INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)
ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIII, Issue III, March 2024

Forecasting Energy Consumption with AI: A Review for Sustainable Energy Management

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DOI: https://doi.org/10.51583/IJLTEMAS.2024.130303

Received: 31 January 2024; Revised: 04 March 2024; Accepted: 12 March 2024; Published: 30 March 2024

Abstract: This paper provides a comprehensive review of the integration of artificial intelligence (AI) within the context of Industry 4.0, emphasizing its transformative impact on various industries and its specific applications in energy consumption forecasting for sustainable energy management. Beginning with a historical perspective on industrial evolution, from automation to the current cyber-physical systems era, the review highlights the pivotal role of AI in reshaping manufacturing processes. The article explores the diverse applications of AI in the energy sector, particularly its effectiveness in short-term load forecasting, demand response optimization, and accurate predictions for renewable energy sources like solar and wind. The growing complexity of power systems due to decentralization and the proliferation of grid-connected devices is discussed, underscoring the importance of effective information exchange facilitated by AI. Additionally, the review delves into various models used for energy forecasting, including supervised learning models, artificial neural networks, and deep learning models. The practical applications of AI in power system control, management, energy market pricing, and policy recommendations are outlined, showcasing its potential in optimizing energy efficiency and balancing electricity production and consumption. The practical examples of AI's role in improving predictions of supply and demand, such as Google's subsidiary DeepMind enhancing wind power output forecasts, highlight the real-world impact of these technologies. However, the abstract also acknowledges existing challenges, including insufficient theoretical background, practical expertise, and financial constraints hindering widespread AI adoption in the energy industry. In conclusion, the article offers valuable insights into the current state, challenges, and potential of AI in forecasting energy consumption, providing a roadmap for sustainable energy management across diverse industries.

Keywords: Artificial Intelligence, Industry 4.0, Energy, Forecasting, Sustainability, Management, Power systems, Deep learning.

I. Introduction

Since the inception of the industrial revolution, practitioners have endeavored to discover innovative approaches to enhance the manufacturing process, emphasizing production efficiency, cost reduction, and product quality (Yang and Gu, 2021). The industrial revolution has progressed through four primary phases: the initial phase concentrated on automation through steam and water-powered mechanization; the second phase emphasized electrification and mass production; the third phase adopted robotics and digital technologies to enhance efficiency; and the fourth phase is currently centered on cyber-physical systems and artificial intelligence. While the industrial age predominantly adhered to a top-down leadership paradigm (Uhl-Bien et al., 2007), the modern information age heavily relies on an escalating volume of data (Baron & Rrustemi), necessitating informed decision-making and timely data utilization to maintain a competitive edge. This shift has given rise to the "Industry 4.0" (hereafter I4.0) era, wherein technology plays a pivotal role in automating and enhancing various industrial processes (Jan et al, 2023). Scholars argue that the rapid evolution of technology and their interconnections will usher in a fourth industrial revolution, termed Industry 4.0 (Skilton and Hovsepian, 2018).

In the contemporary information age, data stands out as the most valuable asset for any company aspiring to gain a competitive advantage in the industry (Harding et al., 2006; Taranto-Vera et al., 2021). Companies strive to leverage available data for data-driven decision-making, seeking a competitive edge. Within the context of I4.0, the concept of "smart manufacturing" has emerged (Kusiak, 2017), where "smart machines" and "smart processes" learn from data to continually optimize production processes, often with minimal human intervention. Industry 4.0 (Rüßmann et al., 2015) represents an intersection of various technologies, including Big Data and Cloud Computing, the Internet of Things (IoT), and Artificial Intelligence/Machine Learning. The amalgamation of these technologies facilitates the capture and storage of data from diverse sources, its analysis for decision-making, and the acquisition of knowledge from it.

Artificial Intelligence (AI) and machine learning technologies, in conjunction with copious amounts of data collected through modern digital technologies, have emerged as fundamental components of the cyber-physical systems underpinning I4.0. While AI is often used interchangeably with machine learning, AI encompasses a broader scope, including aspects of intelligence such as perception, sensing, reasoning, and knowledge representation, beyond the machine learning facet. The term "Industrial Artificial Intelligence" (IAI) is associated with the application of AI technologies in industry (Lee et al., 2018), underscoring the significance of AI as a cornerstone in modern data-driven industrial processes. IAI's scope extends beyond the machine learning domain, encompassing automated configuration, planning, diagnostics, adaptation, and prognostics essential for realizing cyber-physical systems. AI-enabled machines and processes have experienced substantial growth over the past two decades, emerging as major contributors to I4.0. Virtually every industry sector is currently pursuing AI-enabled processes, spanning manufacturing, finance, transportation, healthcare, and science (Jan & Verma, 2020). AI technologies have significantly transformed the operational landscape of various industries, with innovations like predictive maintenance, comprehensive supply chain optimization (Shao et al., 2021), and digital twins revolutionizing manufacturing and service sectors.

