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Integrating Artificial Intelligence in Power Plant Management: A Review of Recent Applications and Future Directions

Journal of Electrical Systems

Abstract: - A significant development in the global energy sector, the incorporation of Artificial Intelligence (AI) into power plant operations aims to improve sustainability, efficiency, and dependability. This review carefully explores current AI applications used in power plants and evaluates their effects in these important domains. We examine various AI solutions targeted at optimizing intricate operational processes in power plants through an extensive examination of the literature. We present a comparison of cloud-based and non-cloud-based AI systems, such as Cloud Machine Learning (CloudML), Tiny Machine Learning (TinyML), and Mobile Machine Learning (MobileML), emphasizing their benefits and drawbacks. This review provides a thorough understanding of the present and potential future states of AI technologies in this crucial industry sector. It does this by summarizing the applications of AI in power plant and assessing their performance metrics in terms of bandwidth usage, data privacy, system reliability, and economic viability.

Keywords: Artificial Intelligence, Power Plant, Reliability, Efficiency, Applications, TinyML, Mobile ML, Cloud ML.

I. Introduction

Energy landscape is dynamically changing due to the rise of technology, with sustainability, adaptability, and efficiency being the driving forces behind this change [1]. AI techniques have been adopted by the power industry as a transformational force in response to these difficulties. The integration of AI technology into power plants is a strategic move toward intelligent and highly responsive infrastructure and reflects a readiness to embrace innovation [2]. Using AI in power plants has attracted a lot of attention during the last two decades, according to many studies, indicating a strong interest in using technology to improve sustainability and operational efficiency. Since 2000, researchers have concentrated more on the various ways in which AI can maximize energy output, lower operating costs, and more effectively integrate renewable energy sources. Figure (1) shows the rise in research articles on AI applications in power plants.

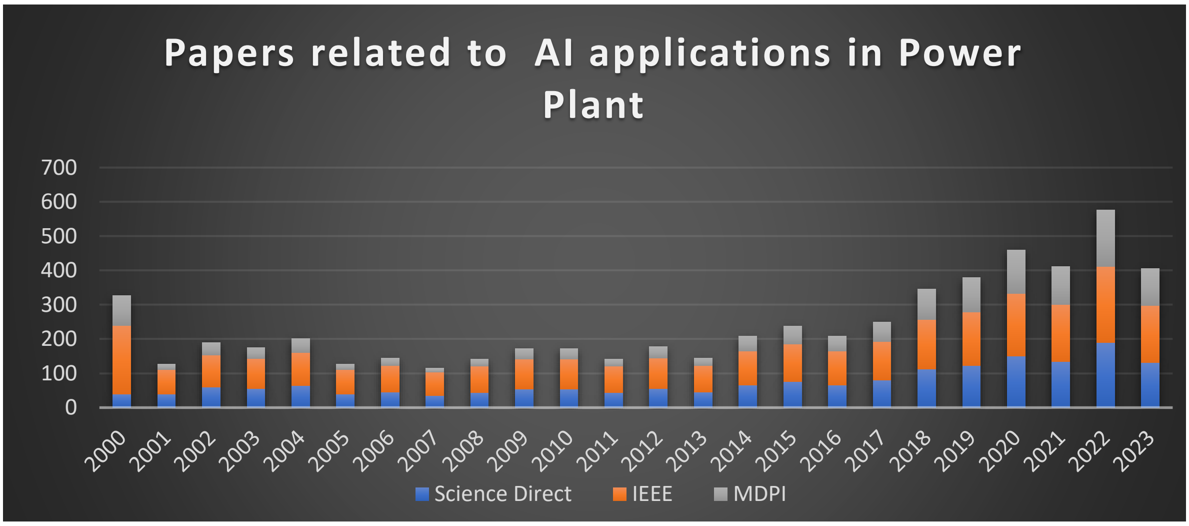

Figure 1. Trends in Power Plant AI-Related Research Publications from 2000 to 2023 on Science Direct, IEEE, and MDPI.

