A Review of Asset Management Using Artificial Intelligence-Based Machine Learning Models: Applications for the Electric Power and Energy System

Gopal Lal Rajora
Institute for Research in Technology
Universidad Pontificia Comillas Madrid, Spain
glrajora@comillas.edu

Miguel A. Sanz-Bobi
Institute for Research in Technology
Universidad Pontificia Comillas Madrid, Spain

Lina Bertling Tjernberg
Division of Electric Power and Energy Systems
KTH Royal Institute of Technology Stockholm, Sweden

José Eduardo Urrea Cabus
School of Electrical Engineering and Computer Science
KTH Royal Institute of Technology Stockholm, Sweden

Abstract— Power system protection and asset management present persistent technical challenges, particularly in the context of the smart grid and renewable energy sectors. This paper aims to address these challenges by providing a comprehensive assessment of machine learning applications for effective asset management in power systems. The study focuses on the increasing demand for energy production while maintaining environmental sustainability and efficiency. By harnessing the power of modern technologies such as Artificial Intelligence (AI), machine learning (ML), and Deep Learning (DL), this research explores how ML techniques can be leveraged as powerful tools for the power industry. By showcasing practical applications and success stories, this paper demonstrates the growing acceptance of machine learning as a significant technology for current and future business needs in the power sector. Additionally, the study examines the barriers and difficulties of large-scale ML deployment in practical settings while exploring potential opportunities for these tactics. Through this overview, we provide insights into the transformative potential of ML in shaping the future of power system asset management.

***Index Terms*— Power System, Asset Management (AM), Artificial Intelligence (AI), Machine Learning (ML), Renewable Energy Source (RES), Grid, and Electricity Generation.**

I. Introduction

Nowadays, technological advancements, governmental mandates for regulatory policy, and environmental concerns all contribute to the ongoing evolution of contemporary power systems. They are currently operating near their nominal ratings, necessitating the availability of control schemes, effective monitoring frameworks, and quick protection countermeasures to sustain secure operations. Power transmission generators, substations, transmission lines, and distribution channels are costly assets [1-3] with prolonged manufacturing/installation procedures. Recent modifications to power systems have significantly impacted the energy sector, not just in terms of technical characteristics but also in the context of managerial features. Implementing new generation systems [4, 5], constructing lines for transmission and distribution, and building substations have recently proven challenging for utilities due to economic and environmental constraints. This fact means that machinery will need to be utilized for a more extended period, close to their operating limits, and towards the end of their useful lives [6]. Consequently, organizations in the electric sector will be required to deploy advanced management and control systems for the manufacturing equipment and elements of the power system.

The utilities have made effective asset management their primary concern. Making efforts to construct and maintain plants at a suitable level of investment and quality can help to increase profitability and durability. The primary objective of asset management is to strike a balance between operating and capital costs to provide the highest possible value for shareholders and power users. The challenge has become more complex, with the cost of new and replacement plants soaring out of control. To solve the issue and consider the particular business procedures involved in building and operating plants, most utilities adopt automation.

AM goal is to manage physical assets in the best possible way to achieve an organization's goal while considering risk. The goal could be to maximize the value of assets, improve benefits, or reduce the lifespan cost, and the risk may be defined as the probability that an incident will occur and have a negative impact, such as cutting off customers' access to power. Electricity is essential for the industrial revolution since it allowed lighting and transportation. The electronic society of today relies heavily on power. Returning to using electricity for transportation is a trend that will make it feasible to use renewable fuels.

According to the indications of AM, network deployment, and system operation, the optimal level of dependability, asset lifecycle, and cost management have typically been found [7, 8]. According to the perception of system engineering, AM is mainly utilized to increase marketing strategy, good earnings, strong credibility, and reduced costs. By adhering to the AM lifecycle's management discipline strategy, these variables can be provided in applications for the power system. While doing operation maintenance, repairing components, and discovering faults, it is crucial to choose the correct option [9]. The AM process is the most effective approach to raising the productivity of industrial goods in power systems. Driven by technology advancements, regulatory mandates, and concerns about the environment and the climate, modern power systems are still developing [10]. The planning, selection, assessment, and asset migration sequence can also characterize AM. Yet, the most difficult duties included in AM techniques are determining the component's lifetime, estimating management costs, assessing its quality, and executing flawless maintenance [11, 12]. The technological, economic, and strategic evaluations must be met to increase the value of AM systems. In power systems, maximizing asset performance is usually one of the most important factors.
The contributions of this specific paper are,

- To examine the principles and methods of various ML approaches applied to enhance the effectiveness of AM in power systems.
- A variety of performance measures should be used to confirm the efficacy of supervised and unsupervised ML models used for AM.
- To evaluate the difficulties and manage the AM techniques based on technical and economic considerations.
- To thoroughly analyze the ML models with their unique benefits and drawbacks.

Also, it aims to identify and discuss the challenges and shortcomings inherent in previous studies related to asset management within electric power and energy systems. While these studies have laid a solid foundation, there remains a gap in integrating machine learning approaches with a comprehensive consideration for data integrity, regulatory standards, and environmental sustainability.
The remaining sections of this paper are as follows: The AM overview and several ML techniques used to enhance AM strategies in the power system networks are presented in Section 2. The detailed examination of the various ML techniques utilized in power system applications is illustrated in Section 3, along with their difficulties, benefits, and drawbacks. In Section IV, the overall study is summarized together with the results and upcoming examples.

II. Related Works

This section looks into various methods and technology for effective AM on networks of power systems. AM is one of the main factors that typically offers information on protection devices, power systems, transmission systems, and support systems. Because of these factors, it is crucial to the industries that deal with the energy distribution. The electric grid represents a complex ecosystem encompassing asset owners, manufacturers, service providers, and government officials. As the energy industry embraces digital transformation, substantial investments are being made across all production, generation, transmission, and distribution levels. This transformation is fueled by cutting-edge technologies, such as sensors, data analytics, privacy-aware markets, and smart meters, which enable the realization of smart grid solutions. These advancements, facilitated by two-way communication technologies, control systems, and powerful computer processing, aim to modernize the grid and enhance its intelligence and resilience. However, the existing electric infrastructure faces challenges, as it is being tasked with functionalities beyond its original design. As part of the energy transition objectives, developing smart power grids necessitates meeting new functional requirements that some legacy energy distribution assets may not fulfill. Equipment obsolescence, aging components, and evolving technological standards may induce premature replacements, driving up costs and posing environmental concerns. Adopting Asset Management (AM) becomes imperative to address these challenges and unlock the electric power system's potential. AM, a concept widely utilized in both the financial and engineering sectors, involves coordinated activities to realize value from assets. For the electric power system, which is a critical enabler for the transition to a sustainable and intelligent energy system (Smart Grid or SG), effective AM practices can optimize the utilization and lifespan of equipment. Moreover, the Reliability Centered Maintenance (RCM) method emerges as a structured approach focusing on reliability when formulating maintenance plans. Originating in the commercial aviation industry in 1978, the RCM method addresses the need to enhance reliability while managing maintenance costs. Reliability and maintenance are of utmost importance in the electric power system context due to significant associated costs and potential production losses or breakdowns that can impact the environment and personal safety. In this research, the focus is on presenting the Reliability Centered Asset Maintenance (RCAM) method. Building on the proven RCM principles, the RCAM method integrates quantitative maintenance optimization techniques. Originally designed for electric power distribution systems by Bertling in 2002, the RCAM method demonstrates promising results for maintenance strategy selection and optimization of wind turbines. The application of advanced Artificial Intelligence (AI) technologies, such as machine learning, within AM and RCAM can provide a significant competitive advantage. AI-driven algorithms can process vast datasets, enable predictive maintenance, and identify patterns and anomalies that human-driven approaches may overlook. By harnessing the potential of AI in AM and RCAM, the electric power system can achieve higher levels of reliability, efficiency, and sustainability, ultimately supporting the transition towards a more innovative and resilient energy landscape.

Koksal and Ozdemir [13] proposed a reliability-centered (RCM) AM approach to create the power transformer's maintenance plan. In this work, a Markov model has been used to assess the dependability and cost of transformers and offer the best solutions. Also, a sensitive examination of the transition rate has been completed, and the lifetime of transformers is calculated using data from real service. The authors thoroughly analyzed the various AM strategies applied to power distribution/transmission systems in [14]. The AM approach is divided into time- and activity-based groups based on how distribution networks are planned and operated. For examining the effects of data quality in power systems, Koziel et al created a ground-breaking AM methodology. The key steps of the AM system, including maintenance and replacement, are explained in this study. Based on the findings of this paper [15], it is determined that asset managers must assess the effects of each device with regard to the reliability of the assessment. *Babu, et al* [16] analyzed various controlling strategies used in a hybrid energy storage systems. The key benefits of using hybrid sources are reduced initial cost, better system efficacy, minimized stress, and better storage capacity. Moreover, the controlling techniques used for hybrid energy systems are categorized into the types of classical controlling models and intelligent controlling models. *Duchesne, et al* [17] reviewed recent works and developments in ML models for improving AM in power systems. *Cao, et al* [18] examined the different reinforcement learning approach for enhancing the AM of modern power systems. Many control and optimization issues in power systems involve typical hierarchical structures and human decision-making. Another interesting method for controlling extensive systems is using hierarchical frameworks, which can lower the deployment costs of communication devices and eliminate the isolation problem. Applications of RL for hierarchical control are uncommon in power systems due to the complexity of the hierarchical structure and the absence of a standard hierarchical framework. Future studies might use a hierarchical control framework based on reinforcement learning for complex systems. Modern power systems [19, 20] are getting larger, more sophisticated, and have more operating conditions & controlling options. Single-agent reinforcement learning algorithms use centralized frameworks that primarily rely on uninterrupted transmission lines, making them unable to scale up to huge systems or handle communication delays.

