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A Review on the Application of Machine Learning Algorithms on Smart Grid Optimization

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ABSTRACT–With the increasing challenge of distributed and renewable energy sources, maintaining the stability of the power grid is becoming increasingly difficult. By incorporating information and communication technologies, along with machine intelligence, the conventional power grid has the potential to evolve into a smart grid. The integration of machine learning equips the smart grid to make its decisions and efficiently handle generation, power outages, transmission line failures, unforeseen shifts in customer demands, overall fluctuations in renewable energy production, or any unexpected catastrophic events. These diverse machine-learning algorithms play a crucial role in enhancing the functionality of smart grids, contributing to their optimization. This article examines various machine learning algorithms and approaches designed to optimize the responsiveness of each facet of smart grid optimization.

KEYWORDS–***Smart Grid, Machine Learning, Components of smart grid, Optimization***

1. INTRODUCTION

Electricity has become indispensable for the progress and well-being of society and its economic development (Gabbar et al., 2010).To establish an equilibrium between demand and supply of electrical power maintaining quality of power is always a challenging task to carry out. Since traditional power grids are designed to handle the unidirectional flow of power, managing the bidirectional flow of power generated by decentralized sources such, as wind and solar poses challenges for electricity grids. With the rapid growth of technology and information, conventional power has the potential to evolve into a smart, automated, and adapted power grid(Azad et al., 2019). Therefore, It is paramount to establish a reliable, secure, integrated, efficient, and sustainable electrical system from generation to consumption, providing quality electricity to end users according to their demands. In this scenario perpective, the concept of the smart grid has transcended ((Gharavi et al., 2011).

Numerous concepts of Smart-Grid vary from literature to literature. The smart grid can be seen as an electrical system that integrates information, bidirectional and cyber-secure communication technologies, and computational intelligence throughout electricity generation, transmission, substations, distribution, and consumption. The aim is to create a system that is environmentally friendly, safe, secure, reliable, resilient, efficient, and sustainable(Fang et al., 2012). International Energy Agency (IEA) defines smart grids as networks that make use of advanced technologies to monitor and manage the distribution of electricity, from power sources serving the diverse electricity requirements of consumers. This technology seeks to coordinate the requirements of all participants in the energy market, optimizing system efficiency, reducing environmental costs and impacts, and maximizing the reliability, resilience, and stability of the system(Tanaka, 2011). Furthermore,(Gabbar et al., n.d.) infers Smart grids utilize information and communication technology, along with intelligence and computational capacity, across every aspect of the electricity domain—from generation to end consumers. The objective is to enhance

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interoperability, sustainability, reliability, quality, and efficiency within the electrical system. Therefore, considering these definitions, it can be concluded that the smart grid is a sophisticated and interconnected electrical system that employs advanced information and communication technologies, bidirectional communication, computational intelligence, and integrated control systems across all facets of electricity generation, transmission, substations, distribution, and consumption enhancing the sustainability, reliability, quality, and efficiency within the electrical system.

A traditional smart grid consists of the following operations: generation, storage, transmission, and distribution toward end-use customers. The generation process refers to the process of producing electrical energy. This involves the conversion of various renewable and non-renewable energy sources. Storage systems store the excess electricity generated during periods of low demand, which can later be used during power outages. Transmission lines are responsible for the transmission of electricity from the generation sources to the distribution networks. Demand-side management plays a pivotal role in balancing the supply and demand of electricity. A demand response program allows utilities to communicate with consumers and adjust their electricity consumption during peak periods, reducing the need for additional generation capacity. Conventional power grids typically transport electricity from small numbers of central generators to a widespread user base. In contrast, the smart grid utilizes bidirectional flows of both electricity and information, establishing an automated and decentralized advanced energy distribution network (Fang et al., 2012). Moreover, modern smart grids embrace a more secure and protected system than the traditional grid. A concise comparison between the grid and the smart grid is shown in Table 1.