Numerous studies have addressed machine learning in the context of I4.0 (Bertolini et al., 2021). However, existing literature lacks a comprehensive examination of AI-based methodologies across diverse industry sectors. There is a discernible research gap concerning how various industries have employed AI to realize Industry 4.0, the challenges encountered, and the solutions devised. This article bridges this gap by spotlighting the issues and concerns faced in different industry sectors, deliberating on introduced solutions, and pinpointing opportunities that have arisen for adopting existing solutions and avenues for future research to advance the next generation of solutions. This work complements broader reviews of I4.0 (Meindl et al., 2021) by scrutinizing specific applications of IAI in several industry sectors. The objective is to enlighten industry practitioners seeking to embrace Industry 4.0 about prevalent concerns and potential IAI solutions to address these concerns. An additional distinctive feature of this article is its accessibility to a broad audience lacking expert knowledge in IAI technologies and their applications. Consequently, the discussion of IAI technologies is framed within the context of an IAI pipeline, where various AI technologies can be employed to tackle concerns related to data acquisition, processing, modeling, and interpretation of outcomes. This discussion is supported by a technical lexicon introducing key AI concepts and technologies underpinning this pipeline.

II. Artificial Intelligence in The Energy Industry

The utilization of Artificial Intelligence (AI) in forecasting energy consumption encompasses various dimensions within the energy ecosystem. Scholars (Salehimehr et al., 2022; Ahmad et al., 2019; Gelazanskas et al., 2014; Currie et al., 2004; Amara et al., 2019; Srivastav et al., 2016; Din and Marnerides, 2017; Mahmoud et al., 2015) have provided a comprehensive overview, highlighted through the following points:

1. Short-Term Load Forecasting (STLF):

AI excels in predicting short-term fluctuations in energy demand, crucial for real-time balancing of electricity grids. Machine Learning (ML) and Deep Learning (DL) models are employed to capture hourly, daily, and weekly patterns. The adaptability of these models allows for real-time adjustments, optimizing energy generation and distribution.

2. Demand Response Optimization:

AI plays a pivotal role in optimizing demand response programs, where energy consumers actively adjust their electricity usage in response to supply conditions. ML algorithms predict peak demand periods, enabling utilities to incentivize consumers to shift their usage, thereby balancing the load on the grid.

3. Solar and Wind Forecasting:

Renewable energy sources, such as solar and wind, exhibit inherent variability. AI models, particularly those based on neural networks, demonstrate proficiency in capturing complex and non-linear relationships influenced by weather patterns, time of day, and seasonal changes. Accurate forecasting enhances grid stability and facilitates the effective integration of renewable energy into the power grid.

The increasing complexity of power systems, driven by growing electricity demand and intensified decarbonization efforts, necessitates significant adaptation. Traditionally, grids directed energy from centralized power stations, but contemporary power systems must accommodate multi-directional flows of electricity between distributed generators, the grid, and users. The proliferation of grid-connected devices, ranging from electric vehicle (EV) charging stations to residential solar installations, adds an element of unpredictability. Concurrently, deeper connections are forming between the power system and the transportation, industry, building, and industrial sectors (Wang et al., 2016). This heightened interconnectivity necessitates an increased information exchange and more potent tools for planning and operating evolving power systems (Salehimehr et al., 2022).

This need coincides with the rapid advancements in the capabilities of AI applications. As machine learning models progress, the computational power required for their development has doubled approximately every five to six months since 2010 (Jan et al., 2023). AI models now reliably offer language or image recognition, convert audio sounds into analyzable data, power chatbots, and automate various tasks. Mimicking aspects of human intelligence, AI analyzes data and inputs to generate outputs swiftly and at a greater volume than a human operator could achieve. Some AI algorithms even exhibit the capability to self-program and modify their own code (Skilton and Hovsepian, 2018).

Rinku and Singh (2023) assert that it is unsurprising for the energy sector to take early steps in harnessing the power of AI to enhance efficiency and drive innovation. AI is uniquely positioned to support the simultaneous growth of smart grids and the vast quantities of data they generate. Smart meters, in comparison to their analog predecessors, produce and transmit several thousand times more data points to utilities. New monitoring devices for grid power flows funnel more than an order of magnitude more data to operators than the technologies they replace (Mahmoud et al., 2015). The global fleet of wind turbines alone is estimated to generate over 400 billion data points per year. This surge in data volume underscores why energy firms perceive AI as an increasingly critical resource. A recent estimate suggests that AI already serves more than 50 different purposes in the energy system, with the market for this technology in the sector projected to be worth up to USD 13 billion.