Tang, et al [21] employed a knowledge graph methodology for developing an effective power AM framework. This study suggests a method for building power equipment knowledge graphs by combining existing multi-source heterogeneous power equipment-related data. This study uses different types of heterogeneous data sources [22], like equipment operation records, equipment inspection records, equipment parameters, manufacturer information, operator information, equipment parameters, manufacturer information, operator information, equipment operation regulations, and other related information. Due to the shortcomings of the current AM system, there is insufficient data sharing between equipment manufacturing businesses and power providers, which leads to low data utilization efficiency. *Bosisio, et al* [23] developed a new meta-modal for multi-AM systems for electric distribution networks. While making operational and strategic decisions, a utility AM system is utilized to store, maintain, and support asset data. Although it has always been a crucial factor for utilities, managing distribution assets is now getting more attention as they aim to strengthen their business models in a changing sector and maximize the lifespan of new and current asset investments. Regulations, network complexity, consumption patterns, and budgetary control are a few of the key issues affecting power AM techniques [24]. Effective AM strategies are built on a solid meta-model. It divides the AM strategies for the power transmission sector into three-time frames: short-, mid-, and long-term. Operational concerns are dealt with in short-term AM; system device maintenance in mid-term AM [25]; and distribution system strategic planning in long-term AM. To achieve the desired levels of service reliability, AM for long-term planning is necessary, along with the identification of asset upgrade and development plans. For distribution networks operating radially, the least reliable equipment already in the system typically determines the efficiency [26]. As a result, decision-making processes used in planning the energy distribution system should evaluate the viability and effectiveness of the system's resources. A multi-utility can manage several asset kinds and associated parameters in its asset portfolio by specifying assets. In order to generate object libraries, the asset's parameters are then categorized into classes. Besides that, during each stage of the distribution network management process, the associated libraries are utilized to represent the assets. The identification of the asset's views makes it easier to identify the parameters.

III. Asset Management

The electric power sector is changing and putting a lot of strain on transmission and distribution assets, which has given rise to AM in the power system. AM [27, 28] is seen as one of the most crucial functions in developing and operating today's transmission and distribution systems. Electric utilities have been pushed to find the best ways to manage installed capacity while minimizing the cost of current components throughout their useful lives by a tendency to increase power system reliability. In order to achieve the best outcomes, researchers separate the operations of the power system into three key stages.

- Grid enlargement
- AM
- System operation and maintenance

Frequently, the phrase "asset" refers to something used in various settings, such as a model, design, system software, piece of instruction, or verification code. Data analysts and computational experts frequently use the term "artifact" to refer to various resources needed for model construction. Due to the experimental nature of ML [29], which necessitates preserving artifacts for later use, these artifacts qualify as assets in this context. Compared to the engineering of systems using ML, traditional software engineering frequently has fewer asset categories because it focuses exclusively on source code assets. For instance, datasets, algorithms, model parameters, and indicators for model evaluation are other fact categories included in ML. It is appealing to use conventional software engineering methods in the state of the art to solve some of the issues with AM [30] that have been highlighted. Also, explicit management tools and procedures are used to gather, arrange, and manage assets during model construction and after creation, which helps to resolve various AM difficulties. In this context, AM is defined as a crucial discipline that helps with the engineering of ML experiments and systems [31]. The objectives of AM are to enhance maintenance schedules, optimize asset life cycles, and develop successful marketing plans for the acquisition of fresh assets. This can be accomplished by creating better information management systems that support data analysis tools, preservation, and retrieval. Moreover, predictive maintenance, network maintenance, procurement and asset tracking, forecasting, and decision-making are some of the outputs of these technologies. The AM system [32] is generally classified into three types such as,

1. Time based
2. Activity-based

The time-based AM models [33-35] are split into short-term, mid-term, and long-term categories. Similarly, the activity-based AM is categorized into technical, economic, and societal types. The primary benefits of using the time-based models are lowering operation costs for serving customers in a competitive environment, optimizing the allocation of volatile and finite natural resources for leveraging company assets, prolonging the useful life of assets through proper maintenance and operation timeframes, and raising investment costs for the creation of fresh assets. Fig 1 shows the primary stages involved in the ML model.

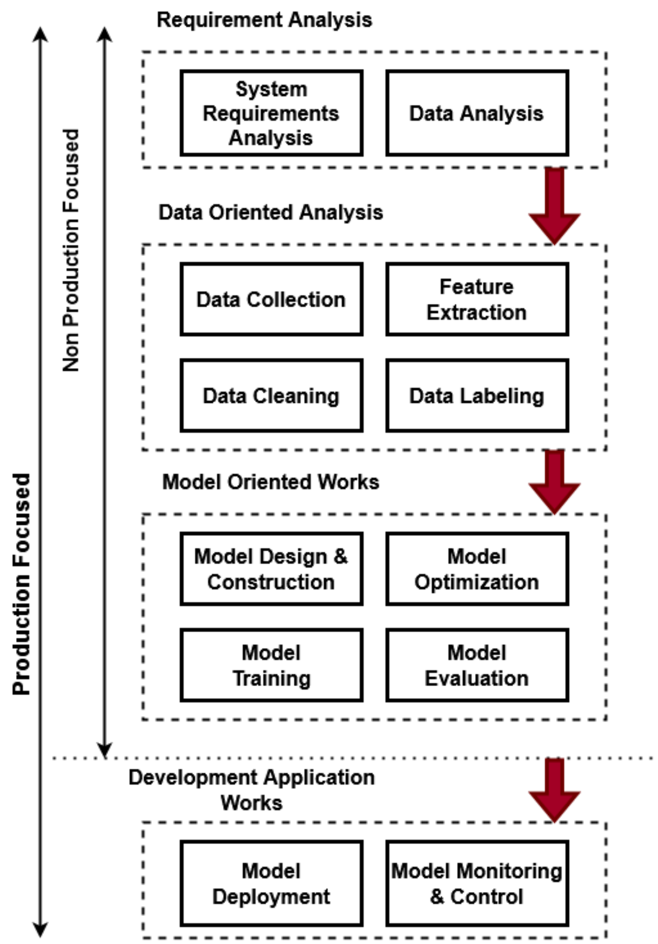

Fig 1. Stages of working in ML model

IV. ML Models used for AM in Power Systems

ML [36, 37] is a kind of data analytics method that aims to teach computers to do tasks similar to those performed by humans and animals based on a learning process. Instead of predetermined equations, ML algorithms [38-40] can directly "learn" information from the given data using computational techniques. They can also improve themselves adaptively as more data becomes available. ML analyses can use guidelines and several algorithms to produce conclusions and accurate predictions. ML must be carefully designed and programmed to accomplish various capabilities, such as classification, sorting, and analysis. ML and deep learning [41, 42] as a specialized field have shown promise in numerous fields of engineering and study during the past ten years. Moreover, the ML techniques [17, 43] are categorized into the following types:

1. Supervised learning
2. Unsupervised learning
3. Reinforced learning
4. Ensemble learning

The goal of supervised learning [44, 45] is to discover a mapping between inputs and outputs using a labeled set of input/output pairs in a training set with a large number of training samples. Unsupervised learning is a subset of ML paradigm, in which an algorithm is trained using data that has neither been classed nor given a label so that the system can group the data based on how similar or different it is. Typically, the unsupervised learning algorithms [46] are more unpredictable than other natural learning techniques and can handle more sophisticated tasks better than supervised learning algorithms. Cluster analysis is one of the most popular unsupervised learning techniques, which involves discovering hidden patterns or groups in data during exploratory data analysis. Furthermore, Reinforcement Learning (RL) is a type of learning [47] in which an agent connects with its surroundings and adapts its behavior in response to the stimuli it receives. The RL is distinct from supervised learning in that it does not call for labeled input/output pairings; instead, the agent is awarded or docked based on how it behaves in the environment. Hence, RL [7, 48] enables the agent to autonomously determine behaviors that are impossible with supervised or unsupervised learning. Compared to a single ML algorithm, an ensemble of methods is more effective, using multiple ML algorithms to enhance the prediction performance. In contrast to individual-based learners, ensemble learning creates a group of hypotheses that are combined and utilized to resolve a single problem. In the paper [49], a hierarchical deep learning machine is applied to predict the transient stability of the power systems. This paper validates the computational effectiveness of various deep learning algorithms in terms of processing time, response time, computational complexity, and memory usage. A Back-Propagation Artificial Neural Network (BP-ANN) technique was used by Trappey et al. [50] to create an intellectual AM system. This work's primary objective is to assess transformer problems under various operating circumstances. Here, using a feature selection technique based on Principle Component Analysis (PCA) decreases the number of important components. Fig 2 shows the typical model of the ML framework used in the power system applications. The electric power system is being updated to support a sustainable energy system [51]. As an integrated energy system component, the generation, delivery, and use of electricity present both opportunities and challenges. This entails updating current power infrastructures and new types of electricity usage, such as demand response and mobility. The power generation trend is toward new, small-scale, and large-scale advancements, such as offshore wind turbines and roofing solar panels. As society becomes more digitalized, new options for automation and control, as well as new business models and energy-related services, are being created. New options for measurement and control are the general trend for technological advancements. As an illustration, consider Phasor Measurements Units (PMUs), which can monitor voltage and current up to 30-120 times per second and are typically found in the transmission network. Others include smart meters installed at the consumer's home, which allow for the integration of home-scale power generation from solar panels, energy storage from electric vehicles, and general distributed control of energy use. The development of diagnostic assessment techniques for evaluating the insulation quality and estimating the useful life of physical assets and innovative approaches for condition monitoring, such as employing sensor networks, are two further trends. The general growth of these several tendencies is toward the handling and analysis of massive volumes of data, and another idea gaining popularity is referred to as "Big Data," which offers new tools for infrastructure asset management.