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The adoption of AI technologies in power plants is driven by various factors. This is because there is an increasing need to improve power generation efficiency and reliability due to the world's growing energy demand [3]. However, minimizing carbon footprints should also be a top priority in the energy debate. Consequently, novel approaches to these problems are being offered by artificial intelligence [4], [5]. This study provides a comprehensive comparison and analysis of many articles on the use of AI in power plants, along with a thorough debate. Power plants are facing mounting pressure to increase efficiency, lower operating costs, and reduce their environmental impact as the world's energy demands rise and sustainability becomes more crucial. By streamlining several elements of power plant operations, AI provides powerful capabilities to satisfy these needs.

1.1. Electric power plants

Electric power plants are vital to the fabric of contemporary society in all its forms and purposes. These amenities, which comprise nuclear [6], renewable energy [7], and fossil fuel-based technologies, [8], are crucial in determining how human growth will proceed. The influence of electric power plants on technical innovation, economic growth, and societal well-being is complex and far-reaching. These facilities are not merely providers of energy; they actively shape the trajectory of human development. Their significance extends across various domains, including technological progress, economic enhancement, lifestyle improvement, and environmental sustainability. Navigating the complexities of an evolving global landscape necessitates effective exploitation of their capabilities [9].

1.2. AI Applications in Power Plants

Here's a summary of the various ways artificial intelligence is being used in power plants, with a focus on predictive maintenance, power plants protection, energy management, and fault identification.

- **Nuclear power plants predictive maintenance:** This type of maintenance involves the continuing, or more frequent, observation of the vital components of nuclear safety equipment during operation in order to identify potential problems. By assessing the equipment's condition, projecting future development trends, creating predictive maintenance plans based on patterns of development and possible failure modes, and determining the frequency, content, and method of equipment maintenance, in addition to the necessary material and technical support [10]. Significant insights into nuclear power plant predictive maintenance have been provided by Gohel et al. (2020). As a result, the author suggested and created a machine learning system for efficiently performing predictive maintenance on nuclear infrastructure. It has a logistic regression method and Support Vector Machines (SVM). An innovative method for correlating the infrastructure of a nuclear power station with its data samples was offered by the author, which is likely to improve the accuracy and relevance of predictive outputs. Despite these advancements, the authors have pointed out several shortcomings in these algorithms, which might include limitations in handling complex data, scalability issues, or the need for higher accuracy [11].
- **Protection of power plants:** It is crucial to guarantee the effectiveness and security of power plant operations. Aminifar et al. conducted a comprehensive review of the use of AI tools in asset management in their 2021 study, emphasizing how these innovations can greatly improve the safety of power systems. Their research detailed the applications of synchronous generators, transmission lines, and power transformers, and discussed advanced methods for maintaining system integrity. They highlighted a range of practical AI applications currently used [3]. To improve AI applications in cybersecurity, Nabil et al.'s research [12] provided a thorough overview of ML and deep learning techniques.
- **Energy management of power plants:** Energy management is vital for both consumers and power plant operators. AI has made a significant development in power plant energy management, improving efficiency, reducing costs, and preserving dependability at these facilities [13]. The efficiency and sustainability of electricity generation can be significantly impacted by the advanced analytics and automation provided by AI technologies. Here are some main areas where AI is making significant contributions to energy management in power plants. Rocha and colleagues (2021) provided valuable insights into an AI-driven scheduling algorithm for monitoring energy consumption in smart homes. This approach used support vector regression to gather real-time data and conduct numerical simulations in smart homes, resulting in an efficiency improvement of 51.4%. However, the study did not compare these results with those of other energy management strategies like distributed generation and battery banks [4].
- **Fault diagnosis and detection in power plants:** AI's role in diagnosing and detecting faults in power plants is becoming increasingly important. Zhao et al. (2019) discussed AI-based methods for fault diagnosis and detection, giving a thorough analysis of the advantages, obstacles as well as potential futures in this area. The paper deeply analyzed each method's

characteristics, emphasizing the importance of fault identification and diagnosis for maintaining power plant reliability [14]. Table (1) provides an overview of a few academic publications that highlight the use of artificial intelligence (AI) technology in power plants. Each study is categorized on the basis of the primary idea, goals, and techniques used, and reference citations are provided for more research. The table highlights the novel techniques and the spectrum of research subjects, which span from operational optimization to safety upgrades, and it demonstrates the many approaches and goals within the field of AI applications in energy systems.