III. Examining Various Models Used for Forecasting

Energy prediction for small-scale consumers is closely linked to domestic energy forecasting, a critical element in controlling and planning load demand within power distribution networks. Various factors influence industrial and commercial energy consumption, encompassing business classifications, facilities, consumer-owned power generation, electricity rates, and overall generation. Accurate peak load demand forecasting is vital for power companies to achieve their core objective of providing affordable and reliable energy delivery to consumers. While long-term forecasting captures energy trends, addressing short-term variability in load demand remains a complex task (Ahmad et al., 2020). Consequently, aspects such as load curve development, short-term load variations, network training flexibility, load demand decomposition, and temporal granularity warrant attention.

In a study aimed at enhancing smart energy forecasting strategies, Ahmad et al. (2020) proposed four supervised learning models: Binary Multiclass Classification Decision Tree (BMCDT), Regression Binary Decision Tree (RBDT), Bootstrap Bagging of Regression Trees (BBRT), and Generated Sampled Data-Based Gaussian Process Regression Model (GSD-GPRM) for both short- and long-term load forecasting. These models, although existing in literature, were structurally modified and employed for energy demand forecasting for the first time.

To establish an optimal benchmark for energy forecasting in utilities and buildings, effective energy forecasting approaches must be complemented by suitable management and operational strategies (Ahmad et al., 2020). The utilization of a web-based parallel genetic model for resource computing has been proposed to reduce network computation time (Xiao et al., 2021). Artificial Neural Networks (ANNs) have been extensively applied, constituting approximately 40% of reviewed energy forecasting models. ANNs emerge as a popular choice for energy forecasting analysis. Additionally, Grey models (Al-shanini, 2015) and Fuzzy prediction (Vaidehi et al., 2008) are inclusive for prediction with incomplete features of input variables. Computational intelligence models prove suitable for both long- and short-term energy forecasting (Fallah et al., 2019).

Deep learning models, a promising type of machine learning (ML) models, demonstrate the capability to explore invariant high-level structures and inherent nonlinear variables in data (Wang, 2019). These models, including Supervised Learning models, contribute to accurate short-, medium-, and long-term load forecasting and management (Din and Marnerides, 2017). Supervised learning models offer ease of network training, clarity in data analysis, and are particularly useful in classification problems. For instance, BMCDT is visually simple and handles both categorical and numerical data with minimal data preparation. RBDT is effective for over-fitting problems and exhibits improved accuracy, suitable for feature selection and interpretability. GSD-GPRM is beneficial for non-linear data characteristics, resistant to over-fitting, and most effective for fully probabilistic prediction (Christimann et al., 2015).

Addressing the complexity of forecasting utilities and building energy requirements has been a primary focus of various research studies. Proposed models prove useful in handling diverse load characteristics and energy forecasting support systems, addressing challenges such as continuous load characteristics, duty-varying loads, duty short-time electrical loads, duty-intermittent loads, non-continuous load, and duty-periodic electrical loads.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIII, Issue III, March 2024

Artificial Intelligence (AI) emerges as a solution to real-world problems in computer vision and natural language processing, holding promise in addressing energy challenges. AI facilitates a comprehensive framework for effective power system control, management, energy market pricing, and policy recommendations (Wang et al., 2023). Machine Learning (ML) and Deep Learning (DL) models contribute significantly to optimizing energy efficiency, conversion, distribution, and decarbonization in smart grids. These data-driven approaches enable timely feedback, fostering efficient two-way communication between the grid and customers, thereby enhancing system security, reliability, and efficiency (Azad et al., 2019). The integration of AI in smart grids allows for the optimization of renewable resource utilization, balancing electricity production and consumption, improving grid reliability, and ensuring security (Sankarananth et al., 2023). The rapid growth of smart grid applications in recent years underscores its increasing market share (Butt et al., 2021).

IV. Artificial Intelligence for Energy Forecasting

One of the prevalent applications of AI in the energy sector revolves around enhancing predictions of supply and demand. Gaining a deeper understanding of both the availability of renewable power and its demand is crucial for the advancement of next-generation power systems. This task is particularly intricate for renewable technologies given the intermittency of sunlight and wind patterns (Ahmad et al., 2020). Machine learning emerges as a valuable tool in addressing this challenge by aligning variable supply with fluctuating demand, thereby optimizing the financial value of renewable energy and facilitating its smoother integration into the grid (Sankarananth et al., 2023).