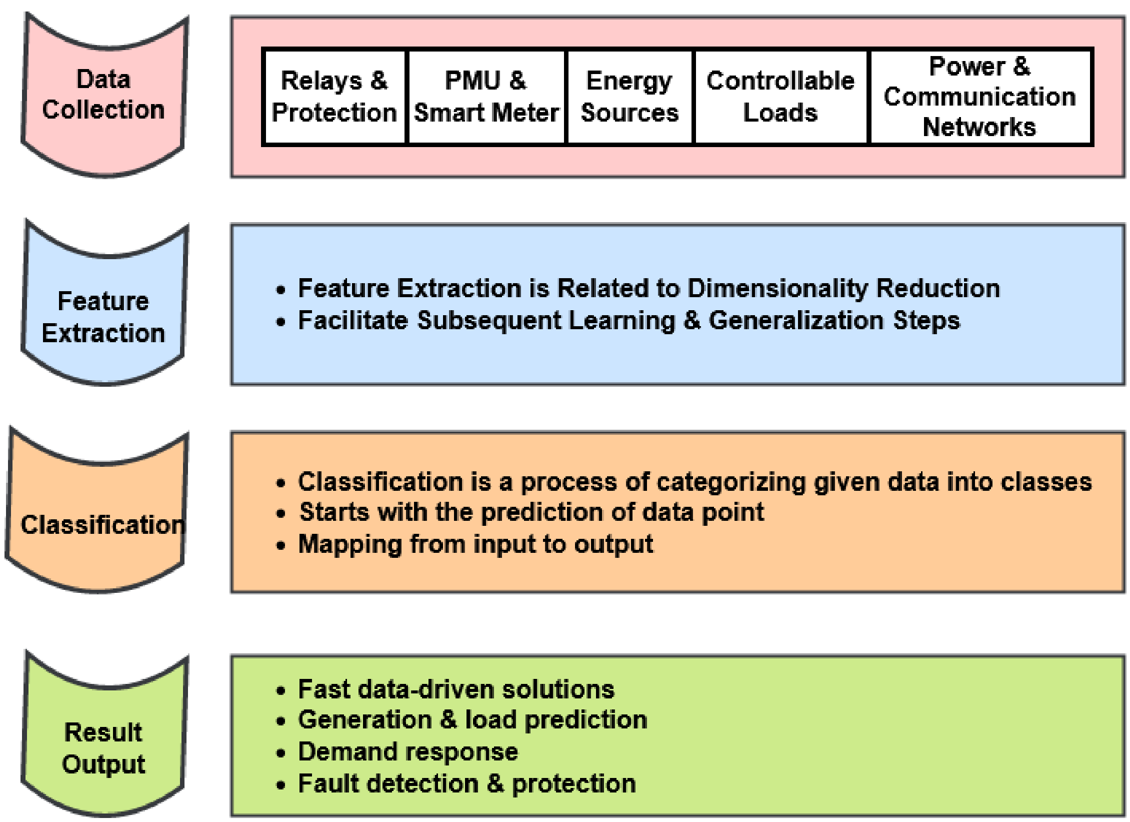

Fig 2. ML framework in power system

A. Support Vector Machine (SVM)

Support Vector Machines (SVMs) are crucial to learning theory [52]. They work rather well for a lot of scientific and engineering applications, especially when it comes to classification problems. Among these techniques, Support Vector Machines (SVM) are among the most widely used to improve the expected result. SVM's outstanding prediction accuracy, optimal judgment, and discriminative capabilities have recently piqued the interest of data analysis, information processing, and machine learning communities [53]. Furthermore, the SVM outperforms other supervised learning strategies in real-world binary classification problems, demonstrating its strength. The decision functions are automatically produced from learning data using SVM to maximize the margin (distance) between decision borders in a big region known as the subspace. To put it another way, there are significant differences between SVMs and the classification capabilities of other techniques, mainly when there are few input data points. This classification approach decreases the training data's prediction error, and a better generalization performance is obtained. SVMs [54] are a powerful tool for data classification and predictive analysis. During the learning phase, SVMs get a subset of support vectors, which is frequently a tiny percentage of the original data set. This tiny bit of data creates a set of support vectors reflecting a particular classification issue. It specializes in processing numerical data and making well-suited choices for continuous monitoring variables such as voltage levels, temperature, and pressure, commonly found in asset management scenarios. Fig. 3 displays the hyperplane separation model of the SVM approach.

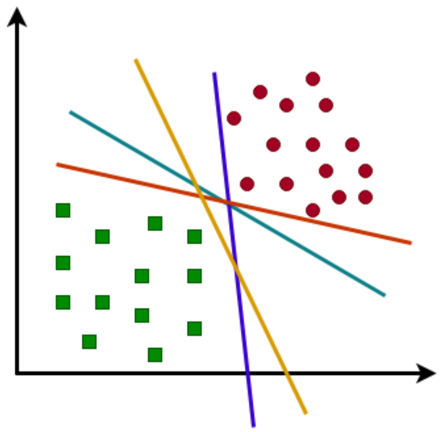

Fig 3. Separation of hyperplane in SVM

B. Naïve Bayes (NB)

The construction and analysis of massive data can be done using the NB model [55]. This technique is an extremely smart and simple classification system that excels even in challenging situations. It is a straightforward probability classifier that determines a set of probabilities by estimating the frequency and variations of values found in a particular data set. By considering the value of the class variable, the algorithm applies Bayes' theorem and assumes that all parameters are unbiased. The method typically learns quickly in various controlled classification problems despite this conditional independence assumption being considered naive because it is rarely true in real-world applications. *Balaraman, et al* [56] utilized several ML models for effective AM and fault diagnosis. This paper aims to categorize the type of transformer faults based on the prediction result of the classifier. *Toubeau, et al* [57] developed a new data-driven methodology for improving the maintenance activities of grid assets. Moreover, the authors used different classification approaches, such as the Bayesian model, SVM, DT, etc., to solve the prediction problem.

C. Artificial Neural Network (ANN)

Artificial neural networks are a framework that many machine learning techniques employ to interpret complex input data. Artificial neural networks (ANNs), a popular machine learning tool, are modeled after the biological neural network seen in the human brain. Feed-forward neural networks, which process inputs from artificial neurons in the layer below and send the weight values of each input neuron as output to the layer above, are ANNs that are often utilized. Regression analysis, linearization, and prediction are only a few applications for artificial neural networks [58, 59]. As seen in Fig. 4, the fundamental unit of an artificial neural network is a neuron that applies a transfer function to the output formulation. The main advantage of ANN models is that they are less challenging to deal with in multivariate situations. The backpropagation algorithm is the most frequently used MLP training technique. To lower error, this adjusts the weights of the neurons. This model does quite well when learning patterns. While the system may readily adapt to new data values, it may show signs of gradual convergence and even reach a local optimum. The number of layers and neurons in the hidden layer and their connectivity are important considerations. The artificial neural network's performance is heavily reliant on these variables and problems. Any one of these components could drastically change the results. Different ANN architectures will yield different results for different problems. However, trial and error is necessary to obtain the optimal ANN architecture. Abu-Elanien et al. [49] used a feed-forward artificial neural network to analyze the health index-based state of the power transformers. High-risk elements are identified, and the health index is computed using AM mainly to extend the life of power transformers. It requires large, diverse datasets that encompass both numerical and categorical data. Their strength lies in modeling complex non-linear relationships, making them ideal for forecasting tasks, including energy consumption and load patterns. The ability to process a mix of time-series data and static asset characteristics allows ANNs to offer comprehensive insights into asset performance and future behavior.

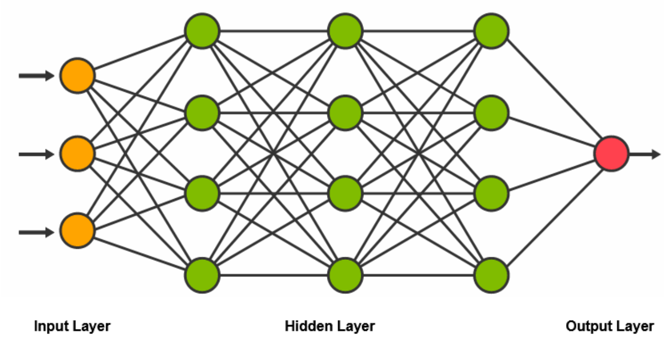

Fig 4. ANN architecture

D. Extreme Gradient Boost (XGB)

XGBoost is a highly scalable ensemble of decision trees based on gradients [60]. By decreasing a loss function, XGBoost creates an additive expansion of the decision variables, much as gradient boosting. The ensemble method is the foundation for this supervised machine learning algorithm, which enhances the gradient-boosting methodology. Through additive techniques, the XGBoost algorithm [61, 62] constructs an efficient learning model by averaging the predictions of base learners. The XGBoost classier solves the overflow problem and maximizes the use of computational resources and is fast and efficient. Regularisation and predictive terms can be integrated with the benefits of the objective functions, which are simplified to enable parallel execution during the training phase. XGB performs well with organized, tabular data, particularly excelling in scenarios where feature selection is critical to the analysis. It is capable of handling missing values and identifying the most relevant features for models, making it invaluable for risk assessment and life-cycle analysis of power system assets, where data can often be incomplete or unevenly distributed.

