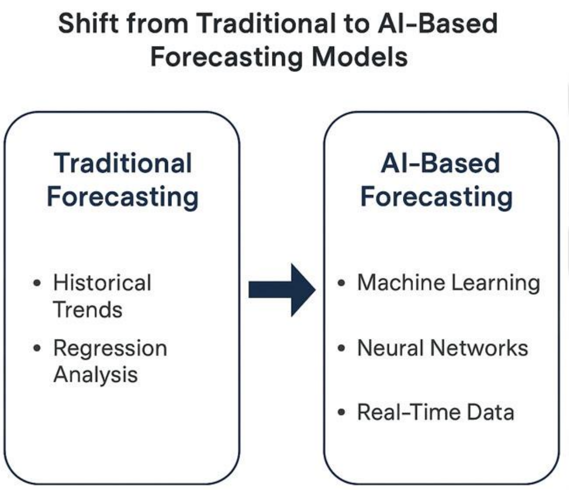

Fig. 1 A shift from traditional to AI forecasting [1].

See Fig. 2, which illustrates the relationships between AI, ML, and DL infrastructure, which is called the pyramid of this relationship and its historical trend. Furthermore, Fig. 3 presents ML functionalities as a high-level diagram of the layout of such an approach.

In addition to enhancing forecasting precision, AI contributes to a more responsive and flexible energy grid. AI can interpret granular, real-time data across residential, commercial, and industrial sectors by integrating smart meters, IoT sensors, and advanced EMSs (energy management systems). This enables utilities and grid operators to shift from reactive to proactive strategies in energy balancing, demand response, and outage prevention.

Furthermore, accurate energy demand forecasting is pivotal in energy economics and policy-making. Governments and energy agencies rely on forecast data to make long-term infrastructure investments, regulate tariffs, and design incentive structures for energy efficiency and decarbonization. By augmenting these efforts with AI-driven insights, stakeholders can make more informed, forward-looking decisions that align with sustainability goals.

This article delves into AI's technological advancements and real-world applications in energy demand forecasting. It investigates how AI is reshaping the way energy is planned, distributed, and consumed while also addressing the challenges associated with its implementation. We aim to illuminate AI's central role in building a resilient and sustainable energy future through detailed analysis and case studies.

2. The Need for Advanced Forecasting Models

Accurate energy demand forecasting is foundational to the reliable and economic operation of energy systems. It influences nearly every aspect of the power sector—from capacity planning, fuel procurement, and load dispatching to long-term infrastructure investment and regulatory policymaking. Traditionally, forecasting models have relied on statistical techniques such as autoregressive models, linear regression, and econometric methods. These approaches typically use historical consumption data, seasonal trends, and macroeconomic indicators to predict future demand [1].

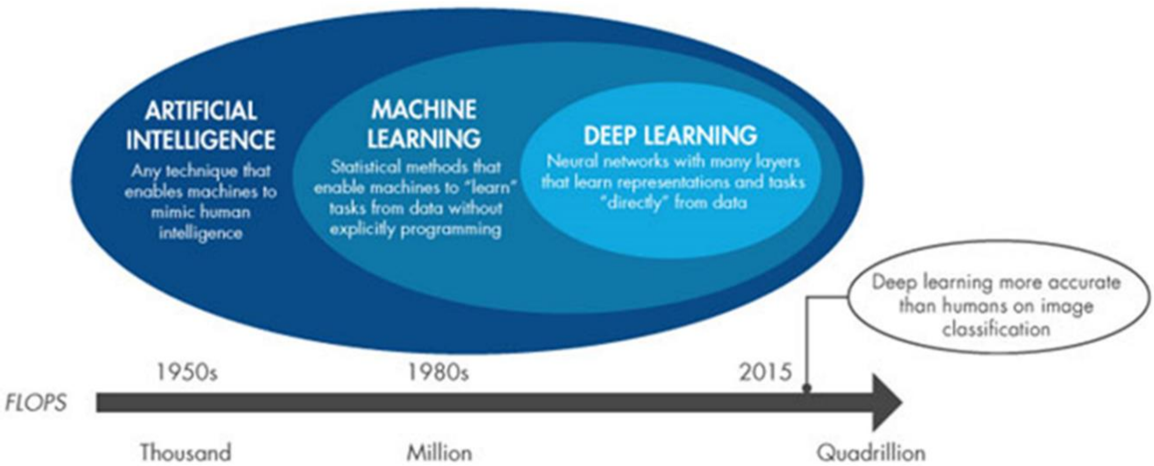

Fig. 2 Pyramid of AI, ML and DL historical trend [2].

