Review Article

Application of Machine Learning Methods for Asset Management on Power Distribution Networks

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Abstract

This study aims to study the different kinds of Machine Learning (ML) models and their working principles for asset management in power networks. Also, it investigates the challenges behind asset management and its maintenance activities. In this review article, Machine Learning (ML) models are analyzed to improve the lifespan of the electrical components based on the maintenance management and assessment planning policies. The articles are categorized according to their purpose: 1) classification, 2) machine learning, and 3) artificial intelligence mechanisms. Moreover, the importance of using ML models for proper decision making based on the asset management plan is illustrated in a detailed manner. In addition to this, a comparative analysis between the ML models is performed, identifying the advantages and disadvantages of these techniques. Then, the challenges and managing operations of the asset management strategies are discussed based on the technical and economic factors. The proper functioning, maintenance and controlling operations of the electric components are key challenging and demanding tasks in the power distribution systems. Typically, asset management plays an essential role in determining the quality and profitability of the elements in the power network. Based on this investigation, the most suitable and optimal machine learning technique can be identified and used for future work.

1- Introduction

Throughout the past decades, power distribution system applications [1, 2] have been widely analyzed. Distribution systems involve huge inventories of equipment, such as power transformers, power lines, and switching devices (e.g. breakers, switches, reclosers, fuses, etc.). It is highly important to maintain the controlling operations, working conditions, and lifespan of these components to ensure the quality of power distribution systems [3]. Typically, the best levels of reliability, lifecycle of equipment, and optimization of costs are determined based on indicators of asset management, network deployment, and system operations [4–7]. Asset management [8–10] is mainly used in engineering to improve marketing opportunities, profits, and reputation, along with reducing costs. These factors can be applied in power systems by following a strategy of optimizing the asset management lifecycle, in which it is highly important to take the appropriate decisions at the right time of operation maintenance, component replacement, and fault identification [11, 12]. In power system networks, asset management is the best option to guarantee a good quality of service while keeping the assets working under a reliable operation. In general, the key benefits of implementing asset management [13–16] strategies are:

- Better lifetime assessment;
- Increased efficiency and excellence;

- Ensured safety;

- Reduced downtime factors;

- Low-cost consumption (both investment and operational);

- Reduced failure rate and improved availability;

- No environmental impacts.

Also, asset management [17] can be defined as the progression of scheduling, decision making, monitoring, and evacuation of assets. The conventional lifecycle model of asset management [18], shown in Figure 1, involves the processes of acquisition, deployment, utilization, maintenance, and retirement.

Figure 1. Lifecycle of asset management

Still, the most challenging tasks that exist in the asset management strategies [19-22] are estimating the lifespan of equipment, computing management costs, monitoring the condition of assets, and improve maintenance. Also, it is necessary to comply with the technical, economic and strategic assessments for enhancing the value of asset management schemes [23, 24]. Typically, optimizing asset performance is one of the essential factors [25] in the field of power distribution systems.

Asset management is considered as a key factor to keep the value of the assets and to improve the return on investment of electrical equipment by reducing both the operational and capital expenditures. In power distribution systems, interruption of power supply is one of the greatest issues that need to be addressed for an effective asset management. The main purpose of asset management is to perfectly optimize the life cycle of electrical equipment using better predictive maintenance and business strategies. For accomplishing this objective, data analysis tools are used that are highly correlated to maintenance management, inventory control, risk assessment, decision making, and condition monitoring.

In previous studies, there are different types of machine learning techniques that can be used for asset management and power system protection. Generally, machine learning techniques are categorized into the types of supervised, semi-supervised and unsupervised, which are mainly used to solve complex classification problems. Due to an intelligent and automated decision-making ability, machine learning techniques are increasingly used to develop an effective asset management framework in existing works. However, conventional methodologies face different types of challenges related to the following factors:

- Increased complexity in algorithm design;

- Training and testing the model of classifiers requires more time for processing;

- Increased error rate and false positives;

- High-cost consumption.

Hence, this work intends to propose an intelligent and advanced machine learning methodology to develop an effective asset management framework for power distribution systems. For this purpose, a detailed comprehensive analysis is conducted in this paper to examine the characteristics, operations, benefits, and limitations of various machine learning methodologies used for asset management in power systems.

The major objectives behind this work are the following:

- To study the principles of various machine learning techniques used for improving the efficacy of asset management in power distribution networks;

- To validate the effectiveness of both supervised and unsupervised machine learning models by using various performance indicators;

- To conduct a comprehensive analysis of the machine learning models, identifying their advantages and disadvantages;

- To examine the challenges and managing operations of the asset management strategies based on technical and economic factors;

- The machine learning techniques are considered as the most suitable option for solving the complex prediction and classification problems. Hence, this work intends to analyze the different types of machine learning techniques for an effective asset management.

The rest of the sections in the study are organized as follows: Section II presents the overview of asset management and various machine learning mechanisms used for improving the asset management strategies in the power system networks. Section III illustrates the comprehensive analysis of the different machine learning mechanisms used in the power system applications with the challenges, advantages, and disadvantages. Finally, the overall paper is summarized with the results and future illustrations in Section IV.