Wind power output, for instance, can be predicted using weather models and turbine locations. However, variations in wind flow can lead to unexpected output levels, impacting operational costs (Queshi et al., 2023). In response, Google and its AI subsidiary DeepMind collaborated in 2019 to develop a neural network aimed at enhancing forecast accuracy for their 700 MW renewable fleet. Utilizing historical data, the network constructed a model capable of predicting future output up to 36 hours in advance with significantly improved accuracy. This enhanced visibility enables Google to pre-sell its power, resulting in a 20% increase in the financial value of its wind power. Notably, this proprietary software is now being tested by a major energy company (Boulanger, 2005).

Furthermore, a more precise understanding of output peaks empowers companies like Google to strategically time peak consumption, aligning it with periods of heavy computing loads. This strategic alignment mitigates the need to purchase additional power in real-time. This capability, if widely expanded, could notably influence the promotion of load shifting and peak shaving, particularly when coupled with improved demand forecasts. For instance, Swiss manufacturer ABB has introduced an AI-enabled energy demand forecasting application allowing commercial building managers to avoid peak charges and leverage time-of-use tariffs effectively (ABB, 2019).

As the dynamics of regional power markets undergo constant and accelerated changes globally, there is a growing need for advanced AI-powered energy forecasting tools. Frequent extreme weather events and the integration of clean yet intermittent and unpredictable energy sources are compelling utility and power market participants to reevaluate how they conduct energy forecasts (Meindl et al., 2021). Concurrently, evolving market regulations in the energy transition era necessitate a more sophisticated approach to energy modeling for precise results.

The shift from a traditional centralized power market system to a decentralized one has introduced greater intricacies in forecasting power market supply and demand fundamentals (Bertolini et al., 2021). Energy transition initiatives, advocating a move away from fossil fuels toward cleaner and distributed energy resources, are reshaping regional generation supply stacks. Nevertheless, accurately forecasting supply and demand poses an increasing challenge, whether involving utility-connected renewables or distributed energy resources such as rooftop solar, battery storage, or electric vehicles (Villali, 2023). Unpredictable extreme weather events further compound the difficulty in generating accurate energy forecasts. To tackle these challenges and adapt to the evolving power markets, utilities are turning to advanced modeling products leveraging AI and machine learning (ML) to enhance their forecasts. Beyond supply and demand predictions, these advanced AI and ML energy forecasting models offer support in areas such as operations, trading, and integrated resource planning (Ahmad et al., 2020).

V. Emerging Trends in Artificial Intelligence

In the constantly changing landscape of Artificial Intelligence (AI), several emerging trends have garnered attention for their potential to reshape industries. Among these, federated learning, explainable AI, and AI governance stand out as transformative forces. In the context of energy forecasting, where precision and reliability are paramount, understanding the implications of these trends is crucial.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIII, Issue III, March 2024

1. Federated Learning

Federated learning is revolutionizing the way AI models are trained by enabling decentralized training across multiple devices or servers. In the realm of energy forecasting, this decentralized approach brings forth a paradigm shift. Traditionally, energy forecasting models required centralized data repositories, leading to privacy concerns and data security risks. Federated learning addresses these issues by allowing models to be trained locally on individual devices without sharing raw data.

In the context of energy forecasting, this means that energy consumption patterns can be analyzed without compromising user privacy. Residential, commercial, and industrial data can stay localized, while the collective intelligence contributes to a more accurate and comprehensive forecasting model. This trend aligns with the growing emphasis on privacy and security in the AI landscape, making it a promising avenue for the energy sector.

2. Explainable AI

Explainable AI (XAI) is gaining prominence as organizations recognize the need for transparency in AI decision-making processes. In energy forecasting, where stakeholders rely on accurate predictions for planning and resource allocation, the ability to understand how AI models arrive at specific forecasts is invaluable.

With XAI, energy forecasting models become more interpretable. This transparency not only enhances trust in AI predictions but also allows stakeholders to identify and address potential biases or errors in the model. In the energy sector, where decisions have significant economic and environmental ramifications, the importance of explainability cannot be overstated. As AI models become more intricate, the demand for explainable and interpretable forecasting tools will likely continue to rise.

3. AI Governance:

The rapid advancement of AI technologies necessitates robust governance frameworks to ensure ethical use and compliance with regulations. AI governance involves defining ethical guidelines, implementing safeguards against bias, and establishing accountability in AI systems. In the context of energy forecasting, adherence to ethical standards and regulatory requirements is crucial for maintaining public trust and mitigating risks.