Table 1: Comparison between conventional and smart grid (Farhangi, 2010)

Conventional Grid	Smart Grid
Unidirectional communication	Bidirectional communication
Centralized generation	Distributed generation
Manual Control	Automatic Control
Less flexible and adaptable	More flexible and adaptable to change
Limited control	Pervasive control
Few sensors	Sensors throughout
Few customer choices	Many customer choices

Despite the concept of the smart grid having been propagated rapidly and it has gone under significant development, many challenges need to be addressed in this field from generation to end-user customers. This incorporates the major challenges from the infrastructure system to the protection and management system. Moreover; renewable energy integration, communication, integration of energy storage systems, power system reliability, security, stability, power flow optimization, power quality improvement, automation, and consumers' motivation are the major challenges to be faced (2010 2nd IEEE International Symposium on Power Electronics for Distributed Generation Systems., 2010). With the swift expansion and its emergent nature, Machine Learning, stemming from artificial intelligence, employs algorithmic construction to instruct and predict outcomes based on datasets. This approach has proven highly effective in resolving numerous issues linked to smart grids(Simon, 2016). Machine learning encompasses diverse algorithms, ranging from supervised to reinforcement learning, each rooted in specific methodologies. Supervised learning involves training algorithms with known inputs and outputs, allowing them to learn patterns and make predictions based on labeled data. Unsupervised learning, in contrast, operates without predefined inputs and outputs, relying on the algorithm to discover inherent patterns and relationships within the data. Reinforcement learning introduces a dynamic element, where algorithms receive feedback from the environment only after taking specific action for a given input(Simeone, 2018).

This paper aims to illustrate a qualitative (Survey) descriptive analysis of the application of machine learning algorithms on smart grid optimization. The primary objective of this article is to explore the utilization of various machine learning algorithms for optimization across different facets, such as generation,

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storage, transmission, and demand-side management with a specific survey about what particular algorithm, is mostly used in each subfield. This study is pertinent for positioning diverse machine learning algorithms within both the smart grids and power systems. It serves to assist professionals in adapting to the technological advancements in smart grid development.

The structure of the article is as follows: section 1 provides an introduction, exploration of generation in smart grid and different ML algorithms implementation for its optimization. Section 2 focuses on storage systems in smart grids and ML algorithm-based optimization, followed by Section 3, which covers transmission in smart grids and its optimization incorporating ML algorithms. Section 4 incorporates how ML algorithms optimize the demand side management. The article concludes with section 5 and explores future avenues for research in section 6. The references are provided in section 7.

1. Generation and its Optimization

In the smart grid, electricity is initially generated by the integration of various renewable energy sources. It often incorporates a mix of renewable and conventional energy sources, such as; solar power, wind turbines, hydroelectric plants, natural gas, and more. The goal is to have a diversified and sustainable mix to meet the energy demands (Papavasiliou et al., 2014). It uses sensors and monitoring devices throughout the generation process. These devices collect real-time data on electricity production, environmental conditions, and equipment health. This data is crucial for the optimization of the performance of the power plants and ensuring efficient energy production. It relies on communication networks to transmit data between various components of the system. This includes the communication between plants, substations, and control centers. The use of advanced communication technologies enables quick decision-making and responses to changing conditions. These systems can automatically adjust the output of power plants based on the demand functions, weather conditions, or other factors. This helps maintain a stable and reliable power supply. The key feature of the smart grid is its ability to adapt to changes in electricity demand and supply. This flexibility is achieved through advanced forecasting algorithms, predictive analytics, and real-time monitoring. It allows the grid to balance generation and consumption dynamically(Gaviano et al., 2012). Hence, Smart grids optimize electricity generation by incorporating advanced monitoring, communication, and control technologies. The integration of diverse energy sources and the ability to adapt to changing conditions make them more resilient and efficient than traditional power systems. To monitor, predict, communicate, and control, various specific machine learning algorithms such as regression models, reinforcement learning, and neural networks are used, which are further discussed separately in the upcoming paragraph.

1.1. Reinforcement Learning

Reinforcement learning (RL) stands out as an effective method for enhancing communication within the smart grid's generation processes. It is a machine-learning paradigm inspired by behavioral psychology where an agent learns to make decisions by interacting with an environment. In RL, the agent navigates through the environment, taking action and receiving feedback in the form of rewards or penalties. The fundamental goal is for the agent to learn a policy strategy that maps steps to actions -maximizing the cumulative reward over time. The learning process involves the agent exploring different actions and exploiting its current knowledge to optimize the decision-making (Proceedings 2011 International Conference on Mechatronic Science, Electric Engineering, and Computer : August 19-22, 2011, Jilin, China, 2011).