E. Random Forest (RF)

As opposed to using a single classifier, ensemble classification methods build a group of classifiers. They then use a vote of the predictions from those classifiers to categorize new data points. The set of classifiers with tree structures makes up the Random Forest (RF) classifier [63, 64]. It is an improved form of bagging in which randomness has been incorporated. Each node is divided using the best split among a subset of predictors that were randomly selected at a certain point, as opposed to using the best split across all variables. The original data set is replaced, a new training data set is produced, and a tree is developed using random feature selection. This tactic gives unmatched RF precision. Moreover, RF is quick, resistant to overfitting, and allows users to build as many trees as desired. Furthermore, RF [63, 65] is a hierarchical grouping of base classifiers with a tree topology. For the classifier model, just a few significant attributes are informative. The RF algorithm uses a straightforward predefined probability to choose the most crucial considerable property. Breiman [66] developed the RF technique by mapping a random sample of feature subspaces to sample data subsets and building multiple decision trees. Fig 5 shows the architecture model of RF.

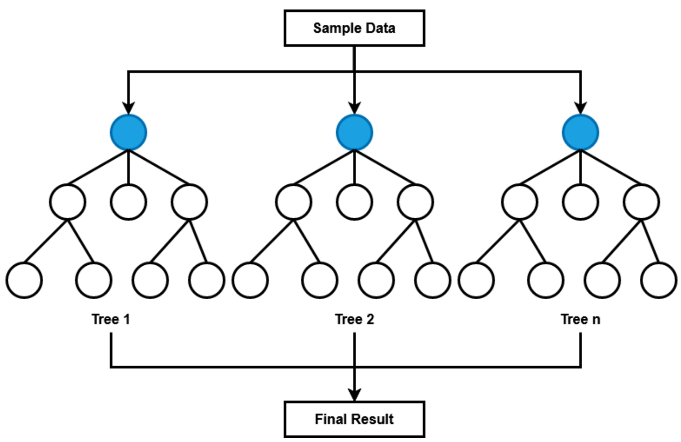

Fig 5. Architecture of RF

F. Decision Tree (DT)

With rectangles for the core nodes and oval tracks for the leaf nodes, a decision tree [67] is a tree structure that resembles a flowchart. It is the most widely used algorithm because it is easier to create and understand than other classification algorithms. Decision tree classifiers attain equivalent, and sometimes even higher, accuracy than other classification algorithms. Decision tree implementation can be carried out sequentially or concurrently, depending on the volume of data, the amount of memory that is available on the computer resource, and the scalability of the algorithm. Every node in a decision tree [68] represents an attribute, every connection denotes a choice, and every leaf shows the result (continuous or categorical value). Decision trees mimic how humans think, making it incredibly simple to collect data and derive insightful conclusions. The goal is to process a single result at each tree leaf created by organizing the data in this manner [69]. The decision tree explicitly lists every possible option and tracks each one through to completion in a single display to make it easier to compare the many options. Transparency is one of the best aspects of the Decision Tree. Another significant advantage is the ability to select the most biassed feature and comprehensibility nature [70, 71]. It is also easier to categorize and understand and works better with discrete and continuous data sets. Decision trees can efficiently use feature parts and continuous screening for precise prediction results. It offers the flexibility to handle both numerical and categorical data efficiently. This characteristic is beneficial for developing decision support tools that guide maintenance and operation decisions. The DT architecture model is displayed in Fig. 6.

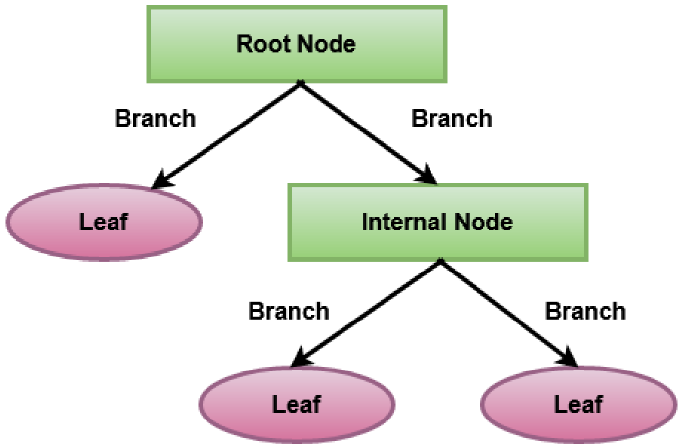

Fig 6. DT architecture

G. *Logistic Regression (LR)*

A linear model lays out the connection between one or more independent variables [72, 73] and a dependent predicted value. If the labels are known, supervised learning is the phrase used in ML to describe mapping qualitative or quantitative input qualities to a target variable that is being intended to be predicted, such as economic, biological, or sociocultural data. Logistic regression is one of the most often used linear statistical models for multiple regression. Fig 7 shows the typical architecture model of LR, which demonstrates that the LR can predict the output label according to the weight values of the input data.

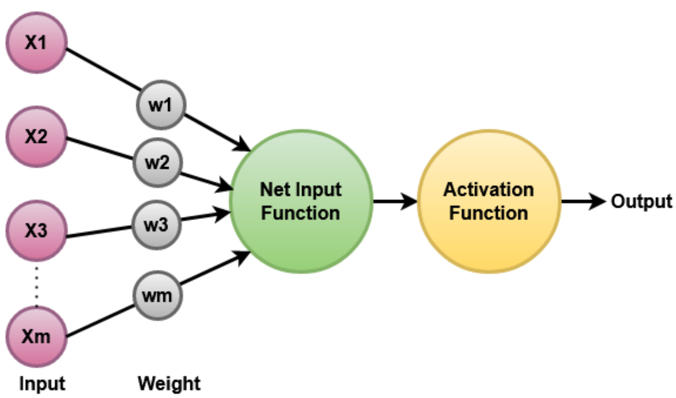

Fig 7. Architecture of LR

H. *Fuzzy Logic (FL)*

The conclusions generated by fuzzy logic are identical to those produced by human vision and reasoning. It has been demonstrated that fuzzy logic works effectively in expert systems. The construction of fuzzy sets, which range from 0 to 1, aids in deciding whether a member belongs to the set. It is employed when making decisions under ambiguous circumstances. Fuzzy logic calculates the problem's degree of confidence, and its algorithms are reliable and flexible enough to adapt to shifting conditions. Fuzzy logic was used by Arshad and Islam [74] to enhance the AM procedures in power transformers. An AM strategy is primarily used to calculate power transformers' age (retirement/replacement) to reduce failure rates. The aging effect can be calculated during this process based on the power transformers' dependability, lifespan, and performance rate. In this case, the fuzzy logic technique supports the AM system's dependability, availability, and efficiency. Additionally, it aids in extending life and managing power transformers with higher dependability measures. The typical architecture of fuzzy logic is shown in Fig 8. In the paper [75], the risk assessment for the ideal AM strategy in the power distribution systems uses a fuzzy logic model. They include economic, environmental, safety, regulatory, vulnerability, and risks related to supply quality and supply chain vulnerability. The production of inference rules, fuzzification, and defuzzification are the three main working phases of the fuzzy logic system. Here, the AM is mainly carried out to estimate the risk variables that could have an impact on the operation system as a whole.

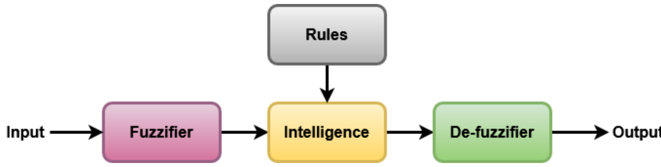

Fig 8. Architecture of FL

Looking ahead, a viable path toward improving asset management in power systems is the incorporation of symbolic data into machine learning models. Symbolic data, such as operational statuses, maintenance records, and safety codes, encapsulate qualitative information that can provide deeper context and insights into the health and performance of power system assets. For instance, symbolic data can enhance model predictions by directly incorporating expert knowledge and regulatory standards into the analytical process.
Considering symbolic data requires methodologies capable of interpreting and processing this form of information alongside traditional numerical and categorical data. Techniques such as symbolic regression, logic-based AI models, and hybrid approaches that combine symbolic reasoning with conventional machine learning could be explored. These methodologies can uncover patterns and relationships that purely numerical data might not reveal, leading to more holistic and robust asset management strategies.

V. Results and Discussion

As shown in Table 1, some of the recent state-of-the-art model approaches used for AM in power systems are reviewed, as well as their pros and cons.

Table 1. Comparative analysis between various ML models

Author Name & Year	***ML Model***	***Application***	***Description***	***Advantages and Disadvantages***
Hu, et al [76]	SVM	A real-time Transient Stability Assessment (TSA) scheme is developed using SVM for power systems.	One of the most crucial methods for preventing cascading failures, massive blackouts, and transmission line instability is real-time TSA.	• High level of robustness • Better speed • Incapable for handling complex datasets • Reduced dependability
Alimi, et al [77]	MLP-SVM	Security in power systems.	A new hybridized classification model is developed by integrating the functions of standard SVM and MLP to ensure security in power systems.	• Lower error rate • Reduced risk • System complexity • Reduced detection efficiency.
Piryonesi, et al [78]	LR	Minimization of Quality Problems using AM.	The goal is to investigate how various algorithms handle the often small and poor-quality data sets used in infrastructure AM.	• Accepted accuracy • Reliable prediction performance • Higher error rate • Low robustness
Piryonesi, et al [79]	DT	Power system data management.	This work intends to perform a proper AM using the DT algorithm.	• Ensured safety • Better maintenance • Lack of dependability • High-risk factors
Rocchetta, et al [7]	ANN	Optimal management of power grids.	Here, an ANN-based ML algorithm is deployed to perform grid operation and maintenance effectively.	• High training efficiency • Better robustness • Reduced effectiveness