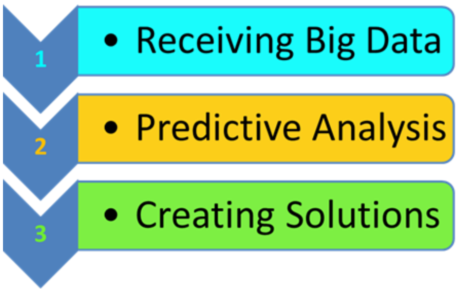

Fig. 3 ML functionality [2].

However, the energy ecosystem of the 21st century is vastly more dynamic, decentralized, and uncertain than in previous decades [3, 4]. Several key factors are driving the need for more advanced forecasting models.

2.1 Increasing Demand Complexity

Energy consumption patterns have become more variable due to shifts in lifestyle, digitization, and economic structures. This complexity is further amplified by the rise of DERs, including rooftop solar and home battery storage, which make consumption significantly less predictable at individual and neighborhood levels.

2.2 Electrification of End-Use Sectors

The electrification of transport (e.g., electric vehicles), heating (e.g., heat pumps), and industrial processes fundamentally alters energy load profiles and creates new demand peaks. This trend introduces significant unpredictability; the charging behavior of electric vehicles (EVs) alone, for instance, adds a new layer of complexity that legacy models cannot adequately capture.

2.3 Integration of Intermittent Renewable Sources

Renewable energy sources like solar and wind are inherently variable and dependent on weather conditions. As their penetration in the generation mix increases, accurately forecasting the *net load* (total demand minus renewable generation) becomes critically important. This necessitates coupling precise energy demand forecasts with equally accurate renewable generation forecasts—a complex task where AI excels due to its capability in multi-variable, non-linear modeling.

2.4 Smart Devices and Prosumer Behavior

Customers are becoming "prosumers" who actively control their energy consumption as a result of the widespread usage of smart appliances, home EMSs, and dynamic pricing schemes. They now exhibit very erratic behavior, reacting quickly to weather predictions, price signals, and individual preferences. This introduces a level of complexity and non-linearity that traditional forecasting techniques struggle to model accurately.

2.5 Climate Change and Weather Volatility

Climate change-driven unpredictable weather patterns, such as heat waves, cold snaps, and severe storms, have a big influence on energy consumption, especially for heating and cooling. Models that can incorporate current meteorological information and climatic patterns are necessary to accurately estimate demand in this unstable environment. AI models are uniquely suited for this task, enabling more adaptive and accurate predictions.

2.6 Real-Time Grid Operations

Grid operators demand near real-time forecasting capabilities to effectively enable demand response, facilitate load shifting, and optimize storage systems. Traditional batch forecasts, typically updated only daily or weekly, are fundamentally too slow for these dynamic operational needs.

2.7 Summary

Collectively, these drivers underscore an urgent need for adaptive, high-resolution, and scalable energy forecasting models. AI presents a compelling solution.

AI models are capable of processing the unprecedented volume and variety of data generated by modern energy systems, identifying complex, non-obvious patterns, and delivering both short- and long-term forecasts with a precision far exceeding traditional techniques.

Table 1 compares traditional forecasting methods with AI-based approaches.

The visual chart of Table 1, which is comparing traditional and AI-based forecasting methods across key performance aspects, could be presented as in Fig. 4.

Table 1 Traditional vs. AI-based forecasting methods.