2- Survey on Asset Management

This section investigates various methodologies and tools used for efficient asset management on power system networks. Typically, asset management is one of the key factors that provide information related to protection devices, power transformers, transmission lines, and support structures. Due to this, it plays an essential role in electric power distribution sectors.

Ayu & Yunusa-Kaltungo [26] developed a holistic framework for analyzing the cost-maintenance and asset management in a power system. Here, the total cost estimation is performed based on the Preventive Maintenance Cost (PMC), Breakdown Maintenance Cost (BMC), and Failure Cost (FC) reports. Dehghanian et al. [27] implemented an Analytical Hierarchy Process (AHP) based on fuzzy set theory for asset management of power distribution systems. In this study, the reliability factor is mainly considered during asset management, where the demand optimization is also concentrated by the use of Reliability Centered Maintenance (RCM). Based on this work, the importance of using fuzzy systems for asset management is analyzed in detail. Abu-Elanien & Salama [28] examined the performance of different asset management techniques used for a power transformer. Here, the asset management activity is classified into the following categories:

- Generating the preservation plans;

- Utilization of condition assessment and monitoring factors;

- Life profile assessment.

Moreover, this study provides a clear illustration about the power transformer asset management, activity plans, and low-cost maintenance models, which could be more helpful for analyzing the efficiency of power transformers. Koksal & Ozdemir [29] suggested a RCM asset management model for generating the maintenance plan for power transformers. For this purpose, a Markov model has been utilized in this work, which provides the optimal solutions to estimate the reliability and cost. In addition to that, a sensitivity analysis has been accomplished to analyze the transition rate, and the actual service data is utilized to compute the lifetime of the power transformers. Martins [30] formed a health index for analyzing the performance of the power transformers based on risk monitoring and condition assessment. During this stage, the asset management process could be optimized for reducing the risk factor and enhancing the lifespan of equipment. The general structure of asset management with its appropriate actions is depicted in Figure 2. Also, it comprises the stages of monitoring, conservation, replacement, and planning generation. Moreover, this work [31] stated that the condition asset management is one of the essential and most demanding tasks for asset managers.
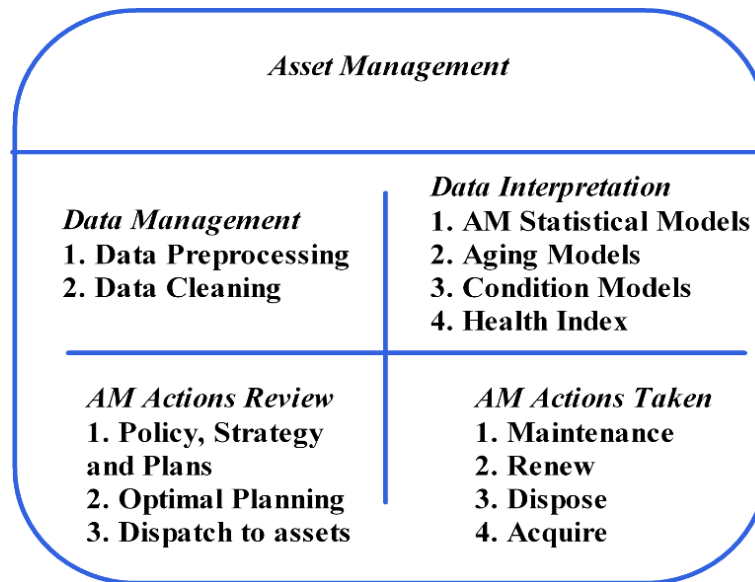
Asset Management

Data Management
1. Data Preprocessing
2. Data Cleaning

Data Interpretation
1. AM Statistical Models
2. Aging Models
3. Condition Models
4. Health Index

AM Actions Review
1. Policy, Strategy and Plans
2. Optimal Planning
3. Dispatch to assets

AM Actions Taken
1. Maintenance
2. Renew
3. Dispose
4. Acquire

Figure 2. Typical structure of asset management

The following subsections describe the classification of an asset management strategy and the importance of using machine learning techniques in power system networks.