Idrees, et al [80]	Fuzzy logic	Health index estimation in power systems.	This paper aims to combine the sub-modules of fuzzy logic for detecting faults in power systems based on the health index.	• It does not require any precise inputs for processing. • Robust in nature. • Inaccurate prediction results
Protolinsky, et al [81]	ANN	Power AM using hierarchical confinement models	A communication graph has been generated for each element in the electricity network management system.	• Imprecise information. • Low cost. • It supports a wide range of operating conditions. • Not suitable for large applications.
Tanfilyeva, et al [82]	K-Nearest Neighbor (KNN)	Conditional AM scheme	The k-NN classification model based on the insulating liquids of power transformers has been used to identify and detect the faulty condition of power transformers.	• Flexibility. • Better classification accuracy. • It is challenging to compute thresholds.
Mirhosseini, et al [83]	Multi-criteria decision-making model	Proper AM in power system networks	The various AM and maintenance tactics applied to the power systems are presented.	• Computational burden. • Moderate accuracy. • Reduced failure rate. • Low time requirement.
Nyong, et al [84]	Reinforcement Learning	Effective energy and AM in hybrid systems	It considers several asset kinds, such as generating, multi-storage, and control, to enhance energy storage capacity in hybrid power generation systems.	• Low system complexity. • Adaptive in nature. • Difficult to deploy. • High time consumption for data training.
Wang, et al [85]	Ensemble learning mechanism	Resilient energy system using ML	The authors intend to investigate various ML algorithms for power AM.	• Ensured sustainability. • Low computational burden. • Lack of security.
Alzoubi, et al [86]	Standard ML models	AM for smart home applications	Here, the different AI-based algorithms are studied for proper AM and energy management in smart home applications.	• It is not capable of adapting to changes in the environment. • Complexity in handling massive dimensional data. • Better stability.
Aguilar, et al [87]	Extreme gradient boost (XGB)	Short-term forecasting using ML	This paper implements the XGB classification model to reduce the electricity production cost.	• Local optimum. • It requires to train more models for decision making. • Sensitive to outliers. • Moderate accuracy.
Hossam, et al [88]	Fuzzy Logic (FL) technique	AM for power transformer	Here, the standard fuzzy logic technique has been used to perform the lifetime assessment of the power transformer.	• It does not require the exact information for prediction. • Simple to implement & understand. • It is not suitable for handling imprecise data. • Requires human interference.
Majzoobi, et al [89]	Adaptive Network Fuzzy Inference System (ANFIS) model	AM using ML for power transformers	The authors intend to predict power transformers' life using an ANFIS based AM scheme.	• Highly efficient. • Minimized complexity. • Suitable for handling large data. • Error outcomes.
Li, et al [90]	Multi-kernel SVM	Fault diagnosis and AM using	Here, the clustering integrated ML model is implemented for fault diagnosis in power transformers.	• Increased training speed. • Moderate accuracy. • Low efficiency.

		multi-kernel SVM model.		
Cui, *et al* [91]	Recurrent Neural Networks (RNNs)	Fault detection for condition monitoring of wind turbines.	The framework analyzes data from supervisory control and data acquisition (SCADA) systems, incorporating log information and operation data. Log events are mapped to specific assemblies using the Reliawind taxonomy, while RNNs model normal behaviors based on operation data.	Advantages: 1. Automatic Learning 2. Enhanced Fault Detection 3. Real-time Monitoring 4. Versatile Application Disadvantages: 1. Data Requirements 2. Computational Complexity • 3. Interpretability
Cui, *et al* [92]	Deep Learning with Autoencoders and Gated Recurrent Unit (GRU)	Data-driven fault diagnosis for high voltage equipment condition monitoring, particularly power transformers.	The paper aims to develop a data-driven fault diagnosis approach utilizing operation data to monitor the condition of high-voltage equipment, specifically power transformers. The study incorporates expertise input from interviews to enhance asset management practices for power transformers. The deep learning technique is employed in an unsupervised manner to model normal behaviors and identify underlying operational risks.	Advantages: 1. Data-Driven Approach 2. Unsupervised Learning 3. Key Feature Extraction 4. Temporal Dependency Modeling Disadvantages: 1. Data Accessibility 2. Computational Complexity 3. Interpretability
Urrea Cabus *et al* [93]	Autoencoders	Anomaly detection for wind turbine condition monitoring.	The research presents an anomaly detection approach based on autoencoders for assessing wind turbine health and enabling preventative maintenance programs. SCADA signals serve as the data input for the approach. The methodology involves examining the differences between the estimated values generated by the autoencoder models and the measured signals from the SCADA system. The Kernel Density Estimation is then utilized to determine the distribution of the expected output's error. A novel dynamic thresholding approach efficiently extracts anomalous activity in the data.	Advantages: 1. Anomaly Detection 2. Unsupervised Learning 3. Distribution-Based Analysis 4. Real-time Alerting Disadvantages: 1. Data Quality and Availability 2. Computational Resources 3. Interpretability
Cui *et al* [94]	Autoencoder-based Anomaly Detection Method	Asset management and preventive maintenance using condition monitoring for wind turbines.	The chapter proposes a novel method for asset management (AM) and preventive maintenance of wind turbines, leveraging condition monitoring. The suggested model is based on autoencoder-based anomaly detection, which tracks the condition of wind turbines. The method utilizes supervisory control and data acquisition (SCADA) signals as input data. It then analyzes the discrepancies between the SCADA data and the estimated values generated by the autoencoder models. The distribution of the output error is calculated using Kernel Density Estimation.	Advantages: 1. Enhanced Asset Management 2. Proactive Maintenance 3. Unsupervised Learning 4. Statistical Analysis Disadvantages: 1. Data Quality and Availability 2. Computational Resources 3. Interpretability
Urrea Cabus [95]	Unsupervised Feature	Fault detection and	The paper conducts a comparative analysis of various unsupervised feature	Advantages: 1. Dimensionality Reduction

	Extraction Techniques and Supervised Machine Learning Models	classification over a power distributed generation system.	extraction techniques and supervised machine learning models for fault detection and classification in a power-distributed generation system. The study utilizes the modified IEEE 34 bus test feeder simulated through PowerFactory DigSILENT software. Data analysis is performed in Python using three-phase voltages and currents collected from the simulation.	2. Enhanced Accuracy 3. Overfitting and Underfitting Prevention 4. Real-World Application Disadvantages: 1. Data Preprocessing Complexity 2. Model Selection 3. Data Collection and Availability
P. Bangalore and L. B. Tjernberg [96]	Artificial Neural Network (ANN)	Condition monitoring of gearbox bearings in wind turbines for effective predictive maintenance.	The paper introduces a self-evolving maintenance scheduler framework for the maintenance management of wind turbines, specifically focusing on gearbox bearings. The goal is to detect early indications of possible wear and tear in the gearbox bearings to enable effective predictive maintenance, ultimately reducing the overall maintenance cost. The proposed approach utilizes an artificial neural network (ANN)--based condition monitoring method.	Advantages: 1. Predictive Maintenance 2. Real-Time Monitoring 3. Data-Driven Insights 4. Scalability Disadvantages: 1. Data Quality and Availability 2. Model Complexity 3. Interpretability

Perhaps the most challenging aspect of AM is coming up with predictions with the highest level of accuracy feasible to serve as the basis for distribution networks and long-term planning systems. Data-driven intelligent systems (AI) are defined as a collection of techniques and algorithms that use approaches from statistics to learn from, project, and make choices that depend on the construction of models from a set of data. These techniques embrace deep learning and evolutionary algorithms, which are not solely based on the work of data researchers or statistical experts in the past. Using different data-driven intelligence algorithms to develop predictive maintenance policies and skills helps to improve scheduled maintenance to avoid breakdowns and safeguard associated costs. Before implementing data-driven AI methods, a historical deterioration set of information needs to be gathered. Moreover, it is challenging to provide general adaptive maintenance support due to the intricate nature of the numerous assets in terms of data sources, knowledge, and information available. To exchange and exploit knowledge in a domain, taxonomy are detailed formal descriptions of ideas and attributes of features in a specific domain. This literature review concludes that numerous machine learning and deep learning approaches have been established in earlier studies for asset management in power systems. Based on the findings, it is evident that most conventional systems suffer from issues related to interpretability, resource collection complexity, erroneous consequences, inability to handle large-dimensional data, and high risk. Also, Integrating AI-based approaches into existing workflows requires careful planning to avoid operational disruptions. Thus, the proposed work aims to create an effective and lightweight learning algorithm for asset management in power systems.

VI. GREEN GRIDS

The transition of the electricity grid, often referred to as the "Green Grid," represents a shift towards energy solutions. This shift is driven by concerns about climate change and the desire for energy systems. In addition to sustainability, there is also a focus on cost-effectiveness and efficient use of resources. In this context, infrastructure asset management technologies provide avenues for grid operation and maintenance [97]. Advancements in technology, such as Phasor Measurement Units (PMUs) in transmission grids and widespread usage of meters at consumer endpoints, enable the integration of distributed energy resources like solar panels, electric vehicles, and energy storage systems [98]. Additionally, artificial intelligence (AI) and machine learning (ML) are playing roles in making the grid greener by enabling maintenance, optimizing energy distribution, managing demand-side resources effectively, and refining diagnostic assessment techniques used to evaluate insulation quality and predict the lifespan of physical assets [99]. Integrating AI and ML in the grid allows for more efficient and effective management of energy resources. ML algorithms can analyze large amounts of data collected from PMUs and other sensors to optimize energy distribution and detect real-time anomalies. These algorithms can also be used to refine diagnostic assessment techniques, such as evaluating insulation quality, which can help predict the lifespan of physical assets [100]. By leveraging AI and ML, the grid can be operated more intelligently, improving reliability and efficiency. Additionally, the adoption of modern condition monitoring mechanisms, like sensor networks and the subsequent influx of data they generate, has underscored the significance of "Big Data" analysis.

