Data-Driven Methods of Machine Learning in Modeling the Smart Grids

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***Abstract*—Electricity demand is rising in lockstep with global population growth. The present power system, which is almost a century old, faces numerous issues in maintaining a steady supply of electricity from huge power plants to customers. To meet these issues, the electricity industry has enthusiastically embraced the new smart grid concept proposed by engineers. If we can provide a secure smart grid, this movement will be more useful and sustainable. Machine learning, which is a relatively recent era of information technology, has the potential to make smart grids extremely safe. This paper is a literature survey of the application of machine learning in different areas of smart grids. This paper concludes by mentioning the best machine learning algorithms that can be used in different aspects of the smart grid.**

Keywords—* *Machine Learning, Smart Grid, Machine Learning Algorithms

I. INTRODUCTION

In recent years, the extraction of renewable energy resources (RERs) has become a hot topic across the world. In traditional power grids, billing, fault detection, recovery from the fault, and all other power flow concerns are handled manually. The need for power has risen dramatically in recent years. The efficient distribution of such a large amount of surplus power is urgently required. The significant drop in the price of renewable energy technology such as solar cells, wind turbines, and the concept of green energy has heightened consumer awareness that they can not only create their electricity but also return it to the primary grid. It raises the need for two-way power transmission. Self-rejuvenation from flaws without disturbing the load is another twenty-first-century necessity. Smart grid (SG) features include unity power factor, load balancing, two-way power flow, self-healing without affecting the load, and an automated monitoring system. The use of machine learning (ML) is becoming very popular in SG systems for power demand and predicting consumer supply. The most common ML algorithms used in the SG analysis are artificial neural networks (ANN), Gaussian Regression (GR), Support Vector Machine (SVM), Random Forest (RF), Linear Regression (LR), and K-nearest neighbor (KNN) [1]. An ML-based energy optimization algorithm enables to tracking of real-time energy use, irreversible transaction records of electricity trading, managing electricity trading, and model reward [2]. The Gray-Wolf algorithm helps to manage the optimum programming of agents, loads, storage, and switches in the SG [3]. The AMI network's communication methods are largely similar to those of the most recently developed Internet of Things (IoT) communication models. This utilizes a variety of communication standards like cellular, WiFi, etc., multi-layered structures like fog, edge, cloud, and protocols to provide remarkable end-to-end IoT services in the SG system at greater range, lower power consumption, and lower costs [4]. The electricity grid is vulnerable to a variety of disruptions as a result of the rising limitations. This can lead to a defect and catastrophic failure. The wiring difficulties, grounding, switching transients, load changes, and harmonic production are all examples of these disturbances [5]. The computer vision algorithms like Brute-Force, Autoencoder, Fast Library for Approximate Nearest Neighbors, Speeded Up Robust Features, Features from Accelerated Segment Test, and support vector machines help to estimate the angular velocity of turbine blades. This is done using vision sensors and signal processing. This also helps to determine the blade presence and hub location [6]. ML-based algorithms also help in producing reliable data and the addition of other sources of information. This enhances the flow of information between different parts of the SG [7]. In intellectual property law, there are various legal issues in classifying and protecting ML systems, as well as the related target algorithms or other innovations [8]. By situating micro-synchrophasor units, ML aids in the development of an aggregated integer linear programming approach.

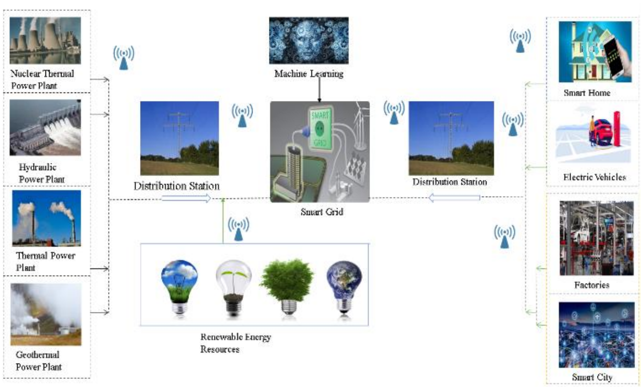

Fig. 1 Machine learning application in making traditional power grid into the smart grid.