2-1- Classification of Asset Management Perspectives

Khuntia et al. [32] conducted a comprehensive review of various asset management techniques used for power distribution/transmission systems. Based on the planning and operation of distribution systems, the asset management strategy is classified into two categories: time-based and activity-based. The classification of asset management is shown in Figure 3, where the time-based model is further split into three models including long-term, mid-term, and short-term. Koziel et al. [12] designed an innovative asset management framework for analyzing the impacts of data quality in power systems. Here, the major steps involved in the asset management system are discussed, which include maintenance and replacement. Based on this paper, it is observed that the asset managers are required to evaluate the impacts of each device with respect to the accuracy of evaluation.
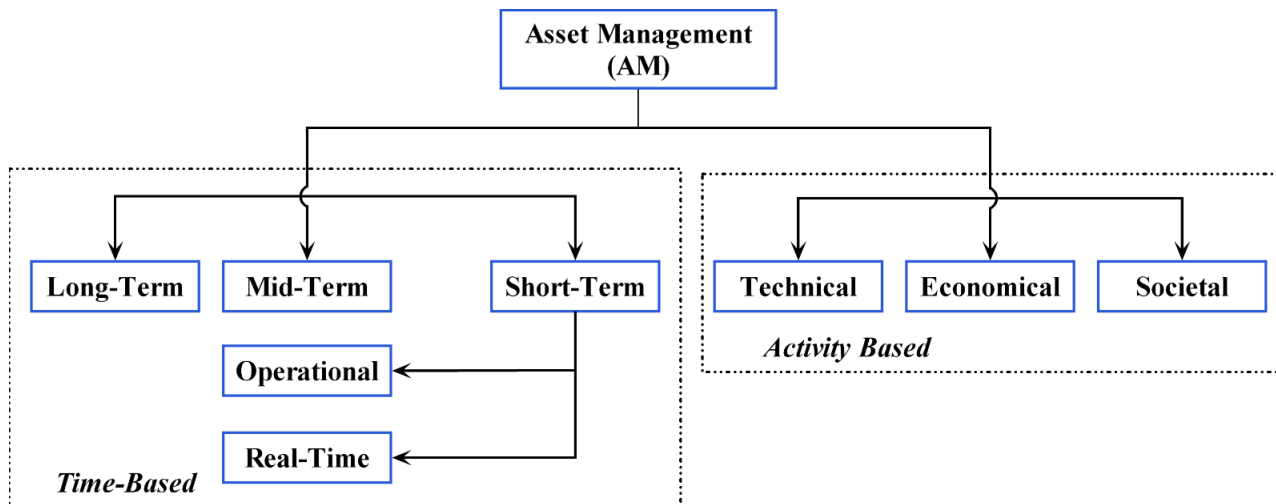

Figure 3. Classification of asset management models

2-2- Machine Learning Approaches

Generally, machine learning techniques [33, 34] play a vital role in many application systems, which is extensively used to provide the suitable solution for solving the complex classification problems. It is a group of Artificial Intelligence (AI) methodologies that is highly suitable for all kinds of detection systems. The machine learning approaches [35-37] are widely used in power system applications for solving data-driven problems with reduced complexity and time consumption. Aminifar et al. [38] reviewed the performance of various machine learning techniques used for asset management.

The major scope of this study is to analyze the issues related to the power transformers, synchronous generators, transmission lines, and system integrity lines. In recent days, asset management and power system protection have gained significant attention in the scientific community. This paper conducts a detailed analysis of various machine learning techniques used for power systems including their protections.

Here, the different types of machine learning techniques are illustrated with their features, including the following:

- Supervised Machine Learning;

- Unsupervised Machine Learning;

- Reinforcement learning.

Normally, machine learning techniques are mainly used to address different types of applications in power distribution systems, as shown in Figure 4. Machine learning approaches are also used to protect the transmission lines of distribution systems. The main applications related to protection system are shown in Figure 5. According to this, it is concluded that machine learning techniques play a vital role in the power distribution/transmission systems.
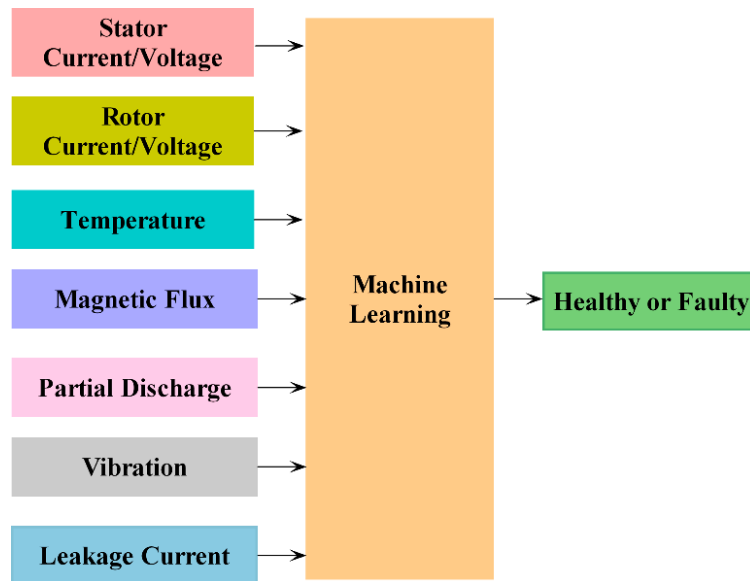

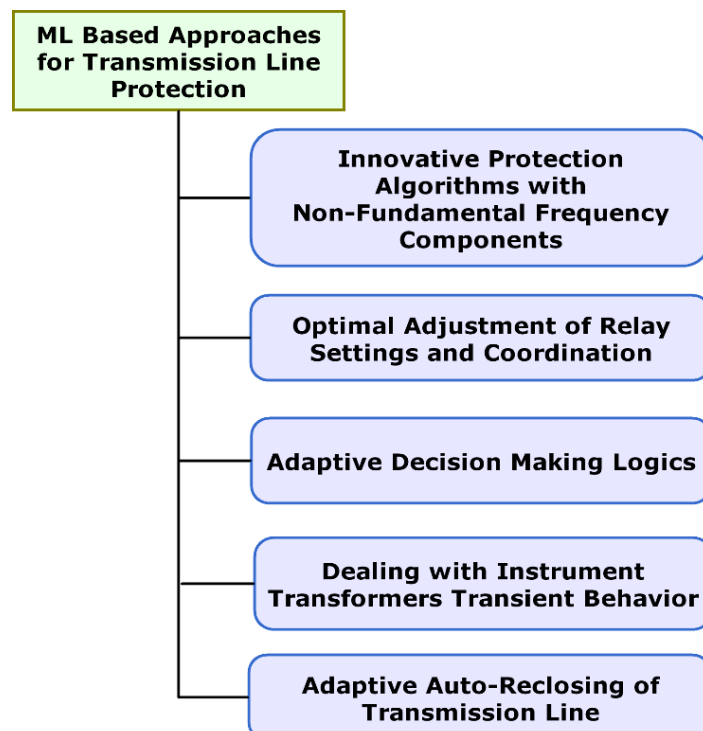**Figure 4.** Use of machine learning technique in power distribution systems