VII. Discussion

An extensive literature review shows that machine learning and deep learning approaches are gaining significant traction in addressing various asset management challenges within power systems. Considering the surge in development and interest across diverse ML applications, the electric power industry benefits substantially from integrating ML technology. In this study, we conducted a comprehensive review of the existing and potential applications of ML in asset management and power system protection. Our analysis encompassed a quick overview of machine learning research publications within the power systems domain and the popularity of machine learning techniques in the last five years. Various machine learning techniques have been thoroughly researched to tackle the technological complexities inherent in different power system application domains. It becomes evident that ML becomes an indispensable paradigm shift when substantial amounts of data exhibiting suitable spatial and temporal diversity are made available. In such cases, ML intelligence possesses the capability to offer valuable insights and informed decisions solely based on the input data, surpassing the limitations of traditional model-based or analytical approaches. Additionally, we identified ML's potential in exploring opportunities in scenarios where certain phenomena remain unidentified and conventional modeling methods prove impractical. This paper provides a comprehensive summary of the adopted machine learning approaches, outlining the input variables and performance indicators and the associated benefits and drawbacks. Based on these justifications, ML can significantly enhance power system protection and condition monitoring, leading to instant diagnostics and reduced operating costs while simultaneously prolonging the lifespan of critical electrical components. Furthermore, the continuous advancement of sophisticated computing systems and cutting-edge technological progress in the field of computing encourages the integration of intricate and computationally demanding algorithms. These innovations effectively address various academic and engineering challenges, positioning powerful machine learning technologies as promising tools for efficient asset management within power systems. As we conclude this study, it is evident that the application of machine learning in power systems holds immense potential for future research prospects. Embracing this technology promises to enhance asset management practices further, thereby optimizing power system operations and contributing to a more sustainable and reliable energy landscape. By continuously exploring and harnessing the capabilities of ML in the power sector, we can truly unlock novel opportunities to shape the future of efficient asset management in power systems. AI has made it possible for advanced asset management to more effectively interpret business objectives into decisions concerning the acquisition of assets, analytics for tracking the performance of assets, forecasting and restricting operations, planning the supply chain, replacement components optimization, and final stages of life asset management.

Integrating AI-based AM systems into existing infrastructure and workflows at scale presents several challenges, including ensuring data quality and availability, seamless integration with legacy systems, scalability, security, and privacy, and addressing the skill gap among the workforce. To overcome these hurdles, organizations can adopt a multifaceted approach. First, establishing robust data governance frameworks can enhance data quality, while modular and API-driven integration strategies can facilitate the incorporation of AI functionalities into existing systems without significant disruptions. Scalability can be achieved through cloud computing and scalable AI architectures, ensuring the system can handle growing operational demands. Addressing security and privacy concerns is critical, requiring the implementation of robust security protocols and adherence to regulatory standards to protect sensitive data. Finally, addressing the skill gap by investing in training programs for existing employees and fostering partnerships with educational institutions can equip the workforce with the necessary skills for AI implementation. By tackling these challenges head-on, organizations can effectively integrate AI-based asset management systems, improving efficiency and decision-making without adding undue complexity to operations.

VIII. Conclusion

The overall review of the study indicates that AM has become a crucial component in the ever-changing electric power market environment. The power industry constantly changes due to environmental, socioeconomic, and technical variables. This study focused on transmission and distribution assets, including power converters, grids, security protocols, intermediate systems, and structural components. It also extensively explored various ML strategies and their respective benefits and drawbacks. The significance of maintenance tasks and adherence to asset management guidelines were underscored as crucial elements in ensuring electrical equipment's functioning stability and lifespan prediction. These factors play a vital role in enhancing the overall efficiency of power system networks.

While this study focused on exploring the potential of ML, for future research, applying machine learning algorithms alongside appropriate asset management policy frameworks holds the promise of achieving optimal asset management and system performance. Moreover, we discover that deep learning methods present a viable path for power system applications due to their reduced complexity and increased efficiency. The power industry can benefit from enhanced asset management procedures and enhanced decision-making processes by utilizing deep learning capabilities. To support the power sector in its goal of efficient asset management, we must keep investigating and developing ML-based strategies. By doing this, we can ensure sustainable, dependable, and effective energy networks for the future while fostering resilient power systems that satisfy the changing demands of a changing world.

There are several interconnected issues facing the electrical industry AM in light of rising temperatures, aging infrastructure, and growing dependability needs. These include:

- Need for prioritizing assets to maximize performance while limiting costs and risks across the entire energy production, distribution, and dissemination chain.

- A notable rise of in asset management.
- Restricted human and financial assets.
- Potential advantages of the use of new techniques existing in the current state-of-the-art to assist asset management.

To resolve these problems, a detailed assessment of the influence of Industry 4.0 tools on the AM of electrical industries can be conducted. It is evident that the following are the primary tools that would enable the energy generator, transmission supplier, and power suppliers to apply an integrated AM model and surpass AM issues:

- Computerized modeling and training of the whole intricate reliability of the system, which takes into account.
- The remaining life expectancy of getting older supplies.
- Failure planning.
- Adverse conditions and resilience to disturbances.
- The predictive maintenance techniques are integrated.
- Machine learning algorithms based on appropriately structured data from these three functions' apparatus and systems are integrated to enhance simulation models.
- Assets are ranked depending on the safety index calculation's use of suitable methods.

These components can concentrate resources on vital infrastructure and machinery while limiting the use of limited assets. In the future, we plan to prioritize the maintenance tasks by optimizing asset replacement using simulation models.

References

[1] B. Mohandes, M. S. El Moursi, N. Hatziargyriou, and S. El Khatib, "A review of power system flexibility with high penetration of renewables," *IEEE Transactions on Power Systems,* vol. 34, pp. 3140-3155, 2019.

[2] N. Hatziargyriou, J. Milanovic, C. Rahmann, V. Ajjarapu, C. Canizares, I. Erlich*, et al.*, "Definition and classification of power system stability–revisited & extended," *IEEE Transactions on Power Systems,* vol. 36, pp. 3271-3281, 2020.

[3] S. Ashraf, O. Alfandi, A. Ahmad, A. M. Khattak, B. Hayat, K. H. Kim*, et al.*, "Bodacious-Instance Coverage Mechanism for Wireless Sensor Network," *Wireless Communications and Mobile Computing,* vol. 2020, p. 8833767, 2020/11/28 2020.

[4] H. Haes Alhelou, M. E. Hamedani-Golshan, T. C. Njenda, and P. Siano, "A survey on power system blackout and cascading events: Research motivations and challenges," *Energies,* vol. 12, p. 682, 2019.

[5] J. Zhao, A. Gómez-Expósito, M. Netto, L. Mili, A. Abur, V. Terzija*, et al.*, "Power system dynamic state estimation: Motivations, definitions, methodologies, and future work," *IEEE Transactions on Power Systems,* vol. 34, pp. 3188-3198, 2019.

[6] T. Heggarty, J.-Y. Bourmaud, R. Girard, and G. Kariniotakis, "Quantifying power system flexibility provision," *Applied energy,* vol. 279, p. 115852, 2020.

[7] R. Rocchetta, L. Bellani, M. Compare, E. Zio, and E. Patelli, "A reinforcement learning framework for optimal operation and maintenance of power grids," *Applied energy,* vol. 241, pp. 291-301, 2019.

[8] P. E. Love and J. Matthews, "The 'how'of benefits management for digital technology: From engineering to asset management," *Automation in Construction,* vol. 107, p. 102930, 2019.

[9] X. Deng and T. Lv, "Power system planning with increasing variable renewable energy: A review of optimization models," *Journal of Cleaner Production,* vol. 246, p. 118962, 2020.

[10] S. Petchrompo and A. K. Parlikad, "A review of asset management literature on multi-asset systems," *Reliability Engineering & System Safety,* vol. 181, pp. 181-201, 2019.

[11] N. S. P. Peraka and K. P. Biligiri, "Pavement asset management systems and technologies: A review," *Automation in Construction,* vol. 119, p. 103336, 2020.

[12] M. S. Ibrahim, W. Dong, and Q. Yang, "Machine learning driven smart electric power systems: Current trends and new perspectives," *Applied Energy,* vol. 272, p. 115237, 2020.

[13] A. Koksal and A. Ozdemir, "Composite system reliability assessment to reduce the curtailment risk using the storage systems," in *2022 IEEE 7th International Energy Conference (ENERGYCON)*, 2022, pp. 1-6.

[14] J.-S. Hwang, S.-D. Mun, T.-J. Kim, G.-W. Oh, Y.-S. Sim, and S. J. Chang, "Development of data cleaning and integration algorithm for asset management of power system," *Energies,* vol. 15, p. 1616, 2022.

[15] D. L. Alvarez, L. S. Rosero, S. R. Rivera, and A. A. Romero, "A Framework For Asset Management in Electrical Systems, Part I: Conceptual Model," in *2019 IEEE Workshop on Power Electronics and Power Quality Applications (PEPQA)*, 2019, pp. 1-6.

[16] T. S. Babu, K. R. Vasudevan, V. K. Ramachandaramurthy, S. B. Sani, S. Chemud, and R. M. Lajim, "A comprehensive review of hybrid energy storage systems: Converter topologies, control strategies and future prospects," *IEEE Access,* vol. 8, pp. 148702-148721, 2020.

[17] L. Duchesne, E. Karangelos, and L. Wehenkel, "Recent developments in machine learning for energy systems reliability management," *Proceedings of the IEEE,* vol. 108, pp. 1656-1676, 2020.