1.1.1 Implementation of Reinforcement Learning

In the exclusive domain of the smart grid's generation process, reinforcement learning (RL) emerges as a dynamic and adaptive solution for optimizing data communication between diverse components of the system. The process commences with the meticulous modeling of the communication environment, encompassing the nodes, channels, and intricate dynamics of the data transmission, considering factors such as the output of the diverse generation sources and prevailing environmental conditions. RL agents, acting with the environment, embark on a learning journey by iteratively taking actions such as adjusting communication protocols prioritizing channels- and receiving feedback in the form of rewards. These rewards are intricately designed to reflect data transmission efficiency, increased reliability, and optimal utilization of available bandwidth. The adaptability of the RL models to changing conditions, achieved through a delicate balance between exploration and exploitation, ensures the system's responsiveness to variations in generation sources and environmental parameters. The integration of the RL with the generation process allows for real-time adjustments based on the status of the energy generation, providing a dynamic and adaptive communication framework aligned with the specific goals and complexities of the generation phase within the smart grid(Zhang et al., 2018). Through rigorous validation and testing, followed by seamless implementation, reinforcement learning emerges as a pivotal tool for autonomously and optimally communicating data in the smart grid's generation landscape, contributing to the heightened efficiency and adaptability in electrical energy production.

2. STORAGE AND ITS OPTIMIZATION

Storage in the smart grid is a crucial component that enables the system to efficiently manage and balance the supply and demand of electricity. Energy storage plays a vital role in storing excess energy during periods of low demand or high generation releasing it during peak demand or low generation periods. The primary types of energy storage technologies include batteries, pumped hydro storage, and thermal energy storage. The fundamental mechanism involves capturing the surplus energy during periods of abundance and releasing it during times of scarcity. The storage process commences with the charging phase, where excess electricity, often generated from renewable energy sources during off-peak hours, is utilized in the energy reservoirs. The reservoirs come in various forms, including batteries, pumped hydro storage, and thermal energy storage. In batteries, the surplus electrical energy is converted into chemical energy and stored until needed(Aktas et al., 2017). By alleviating the strain on the grid during periods of high demand or low generation, energy storage ensures a stable reliable power supply, making it an indispensable player in the smart grid's search for optimization and adaptability. Some machine learning algorithms used for storage optimization are discussed below.

2.1. Decision Tree

The decision tree algorithm operates by recursively partitioning a dataset into subsets based on the values of different features, creating a hierarchical tree structure where each internal node represents based on the feature, and each leaf node represents the outcome or prediction. During the training phase, the algorithm evaluates various features and selects the one that maximally separates the data according to certain criteria, such as information gain. This process continues for each subset, further branching the trees until a stopping condition is met, such as a predetermined depth or minimum number of samples in a node. The result is a tree structure with decision rules based on the feature values of the instance (2011 IEEE Control and System Graduate Research Colloquium., 2011). Decision trees are interpretable, making them valuable for understanding the reasoning behind the predictions. However, they can be prone to overfitting and capturing noise in the data, which is mitigated by techniques like pruning. Overall, decision trees excel in a variety of tasks, including classification and regression, and their adaptability and interpretability contribute to their widespread use in machine learning applications.

2.1.1 Implementation of Decision Tree

The decision tree algorithm plays a pivotal role in the optimization of storage systems within the smart grid, providing a robust framework for intelligent decision-making based on historical data and real-time conditions. The process starts with rigorous data collection, encompassing factors such as energy generation patterns, demand fluctuations, and storage system parameters. The algorithms then undertake the feature selection, identifying key variables that influence the performance of the storage system. these features become the basis for decision-making within the tree structure. The target variable is defined to encapsulate the optimization goal, it could be the optimal charging and discharging schedule, storage capacity utilization, or any other metric that reflects the efficiency and the performance of the storage systems. Data pre-processing follows, ensuring the dataset is cleansed of the anomalies and formatted appropriately for the decision tree algorithm. In the training phase, the decision tree recursively positions the dataset based on the feature values. Decision rules emerge from the tree, offering actionable insights into when and how to optimize the storage systems' operations. For instance, the decision tree might recommend charging the system during periods of low energy prices and discharging during peak demand. These rules become the bedrock for optimization strategies, guiding the storage system's actions in response to varying grid conditions. Importantly, decision trees provide transparency, offering a clear understanding of the logic behind the suggested decisions. Their adaptability is a crucial asset, enabling dynamic adjustments based on real-time data to ensure relevance and effectiveness in diverse scenarios. The decision tree model undergoes validation using a separate dataset of cross-validation, assessing its accuracy in making predictions or decisions for unseen data. The integration of decision tree-derived optimization strategies into the broader smart grid ecosystem ensures coordinated and efficient operation, contributing to the grid's stability and responsiveness. The decision tree algorithm, with its ability to handle both categorical and numerical data, proves to be a versatile tool in navigating the intricacies of storage optimization within the dynamic landscape of the smart grid to make informed decisions that enhance the efficiency and, reliability, and sustainability of the storage system.

