Smart and Sustainable Grids Using Data-Driven Methods; Considering Artificial Neural Networks and Decision Trees

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***Abstract*—Sustainability is the essential part of smart grids and the ultimate future of energy systems. Providing a state-of-the-art review on the progress of advanced learning systems which contribute to the sustainability of smart grid is essential. This paper reviews the applications of data-driven methods of machine learning in sustainable smart grid systems. The machine learning methods had been classified and reviewed in various groups based on the proposed taxonomy. The applications and methods had been identified and systematically reviewed based on the PRISMA guideline.**

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

I. Introduction

AS per the European Technology platform, a smart grid (SG) is a kind of electricity network that provides intelligent integration of the actions and behavior of all the users associated with it. This provides a sustainable, secure, and economical power supply [1]. The SG needs continuous modernization of the distribution grid. This is the core objective of SG innovations. The automation in the distribution allows automation, control operation, and real-time monitoring of the distributed network [2]. The demand response of the power system can be improved using the artificial neural network (ANN) and decision trees (DT) methods. This further helps in short and long term load and price forecasting, imperfect competition, and generation expansion [3]. SG also plays a significant role in the plug-in electric vehicle. ANN and DT help to optimize plug-in electric vehicle penetration level. It also helps to calculates the total sustainable performance of the power distribution system [4]. The importance of obtaining the sustainable SGin the power system includes the mapping of factors like decentralization and their interactions that can influence the load profile. This provides a methodology for modeling the behaviors of electricity prosumers [5]. The high number of system components makes SG highly complex, therefore, symbolic model reduction techniques help to analyze a set of equations and remove equations that don't influence the specified variables, and make the grid sustainable [6]. The future SG involves modernizing existing networks, facilitating changes in behaviors of energy consumers, and supporting the transition to a sustainable economy with low carbon [7].

Figure 1 represents the progress of SG in the past 10 years. The graph is plotted after observing the 50,000 articles published in the past decade. This shows that the development of SG is gaining more importance than the traditional power grid system.

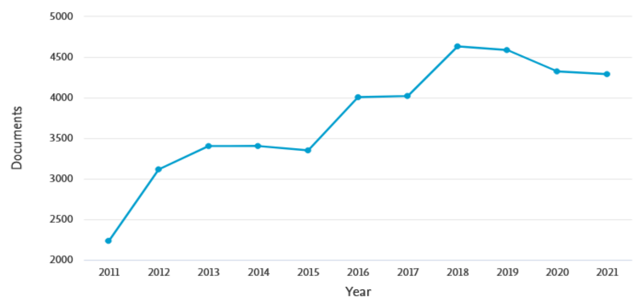

Fig. 1 Progress of smart grid within the past decade; over 50.000 articles had been published.

The recent developments in data-driven materials engineering propose that machine learning (ML) algorithms improve the production and design of advanced energy materials which transform the SG in the customer domain of the maturity domain [8,9]. The sustainable smart energy industry distribution can be achieved using ML algorithms and helps to make SG resilient, high speed, and low-latency connectivity to achieve sustainable, affordable, and clean energy. This sustainable development has short-term and long-term contributions which is being predominant in developing countries due to the pre-existing infrastructures [8,9,10]. Blockchain technology helps to achieve sustainable development of the SG. This transforms the SG and how it can help the developed and developing countries to accomplish its sustainable development goals in the consumer domain of the maturity model [9,11]. There are several competitive strategies at a network level for sustainable development. Different companies' collaboration brings competition may bring benefits but they implement enablers to prevent upfront risks [9,12]. The net-zero energy building helps to produce independent energy which can be used by different companies to export to the central grid [12,13]. The sustainable development of SG innovates in regulating incumbents. It requires to provide sufficient regulatory incentives for advancing the SG developments in China. On the other hand, in India, the SG market contributes to improving equitable and just access to electricity services [14,15]. The demand response is the dominating factor in the energy market which relatively has four barriers like privacy, cyber security, costs, and regulatory aspects. Therefore, SG pilot projects are building a strong foundation for SG technology like advanced metering infrastructure [15,16,17]. The best long-term development strategy is implementing the set of workable development plans that have been made available by SG. Dynamic management of systems development aids in managing the long-term process of the power system's sustainable development through the technical and economic appraisal of projects and the discovery of the best solution [18,19,20]. Figure 2 shows the development of sustainable SG in the past decade.