Table 1: Summary of research on artificial intelligence applications in power plant operations

Main Idea	**Objective**	**Method use**	**Refe**
Since NEOM is regarded as a city that solely runs on renewable energy, this includes thermal, photovoltaic, solar, and battery energy storage that is integrated with artificial intelligence.	The main objective of this work is to evaluate the viability of solar thermal energy as a dispatchable, cost-effective energy source for NEOM.	A range of solar thermal plant scenarios are simulated, with variations in temperature, pressure, and thermal and solar field storage capacity.	[15]
This study suggested a data-driven methodology that uses AI and machine learning to optimize Combined Cycle Power Plant (CCPPs) operation.	The main objective was to evaluate and highlight the efficacy of CCPPs under various control and environmental variables.	Through the use of AI and machine learning, this work offered a data-driven way to optimize CCPP functioning.	[16]
The article summarizes current advancements and the challenges associated with fusing machine learning and smart energy.	It provides a thorough analysis of the advancements and future potentials of ML applications in power plants.	This paper provides systemic reviews to evaluate and impact of machine learning, on smart energy and electric power systems, exploring seven advanced ML methods and their applications in optimizing and managing smart grids and Energy Internet.	[17]
The article introduced a new artificial neural network model that uses electrostatic discharge optimization and preprocessing procedures to predict combined cycle power plants' electrical power production.	It measures the performance and accuracy of the suggested Artificial Neural Network (ANN) model concerning other models such as Neural Network (NN), AI, Random Forest (RF), and SVM models.	A realistic CCPPs simulation using Matrix Laboratory (MATLAB)/Simulink and data gathering from actual CCPPs in Iran.	[18]
This paper offered a solid Stackelberg game model for efficient collective energy management through a Virtual Power Plant (AI VPP) application.	This article's primary goal is to maximize the market transactions and energy scheduling of all prosumers in the face of fluctuating prices and renewable energy output.	An efficient two-stage linearized robust optimization model that includes an Automatic Generation Control (AGC) mode and a column and constraint generating approach is utilized.	[19]
The essay analyzed emerging and current technologies for distributed energy sources, electric vehicles, cybersecurity, power electronics, and smart grid connectivity.	The main objective of this article is to provide a comprehensive overview of the situation of artificial uranium (AU), blockchain (BC), and the internet of things (IoT) in smart grids, as well as their future potential.	Approximately 101 papers are thoroughly reviewed using a comprehensive, systematic literature review methodology.	[20]
The core thesis is that high-power electronics systems depend on reliable data and command integrity to remain stable.	To detect errors or anomalies in operational data and control commands across a range of use cases.	Proposed techniques for detecting anomalies in the MARS power plant consist of hardware-in-the-loop (HIL) testing and simulations.	[21]

1.3. Artificial Intelligence Techniques

The provided flowchart (Figure 2) tends to organize a variety of AI strategies for which it may be possible to find various data kinds that can assist with energy management, predictive maintenance, asset management, and problem detection efficiently. These available data kinds are expanded to provide optimization while also addressing the problem categories listed [22]. This is how data regarding various AI applications is gathered, utilizing a variety of AI and machine learning methods, as well as AI-driven analysis aimed at achieving notable performance gains. Demand forecasting is improved as part of the optimization process, and early anomaly identification enables timely problem-solving [23].