[18] D. Cao, W. Hu, J. Zhao, G. Zhang, B. Zhang, Z. Liu, *et al.*, "Reinforcement learning and its applications in modern power and energy systems: A review," *Journal of modern power systems and clean energy,* vol. 8, pp. 1029-1042, 2020.
[19] C.-M. Jung, P. Ray, and S. R. Salkuti, "Asset management and maintenance: a smart grid perspective," *International Journal of Electrical and Computer Engineering (IJECE),* vol. 9, pp. 3391-3398, 2019.
[20] Y. Rui, Z. Hu, S. Qian, Y. Li, R. Wei, and Q. Tang, "Research on Asset Management of Power Grid Engineering Based on Asset Group," in *IOP Conference Series: Materials Science and Engineering*, 2019, p. 055063.
[21] Y. Tang, T. Liu, G. Liu, J. Li, R. Dai, and C. Yuan, "Enhancement of power equipment management using knowledge graph," in *2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*, 2019, pp. 905-910.
[22] E. Gavrikova, I. Volkova, and Y. Burda, "Implementing asset data management in power companies," *International Journal of Quality & Reliability Management,* vol. 39, pp. 588-611, 2022.
[23] A. Bosisio, D. Della Giustina, S. Fratti, A. Dedè, and S. Gozzi, "A metamodel for multi-utilities asset management," in *2019 IEEE Milan PowerTech*, 2019, pp. 1-4.
[24] F. Dori, E. Ruetsche, and U. Schubiger, "Artificial Intelligence-Chances and Challenges in Quantitative Asset Management," *Available at SSRN 3122237,* 2018.
[25] D. Flynn, W. Tang, D. Roman, R. Dickie, and V. Robu, "Optimisation of hybrid energy systems for maritime vessels," in *9th International Conference on Power Electronics, Machines and Drives 2018*, 2018.
[26] L. Weijs, "Reinforcement learning in Portfolio Management and its interpretation," *Erasmus Universiteit Rotterdam,* vol. 81, p. 82, 2018.
[27] G. Wenjun, "Design and implementation of asset management system based on RFID," in *2021 IEEE International Conference on Power, Intelligent Computing and Systems (ICPICS)*, 2021, pp. 579-583.
[28] E. Gavrikova, I. Volkova, and Y. Burda, "Strategic aspects of asset management: An overview of current research," *Sustainability,* vol. 12, p. 5955, 2020.
[29] E. T. Mharakurwa, G. N. Nyakoe, and A. Akumu, "Transformer remnant life estimation and asset management model based on insulation stress assessment," in *2019 IEEE Electrical Insulation Conference (EIC)*, 2019, pp. 325-329.
[30] P. Xie, L. Li, and Y. Hao, "Asset management of power transformer: optimization of transformer liftime cost based on quality management strategy," *The 16th IET International Conference on AC and DC Power Transmission (ACDC 2020),* 2021.
[31] M. Anandakumar and K. Varughese, "Infrastructural Asset Management and Maintenance of System Health in Power Sector Utilities: An Overview," *Power Research-A Journal of CPRI,* pp. 79-85, 2020.
[32] B. Das, "Advanced analytics for transformer asset management," *Transformers Magazine,* vol. 7, pp. 78-88, 2020.
[33] W. C. Khoo, J. Teh, and C.-M. Lai, "Demand response and dynamic line ratings for optimum power network reliability and ageing," *IEEE Access,* vol. 8, pp. 175319-175328, 2020.
[34] N. Helistö, J. Kiviluoma, H. Holttinen, J. D. Lara, and B. M. Hodge, "Including operational aspects in the planning of power systems with large amounts of variable generation: A review of modeling approaches," *Wiley Interdisciplinary Reviews: Energy and Environment,* vol. 8, p. e341, 2019.
[35] M. Mirhosseini and F. Keynia, "Asset management and maintenance programming for power distribution systems: A review," *IET Generation, Transmission & Distribution,* vol. 15, pp. 2287-2297, 2021.
[36] J. R. Kala, D. M. Kre, A. N. G. Gnassou, J. R. K. Kala, Y. M. A. Akpablin, and T. Coulibaly, "Assets management on electrical grid using Faster-RCNN," *Annals of Operations Research,* vol. 308, pp. 307-320, 2022.
[37] S. R. Khuntia, J. L. Rueda, and M. A. van der Meijden, "Smart asset management for electric utilities: Big data and future," in *Asset Intelligence through Integration and Interoperability and Contemporary Vibration Engineering Technologies: Proceedings of the 12th World Congress on Engineering Asset Management and the 13th International Conference on Vibration Engineering and Technology of Machinery*, 2019, pp. 311-322.
[38] S. Ashraf and T. Ahmed, "Dual-nature biometric recognition epitome," *Trends Comput. Sci. Inf. Technol,* vol. 5, pp. 008-014, 2020.
[39] A. Shahzad, A. Arshad, Y. Adnan, and A. Tauqeer, "Underwater routing protocols: Analysis of link selection challenges," *AIMS Electronics and Electrical Engineering,* vol. 4, pp. 234-248, 2020.
[40] S. Ashraf, T. Ahmed, Z. Aslam, D. Muhammad, A. Yahya, and M. Shuaeeb, "Depuration based Efficient Coverage Mechanism for Wireless Sensor Network," *Journal of Electrical and Computer Engineering Innovations (JECEI),* vol. 8, pp. 145-160, 2020.
[41] A. H. M. Niaki, "Asset Management in Smart Grids: A Review," in *2021 11th Smart Grid Conference (SGC)*, 2021, pp. 1-6.
[42] S. Bahrami and M. Rastegar, "Security-based critical power distribution feeder identification: Application of fuzzy BWM-VIKOR and SECA," *International Journal of Electrical Power & Energy Systems,* vol. 134, p. 107395, 2022.
[43] S. Amelete, R. Vaillancourt, G. Abdul-Nour, and F. Gauthier, "Asset management, industry 4.0 and maintenance in electrical energy distribution," in *Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems: IFIP WG 5.7 International Conference, APMS 2021, Nantes, France, September 5–9, 2021, Proceedings, Part V*, 2021, pp. 199-208.
[44] L. Cheng and T. Yu, "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*, vol. 43, pp. 1928-1973, 2019.

[45] B. Ibrahim, L. Rabelo, E. Gutierrez-Franco, and N. Clavijo-Buritica, "Machine Learning for Short-Term Load Forecasting in Smart Grids," *Energies,* vol. 15, p. 8079, 2022.

[46] Q. Huang, R. Huang, W. Hao, J. Tan, R. Fan, and Z. Huang, "Adaptive power system emergency control using deep reinforcement learning," *IEEE Transactions on Smart Grid,* vol. 11, pp. 1171-1182, 2019.

[47] S. Wang, J. Duan, D. Shi, C. Xu, H. Li, R. Diao, *et al.*, "A data-driven multi-agent autonomous voltage control framework using deep reinforcement learning," *IEEE Transactions on Power Systems,* vol. 35, pp. 4644-4654, 2020.

[48] Z. Zhang, D. Zhang, and R. C. Qiu, "Deep reinforcement learning for power system applications: An overview," *CSEE Journal of Power and Energy Systems,* vol. 6, pp. 213-225, 2019.

[49] L. Zhu, D. J. Hill, and C. Lu, "Hierarchical deep learning machine for power system online transient stability prediction," *IEEE Transactions on Power Systems,* vol. 35, pp. 2399-2411, 2019.

[50] A. J. Trappey, C. V. Trappey, L. Ma, and J. C. Chang, "Intelligent engineering asset management system for power transformer maintenance decision supports under various operating conditions," *Computers & Industrial Engineering,* vol. 84, pp. 3-11, 2015.

[51] D. Qiu, Y. Wang, W. Hua, and G. Strbac, "Reinforcement learning for electric vehicle applications in power systems: A critical review," *Renewable and Sustainable Energy Reviews,* vol. 173, p. 113052, 2023.

[52] F. Kaytez, "A hybrid approach based on autoregressive integrated moving average and least-square support vector machine for long-term forecasting of net electricity consumption," *Energy,* vol. 197, p. 117200, 2020.

[53] Q. Tang, W. Qiu, and Y. Zhou, "Classification of complex power quality disturbances using optimized S-transform and kernel SVM," *IEEE Transactions on Industrial Electronics,* vol. 67, pp. 9715-9723, 2019.

[54] H. Yang, X. Liu, D. Zhang, T. Chen, C. Li, and W. Huang, "Machine learning for power system protection and control," *The Electricity Journal,* vol. 34, p. 106881, 2021.

[55] M. Khorasany, Y. Mishra, and G. Ledwich, "A decentralized bilateral energy trading system for peer-to-peer electricity markets," *IEEE Transactions on industrial Electronics,* vol. 67, pp. 4646-4657, 2019.

[56] S. Balaraman, R. Madavan, S. Vedhanayaki, S. Saroja, M. Srinivasan, and A. A. Stonier, "Fault Diagnosis and Asset Management of Power Transformer Using Adaptive Boost Machine Learning Algorithm," in *IOP Conference Series: Materials Science and Engineering*, 2021, p. 012133.

[57] J.-F. Toubeau, L. Pardoen, L. Hubert, N. Marenne, J. Sprooten, Z. De Grève, *et al.*, "Machine learning-assisted outage planning for maintenance activities in power systems with renewables," *Energy,* vol. 238, p. 121993, 2022.

[58] A. R. Pazikadin, D. Rifai, K. Ali, M. Z. Malik, A. N. Abdalla, and M. A. Faraj, "Solar irradiance measurement instrumentation and power solar generation forecasting based on Artificial Neural Networks (ANN): A review of five years research trend," *Science of The Total Environment,* vol. 715, p. 136848, 2020.