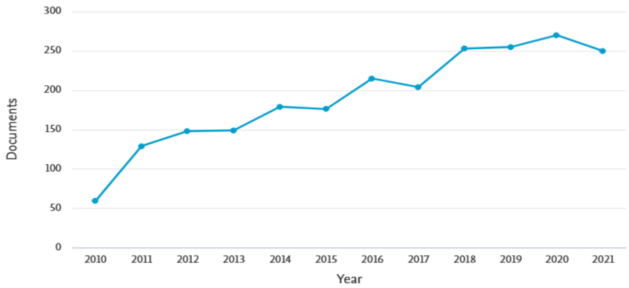

Fig. 2 Sustainable smart grid: over 2200 documents on the sustainable smart grid had been published within the past decade

The modified grey wolf optimizer approach can be used for hybrid renewable microgrid development. The integration of the solar system and wind system with the meta-heuristic optimization system dispatches the optimal energy in a grid-connected hybrid microgrid system [21]. To perfectly model the dynamic behaviors of contemporary power grids influenced by RES or system reconfiguration, a long short-term memory (LSTM) recurrent neural network can be designed. This can be embedded by the dynamically time-evolving power system's characteristics. This helps in distinguishing real-time attacks and natural changes to the SG [22]. The data mining techniques perform time-series analysis which helps in extracting and analyzing underlying patterns which help in energy trading [23]. The big data obtained from the SG provides information that benefits demand response and load profiling [24]. The emerging artificial intelligence is a powerful technique that reduces the complexity of the energy management model by developing a single trained model based on a multi-agent and multi-criteria negotiation protocol that supports the generation of power from efficient energy distribution, a wide range of sources, and sustainable consumption [25-28]. Renewable energy resource biofuels can be also useful for several types of energy production and by using the 6-Shin network the entry of renewable energy resources shows a reduction in energy costs. However, due to uncertainty the cost of the reserve market increases [29,31]. For the voltage regulation and power control of the doubly-fed induction generator wind turbine, a neural fuzzy showed pmising results in controling the converter [30]. Extreme gradient boosting estimates the solubility of hydrogen in hydrocarbons and the LSTM method is the best suitable for predicting the parameters of vortex bladeless wind turbine and wave energy converter modeling [32-35]. The stochastic fractal search paradigm and ANN can be used to predict the cooling load in residential buildings that helps in modeling the renewable energy systems for power prediction using a self-evolving nonlinear consequent part recurrent type-2 fuzzy system [36,37]. Residential buildings are the key element for sustainable development, heating load in residential buildings can be predicted using the ant lion Based dragonfly algorithm, league champion optimization hybrid algorithms, and double-target-based neural networks [38,39]. Solar and wind energy are the eminent source of renewable energy, electromagnetic field optimization can be used to optimize neural networks for solar energy [40]. The interval type-3 fuzzy logic system can be used in designing the photovoltaic system's power management and battery charging strategies [42]. ANN predictive algorithms, like satin bowerbird searching Optimizers, genetic algorithms, multi-layer perceptron algorithm, and whale optimization algorithms are used for electrical power prediction, generation expansion planning, and wind speed prediction in the presence of wind power plants, respectively [41,43-45]. The ANN helps in voltage regulation of the photovoltaic-battery fuel system together with least squares support vector machines. The neuro-fuzzy can boost forecast models of a photovoltaic collector [46,48]. The committee machine intelligent systems are used to improve the accuracy of sustainable SG whereas using weather data, ANN, and support vector machines are used for accurate short-term prediction of electric energy usage [47,49]. Figure 3 shows the development of sustainable SG in the past decade.

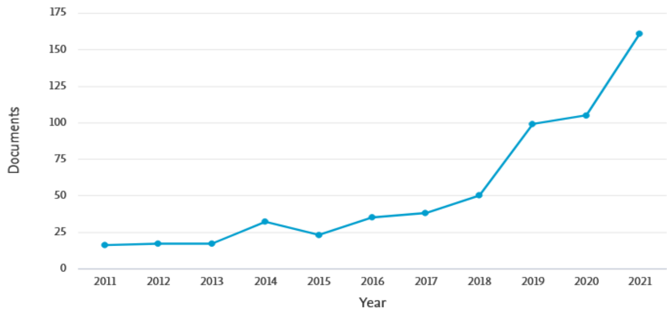

Fig. 3 Over 700 documents published on the applications of machine learning in the sustainable smart grid which indicates the essential role of machine learning

II. MATERIALS AND METHODS

The methodology is based on the inquiries in the Scopus integrated with the PRISMA to systematically review the documents. The method of review is adapted from the former review methods used for developing the state of the review on machine learning in various applications [50-62].

III. STATE-OF-THE-ART REVIEW

Review shows that artificial neural networks and decision trees are the essential machine learning applied in sustainable SG. In the following, these two essential methods are reviewed.