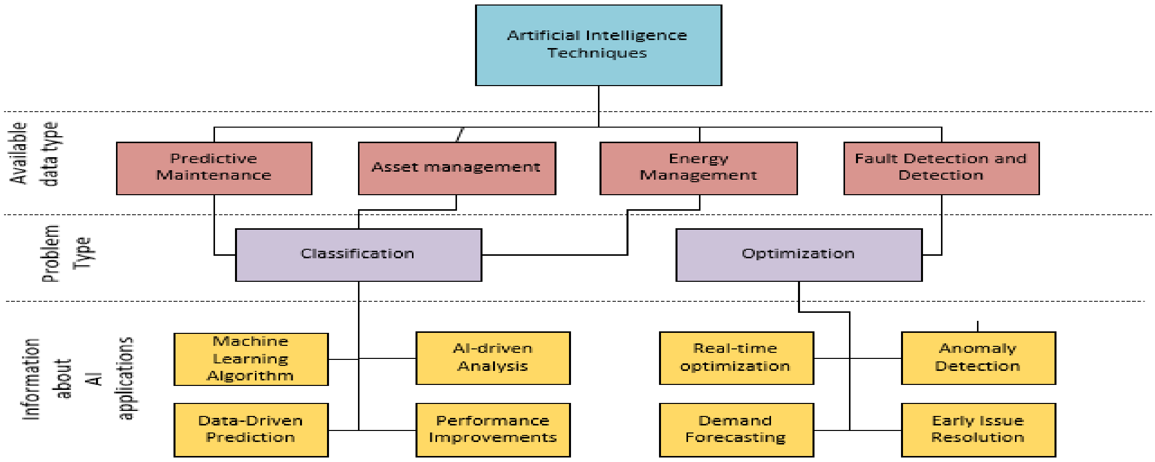

Figure 2. A framework of AI techniques applied in power plant operations

II. Discussion

Numerous academics have made significant advances in our understanding of how AI is applied in power plant operations. This section explores their work in great detail, explaining different AI concepts and how they are used in real-world scenarios (Table 2). This table offers a succinct summary of several research articles published between 2018 and 2024, all of which concentrate on distinct facets of artificial intelligence applications in the energy industry, such as renewable energy management, smart cities, and power plants. Every entry showcases a different study, from advanced AI-driven Strategies for energy management and the use of renewable energy sources in smart network grids to machine learning optimizations in combined cycle power plants.

A perceptive examination of deep learning applications in load forecasting, a vital part of efficient power plant management, is also included in this review. Recurrent and convolutional neural networks are used in the reviewed study to improve operational planning and forecast accuracy [3]. Another important article by Zhao looks at AI applications in power electronics with an emphasis on industries like smart grids and electric cars. This article examines the use of AI in the design, maintenance, and lifecycle phases of power systems [5]. Additionally, a novel use of an artificial neural network to schedule maintenance in hydroelectric power plants is covered, backed by a multi-criteria decision-making framework. To minimize failures and maximize performance, this strategy incorporates a variety of approaches and expert evaluations [24]. Furthermore, the potential of AI to promote power plants' sustainability is examined, with a focus on how AI increases the predictive accuracy of sustainable energy resources, like solar and wind, to maximize their efficiency [25].

Zhou and his associates [26] conducted significant research on the use of a triboelectric Nano generator-based self-powered sensor in power plants. Using the triboelectric phenomenon and electrostatic induction, this novel gadget transforms mechanical energy into electrical energy. The study carefully outlines the main applications, benefits, and possible further advancements of this sensor, emphasizing its function in improving power generation's operational efficiencies.

A hybrid model that combines AI and IoT technology to produce electricity from renewable resources is also shown in another study. This model collects solar and thermal energy from the surroundings using a variety of sensors, such as piezoelectric and solar panels. To lessen dependency on fossil fuels and increase energy consumption efficiency, it estimates the total power produced from renewable sources using cutting-edge AI models, including ANNs and adaptive network-based fuzzy inference systems [27].

A comprehensive review further delineates the use of ANNs in a variety of fields, including computers, environmental research, and power energy generation. A full taxonomy of ANNs, which mimic the structure and operation of biological neural networks, is provided, along with a thorough analysis of their current trends and potential future directions [28].