[59] T. Ahmad, D. Zhang, C. Huang, H. Zhang, N. Dai, Y. Song, *et al.*, "Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities," *Journal of Cleaner Production,* vol. 289, p. 125834, 2021.

[60] P. Kumari and D. Toshniwal, "Extreme gradient boosting and deep neural network based ensemble learning approach to forecast hourly solar irradiance," *Journal of Cleaner Production,* vol. 279, p. 123285, 2021.

[61] M. S. Hosen and R. Amin, "Significant of Gradient Boosting Algorithm in Data Management System," *Engineering International,* vol. 9, pp. 85-100, 2021.

[62] C. Bentéjac, A. Csörgő, and G. Martínez-Muñoz, "A comparative analysis of gradient boosting algorithms," *Artificial Intelligence Review,* vol. 54, pp. 1937-1967, 2021.

[63] G.-F. Fan, M. Yu, S.-Q. Dong, Y.-H. Yeh, and W.-C. Hong, "Forecasting short-term electricity load using hybrid support vector regression with grey catastrophe and random forest modeling," *Utilities Policy,* vol. 73, p. 101294, 2021.

[64] M. Zolfaghari and M. R. Golabi, "Modeling and predicting the electricity production in hydropower using conjunction of wavelet transform, long short-term memory and random forest models," *Renewable Energy,* vol. 170, pp. 1367-1381, 2021.

[65] A. Frankó, G. Vida, and P. Varga, "Reliable identification schemes for asset and production tracking in industry 4.0," *Sensors,* vol. 20, p. 3709, 2020.

[66] H. Musbah, H. H. Aly, and T. A. Little, "Energy management of hybrid energy system sources based on machine learning classification algorithms," *Electric Power Systems Research,* vol. 199, p. 107436, 2021.

[67] X. Kong, X. Liu, L. Ma, and K. Y. Lee, "Hierarchical distributed model predictive control of standalone wind/solar/battery power system," *IEEE Transactions on Systems, Man, and Cybernetics: Systems,* vol. 49, pp. 1570-1581, 2019.

[68] J. A. Dowling, K. Z. Rinaldi, T. H. Ruggles, S. J. Davis, M. Yuan, F. Tong, *et al.*, "Role of long-duration energy storage in variable renewable electricity systems," *Joule,* vol. 4, pp. 1907-1928, 2020.

[69] Z. Jiang, Y. Guo, and Z. Wang, "Digital twin to improve the virtual-real integration of industrial IoT," *Journal of Industrial Information Integration,* vol. 22, p. 100196, 2021/06/01/ 2021.

[70] M. Mahzarnia, M. P. Moghaddam, P. T. Baboli, and P. Siano, "A review of the measures to enhance power systems resilience," *IEEE Systems Journal,* vol. 14, pp. 4059-4070, 2020.

[71] Z. Yan and Y. Xu, "A multi-agent deep reinforcement learning method for cooperative load frequency control of a multi-area power system," *IEEE Transactions on Power Systems,* vol. 35, pp. 4599-4608, 2020.

[72] J. C. T. Gaytan, K. Ateeq, A. Rafiuddin, H. M. Alzoubi, T. M. Ghazal, T. A. Ahanger, *et al.*, "Ai-based prediction of capital structure: Performance comparison of ann svm and lr models," *Computational Intelligence and Neuroscience: CIN,* vol. 2022, 2022.

[73] G. C. Montanari, R. Hebner, P. Morshuis, and P. Seri, "An Approach to Insulation Condition Monitoring and Life Assessment in Emerging Electrical Environments," *IEEE Transactions on Power Delivery,* vol. 34, pp. 1357-1364, 2019.

[74] M. Arshad and S. Islam, "A novel fuzzy logic technique for power transformer asset management," in *Conference Record of the 2006 IEEE Industry Applications Conference Forty-First IAS Annual Meeting*, 2006, pp. 276-286.

[75] A. Yazdani, S. Shariati, and A. Yazdani-Chamzini, "A risk assessment model based on fuzzy logic for electricity distribution system asset management," *Decision Science Letters,* vol. 3, pp. 343-352, 2014.

[76] W. Hu, Z. Lu, S. Wu, W. Zhang, Y. Dong, R. Yu*, et al.*, "Real-time transient stability assessment in power system based on improved SVM," *Journal of Modern Power Systems and Clean Energy,* vol. 7, pp. 26-37, 2019.

[77] O. A. Alimi, K. Ouahada, and A. M. Abu-Mahfouz, "Real time security assessment of the power system using a hybrid support vector machine and multilayer perceptron neural network algorithms," *Sustainability,* vol. 11, p. 3586, 2019.

[78] S. M. Piryonesi and T. E. El-Diraby, "Role of data analytics in infrastructure asset management: Overcoming data size and quality problems," *Journal of Transportation Engineering, Part B: Pavements,* vol. 146, p. 04020022, 2020.

[79] S. M. Piryonesi and T. E. El-Diraby, "Data analytics in asset management: Cost-effective prediction of the pavement condition index," *Journal of Infrastructure Systems,* vol. 26, p. 04019036, 2020.

[80] M. Idrees, M. T. Riaz, A. Waleed, Z. J. Paracha, H. A. Raza, M. A. Khan*, et al.*, "Fuzzy logic based calculation and analysis of health index for power transformer installed in grid stations," in *2019 international symposium on recent advances in electrical engineering (RAEE)*, 2019, pp. 1-6.

[81] O. Protalinsky, A. Khanova, and I. Shcherbatov, "Simulation of power assets management process," in *Recent Research in Control Engineering and Decision Making*, 2019, pp. 488-501.

[82] D. Tanfilyeva, O. Tanfyev, and Y. Kazantsev, "K-nearest neighbor method for power transformers condition assessment," in *IOP Conference Series: Materials Science and Engineering*, 2019, p. 012016.

[83] M. Mirhosseini and F. Keynia, "Asset management and maintenance programming for power distribution systems: A review," *IET Generation, Transmission & Distribution,* 2021.

[84] B. E. Nyong-Bassey, D. Giaouris, C. Patsios, S. Papadopoulou, A. I. Papadopoulos, S. Walker*, et al.*, "Reinforcement learning based adaptive power pinch analysis for energy management of stand-alone hybrid energy storage systems considering uncertainty," *Energy,* vol. 193, p. 116622, 2020.

[85] J. Wang, P. Pinson, S. Chatzivasileiadis, M. Panteli, G. Strbac, and V. Terzija, "On machine learning-based techniques for future sustainable and resilient energy systems," *IEEE Transactions on Sustainable Energy,* 2022.

[86] A. Alzoubi, "Machine learning for intelligent energy consumption in smart homes," *International Journal of Computations, Information and Manufacturing (IJCIM),* vol. 2, 2022.

[87] E. Aguilar Madrid and N. Antonio, "Short-term electricity load forecasting with machine learning," *Information,* vol. 12, p. 50, 2021.

[88] A. Hossam-Eldin, M. Refaey, and H. Ramadan, "New approach to power transformer asset management and life assessment using fuzzy logic techniques," in *2017 nineteenth international middle east power systems conference (MEPCON)*, 2017, pp. 901-908.

[89] A. Majzoobi, M. Mahoor, and A. Khodaei, "Machine learning applications in estimating transformer loss of life," in *2017 IEEE Power & Energy Society General Meeting*, 2017, pp. 1-5.

[90] J. Li, Y. Zhu, Y. Xu, and C. Guo, "A transformer fault diagnosis method based on sub-clustering reduction and multiclass multi-kernel support vector machine," in *2017 IEEE Conference on Energy Internet and Energy System Integration (EI2)*, 2017, pp. 1-6.

[91] Y. Cui, P. Bangalore, and L. Bertling Tjernberg, "A fault detection framework using recurrent neural networks for condition monitoring of wind turbines," *Wind Energy,* vol. 24, pp. 1249-1262, 2021.

[92] Y. Cui and L. B. Tjernberg, "Fault Diagnostics of Power Transformers Using Autoencoders and Gated Recurrent Units with Applications for Sensor Failures," in *2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2022, pp. 1-5.

[93] J. E. U. Cabus, Y. Cui, and L. B. Tjernberg, "An Anomaly Detection Approach Based on Autoencoders for Condition Monitoring of Wind Turbines," in *2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2022, pp. 1-6.

[94] Y. Cui, J. E. Urrea Cabus, and L. B. Tjernberg, "A Fault Detection Approach Based on Autoencoders for Condition Monitoring of Wind Turbines," in *Women in Renewable Energy*, ed: Springer, 2023, pp. 193-211.

[95] J. E. U. Cabus and İ. H. Altaş, "Machine Learning Model Applications for Fault Detection and Classification in Distributed Power Networks," *Data Science and Applications,* vol. 4, pp. 11-18, 2021.

[96] P. Bangalore and L. B. Tjernberg, "An artificial neural network approach for early fault detection of gearbox bearings," *IEEE Transactions on Smart Grid,* vol. 6, pp. 980-987, 2015.

[97] (2020). *World Energy Outlook 2020*. Available: https://www.iea.org/reports/world-energy-outlook-2020

[98] D. Ghosh, T. Ghose, and D. Mohanta, "Reliability analysis of a geographic information system-aided optimal phasor measurement unit location for smart grid operation," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability,* vol. 227, pp. 450-458, 2013.

[99] P. Kansal and A. Bose, "Bandwidth and latency requirements for smart transmission grid applications," *IEEE Transactions on Smart Grid,* vol. 3, pp. 1344-1352, 2012.

[100] H. Gharavi and B. Hu, "Distributed Control and Communications for Grid Systems," in *2016 IEEE Global Communications Conference (GLOBECOM)*, 2016, pp. 1-6.