Figure 5. Transmission line protection using a machine learning model

The different types of machine learning techniques and AI mechanisms used for improving the strategy of asset management in power distribution systems are illustrated in the upcoming sections.

2-2-1- Deep Learning

Wang et al. [39] utilized a deep learning approach for analyzing the faults in the power transformer with the help of the RFID sensor. Here, it is stated that deep learning is one of the machine learning techniques, which is mainly used for classifying the data items based on the set of extracted features. Still, this technique consumes more time for processing the data, which is the major limitation of this methodology. In Mlakić et al. [40] study, a deep learning model is utilized to accurately detect the faults in the power transformer. This study compares the performance of three different classification techniques such as CNN, deep learning, and ANN for analyzing the effectiveness of the best classifier [41]. Mehdipour Picha et al. [42] utilized a deep learning model for detecting the faults in the transformers. In this mechanism, deep information is processed based on the neural network architecture. In Zhu et al. [43], a Hierarchical Deep Learning Machine (HDLM) is utilized for predicting the transient stability of the power systems. The computational efficiency of different deep learning mechanisms has been validated in this work with respect to the measures of processing time, response time, computational complexity and memory consumption. The techniques compared in this work are SVM, RF, Ensemble Learning Machine (ELM), ANN, and CNN, and the results stated that the HDLM provides an improved result compared to the other techniques.

2-2-2- Neural Network

Generally, the Neural Network (NN) technique [44, 45] is developed based on the working function of the human brain, which is one of the basic models widely used in many application systems. The NN contains three different types of working layers as input, hidden, and output, and these layers are linked together with respect to the varying weight values, as shown in Figure 6. Also, the processes involved in this technique are forward and backward propagation [46]. During the forward propagation, the raw data is fed to the hidden layer from the input layer, and the hidden layer uses some activation function for extracting the information from the given data. Finally, the output layer performs the classification process based on the extracted features. Then, the weight values of the edges can be modified for generating the classified results at the time of back propagation.
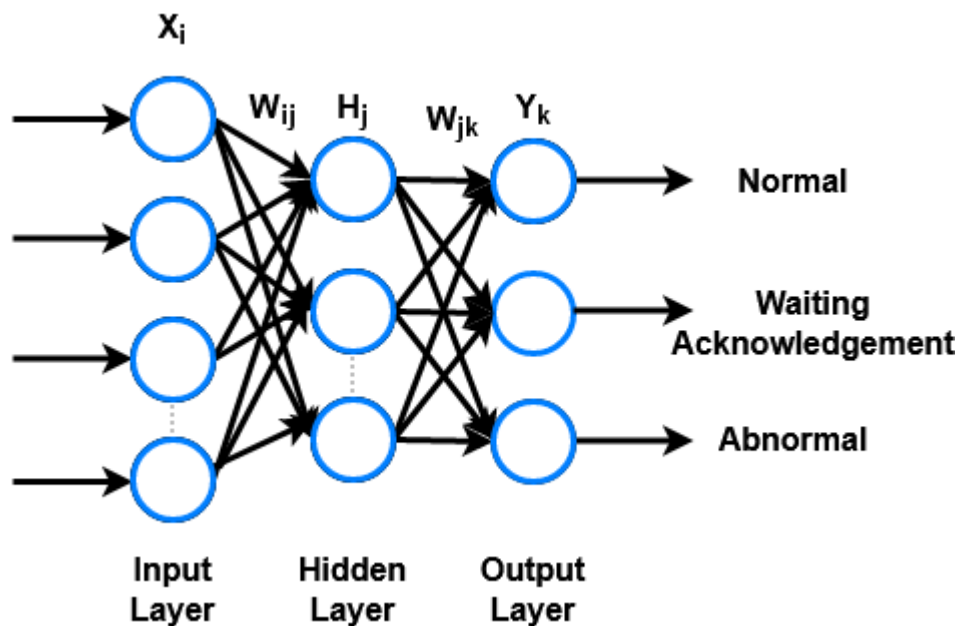

Figure 6. Architecture of neural network classification scheme

Yang et al. [36] suggested a Probabilistic Neural Network (PNN) algorithm for analyzing the faults in the power transformers. This work also utilizes the Bat Algorithm (BA) for improving the classification efficiency of PNN by reducing the dimensionality of features. Here, the importance of using asset management in analyzing the faults in power transformers has been illustrated. In Velasquez-Contreras et al. [47], the general asset management model is provided for identifying and detecting the failures in a power transformer. Also, it utilized Hidden Markov Models (HMMs) for improving the failure rate estimation with the help of the DAG analysis. During the optimization and scheduling, the reliability computation and economic cost evaluation processes are applied for improving the asset management. In addition to that, the major asset factors considered in this work are ambient conditions, transformer age analysis, working operations, and availability.