Additionally, a different study explores the potential applications of AI and ML within the oil and gas sector, showing how these technologies can forecast how much gas and oil power plants will need. The report provides insights into how accurate measurements can be attained through AI applications and analyzes the many benefits and problems connected with implementing AI in this area [29].

Lastly, an innovative study describes an evolutionary methodology in neural networking—an optimization method based on AI—to predict future energy demands. This study focuses on a hybrid approach that offers notable advantages in operational planning and resource management by improving power plant load forecasting efficiency and accuracy [30].

Table 2: A Summary of the Most Important review papers regarding AI applications in power plants.

Reference	Year	Focus
[15]	2021	Given that NEOM is seen as a city solely powered by sources of green power, like solar, photovoltaic, thermal, and battery power storage that is combined with artificial intelligence.
[16]	2023	This paper proposed a data-driven approach to optimize CCPPs functioning through AI and machine learning.
[17]	2019	The paper simply provides a summary of recent developments and the difficulties in integrating machine learning with smart energy.
[18]	2022	This article introduced a unique artificial neural networks (ANNs) model for the forecast of the combined cycle power plants' electrical power production through electrostatic discharge algorithms for optimization and preprocessing.
[19]	2020	This research presents a novel two-stage resilient Stackelberg game model for controlling aggregate day-ahead energy using AI for VPP applications.
[20]	2020	The most recent advancements in power electronics, cybersecurity, distributed energy sources, electric vehicles and smart grid connection were evaluated in this study.
[21]	2024	This article provided a significant model and data-driven method for identifying irregularities in the measurements and the orders that big power electronic systems send out.
[31]	2019	This article examined a few recent and innovative neural network trends that can be used to solve pattern recognition problems across a variety of industries.
[32]	2020	This article explores 10 ways that AI and ML might be used in cities with intelligence to control traffic and electricity plants.
[33]	2018	The paper included a comprehensive and methodical analysis of the theories and techniques for forecasting and improving photovoltaics.
[34]	2019	The article discusses the technological difficulties and mitigating strategies involved in assimilating huge wind power to the electrical network and presents a research agenda for future advancements in wind energy.

III. Comparative Analysis of TinyML, MobileML, and CloudML in Machine Learning Deployments

Machine learning technologies are developing, and their applications are being used on edge devices as well as cloud infrastructures [35], which moved from centralized cloud computing to edge devices and increased the revolutionary concept of TinyML [36]. The demand for improved security, lower latency, and faster data processing in applications ranging from industrial automation [37] to personal healthcare [38] is what is driving this growth. In this comparison analysis, the deployment models of TinyML, MobileML, and CloudML are examined. Each offers particular advantages and confronts particular difficulties. The unique features and benefits of TinyML over MobileML and CloudML are analyzed in this evaluation, with particular attention paid to platform requirements, performance indicators, and general factors like bandwidth, privacy, dependability, and affordability [39].

Machine learning models are run using mobileML, which makes use of the computing power of smartphones and tablets [40]. Because of these devices' short battery lives, this method can only provide portability and a minimal amount of processing power; hence, it is less appropriate for applications that need to run continuously without interruption. Furthermore, because data is transferred over the internet, MobileML frequently uses cloud-based services for model training and updates, which might cause latency and privacy issues [41]. CloudML, on the other hand, makes use of the vast processing capacity and scalability of cloud infrastructure, making it perfect for training sophisticated machine learning models. Reliable techniques and on-demand resource scaling are offered by cloud computing, which helps to reduce some delay problems brought on by network dependence [42]. However, the use of cloud services creates serious issues with data security and privacy, leading companies to look into other data processing options to protect sensitive data.

3.1. Platform Specification Comparison

The review's investigation into a thorough comparison of the platform specifications between CloudML, MobileML, and TinyML forms the basis of this section. A thorough summary of the important factors, such as frequency, memory, storage, power, latency, and cost, is provided in the table that follows (Table 3).