Fig 1 shows how the ML is upgrading the traditional sources of power system into SG. This SG uses ML to provide secure and optimized power by using the RERs and helps make smart homes, and smart cities. Because all control operations are based on data provided by a communication network, a digital communication network is critical to the SG's reliability. The same digital communication network, however, might experience abnormalities such as unexpected disturbances, load shedding, malicious attacks, and power theft if fraudulent data is used [10].

TABLE I. State of the art of novel machine learning methods

Reference	Application	Year	Source	Methods/ Algorithm
[11]	Forecast wind power	2021	Energies	RF, KNN, DT, and ET
[12]	Detection of power system	2021	Transactions on Emerging Telecommunications Technologies	Weighted PSO, RF and NN
[13]	Estimate network flexibility potential.	2021	Sustainability (Switzerland)	CA, Sparse mean confusion matrices
[14]	Mitigate the difficulties	2021	Expert Systems	CNN,
[15]	Analyzing the SG.	2021	International Journal of Nonlinear Analysis and Applications	IoT, Packet loss accuracy
[16]	Online Short-term voltage stability assessment	2021	IEEE Transactions on Automation Science and Engineering	Shapelet-CNN, LSTM-based method, RVFL-based method
[17]	Intrusion detection system	2021	Symmetry	DT, RF, SVM, KNN
[18]	Real-time assistance, day-ahead control, and generation scheduling of the grid	2021	IEEE Access	Bi-directional LSTM, Predictive analysis using RNN module.
[19]	Forecasting short-term and mid-term load	2021	International Journal of Sustainable Energy	Support vector regression,
[20]	Prediction	2020	Systems Engineering	ANN and RF

Table 1 shows the recent works done in SG using ML. The higher penetration of RERs escalates associated challenges in the power system. Among all the RERs, solar and wind energy resources have gathered ample importance due to their free availability, non-polluting nature, and sustainability [11]. The integration of information technology and RERs with the power system makes it system smart. This helps the power system to communicate in two ways. This gave the birth of the smart grid (SG) which has more optimized uses of electrical power. Additionally, such an arrangement of the power grid enables novel applications that need the coordination of various equipment in the system. For instance, dynamic adaptive protection and microgrid power management [12].

The innovation of SG, like MG and distributed energy resources (DERs) has changed energy generation and consumption in two different ways, a) availability of prosumer as a grid participant contributes energy to main grid storage. This provides grid decentralization, b) Transfer of utilities from the power retailer to service providers. This provides transmission lines to prosumers [13]. The major problem with SG is that users are unaware of its benefits and have a trust issue with the consumers. The transition from the traditional grid to the SG requires a trustworthy energy platform, distributed operations, control algorithms, and a mathematical model [14]

Bidirectional communication tools, control systems, and information systems are all included in smart grid systems. Cutting-edge phasor networks are included in these powerful technologies. These phasor networks consist of phasor data, concentrators, supervisory control, phasor measurement units, and a data acquisition system [15].

The smart digital meters present in SG provide better information about the customer's energy usage and spontaneous feedback, as well as automated feeder switches. This helps in power re-routing in the event of grid failure and batteries with extra energy. This fulfills future consumer demand. The exciting transition of the electric grid creates problems and opportunities for improving the current power distribution system's capabilities [16]. The SG relies heavily on electricity forecasting to reduce operational costs and improve management. In various energy industries, load forecasting is an essential tool for optimal planning and operation (such as in industrial, residential, and commercial sectors). It is critical for decision-making, effective economic operations in the power system, and demand-side management. This can be done by encouraging customers to change their electrical demand and utilities to generate energy as needed [17]. System-of-System is the involvement and performance of constituent systems, as well as the network performance that connects them, which are inextricably linked to system capacity [18].

II. MACHINE LEARNING ALGORITHMS USED FOR SMART GRID

There are several methods of machine learning used for the analysis of SG. Some of them are LR, DT, RF, Linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), Naïve Bayes (NB), SVM, and KNN.

LR method is used for modeling the discrete outcome probability of an input variable. Multimodal LR is used to model a situation where there are many discrete outcomes. A value of 0 or 1 is applied to the probability-dependent feature. It restricts the output to the range [0,1] by using the Sigmoid function. Its hypothesis is represented in equation 1 [21].

$$h_{\varphi}(x) = \frac{1}{1+e^{-\varphi^{T}x}} \qquad (1)$$

where, $\varphi^T = [\varphi_0\ \varphi_1\ \varphi_2 \dots \varphi_j]$ and $x = [x_0\ x_1\ x_2 \dots x_j]$

In LR, the most common outcome model is a binary result.