2-2-3- Convolutional Neural Network

The Convolutional Neural Network (CNN) is an extensively used unsupervised machine learning algorithm, which provides the benefits of increased accuracy, reduced complexity in design, cost efficiency, and low time consumption. Afrasiabi et al. [48] suggested an accelerated CNN algorithm for performing a fault diagnosis on a power transformer. This work mentioned that the CNN could offer an increased accuracy rate when compared to the other state-of-the-art models. In this mechanism, a convolutional operator has been utilized to extract the features used for fault classification. However, this technique has the limitations of increased time consumption and high nonlinearity.

2-2-4- Artificial Neural Network

Trappey et al. [49] employed a Back-Propagation Artificial Neural Network (BP-ANN) algorithm for developing an intellectual asset management system. The main scope of this work is to analyze the transformer faults under varying operating conditions. Here, the Principle Component Analysis (PCA) based feature selection mechanism is utilized to reduce the number of key factors. Zrcovic et al. [50] employed an ANN mechanism for estimating the exploited aging factor of power transformers with the help of a monitoring history. In this work, both the Condition Based Maintenance (CBM) and Risk Based Maintenance (RBM) factors were evaluated to validate power transformers' maintenance efficiency. This paper stated that the ANN based machine learning technique is more convenient for forming the maintenance plan with the ranking of power transformers. Abu-Elanien et al. [51] employed a Feed-Forward Artificial Neural Network (FFANN) for analyzing the condition of the power transformers based on its health index. The asset management is mainly deployed to analyze the high risk factors and to estimate the health index for improving the lifespan of power transformers.

2-2-5- Supervised Machine Learning

Bacha et al. [52] recommended a Support Vector Machine (SVM) based classification approach for identifying the faults on the power transformers based on Dissolved Gas Analysis (DAG). Here, the major impact of using SVM technique is stated, and its efficiency is compared with some other classification techniques like Genetic Algorithm (GA), Fuzzy Logic (FL), and Back Propagation (BP). Moreover, the different types of faults that are exactly identified by the SVM classifier [53] are energy discharge (low and high), partial discharge, and thermal faults. During the SVM classification, the kernel function estimation, and radial basis function computation processes are done, which helps to increase the efficacy of the classifier.

2-2-6- Reinforcement Learning

Benhamou et al. [54] suggested a Deep Reinforcement Learning (DRL) mechanism for improving the asset management process. The key factors of this work are to analyze the contextual information under a noisy condition, estimation of price observation and action, and time-dependent data analysis. Glavic et al. [55] implemented a reinforcement learning strategy for solving the power quality problems in an electric power system. This paper indicated that the major benefits of using reinforcement learning techniques are reduced designing complexity and a perfect decision making capability. Lincoln et al. [56] designed an improved electric power system model by using the functionalities of both a reinforcement learning model and an ANN technique. The intention of this work was to construct an electricity trading network for solving the optimal power flow problem based on the linear cost functions. Nyong et al. [57] employed an adaptive reinforcement learning technique for improving the power storage efficiency of hybrid storage systems. The different types of asset indicators utilized in this study are generation asset, storage asset, load, and controllable assets. In addition to this, the power pinch analysis is performed with the use of the Kalman filtering approach. In Rocchetta et al. [58] research, the reinforcement machine learning model is integrated with the ANN mechanism for the maintenance of power grid systems. Ibrahim et al. [59] suggested different machine learning based on solutions for addressing the technical challenges in the smart grid electric power systems. The key factor of this paper is to strengthen the processes of conditional monitoring and data analysis based on the aspects of system asset maintenance, power generation, load management, and safety.

2-2-7- K-Nearest Neighbour

The kNN [60] an extensively used supervised learning algorithm in which the distance computation is performed in order to categorize the unclassified data. Also, it estimates the distance for each random data point, and its class segregation is shown in Figure 7. The major advantages of using this technique are simple execution and reliable results. Still, it has limits with the issues of increased time complexity at the time of processing a large amount of data.
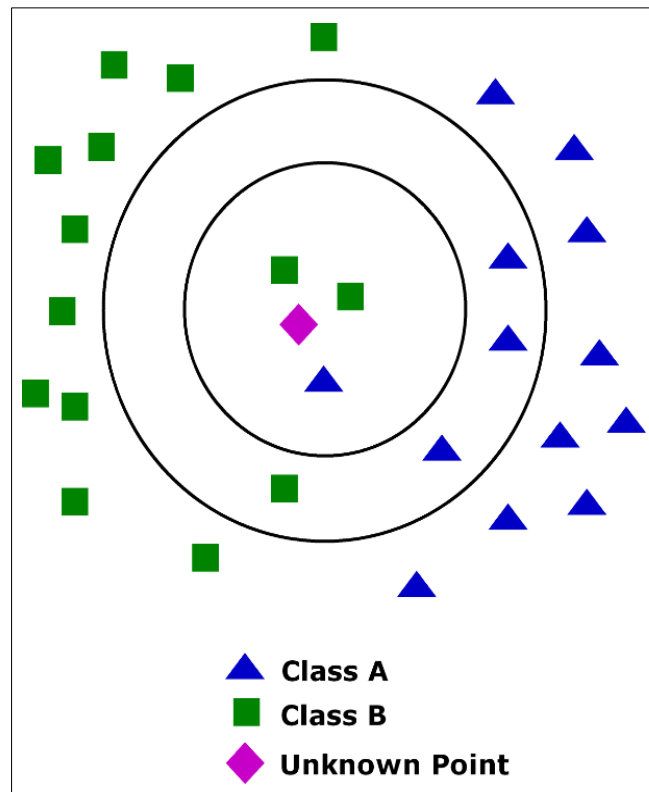
Figure 7. KNN clustering model