	Aspect	Traditional forecasting	AI based forecasting
1	Modeling approach	Statistical models (e.g., regression, ARIMA)	ML, NNs, DL
2	Data inputs	Historical consumption & economic indicators	Multi-source data (weather, IoT, consumption)
3	Adaptability	Limited adaptability	Highly adaptive self-learning
4	Accuracy with complex patterns	Low to moderate	High
5	Response to real-time data	Not real-time; often batch-processed	Real-time capable
6	Integration with smart grid/IoT	Minimal to more	Fully compatible
7	Handling of nonlinear relationships	Poor	Excellent
8	Scalability	Low	High
9	Forecasting resolution	Daily to monthly	Hourly to sub-minute
10	Suitability for renewable integration	Challenging	Highly suitable

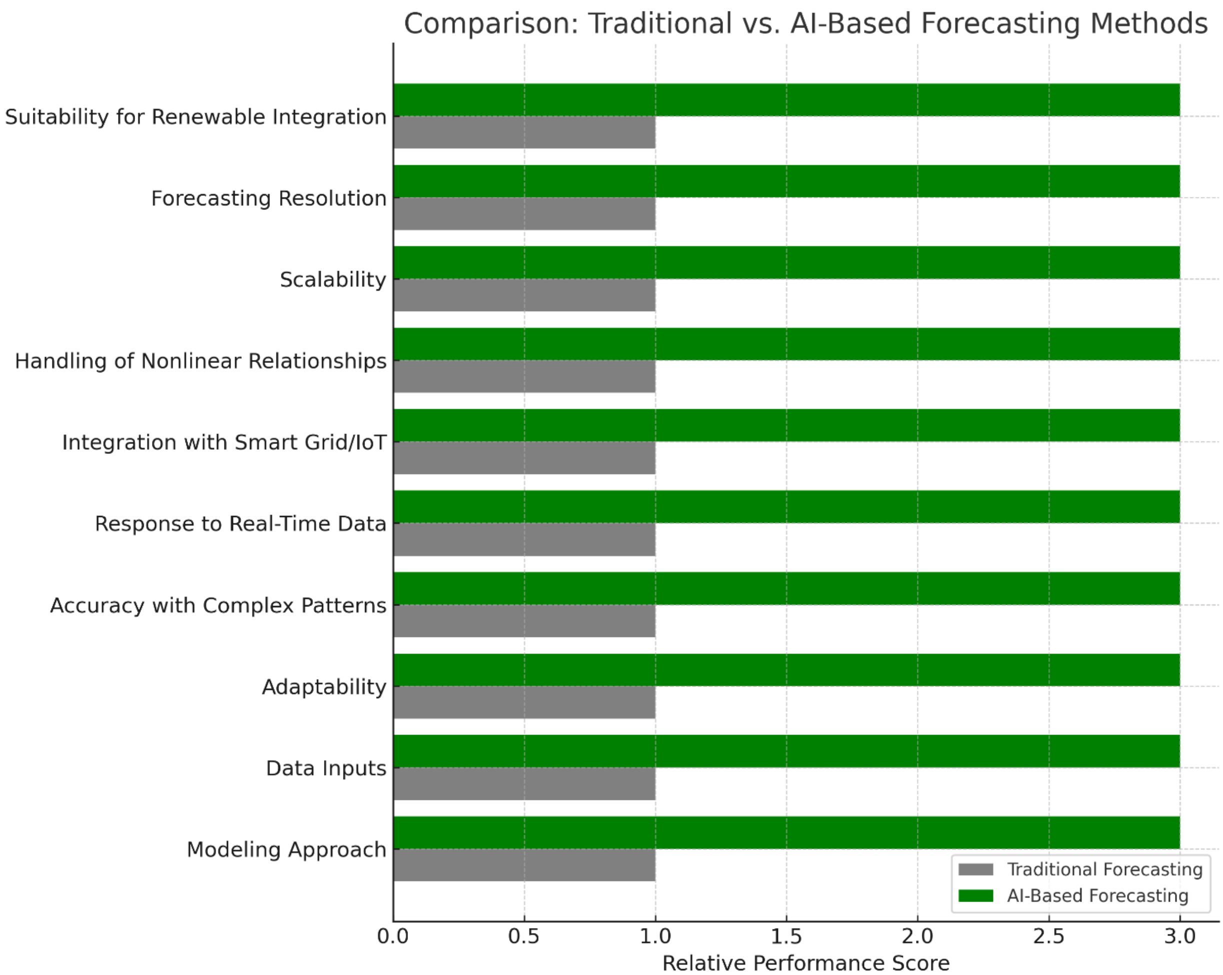

Fig. 4 Forecasting comparison chart.