The DT is a supervised learning-based tree-structured classifier strategy. This consists of decision nodes. It defines a test or choice of some characteristic. RF is a supervised learning-based meta-heuristic classifier that comprises numerous independent decision trees that act together. LDA is a dimensionality reduction technique that is commonly used in supervised classification. It's used to represent class differences, such as separating two or more classes.

SVM uses both classification and regression, but the majority of the time classification is employed. SVM works by determining the best line for splitting datasets into classes. The KNN classifier classifies similar instances and is the instance-based algorithm. The calculation for this classifier is based on the Euclidian distance formula as shown in equation 2 [22].

$$d\,(p,q) = \sqrt{(q1 - p1)^2 + (q2 - p2)^2 + \dots (qn - pn)^2} \qquad (2)$$

The Bayes theorem is used in the NB classifier. It's commonly used to solve problems like disease diagnosis, spam filtering, and document classification. The calculation is based on the formula represented in equation 3 [23].

$$P\left(\frac{Y}{X}\right) = \frac{P(X/Y)P(Y)}{P(X)} \qquad (3)$$

Anomalies are data objects with densities that are significantly lower than those of their neighbors. The elliptic envelope (EE) tries to draw an ellipse by enclosing the normal class members within it. Any observation that falls outside the ellipse is labeled an outlier or anomaly. EE estimates the size and form of the ellipse using the FAST-Minimum Covariance Determinant. This represents the data as a high-dimensional Gaussian distribution with various covariances between feature dimensions. An isolation forest is a type of ensemble regressor made up of several isolation trees. A random subset of the training data is used to train each tree. A measure of normalcy and the decision function is the path length from root to leaf. This will be averaged over a forest of such random trees.

III. NOTABLE AND NOVEL MACHINE LEARNING IN SMART GRID APPLICATIONS

Table 2 shows some of the noticeable and novel work done in the recent year on SG using ML. In recent years, several scientific works have been done to implement machine learning in the SG.

TABLE II. Novel work using machine learning in smart grid

Reference	Application	Year	Source	Methods/Algorithms
[21]	Energy consumption based prediction on dishonest entities	2020	Sustainable Cities and Society	NB ML algorithm, Energy efficiency evaluation method.
[22]	Identifying covert bogus data injection attacks	2020	Computers and Security	One-class SVM, RC, IF
[23]	Designing EMM	2020	IEEE Access	Gaussian Process Regression, GA based optimization, ,
[24]	Detection of false data injection	2020	International Journal of Reasoning-based Intelligent Systems	KNN, RT, RF, and SVM.
[25]	Data compression and extraction	2020	Applied Energy	Lempel Ziv Markov chain Algorithm, Block Zip 2
[26]	Predicting the energy demand	2019	Processes	NN model
[27]	Detecting the covert data integrity	2019	IEEE Transactions on Information Forensics and Security	iForest-algorithm, Radial basis function kernel, RF
[28]	Developing a hybrid prediction system	2019	IEEE Systems Journal	Least Squares Support Vector Regression, Metaheuristic firefly algorithm
[29]	Assessment of the implementation of demand response	2019	Applied Energy	Rule-based algorithm
[30]	Recognizing the different cyber-attacks	2019	Journal of Computational and Theoretical Nanoscience	iForest-algorithm, Radial basis function kernel, RF, IF

These implementations have shown impressive results in making the grid advance and secure. Security is one of the main severe concerns and the biggest challenge in SG. Detection of stealthy fake data injection assaults on state estimation using machine learning [24]. ML approaches develop a method for the energy management model that is a viable alternative because it minimizes the model's complexity. This creates a single trained model that can forecast energy management model performance characteristics for numerous scenarios [25]. ML models generate the stochastic prosumer-based SG remains a difficult task. False data injection in the electrical grid is a big threat to the smart grid's proper and safe operation [26]. ML and five classifiers KNN algorithm, random trees, RF, DT, multilayer perceptron, and SVM can be employed to create an effective detection. When Autoencoder compresses data, it first extracts an appropriate structure from the data before compressing it. Different ML models can be used to estimate energy consumption by using weather forecasts and electrical energy pricing characteristics, like L-ARX regression, N-ARX regression, and N-ARX neural network [27].