Governance frameworks ensure that AI models used in energy forecasting are aligned with societal values and environmental sustainability goals. They also help address concerns related to fairness, accountability, and transparency. As energy forecasting plays a pivotal role in shaping policies and strategies, the integration of AI governance principles ensures responsible and ethical decision-making.

Implications for Energy Forecasting

These emerging AI trends collectively hold significant implications for the field of energy forecasting. The decentralization facilitated by federated learning addresses privacy concerns, allowing for more comprehensive and accurate forecasting models. Explainable AI enhances transparency, fostering trust among stakeholders and enabling a deeper understanding of the decision-making process behind energy predictions. AI governance, on the other hand, ensures that ethical considerations and regulatory compliance remain at the forefront of AI applications in energy forecasting.

As organizations leverage AI to optimize energy consumption, reduce waste, and meet sustainability goals, the intersection of these trends becomes increasingly relevant. The potential benefits include more accurate forecasts, improved decision-making processes, and a heightened awareness of the ethical and regulatory dimensions associated with AI applications in the energy sector.

VI. Areas for Improvement

Numerous studies (Ahmad et al., 2020; Andelkovic and Bajatovic, 2020; Baldacci et al., 2016) have outlined challenges and concerns associated with the implementation of Artificial Intelligence (AI) in various sectors. These issues are articulated as follows:

1. Insufficient Theoretical Foundation: A primary obstacle hindering the widespread adoption of AI in business strategies is the lack of requisite knowledge. Many energy companies face a dearth of technical background knowledge, impeding their ability to comprehend the potential benefits of incorporating AI into their operations. Consequently, these companies often adhere to established methods and tools, hesitant to embrace new technologies due to a perceived lack of understanding.

2. Limited Practical Expertise: Despite being a cutting-edge technology, AI is still in its infancy, with only a select few professionals having mastered its intricacies. While there are individuals possessing substantial theoretical knowledge of AI, the number of professionals capable of designing robust AI-enabled systems with tangible practical value for the industry remains limited.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIII, Issue III, March 2024

Compounding this issue is the inherent conservatism within the energy sector, further impeding the widespread practical application of AI.

3. Data Management Challenges: While energy entities collect and manage data, the effective digitization and management of this data using innovative technologies present significant challenges. This struggle manifests in issues such as poor customization, unauthorized access, data loss, system failures, and other potential dangers. Moreover, the high cost of errors in the energy industry amplifies the reluctance of companies to experiment with new technologies.

4. Financial Constraints: Financial pressures pose a formidable hurdle for energy companies looking to embrace innovative smart technologies, including AI. Despite being a superior option, the incorporation of AI in the energy sector comes with a substantial financial burden. Identifying a dependable software service provider, creating and customizing software, adjusting, managing, and monitoring the technology demand considerable time and resources. To fully harness the advantages of integrating AI and other advanced technologies into their strategies, energy companies must allocate a significant budget and be prepared to navigate the risks associated with transitioning from outdated to modern energy systems.

VII. Conclusion

The integration of artificial intelligence (AI) in Industry 4.0 has profoundly impacted various sectors, with a particular focus on energy consumption forecasting in the energy industry. The article highlights AI's pivotal role in reshaping industrial processes, emphasizing its applications in short-term load forecasting, demand response optimization, and accurate predictions for renewable energy sources. The increasing complexity of power systems, coupled with the need for effective information exchange, underscores the significance of AI in modern energy management. The practical applications of AI in optimizing energy efficiency, distribution, and decarbonization in smart grids are evident, showcasing its potential for real-world problem-solving. The article acknowledges the advancements in deep learning models and their ability to explore complex data structures. It also sheds light on the valuable role of AI in improving predictions of supply and demand, with examples such as Google's subsidiary DeepMind enhancing wind power output forecasts. The emerging trends of federated learning, explainable AI, and AI governance are poised to revolutionize energy forecasting. These trends not only address existing challenges but also pave the way for a more responsible, transparent, and efficient energy landscape. As the energy sector embraces these advancements, the potential for positive societal and environmental impact becomes increasingly evident

However, scholarsrecognizes areas for improvement, such as the need for a stronger theoretical background, practical expertise, and financial support to facilitate widespread adoption of AI in the energy industry. Despite these challenges, the overall review provides a comprehensive overview of the current state, challenges, and potential of AI in forecasting energy consumption, offering valuable insights for sustainable energy management across diverse industries.

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