In Benhmed et al. [61] work, the accuracy of different classification techniques has been analyzed in diagnosing the health index of power transformers. It includes the methods of kNN, J48, random forest, ANN and SVM, which are compared based on the set of extracted features used for health index determination. The classification results stated that the random forest technique could offer an improved accuracy rate compared to the other techniques. Tanfilyeva et al. [62] utilized an integrated kNN-Bayesian machine learning model for recognizing the faults in the power transformers. The kNN technique is mainly used to analyze the working conditions and operations of the power transformers with a better accuracy rate. Balaraman et al. [63] investigated the performance of various machine learning models such as k-NN, SVM, ensemble, and decision for perfect asset management. From the paper, it is observed that the k-NN technique is most suitable for the regression and classification problems, and it offers the expected outcomes with better asset management.

2-2-8- Decision Trees

Koziel et al. [64] analyzed the performance of different classifiers by estimating the failure rate of the power transformer. At this point, the asset management and maintenance scheme is deployed for analyzing the risk factors related to the power transformer failures. The different types of classification techniques used in this evaluation are J48 and Naïve Bayes classifier. Then, the conclusions stated that the Naïve Bayes could provide efficient results, when compared to the J48 classifier. Alqudsi & El-Hag [65] discussed the usage of machine learning techniques for predicting the health index of power transformers. This work intends to reduce the asset maintenance cost by using the machine learning methodology. Also, it performs both the full and reduced feature modeling based on the set of trained feature sets. Moreover, the feature selection methodology could be implemented to attain high quality and relevant models.

2-2-9- Naïve Bayes

The NB is a kind of probabilistic classifier that works based on the conventional Bayes theorem, in which the class prior probability is determined based on the likelihood of the predictor variable. Silva et al. [66] implemented a Naïve Bayes (NB) classification technique for identifying and detecting incipient faults in the transmission lines. This work is intended to detect both the transmission line current and voltage faults with improved accuracy and reduced error rate. In work [67], the NB classification technique is utilized to predict the lifespan of the lithium-ion batteries used in the battery powered systems. The capacity depletion model of the NB classification technique is illustrated with respect to the set of discriminate functions. During the performance validation, the conventional SVM and NB techniques are compared based on the training and test time values. Finally, the results indicated that the NB outperforms the SVM technique with improved efficiency.

2-2-10- Relevance Vector Machine

Wang et al. [68] utilized a multi-kernel RVM technique for analyzing the lifespan and working condition of the power transformers. Here, a data storage mechanism is utilized to reduce the response time and power consumption factors with high prediction accuracy. In work [69], the comparative analysis between the SVM and RVM mechanisms is performed based on the lifetime prediction for the engineering assets. Also, the NB is one of the best multi-class prediction models that precisely predicts the faults from the given set.

2-2-11- K-Means Clustering

Domn et al. [70] utilized a K-Means clustering technique to predict the power systems' failures based on the asset condition. In this study, the inner structure of the historical data is analyzed by estimating the relationship status between the asset conditions and operations. For this purpose, the average aging rate and conditional age have been predicted with respect to the long term features of the assets. The major stages involved in this work are learning process and prediction process, in which the data assessment and learning model training based conditional age are performed first. Then, the detection of failure probability and future assets are done at the time of the prediction process. The major benefits of this work were, increased feasibility and better asset management. Peng et al. [71] intended to improve asset management efficiency by using the k-means clustering technique for monitoring on-line partial discharge in the power cables. The main technical challenges behind the partial discharging the monitoring of generators, motors, transformers and switchgear have been investigated in this work. It comes under the following categories:

- It is more difficult to estimate the reference of phase voltage;

- It is tough to monitor the three-phase components using the online systems.