A PCA-based FE mechanism can be used to convert high-dimensional space into a low-dimensional space where data points can be easily separated without sacrificing accuracy. The unsupervised I-Forest-based anomaly detection system uses the modified data as input. The SG comprises the hybrid Prediction system that mixes a nonlinear nature-inspired metaheuristic optimization-based prediction model with a linear autoregressive integrated moving average model [28]. Improved demand response control system in all-electric residential structures, paired with the rising acceptance of time of use pricing aids in the development of flexible power system frameworks targeted at lowering building stock carbon footprints and facilitating the transition to a more sustainable power generating mix [29]. SG is among the most accessible cyber-physical systems. Therefore, different ML strategies can act as a means for detecting and classifying these attacks, as well as examining the practical application of these procedures as an upgrade to previous power system architectures. These are quite vulnerable to cyber threats. A covert data integrity attack on a communications network could jeopardize the security and reliability of SG operations [30].

IV. ADVANCED MACHINE LEARNING IN SMART GRID APPLICATIONS

Table 3 shows the previous works that have been done using advanced ML techniques for SG. The advanced ML techniques help in solving the difficult case scenario, like a prediction for long-term, cyber security, making an optimum decision, etc. ARIMA, deterministic PSO techniques, adaptive boosting algorithms, PART algorithms, etc., can be used for such applications.

TABLE III. Advanced machine learning in smart grid applications

Reference	Application	Year	Source	Methods/ Algorithm
[31]	Prediction	2018	Energy	Multivariate LR algorithm, Adaptive boosting algorithm
[32]	Detecting cyber-assault	2018	Applied Sciences	GA
[33]	Detection of a covert cyber deception assault	2018	IEEE Access	GA and SVM
[34]	Detection of the stealthy attack detection	2017	IEEE Systems Journal	Anomaly detection, SVM algorithm
[35]	Encrypting the meter data	2016	Energies	KNN, Deterministic PSO technique
[36]	Detection of attacks	2016	IEEE Transactions on Neural Networks and Learning Systems	KNN, SVM, Decision- and Feature-Level Fusion Methods
[37]	Cost reduction monitoring	2016	IEEE Transactions on Smart Grid	MinEntropy algorithm, Monte Carlo predicted error algorithm,
[38]	Optimum customer decisions	2015	IEEE Systems Journal	Baum-Welch algorithm, value iteration based exact solution algorithm, Incremental pruning algorithm
[39]	Security maintenance	2013	Green Energy and Technology	NB, SVM, and PART algorithm, C4.5 algorithm

Forecasts for renewable energy generation and consumption are very useful in SG. Forecasts are essential for sector coupling, which connects energy-consuming and power-generating sectors to address electricity storage issues by increasing power system flexibility. The necessity for expert knowledge, which includes ML skills and a thorough grasp of the application's process, hinders the large-scale deployment of ML methods in energy systems. The problem formalization, as well as the model validation and application, require process expertise [31].

For the proper planning and operation of the SG ecosystem energy prediction plays a vital role. The prediction can be either long or medium-term. The ANN, adaptive boosting model, multivariate linear regression model, and ARIMA model can be used for the development of accurate and exact long- and medium-term district-level energy projection models using ML-based models [32]. Smart meters are very helpful in collecting the data which is helpful in prediction. Because of the consistent power transmission and stable meter placements, the position of smart meters calculated by the received signal strength-based technique is practically constant [33]. However, monitoring power quality is difficult due to the high cost of measurement. The power network can be explained as a data-driven network using the latent feature model. This opens up the possibility of using a well-studied network that can monitors and estimates data which can be further used to solve the network quality monitoring problem in the SG [34].

A supervised ML-based technique for detecting a covert cyber deception attack in state estimation–measurement feature data received over an SG communications network [35]. To detect anomalies in the SG measurement samples, the identified optimum features are fed into two Euclidean distance-based anomaly detection techniques. This helps to covert assault detection in SG networks utilizing the features selection and Euclidean distance that is based on the ML [36]. For different assault scenarios, the attack detection problem was framed as an ML problem. The performance of supervised, semi-supervised, classifier and feature space fusion, and online learning methods can be used for attack detection problems. The SVM's performance is influenced by the kernel types chosen. The sparsity of the systems affects the SVM. Sparse SVM and kernel machines can be used to solve assault problems in the SG [37]. A GA can also be used to select discriminative and differentiating characteristics in SG performance analysis. The use of a genetic approach to select features enhances detection accuracy while reducing computational complexity.