Table 3: Detailed comparison of specifications across Cloud Machine Learning, Mobile Machine Learning, and Tiny Machine Learning platforms

System	**Configuration**	**Frequency**	**RAM**	**Capacity**	**Energy Consumption**	**latency**	**Cost**
Cloud ML E.g. Nvidia V100	GPU	High (GHz)	High HBM 16G	Very High SSD/disk TB-PB	High ~250W	High	High ~9000$
Mobile ML E.g. cellphone	CPU	Moderate (GHz)	Moderate DRAM 4GB	Moderate Flash 64GB	Moderate ~8W	Moderate	Moderate ~750$
TinyML E.g.ESP32	MCU	Low (MHz)	Low SRAM 520KB	Low eFlash Up to 4 x16 MB	Ultra-low~ 1mW	Low	Low ~ 10$

3.1.1. CloudML

The majority of cloud machine-learning platforms run at high frequencies and make use of potent server-based processors that can handle demanding calculations [42]. It has adequate memory resources, making it possible to store huge datasets and model parameters. Large storage capacities provided by CloudML platforms make it easier to store datasets and enable model training and improved metadata [43]. Power-wise, the CloudML platform uses a lot of energy since it needs to use cooling systems and high-performance computer hardware. The communication network and data transfer have an impact on latency in CloudML, which can lead to higher latencies than in computer solutions [44]. The price of CloudML services is based on the substantial cost related to the computational resources' storage, data transfer, capacity, and service subscription.

3.1.2. MobileML

The second computing solution, known as MobileML, expanded the processing capabilities of mobile devices, such as smartphones and tablets, and runs at a moderate frequency across various platforms. MobileML devices have a moderate amount of memory that is suited for mobile applications while maintaining a balance between power efficiency and performance [45]. A competitive solution like this one offers enough storage space for storing machine learning models and application data. Because mobileML devices rely on batteries, which must last for extended periods, they have a reasonable power consumption. The processing power of mobile devices and network connectivity, which encounter lags when evaluating and utilizing cloud-based services, have an effect on mobile machine learning latency [41]. Mobile machine learning solutions range in cost based on the requirement product and market demand.

3.1.3. TinyML

The next gadget is a tiny machine-learning platform that runs at low frequencies and is designed to work with embedded systems and microcontrollers to convert power and provide sufficient performance [46]. These devices are designed to operate lightweight machine-learning models and store small amounts of data, and they have minimal memory resources. TinyML offers very little storage space, which is typically sufficient for sensor data and firmware model parameters. Because of its extremely low power consumption, it is regarded as perfect for energy-efficient systems that run on batteries. TinyML processes the data without logging particular network communications or cloud-based services, outperforming low latency inference. These devices have low operating costs, reasonable hardware options, and are reasonably priced [47], [48].

3.2. Performance Metrics Analysis

The performance matrix that is used to compare TinyML, MobileML, and CloudML is thoroughly analyzed in this area of the review, taking into account many factors like bandwidth, privacy, reliability, and economics.

3.2.1. Bandwidth

In terms of bandwidth efficiency, TinyML outperforms the other two solutions. By doing machine learning inference directly on the device, TinyML may lessen the need for frequent data transmission to distant servers, which will cause network congestion and save bandwidth [39]. In contrast, mobile machine learning typically relies on cloud-based services for model inference, necessitating continuous data transfer over the Internet and potentially increasing bandwidth consumption. Similar to this, CloudML involves sending a lot of data to distant service servers for processing, which raises the need for bandwidth [49].

3.2.2. Privacy

Tiny ML helps protect privacy by processing data locally, which might lessen the need to transfer sensitive information and mitigate the privacy risk associated with centralized processing. By ensuring that user data is saved on the device, such decentralized techniques promote user confidentiality and privacy. In contrast, transmission to outside services is a feature of both mobile and cloud machine learning, which raises concerns over data privacy [50].

3.2.3. Reliability

Reliability is increased and reliance on external networks is decreased with TinyML. The TinyML model, in contrast to the other two devices, is always working in offline conditions to guarantee the continuing operation of vital applications. By implementing interference locally and enhancing system reliability, TinyML relies on external influences [36], [51].