1) *Artificial neural networks*

ANN is a computational model that working principle is similar to the nerve cells of the human brain. It is the foundation of manu neural networks and deep learning methods, e.g., CNN, MLP. A ANN model includes one or multiple input layer, hidden layer, and one more more output layers. The output variable is designated as y, whereas the input data, which contain the independent variables, also known as features or attributes, are denoted as x1, x2, and xn. The weights that connect the input and hidden nodes are identified by the letters w1, w2, and wn. By using a cost function, the ANN seeks to reduce the error, which is the discrepancy between the correct and anticipated values for y.

This error is computed by the cost function, where "cost" is a colloquial name for the error [64,65].

TABLE I. Artificial neural networks for sustainable smart grid

References	Application	Year	Source	Modeling domain
[63]	Operational lifetime maximization of the pumps in the water storage plant	2022	Journal of Energy Storage	Storage dispatch
[64]	Energy demand-supply prediction	2022	Sustainability (Switzerland)	Energy Demand-Supply Prediction
[65]	Energy output prediction	2021	Energy Reports	PV–wind renewable energy
[66]	Day-ahead energy forecasting	2021	Sustainability (Switzerland)	Energy forecasting
[67]	Energy storage	2021	Chemical Engineering Research and Design	Sustainable energy
[68]	Continuous electricity supply.	2021	International Journal of Power Electronics and Drive Systems	Multi-source energy management
[69]	Forecasting	2021	IEEE Transactions on Industrial Electronics	Power
[70]	Day-ahead dynamic optimal power flow.	2021	Frontiers in Energy Research	Day-Ahead Dynamic Optimal Power Flow
[71]	Electricity grid flexibility assessment	2021	Sustainability (Switzerland)	Node characterization
[72]	Electricity demand management	2021	IEEE Access	Efficient Demand-Side Management
[73]	Voltage regulation	2021	Energy Sources, Part A: Recovery, Utilization and Environmental Effects	Reactive power management
[74]	Load forecasting	2020	Applied Energy	Load forecasting
[75]	Short-term forecasting	2020	Electric Power Systems Research	Load forecasting
[76]	Energy management and forecasting	2020	Electric Power Systems Research	Efficient energy management
[77]	Cost management	2020	IEEE Transactions on Systems, Man, and Cybernetics: Systems	Dynamic Pricing
[78]	Cost leverage	2019	Processes	Energy storage
[79]	Energy management	2018	Energies	Energy management
[80]	Reverse power flow protection	2018	Sustainability (Switzerland)	Reverse power flow
[81]	Energy flow management	2017	Proceedings of the IEEE	Renewable Energy
[82]	Prediction	2015	Neurocomputing	Price Prediction
[83]	Forecasitng wind power	2014	Renewable Energy and Power Quality Journal	Wind estimation
[84]	Prediction and monitoring	2013	Information (Japan)	Electric vehicle

The Genetic Algorithm based method can be used to optimize the dispatch schedule of the demand-side storage which improves the operational lifetime of the variable frequency drive-driven motor-pump set [63]. An ant colony optimization algorithm helps to model an efficient energy management system for the microgrid. This systematical schedules load and EVs charging/discharging and predicts solar irradiation and wind speed to ensure efficient energy optimization [66]. ANN is the most preferred and most powerful technique over ML as of its generalization capabilities for modeling in energy systems. This will guarantee a steady flow of electricity to customers while maximizing the use of renewable energy. [67,68]. The bi-directional LSTM assists in handling data with significant stochastic behavior and abrupt fluctuations [69]. The particle swarm optimization combined with the NN can predict a model to predict a day-ahead wind-flow and solar irradiance [70]. The integration of sparse mean confusion matrices CNN-based model helps in quantifying the network flexibility potential. This can be used for the safe integration of sustainable development and renewable energy resources [71]. The hybrid genetic ant colony optimization algorithm helps in modeling the demand side management in terms of user discomfort minimization, energy cost minimization, carbon emission control, and management of peak load [72]. ANN helps to improve the voltage profile in the hybrid SG [73]. A multi-objective grasshopper optimization algorithm, Kalman filtering, and wavelet neural network optimize the ANN parameters that help in short-term forecasting [74, 75]. The mixed-integer linear programming helps in scheduling smart appliances and electric vehicles to develop an efficient energy management scheme [76]. The optimal power allocation algorithm exploits a NN to sheathed the uneven relationship between the export price of power by an SG and the user demands [77]. L-ARX regression, N-ARX regression, N-ARX NN, and fog-based computing models help electrical energy storage and smart heating, ventilation, and air conditioning to leverage. This regulates the operation of the SG and avoids its complications [78,79]. ZigBee technology helps in complying with the IEEE 802.15.4 standard. This helps to reduce the rate of data, and lower the power consumption, and costs [80]. Experts' systems, fuzzy logic, and ANN help to design the fault pattern identification of an SG system that controls on a real-time simulator [81]. In forecasting, electricity price forecasting is a big problem. Kalman filters and Echo state networks help in solving this problem [82]. However, a nonlinear autoregressive network with exogenous inputs and focused time-delay NN is used to forecast and estimate daily wind speed to calculate energy management for planning the SG. This helps in dispatching the schedule of the demand-side storage, [83,84].