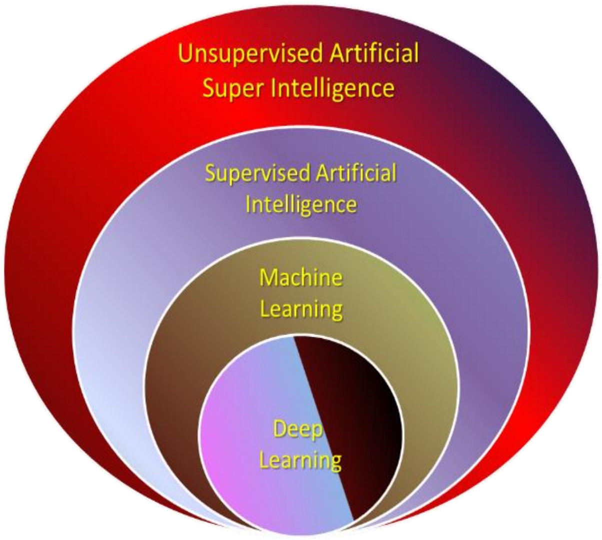

Fig. 5 Schematic of AI levels [2].

3. Role of AI in Energy Demand Prediction

AI as depicted in Fig. 5, has emerged as a powerful tool for forecasting energy demand in an increasingly complex and dynamic global energy system.

Traditional methods, while useful for linear and stable environments, often fall short in capturing the nonlinear, high-frequency, and multi-dimensional nature of modern energy consumption.

AI, particularly through ML and DL algorithms, addresses these shortcomings by learning patterns directly from data—without requiring strict assumptions about underlying relationships.

3.1 AI Techniques in Demand Forecasting

AI offers a range of methods that can be tailored to short-term, medium-term, and long-term forecasting needs [1, 5-7]:

- ML models such as SVMs (support vector machines), Random Forests, and Gradient Boosted Trees are well-suited for handling multivariate inputs and capturing complex interactions between features.
- DL techniques, particularly RNNs (recurrent neural networks) and their enhanced variant LSTM (long short-term memory) networks, excel at modeling sequential and time-dependent data, making them ideal for forecasting hourly or sub-hourly load.
- CNNs (convolutional neural networks) are also used, particularly when spatial energy usage data (e.g., from smart cities or building clusters) are involved.
- Hybrid AI models, combining ML/DL with statistical methods or optimization algorithms, are increasingly popular for improving accuracy and robustness.

3.2 Input Data Sources

Traditional Techniques Common (TTC) inputs include:

- Historical consumption data
- Real-time weather information (temperature, humidity, solar radiation)
- Calendar and behavioral factors (holidays, day of week, events)
- Economic indicators (GDP (gross domestic product), industrial activity)
- Smart meter and sensor data (from IoT (Internet of Things) devices)
- Energy price signals and tariffs

By integrating these diverse inputs, AI models generate forecasts that are both granular and context-aware, adapting to behavioral shifts and environmental conditions in real time.

3.3 Applications across Time Horizons

AI is used across various forecasting horizons:

- Short-term (minutes to hours): For operational decisions, load balancing, and grid stability
- Medium-term (days to weeks): For maintenance planning, unit commitment, and fuel procurement
- Long-term (months to years): For infrastructure development, capacity expansion, and energy policy planning

Each of these horizons can benefit from different AI model architectures and learning paradigms.

3.4 Predictive and Prescriptive Power

Beyond forecasting (predictive analytics), AI also enables prescriptive analytics—recommending optimal actions based on predicted demand. For instance, AI models can trigger automated demand response mechanisms, adjusting thermostats, EV charging rates, or industrial processes to balance the grid efficiently [1].

3.5 Enhancing Situational Awareness

AI-based forecasting tools can be integrated into EMS and SCADA (supervisory control and data acquisition) systems. This improves the situational awareness of grid operators, allowing them to proactively manage anomalies, outages, or surges.

3.6 Case in Point: Google's DeepMind & UK National Grid

A notable example is the collaboration between Google DeepMind and the UK's National Grid, where AI models were deployed to predict electricity demand with high accuracy and help manage energy flows more efficiently. These systems used weather, market, and consumption data to forecast grid behavior and optimize energy distribution, reducing carbon emissions and improving reliability.