In Yan et al. [72], consensus clustering techniques are deployed for performing asset management on the power systems, which includes the Genetic Algorithm (GA), Power System Document (PSD) depository, and Weighted Partitions via Kernels (WPK) methods. In order to validate the efficiency of these mechanisms, two separate experiments were conducted during the analysis part. Based on this evaluation, it is concluded that the PSD methodology could be more helpful for asset management in power system applications. Kooksal et al. [73] introduced a Reliability Centered Asset Management (RCAM) model with the conventional k-means clustering technique for improving the maintenance of power transformers. This technique is mainly utilized to efficiently maintain the system components by generating an optimal plan. The key merits of this mechanism were increased reliability and reduced maintenance cost, which help to improve the overall performance of the asset management scheme. Moreover, this paper indicated that the critical assessment is one of the essential factors in power transformers, which must be addressed with the help of maintenance applications. The major stages involved in the critical assessment process are listed as follows:

- Estimation of criticality measures;

- Implementation of clustering methodology;

- Generation of an accurate asset management plan used for best decision making.

2-3- Artificial Intelligence (AI) Mechanisms

Mattoli et al. [74] suggested the AI mechanisms for an efficient asset management, where the major issues related to the life cycle of asset management were discussed. This work analyzed the competence of various AI mechanisms used for an efficient asset management system. In addition to this, the importance of using Supply Chain Management (SCM) could be illustrated with respect to the AM perspective.

2-3-1- Expert Systems

Ahnfelt [75] recommended an expert system for estimating the cost of beneficiaries and ensuring an efficient delivery in asset management. Zarkovic and Stojkovic [76] utilized an expert system for monitoring and analyzing the faults on the power transformers. Here, the exact type of fault is accurately predicted with the help of fuzzy logic systems based on the characteristics of operating conditions. Spatti et al. [77] constructed an optimized asset management strategy for enhancing the efficiency of power transmission systems. The health condition and lifespan of the components used in the electric systems must be estimated for taking the necessary actions such as repair and replacement.

2-3-2- Fuzzy Logic

Arshad & Islam [78] implemented a fuzzy logic technique for improving the asset management processes in power transformers. The main reason for using an asset management scheme is to estimate the age (retirement/replacement)

of power transformers in order to avoid failure rates. During this process, the aging effect can be calculated based on the reliability, life span, and performance rate of the power transformers. Here, the fuzzy logic technique helps to ensure the reliability, availability, and efficiency of the asset management scheme. Moreover, it helps to obtain a successful life span and management of power transformers with better reliability measures. In Yazdani et al. [79], a fuzzy logic model is utilized to perform the risk assessment for a perfect asset management scheme in the power distribution systems. The different types of risks identified in this work are economic, environmental, safety, regulatory, vulnerability, and quality of supply. The major working stages involved in the fuzzy logic system are fuzzification, inference rules generation, and defuzzification. Here, approximately 25 rules are generated during the inference rule generation process, which helps to improve the prediction accuracy of the classifier. Here, asset management is mainly conducted to estimate the risk factors that could affect the performance of the entire operating system.

Baker et al. [80] deployed a fuzzy logic model for making an appropriate decision for perfect asset management in power transformers. The main consideration of this paper is to estimate the operational lifespan of the power transformers based on the asset management decision-making process. The different parameters used in this work are under the following categories:

- Aging factor;
- Faults imminence;
- Life estimation;
- Accelerated aging effects;
- Contamination incitement.

Moreover, this paper mentioned that the effectiveness and decision-making capability of asset management could be improved.

3- Comparative Analysis

This section illustrates the overall comparative analysis of the different types of machine learning models based on asset management in power system networks. Also, it discusses the advantages and disadvantages of each model with its application field, as depicted in Table 1.

Table 1. Comparative analysis between various machine learning models

Authors (Year)	Machine Learning Model	Application	Description	Advantages and Disadvantages
Afrasiabi et al. (2019) [48]	Deep Neural Networks (DNN)	Fault detection in power transformers	This paper aims to identify the internal faults in the power transformers by estimating the computational burden, threshold, and model dependency.	Advantages: • High robustness • Improved speed Disadvantages: • It has the difficulty of processing the large datasets. • Reduced reliability.
Bacha et al. (2012) [52]	Support Vector Machine (SVM)	Fault diagnosis in power transformers	Here, the different types of faults such as low energy discharge, high energy discharge, partial discharge, and thermal faults have been spotted by using the Dissolved Gas Analysis (DGA) strategy.	Advantages: • Risk minimization • Reduced error rate Disadvantages: • Computational complexity is high. • Inefficient detection rate.
Selina et al. (2014) [67]	Naïve Bayes (NB)	Battery Health Management	This paper suggested a NB based classification approach for predicting the battery life under varying operating conditions and ambient temperatures.	Advantages: • Improved prediction performance • Accepted accuracy value. Disadvantages: • Increased error value • Reduced robustness
Spatti et al. (2019) [77]	Expert Systems	Optimized Asset Management	It is intended to prevent the electrical systems from unknown failures by analyzing the fault history of the equipment by using the asset management strategy.	Advantages: • Better reliability • Improved safety level • Optimized maintenance policies Disadvantages: • High risk factors