2) Decision trees

A distribution-free supervised learning technique that can be used for classification and regression is known as a DT. The objective of DT is to learn straightforward decision rules derived from the data features to build a model that predicts the value of a target variable. DecisionTreeClassifier may do multi-class classification on a dataset. A well-known decision tree approach called random forest regression creates numerous decision trees from an input dataset [88,89]. Table II surveys the nobel application of DT in attaining sustainable SG in the past decade. This shows that DT has wide applications and advantages in SG.

TABLE II. Decision trees in sustainable smart grids

References	Application	Year	Source	Modeling domain
[85]	Optimization	2022	Production Engineering Archives	Cost optimization in smart grid
[86]	Electric-vehicle management	2022	Sustainable Cities and Society	Smart grid management
[87]	Forecasting	2021	Sustainable Cities and Society	Solar and wind
[88]	Forecasting	2021	Energies	Wind power production
[89]	Power management	2021	IETE Journal of Research	Wind Power Flow Management
[90]	Demand and price forecasting	2021	International Journal of Sustainable Engineering	Electricity and solar power
[91]	Load forecasting	2020	Sustainable Computing: Informatics and Systems	Lightweight sustainable intelligent load
[92]	Power integration	2019	Energy Conversion and Management	Wind power
[93]	Load forecasting	2017	Sustainability (Switzerland)	Electric energy loads
[94]	Hybrid classification	2017	Intelligent Decision Technologies	Intelligent data analysis
[95]	Prediction	2015	IEEE Transactions on Knowledge and Data Engineering	Holistic measures
[96]	Intelligent communication	2014	IEEE Transactions on Industrial Informatics	Solar simulation

The precise location of the power availability can be identified using a random forest-based identification technique. This requires less time-interval and provides speedy responses to the demand end requestor [85]. The Gray wolf algorithm can reduce the running costs of the entire microgrid to the greatest possible option of electric vehicle-based reconfigurable SG [86]. The k-nearest neighbor algorithm allows the utilities of SG to cost-effectively balance and manage the renewable energy production and daily, monthly, seasonally, and yearly load of the power system [87]. The gradient boosting regression-based ensemble algorithm forecasts the wind power with the best accuracy as compared with RF, k-NN, DT, and ET alalgorithms [89]. Random Forest Manta-Ray Foraging algorithm is the best model for renewable energy sources and should be operated as efficiently as possible to reduce the cost of power generation, including real-time scheduling [90]. Despite its conceptual simplicity, LSTM-based sequence-to-sequence networks can anticipate power demand and price for time-series data from smart cities with good accuracy [91]. The DT-based embedded system can help to design a low-cost approach to electrical and electronic device networking, guided by perceptive Internet of Things (IoT) concepts [92]. The bagged trees regression approach estimates the wind power requires in the sustainable SG. This approach can be preferred over principal component regression, multivariate linear regression, support vector regression, and partial least squares regression [93]. An almost zero cooperative probabilistic scenario analysis and DT model can be used to solve the gap of enormous predictive error experienced by the state-of-the-art models [94]. In this work the advanced variation of decision tree and ANN provided a reliable model for electricity consumption [95]. Sustainable SG model based on abstract metrics reduces residual errors between the observed and anticipated values as estimated by abstract metrics [96]. A DT assesses the relative merits of the various simulation platforms in use and offers instructions on how to transform the current power grid into the SG using the available machine learning techniques [97].

CONCLUSION

Future SGs will be supported by an effective and dependable communication infrastructure that enables a two-way information exchange channel between consumers and utilities. This study gives a general review of the theoretical application of ANN and DT in achieving sustainable SG. Different ANN and DT algorithms are used for different purposes. Scale independence ensures that accuracy, sustainability and performance can be compared across models. ANN and DT indicated fundamental application in sustainable smart grid. The hybrid and ensemble models of these two machine learning methods have showen to be fundamental and expand in the future. The accuracy and the cost had been shown to be be essential factors considering the sustainability in SG. For the future work considering other ML methods for SG is recoemnded.

ACRONYMS

SG	Smart Grid
ML	Machine Learning
DT	Decision Tree
RF	Random Forest
ET	Extra Tree
ANN	Artificial Neural Network

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