In summary, an overview of all the above points is depicted as a flowchart or diagram illustrating of Fig. 6 that shows how AI forecasting models process and integrate multi-source data in real time.

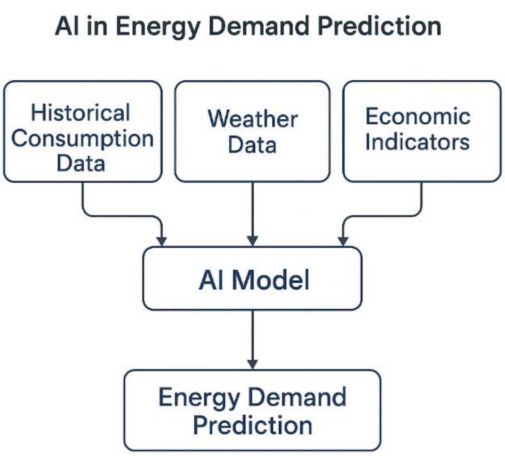

Fig. 6 AI driven energy demand prediction [1].
Source: AI Generated image.

4. Integration with Smart Grid and IoT

The deployment of AI in energy demand forecasting is significantly amplified by its integration with smart grid technologies and the IoT. Together, they form a real-time, interconnected ecosystem that collects, analyzes, and responds to dynamic energy usage patterns—enabling grid operators, utility providers, and consumers to act on insights with unprecedented precision, as artistic art depiction of it is illustrated in Fig. 7.

4.1 The Smart Grid Framework

A smart grid is an upgraded version of the traditional electrical grid that uses digital communication technologies to monitor, automate, and control the flow of electricity from generation to end-users. It supports:

- Bidirectional energy flow (enabling both consumption and prosumption)
- Real-time monitoring and diagnostics
- DER integration
- Demand-side management and peak load reduction

Within this intelligent infrastructure, AI acts as the central decision engine, continuously analyzing data and predicting future demand patterns. This ensures that energy supply and consumption remain balanced and optimized in real time

4.2 Role of IoT in Data Acquisition

The IoT layer of the energy system consists of a wide array of connected sensors, meters, and actuators that generate high-resolution data on energy usage, grid health, environmental conditions, and device status. Examples include:

- Smart meters (track electricity consumption in real time)
- Home EMSs (monitor appliances and EVs)
- Weather stations (feed real-time forecasts to AI models)
- Industrial IoT devices (measure and control energy use in factories)

AI leverages this rich data stream to uncover demand anomalies, detect inefficiencies, and anticipate energy needs at granular spatial and temporal resolutions.

4.3 Edge AI and Distributed Intelligence

With increasing volumes of data, processing everything in centralized cloud servers can lead to latency issues. Edge AI offers a solution by deploying ML models closer to the data source—within smart meters, substations, or even smart homes. Benefits include:

- Low latency predictions
- Localized decision-making (e.g., adjusting EV charging)
- Reduced bandwidth usage
- Improved resilience in case of network failure

This decentralized intelligence allows each node in the smart grid to contribute to global demand forecasting while acting independently to optimize local conditions.

4.4 Predictive and Autonomous Grid Management

AI-enhanced smart grids can:

- Anticipate demand surges and reroute power accordingly
- Trigger automated demand response actions (e.g., lower heating, ventilation, and air conditioning (HVAC) use during peak hours)
- Optimize battery storage dispatch to smooth renewable variability
- Predict equipment failures before they occur, improving asset management and minimizing outages

These features reduce operational costs, improve reliability, and support the integration of renewable energy by flattening peaks and balancing intermittent supply.

Fig. 7 AI driving smart grid, smart city illustration.
Source: ClipArt.com.