3.2.4. Economics

TinyML offers comparative benefits in terms of cost-effectiveness from an economic standpoint [36]. Organizations may be able to avoid the costly cloud infrastructure requirements and data transmission costs associated with cloud and mobile machine learning. TinyML solutions are affordable options and have minimum operational expenses that enable efficient utilization of resources and efficiency optimization.

3.2.5. Latency

TinyML performs better in terms of latency because it offers real-time inference right on the device. TinyML could lower processing latency for sensitive data by lowering the need for data transmission to an external server [52]. Due to network communication delays, both mobile and cloud machine learning may limit its applicability for real-time applications [53].

IV. Challenges for AI Applications

The effectiveness and safety of these vital systems are impacted by many significant issues that come with integrating artificial intelligence (AI) into power plant operations. First and foremost, the quality and accessibility of data are critical to the success of AI applications. For AI models to be trained effectively and make accurate predictions, power plants need high-quality data. However, because power plant systems are complicated and real-time data processing is required, gathering accurate and thorough data is a difficult undertaking. The complexity of the operating environment combined with the sheer amount of data produced makes it challenging to keep the correctness and integrity of the data for AI applications. Second, there are major obstacles in the way of integrating AI technologies into the current infrastructure of power plants. A lot of power plants still run on outdated systems that weren't meant to handle cutting-edge AI. It is a significant difficulty to integrate contemporary AI technologies into these legacy frameworks without interfering with ongoing operations. To prevent operational outages and guarantee that the new systems interface with the old systems in an efficient manner, this integration needs to be managed carefully. Thirdly, since power plants are regarded as crucial infrastructure, cybersecurity becomes a crucial problem when using AI. Artificial intelligence (AI) integration has the potential to increase system susceptibility to cyberattacks by either creating new vulnerabilities or exacerbating preexisting ones. Power plants are vital infrastructure, therefore any intrusion might have disastrous effects. Strong cybersecurity measures are therefore essential to preventing malicious attacks on AI systems and larger power plant operations. To ensure that the implementation of artificial intelligence (AI) in power plants improves efficiency and safety without jeopardizing the infrastructure's security or the reliability of the power supply, each of these difficulties requires considerable thought and strategic planning.

V. Future Trends

Predictive maintenance will be crucial in the future, and AI applications will be crucial. This technique makes it possible to properly do preventive maintenance by easily predicting equipment failure before it happens [54]. Advanced control systems are associated with the next trend in the future. AI in power plants will eventually offer some advanced control system capabilities that will make it simple to optimize operations in real time. It will result in less energy waste and more efficiency [22].

VI. Conclusions

This study concludes with a comprehensive assessment of AI applications in the power plant industry, emphasizing important topics including predictive maintenance, energy management, and asset management. These applications greatly improve operational effectiveness and support the power industry's efforts toward sustainability. The application of AI technologies is not without difficulties, though. To achieve the successful integration of these technologies, it is imperative to have proficient individuals, implement strong data security protocols, and give serious thought to the wider implications of these technologies.

Research and innovation in AI applications must continue as the electricity industry moves toward more environmentally friendly methods. By doing so, the urgent problems will be addressed and overcome, and the full potential of AI in this field will be realized. The comparative benefits and drawbacks of TinyML, MobileML, and CloudML were also discussed. In particular, TinyML shows a lot of potential because of its effective on-device inference capabilities, which minimize latency and operating costs by reducing dependency on remote server communications. Although CloudML provides a large amount of processing power, latency and cost concerns limit its potential. Performance and mobility are balanced by MobileML, while network issues and battery life are drawbacks.

All in all, the attention paid to TinyML highlights how well-suited it is for real-time data processing applications and how it might revolutionize the computing environment in power plants. The power sector may effectively use AI to achieve higher sustainability and efficiency by continuing to improve these technologies and handle related issues.

Author Contributions: Each of the authors contributed equally to this study.

Funding: There was no external support for this study.

Conflicts of Interest: No conflicts of interest are disclosed by the authors.

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