3. TRANSMISSION & ITS OPTIMIZATION

In a smart grid, transmission refers to the process of transporting electrical energy from power generation sources to distribution networks and eventually to end users. It involves the high-voltage, long-distance movement of electricity over the transmission infrastructure. The core purpose of the transmission line is to efficiently transport electricity across long distances, ensuring that the power generated at diverse facilities, whether traditional or renewable, is efficiently conveyed to regions with high demand. The process commences at the power plants, where the electricity is generated through various means as mentioned in the generation part. Before entering the transmission grid, the generated electricity typically passes through the step-up transformers. The transformers increase the voltage to minimize the energy losses during long-distance transformers. The electricity is transmitted over a network of high-voltage transmission lines. These lines can span hundreds or thousands of miles and are designed efficiently to transport large amounts of electricity. Along the transmission network, there are substations that house equipment for voltage transformation, monitoring, and control. Substations play a crucial role in maintaining the stability of the transmission system. As the power approaches its destination, the step-down transformers lower the voltage to levels suitable for distribution and then into the local distribution network. Throughout this journey, advanced technologies are employed for monitoring and control. These technologies include sensors, communication systems, and automation that enable real-time monitoring of the parameters such as voltage, current, and line conditions in real-time, offering the optimization of power flows and better management of the grid (Mahin et al., 2022). Communication enables the bi-directional flow of information, facilitating the remote control and quick response to potential issues. Smart machine learning algorithms come into play, optimizing the utilization of the transmission based on factors like demand patterns and real-time conditions. These are discussed in upcoming sections.

3.1 Support Vector Machine

A support vector machine (SVM) is a powerful tool and versatile machine-learning algorithm designed for classification and regression tasks. At its core, SVM excels in finding the optimal decision boundary that separates data points belonging to different classes in a high-dimensional space. The primary objective is to maximize the margin between these classes, representing the distance between the closest data points of each to the decision boundary. SVM is particularly adept at handling complex, non-linear relationships through the use of a kernel trick, which implicitly maps data into higher-dimensional spaces, allowing for the identification of intricate patterns. In a binary classification scenario, the SVM decision boundary is determined by support vector data points that lie closest to the decision boundary. These vectors play a pivotal role in defining the hyperplane and are crucial for the model's generalization to new, unseen data. SVM's robustness lies in its ability to handle datasets with outliers and its inherent regularization properties (Bhavsar et al., 2012).

3.1.1 SVM Implementation

In the scenario of the smart grid, where the reliable functioning of the transmission is paramount, the application of a Support Vector Machine (SVM) stands out as a sophisticated solution for fault detection. The process unfolds with meticulous data collection, incorporating historical records that encapsulate the nuances and behaviors of the transmission line under diverse conditions. A pivotal step in feature selection is where the algorithms identify and prioritize electrical parameters such as voltage, current, and frequency, that are indicative of normal or fault states. Data preprocessing follows suit, ensuring the dataset is cleansed and standardized, optimizing it for SVM's discerning capabilities. The transmission of feature space allows SVM to capture intricate correlations between electrical parameters, making it adept at distinguishing complex fault patterns. The training phase involves finding the optimal hyperplane that maximally separates instances of normal operation from those indicative of faults. Fine-tuning of the hyperparameters further refines the model's accuracy and sensitivity. Once trained, the SVM model becomes vigilant, and capable of real-time fault detection by scrutinizing incoming data against the learned decision boundary. The nuanced approach considers the interplay of various electrical parameters, enabling the algorithm, to identify subtle deviations that might precede or indicate faults. The performance of the model was rigorously evaluated using metrics such as accuracy, precision, recall, and F-1 score, ensuring its efficiency across diverse fault scenarios. The seamless integration of the SVM into the smart grid elevates fault detection to a proactive realm. By considering a spectrum of electrical parameters, SVM provides a holistic defense mechanism against disruptions. In the event of potential faults, the SVM-equipped smart grid responds swiftly and cohesively, mitigating the impact and preserving grid stability(IEEE Computer Society. et al., 2012). Therefore, the amalgamation of SVM represents a paradigm shift in fault detection strategies for the smart grid. This synergy not only enhances the resilience of the transmission lines but also guides us in an era where predictive capabilities of machine learning fortify the backbone of our energy infrastructure, ensuring a robust and adaptive response to the challenges of an ever-evolving electrical grid.