Benhamou et al. (2020) [54]	Deep Reinforcement Learning	Asset management in self-adaptive environment	It intends to analyze the impact of period log based on the observations and actions in the asset management.	Advantages: • Simple training validation • High robustness Disadvantages: • Decreased efficiency level
Bangalore et al. (2015) [81]	Artificial Neural Network (ANN)	Fault detection in electric power system	Here, the condition-based maintenance activities are performed to avoid the failure events of the electrical components.	Advantages: • Minimized overall maintenance cost • Better predictive maintenance Disadvantages: • High replacement cost • Optimal decision making needs to be improved
Koksal et al. (2017) [73]	k-Means clustering model	Maintenance activities based on the asset management strategy in power transformers.	It developed a transformer maintenance plan based on the asset management factors with the k-means clustering model.	Advantages: • Improved system reliability • Longer lifecycles Disadvantages: • Inefficient criticality assessment
Abu-Siada and Islam (2012) [82]	Machine learning model with Gene Expression Programming (GEP)	Dissolved Gas Analysis (DGA) in power transformers	It computes the critical ranking of the power transformers based on the decision of asset management.	Advantages: • Easily to implement • Appropriate decision making at time Disadvantages: • Reduced accuracy
Nyong et al. (2020) [57]	Reinforcement Learning	Energy storage in hybrid systems	It considers the different types of assets like generation, multi-storage, and controllable for improving the energy storage capability on the hybrid power generation systems.	Advantages: • Reduced complexity • Adaptive scheme Disadvantages: • Increased time consumption
Arshad et al. (2006) [78]	Fuzzy Logic systems	Asset management for power transformers	This work intends to estimate the failure rate of power transformers for an appropriate replacement and retirement actions based on their aging factors.	Advantages: • Accurate operational criteria • Appropriate decision making at time • Minimum capital investment Disadvantages: • Increased computational complexity
Mattioli et al. (2020) [74]	Artificial Intelligence (AI) models	Asset management for electrical components	This work implements an asset maintenance scheme with the machine learning models for improving the availability and lifecycle of the electrical equipment.	Advantages: • Better lifecycle of the product • Minimized maintenance cost • Improved performance monitoring
Baker et al. (2016) [80]	Fuzzy Logic model	Asset management for transformer lifecycle prediction	Here, the lifespan and health condition of the power transformers have been predicted by using fuzzy logic systems.	Advantages: • Improved fault prediction • Minimized failure rate • Proper decision making Disadvantages: • Inaccurate prediction results
Mirhosseini et al. (2021) [17]	Multi-criteria decision making models	Asset management for the power distribution systems	It presents the different types of asset management and maintenance strategies used for the power distribution systems.	Advantages: • Accurate evaluation • Better error prediction Disadvantages: • High time complexity
Tanfilyeva et al. (2019) [62]	k-Nearest Neighbor model	Conditional assessment and evaluation in power transformers	The abnormal condition of power transformers has been identified and detected with the help of the k-NN classification model based on the insulation liquids of a power transformer.	Advantages: • Maximal flexibility • Improved classification accuracy Disadvantages: • Threshold defining is complicated
Yan et al. (2015) [72]	Consensus clustering algorithm	Perfect asset management plan for power systems	This paper intends to implement an efficient clustering model for taking the proper action at the time of failure detection by using an asset management plan.	Advantages: • Best optimal solution • Increased efficiency and accuracy Disadvantages: • Requires more time for computation

From the above table, it is inferred that various asset management mechanisms have been used for identifying and recognizing faults in the power system. Most conventional works are heavily focused on analyzing and reducing transformer faults using machine learning mechanisms. Also, the existing techniques comprise both specific advantages and disadvantages according to their working conditions and operating functionalities. Based on this study, it is evident that the ML models are mainly used for proper decision-making based on the asset management planning strategy.

4- Conclusion

The main purpose of this study is to investigate the different types of machine learning techniques used for effective asset management in power distribution systems. Typically, machine learning techniques are extensively used in many engineering applications for solving complex classification and regression problems. This study examines the major implications of using these techniques to solve various types of problems in power distribution systems. Herein, the classic asset management framework is presented with its classification models. The ML techniques compared in this work are Deep Learning, SVM, RVM, k-NN, k-means, fuzzy systems, ANN, CNN, expert systems, J48 classifier, reinforcement learning, and other AI mechanisms. These algorithms, in general, share the requirement of needing large input datasets for training the models and obtaining good results. But when these datasets are available, they are shown to have significant potential for optimizing processes.

This study also examines the performance of each ML technique to identify its merits and demerits. Moreover, the importance of maintenance activities and controlling operations of the electrical components based on asset management policies are discussed in this study, and from this scrutiny, it is identified that the predictions of lifespan and working stability of electrical equipment are important factors, because they help to improve the performance of entire power system networks. Also, it is observed that the deep learning techniques are the most suitable for power system applications due to their capability to represent relationships among variables and accuracy.

Based on this review, the most suitable machine learning technique can be selected for each application and used for developing a new asset management framework to improve the performance of power distribution systems.

In future work, machine learning algorithms have the potential to design and improve proper asset management policy schemes. Deep neural networks, in particular, are an area that has been disruptively evolving in recent years and that could offer very promising results in upcoming years.

5- Declarations

5-1- Author Contributions

G.L.L., M.S.B. and C.M.D. conceived and designed the analysis. G.L.L. collected the data and wrote the paper. M.S.B. and C.M.D. read and approved the manuscript. All authors have read and agreed to the published version of the manuscript.

5-2- Data Availability Statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

5-3- Funding

5-4- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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