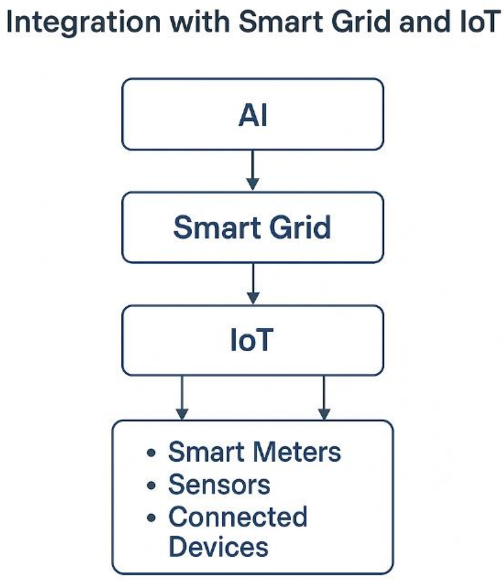

Fig. 8 Integration with smart grid and IoT illustration.
Source: AI generated image.

4.5 Consumer Empowerment and Feedback Loops

The fusion of AI, IoT, and smart grids also empowers consumers through:

- Personalized energy insights
- Dynamic pricing based on real-time demand
- Behavioral nudges for conservation
- Automated control of devices based on AI recommendations

Consumers become active participants in energy management—forming a "prosumer" economy where energy usage decisions are both informed and optimized.

In summary, an overview of all the above points is depicted as a flowchart or diagram illustrated in Fig. 8 that shows how AI integration with smart grid and IoT is mingling with each other.

5. Benefits and Challenges

AI offers transformative benefits for energy demand forecasting, boosting accuracy, efficiency, and responsiveness in power systems. However, like any emerging technology, its implementation introduces a new set of challenges. This section explores both the advantages that AI brings to energy demand management and the obstacles that must be overcome to fully realize its potential. Table 2 summarizing benefits and challenges of this new innovative approach proposed technology in perspective as can be seen below.

In summary, AI enhances energy demand forecasting by delivering high-resolution, real-time predictions and enabling dynamic grid management. However, it introduces challenges such as data quality issues, model transparency, and cybersecurity risks that must be addressed for reliable implementation [8-10].

6. Future Outlook

The convergence of AI, smart infrastructure, and decentralized energy systems is poised to redefine the future of energy demand forecasting. As energy grids transition toward cleaner, more distributed, and digitally connected ecosystems, the role of AI will expand from prediction to proactive system orchestration. This section explores the future trajectory of AI in energy demand forecasting and the transformative possibilities it presents.

Table 3 is summarizing to what future holds for this innovative technology [11, 12].

Table 3 is an overall presentation of future outlook of energy demand forecasting, as energy grids transition toward cleaner, decentralized, and digitally connected systems, AI is expected to evolve from a predictive tool to a proactive orchestrator.

Table 2 Benefits vs. challenges of AI in energy demand forecasting.

Benefits	Challenges
High-resolution, real-time forecasts	Data silos and inconsistent quality
Dynamic adaptation to changes	Lack of transparency in model decision-making
Enhanced renewable integration	High computational and operational costs
Smarter, automated demand response	Cybersecurity and privacy concerns
Reduced generation and operational costs	Unclear regulatory and ethical standards

Table 3 Summary: what the future holds.

Emerging trend	Impact on forecasting
Autonomous AI grid control	Self-adjusting load, real-time dispatch
Climate-aware forecasting	Adaptation to weather volatility and long-term climate shifts
Multi-energy vector forecasting	Unified load predictions across electricity, heating, and hydrogen
Edge AI in microgrids	Localized, fast-response energy intelligence
Democratized AI platforms	Broader access to tools and shared forecasting models
AI in policy design	Data-driven energy laws, dynamic tariffs, resilience planning
Ethical & explainable AI	Transparent, accountable, and trusted predictions

7. Conclusion

The global energy sector is undergoing a profound digital transformation, with AI emerging as a pivotal technology. The increasing complexity and multi-variable nature of modern energy systems—driven by distributed generation, electrification, and climate variability—highlight the limitations of traditional forecasting models. AI directly addresses this gap, offering intelligent, data-driven, and adaptive solutions essential for utilities, policymakers, and consumers alike.

As explored in this article, AI seamlessly integrates with smart grids and IoT systems to harness real-time data from diverse sources like weather sensors, smart meters, and economic indicators. Advanced AI models, including NNs, DL architectures, and hybrid algorithms, learn from this data to generate accurate short- and long-term demand forecasts. These sophisticated forecasts are vital for effectively balancing intermittent renewable supply, reducing operational costs, and ensuring grid reliability in an increasingly decarbonized landscape.