3.2. Neural Network

A neural network is a computational model inspired by the structure and functioning of the human brain. It is a fundamental component of machine learning and artificial intelligence, designed to process and analyze complex patterns in data. The neural network consists of interconnected nodes, or artificial neurons, organized into layers. These layers include an input layer, one or more hidden layers, and an output layer. Each connection between nodes is associated with a weight, and each node applies an activation function to the weighted sum of its inputs. During the training phase, the network learns from examples by adjusting these weights based on the error between its predictions and its actual outcomes. The learning process often facilitated by optimization algorithms like gradient descent, is crucial for the network to generalize and make accurate predictions on new unseen data. Deep neural networks, which have multiple hidden layers, are particularly effective in learning hierarchical representations of complex data. Neural networks find applications in a wide range of fields showcasing their versatility and ability to tackle intricate tasks in the realm of artificial intelligence (Islam et al., 2019).

3.2.1 Neural Network Implementation

The transmission lines, interconnected nodes in a vast neural network, contribute to grid resilience by dynamically adapting to disruptions and redirecting power flows. Neural networks play a pivotal role in the control, communication, and monitoring of transmission lines in smart grids, offering a versatile and adaptive approach to managing the complexities of the electrical grid. Incorporating diverse historical data, encompassing load patterns, weather conditions, and grid dynamics, this network forecasts future grid states, allowing for proactive adjustments in parameters such as power flow and voltage to optimize stability. The adaptability extends to communication protocols, where neural networks contribute to efficiency gains and anomaly detection. By analyzing past communication patterns and network performance, they optimize data routing, predict congestion, and detect anomalies indicative of potential cyber threats. In the monitoring realm, neural networks play the role of vigilant guardians. Engaging in condition monitoring, they analyze the data from sensors distributed along the transmission lines, offering real-time assessments of the equipment's health and .early detection of potential faults. In dynamic line rating, neural networks leverage their predictive capabilities to forecast the impact of changing weather conditions on transmission line capacity, facilitating on-the-fly, adjustments. The prowess of neural networks is further magnified in data fusion, where they seamlessly integrate information from disparate sources such as sensors, SCADA systems, and weather forecasts. By discerning correlations within this amalgamated data, neural networks provide a brief understanding of the grid’s state, informing effective decision-making and fortifying the grid against unforeseen events. Their adaptability and continuous learning from incoming data contribute to a dynamic, responsive, and intelligent electrical infrastructure (IEEE Communications Society. et al., n.d.). As neural networks navigate the complexities of transmission line management, their role transcends mere automation, embodying a transformative force that ensures the reliability and efficiency of the smart grid amid the multifaceted challenges of an evolving energy landscape.

4. DEMAND SIDE MANAGEMENT

Demand-side management (DSM) within the context of a smart grid is a strategic approach to optimizing electricity consumption on the consumer side to achieve a harmonious balance between supply and demand. At its core, DSM is a sophisticated framework that leverages real-time communication, advanced metering infrastructure, and intelligent technologies to empower consumers to make informed and dynamic decisions about their electricity usage. The foundation of DSM lies in establishing a dialogue between utility providers and consumers, facilitated by smart meters that enable bidirectional communication. Through this communication channel, consumers receive real-time information about electricity prices, grid conditions, and predictions of demand fluctuations. DSM introduces dynamic pricing models, such as time-of-use pricing and real-time dynamic pricing, where electricity rates vary based on the time of day or the current state of the grid. Consumers, armed with this information, are incentivized to adjust their electricity consumption patterns during periods of high demand or high prices, and special tariffs serve as motivational tools, encouraging consumers to actively participate in demand response programs. Automated control systems including smart home technologies and energy management systems, play a pivotal role by allowing consumers to program and automate th e operation of appliances and devices based on pricing signals or demand response requests. Energy storage technologies and the integration of renewable energy sources further enhance DSM by enabling the storage and release of energy during optimal periods. Demand Side Management goes beyond mere load shifting; it encompasses a holistic strategy where customers actively engage with the electricity system making dynamic decisions that align with both economic considerations and environmental sustainability. The collaborative nature of DSM transforms consumers from passive users to active participants in the energy ecosystem, fostering a resilient, efficient, and sustainable smart grid where the balance between supply and demand is finely tuned, and the grid adapts to the evolving landscape of energy consumption (Logenthiran et al., 2012). As a cornerstone of smart grid evolution, DSM not only addresses the challenges of grid reliability and efficiency but also marks a paradigm shift toward a future where consumption and utilities collaborate in shaping the energy landscape for the benefit of all stakeholders.