ML algorithms can be used to detect the state estimator's stealthy fake data injection. Smart homes are one of the key components of SG. The smart home concept is expanded in two ways: 1) up-gradation of traditional households with smart gadgets, like enhanced metering infrastructure, to ML entities with immediate and distributive decision-making capabilities; and 2) up-gradation of individual households to large-scale customer units. The use of Q-learning-based approximate dynamic programming creates a low-complexity real-time algorithm. This enables for adaptively absorbing new observations as the environment changes [38].

The use of ML algorithms for denial-of-service attacks for the SG network using a simple databased approach is a relatively new concept. The performance of PART on real-world data can help prevent denial-of-service attacks in the SG network. On both prediction accuracy and the Kappa statistics metric, the PART algorithm surpasses other techniques. PART is not the greatest approach for preventing denial-of-service attacks in terms of computational complexity. Furthermore, the performance of PART was compared against a set of statistical learning methods [39].

V. DISCUSSIONS

The application of the machine learning methods in SG had been significantly increasing. SVM, ANN, and decision trees are the most popular methods. Fig 2. shows the progressive rise of the machine learning methods. It is observed that the ML methods are still limited to the basic methods where advanced ML methods, e.g., those suggested in [33-39] had not been considered. More specifically, the hybrid and ensemble ML methods, e.g., [40-49] are still not frequently used in SG. Similar to other fields of science and technology where advanced ML methods are dominant, e.g., [50-55], the SG will also benefit from the novel methods in the years to come. Novel training and evolutionary optimization algorithms for ML, e.g., [56-59] can indeed improve the quality of the models in SG as had been the case in numerous other applications, e.g., energy and environmental sciences [60-62].

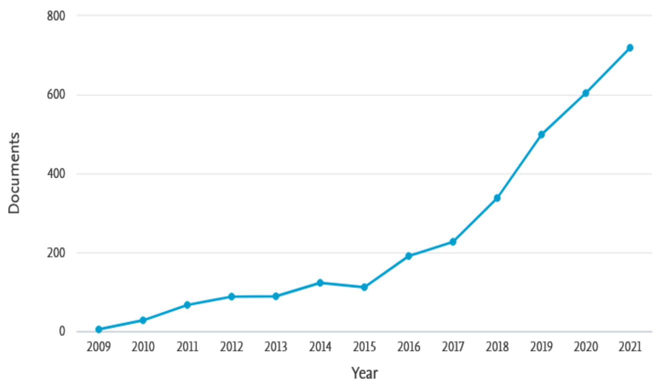

Fig 2. The progress of using machine learning in smart grid

CONCLUSION

Based on the presented survey, the following applications of ML in SG have been seen a) out of several ML algorithms, RF and isolation forest algorithms give the best result for cyber security in SG,b) for prediction in SG, the autoregressive integrated moving average model gives the best results, c) sparse mean confusion metrics help for a robust modeling approach and clustering analysis is effectively helpful for understanding the neighborhood type, such as residential, mixed, or business, d) the blockchain model and bidirectional LSTM algorithm are useful for acquiring a sustainable electric power supply. On the other hand, the naïve-byes algorithm is useful for getting a secure and resilient SG, e) out of the various ML algorithms, the tree RF algorithm is best for false data injection in SG. While the Lempel Ziv Markov chain algorithm is useful in measuring the high frequency in SG, f) the conditional entropy method is much faster for estimating the power quality in SG, Q-learning based approximate dynamic programming is best for smart home applications. Gaussian process regression and GA-based optimizations are effective in finding energy management.

Our future research in this field will focus on surveying the implication of the "blockchain algorithm" of machine learning on the SG. We'll look at how smart grid operators have dealt with sustainable electric power supply issues in particular. A survey like this could aid academics in developing more human-centered and sustainable machine learning solutions.

List of Abbreviations

SG	Smart Grid
ML	Machine Learning
DSM	Demand-side Management
ANN	Artificial Neural Network
KNN	K-Nearest Neighbour
LR	Logistic regression
DT	Decision tree
SVM	Support vector machine
GA	Genetic Algorithm
RF	Random Forest
DERs	Distributed Energy Resources
RERs	Renewable Energy Resources
NN	Neural Network
EE	Elliptic Envelope
LDA	Linear discriminant analysis

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