Evidence from real-world case studies across the UK, U.S., India, France, and Singapore demonstrates that AI deployment in energy is operational, measurable, and scalable, not merely theoretical. Building on the foundation of enhanced forecasting, AI's role is set to expand significantly as systems mature. It will move beyond support functions towards autonomously managing energy flows, guiding energy markets, and informing regulatory frameworks. AI-powered insights will increasingly enable grid operators to implement predictive maintenance, automate demand response, and optimize the integration of intermittent renewables.

Despite its transformative potential, the journey toward fully AI-enabled energy systems faces notable challenges. Issues concerning data quality and governance, computational requirements, cybersecurity, regulatory compliance, and ethical transparency must be proactively addressed to build trust and ensure resilience. The development of XAI (Explainable AI), robust data governance policies, and open-source standardization will be critical enablers in this transition.

Looking ahead, AI is poised to fundamentally redefine how energy systems are planned, consumed, and governed. Its synergistic integration with edge computing, multi-energy systems, advanced climate models, and policy engines points towards a future where energy demand forecasting becomes an autonomous, decentralized, and democratized function. This evolution will be instrumental in powering a smarter, greener, and truly sustainable global energy future.

References

[1] Zohuri, B., Rahmani, F. M., and Behgounia, F. 2022. *Knowledge Is Power in Four Dimensions: Models to Forecast Future Paradigm: With Artificial Intelligence Integration in Energy and Other Use Cases* (1st ed.). New York: Academic Press.

[2] Zohuri, B., and Zadeh, S. 2020. *Artificial Intelligence Driven by Machine Learning and Deep Learning.* Hauppauge, NY: Nova Science Pub Inc.

[3] International Energy Agency (IEA). 2022. "Digitalization and Energy." https://www.iea.org/reports/digitalisation-and-energy.

[4] Ahmad, T., Chen, H., Wang, J., and Guo, Y. 2020. "A Review on Applications of Artificial Intelligence in Building Energy Prediction." *Energy and Buildings* 211: 109831. https://doi.org/10.1016/j.enbuild.2020.109831.

[5] Hong, T., Pinson, P., Fan, S., Zareipour, H., and Troccoli, A. 2020. "Big Data Analytics in Energy Forecasting: Current Status and Future Directions." *Energy and AI* 1: 100006. https://doi.org/10.1016/j.egyai.2020.100006.

[6] Mocanu, E., Nguyen, P. H., Gibescu, M., and Slootweg, J. G. 2018. "Deep Learning for Estimating Building Energy Consumption." *Sustainable Energy, Grids and Networks* 6: 91-9. https://doi.org/10.1016/j.segan.2018.03.002.

[7] DeepMind & National Grid ESO. 2020. "Using AI to Help Manage Energy Systems in the UK." https://www.deepmind.com/blog/deepmind-and-national-grid.

[8] Zhang, Y., Wang, J., Wang, X., and Liu, Y. 2019. "Review on the Research and Practice of Deep Learning and Reinforcement Learning in Smart Grids." *CSEE Journal of Power and Energy Systems* 5 (1): 1-10. https://doi.org/10.17775/CSEEJPES.2018.00710.

[9] Ahmad, T., Chen, H., and Wang, J. 2020. "A Comprehensive Review on the Integration of Artificial Intelligence with Building Energy Systems." *Renewable and Sustainable Energy Reviews* 131: 110001. https://doi.org/10.1016/j.rser.2020.110001.

[10] IEA (International Energy Agency). 2021. "Digitalization and Energy." https://www.iea.org/reports/digitalisation-and-energy.

[11] Schleich, J., Faure, C., Gassmann, X., and Klobasa, M. 2021. "Artificial Intelligence in the Energy Sector: A Systematic Review of Challenges and Opportunities." *Renewable and Sustainable Energy Reviews* 152: 111682. https://doi.org/10.1016/j.rser.2021.111682.

[12] IRENA (International Renewable Energy Agency). 2022. "Artificial Intelligence and Big Data: Enabling Digital Energy Solutions." https://www.irena.org/publications.