4.1 K-means Algorithm

The k-means algorithm, a fundamental clustering technique, operates on the principle of partitioning data into distinct groups based on inherent similarities. The process begins by randomly selecting k initial centroids, representing the centers of the clusters. Data points are then assigned to the cluster whose centroid is closest, typically based on Euclidean distance. Subsequently, the centroids are recalculated as the mean of all data points within their respective clusters. This assignment-recalculation cycle iterates until convergence, where the centroids no longer shift significantly. The result is k clusters with data points grouped based on proximity (Likas et al., 2003). The algorithm's strength lies in its simplicity, efficiency, and scalability. However, its performance can be influenced by the initial choice of centroids, making it sensitive to outliers. Variations like k-means for better centroid initialization or iterative refinement techniques have been introduced to mitigate these challenges. K-means find applications across diverse fields, from customer segmentation in marketing to image compression in computer vision, showcasing its versatility in uncovering underlying patterns within datasets.

4.1.1 Implementation of K-means

Within the intricate realm of smart grid management, k-means clustering emerges as a strategic foundation in the optimization of Demand Side Management (DSM). K-means clustering, a powerful machine-learning algorithm, adapts the segmentation of consumers into discernible groups based on the similarities in electricity consumption patterns. This segmentation is pivotal in unveiling clusters with homogenous load profiles and response behaviors. The algorithm's application doesn't stop at segmentation; it delves into a nuanced analysis of load profiles within each cluster, unraveling the intricacies of peak demand periods and consumer response dynamics. This understanding becomes a keystone for customizing demand response strategies, and tailoring DSM initiatives to the unique needs and preferences of consumers within each cluster. By discerning the distinct characteristics of consumer groups, k-means clustering guides the implementation of optimal price models, resource allocation strategies, and dynamic load forecasting. It empowers utilities to craft targeted DSM programs, dynamically adjusting to the evolving landscape of consumer behavior. The adaptability of K-means clustering ensures that DSM strategies remain agile, accommodating shifts in consumer dynamics over time. Moreover, the algorithm aids in behavioral analysis, shedding light on the factors influencing consumers actions influencing consumer actions and informing utilities about the diversity of demand response, as a result, utilities can design focused awareness campaigns and interventions to foster e specific behavioral changes, further enhancing the effectiveness of DSM initiatives. K-means clustering, in essence, facilitates not only the efficient management of load balancing and grid stability but also fosters a more engaged and responsive consumer base (Institute of Electrical and Electronics Engineers, n.d.). The interpretation of DSM through k-means clustering represents a paradigm shift, transforming the traditional utility-consumer relationship into a dynamic, data-driven collaboration where electricity consumption is finely tuned to the rhythm of consumer needs and grid optimization.

5. CONCLUSION

The article provided a detailed qualitative description of the utilization of machine learning in the smart grid domain, utilizing articles gathered from the IEEE Xplore library. A chronological examination was conducted to analyze the predominant research subjects within the optimization of each component of the smart grid field that incorporates machine learning applications. The analysis determined that out of the numerous machine learning algorithms discussed in section I, only five were notably successful in optimizing each sub-area of the smart grid. Specifically, reinforcement learning emerged as the preferred choice for generation optimization, followed by a decision tree for storage, support vector machine, and neural network for transmission. Lastly, the k-means algorithm was identified as particularly effective for optimizing demand-side management.

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6. FUTURE WORKS

As a suggestion for prospective research endeavors, collecting data for each sub-area of the smart grid and undertaking optimization by employing diverse machine learning algorithms and Python programming for the training and testing of gathered data is recommended.

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