Proc. of the International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME 2024)
4-6 November 2024, Male, Maldives

Machine Learning in Renewable Energy Systems

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***Abstract*— From solar and wind power to hydropower and biomass, smart grids, the catalytic industry, and power storage and distribution, this paper covers the gamut of ML's present-day uses. Among the many domains covered by machine learning are classification issues and the methods used to solve them. Classification schemes have recently attracted a lot of interest as a tool for improving the deployment, administration, and optimization of Renewable Energy Systems. The integration of new data sources (such as innovative sensors) and improved algorithms for creating trustworthy data will improve the data flow between ML and systems. The growth of other important areas of data science, such big data analytics, will determine the significance of unsupervised and reinforcement learning in the energy industry. The development of sustainable uses of ML in non-industrial applications for energy management will be aided by massive implementations, specialized algorithms, and new technologies like 5G. This work aims to survey the state-of-the-art classification algorithms for Renewable Energy situations, including both traditional and cutting-edge methods. Wind speed/power prediction, fault diagnostics in Renewable Energy Systems, power quality disturbance categorization, and other applications in alternative Renewable Energy Systems are some of the particular Renewable Energy topics covered in the paper's extensive literature analysis and discussion. Researchers and practitioners in the area may benefit from the paper's description of categorization algorithms and metrics used to Renewable Energy situations.**

Keywords—machine learning, Renewable Energy Systems, Classification Algorithms, Data Science,

I. INTRODUCTION

Machine-learning methods have gained popularity in data-driven sectors due to their ability to uncover input-output connections without math. These algorithms can be used to forecast for decision-makers and can benefit from data pre-processing. Major approaches include supervised, unsupervised, and reinforcement learning. Supervised learning uses labeled data for training, while unsupervised learning groups pre-labeled training data. Reinforcement learning requires external input for maximum advantages.[1]

Deep learning, a subset of machine learning, has evolved rapidly due to IT hardware and software developments. It can build unique nonlinear characteristics and high-level invariant data structures. Renewable energy forecasting machine-learning models have been examined, but enhancing forecasting with a single model is challenging due to different datasets, time steps, prediction ranges, parameters, and performance indicators[2]. Hybrid machine-learning or overall prediction methods have been used to improve renewable-energy projection models.

The rapid rise of global industrialization has led to the depletion of fossil fuels and the environmental impact of these factors. Renewable energy sources like solar, wind, hydropower, biomass, waves, tides, and geothermal are expanding rapidly, and renewable energy technology can stabilize energy supply and decrease regional energy shortages. However, diversifying renewable energy sources is unpredictable, and accurate energy monitoring can enhance system efficiency.[3]

Renewable energy estimates use machine-learning algorithms, and hybrid machine-learning models have been used to enhance renewable energy forecasts. Research is being conducted to increase power grid renewable energy use, including micro-grids with renewable distributed generation. Modern technology includes solar panels, wind turbines, wind farms, and marine wave energy converters. Enhancing computational methodologies is crucial for creating better renewable energy systems..[4]

II. LITERATURE REVIEW

In the Big Data (BD) age, data science algorithms are crucial for improving the functionality of various applications, particularly in fields that collect daily data and extract useful information. Machine Learning techniques are effective for solving complex challenges from new renewable energy sources, addressing how to teach computer systems to learn and improve. Machine Learning is one of the fastest-growing technical disciplines, at the center of data science, artificial intelligence, statistics, and computer science. The literature on renewable energy applications covers prediction problems, optimization algorithms, new control techniques, and fault diagnosis in renewable energy systems to improve them.[5]

The popularity of machine learning and renewable energy has risen, with the National Science Board's Web of Science expecting scientific publications to expand 2.5% year over time. Machine Learning grew 15% from 2014 to 2015, and its prevalence in research approaches, including ours, is increasing. Recent tutorials highlight major Machine Learning-based renewable energy applications, and reviews on neural computing, evolutionary computation, and fuzzy logic aid academics and professionals in relevant fields.[6]

This comprehensive renewable energy classification evaluation combines contemporary and traditional methods, analysing contemporary renewable energy categorization difficulties and approaches in its extensive literature assessment. Several renewable energy prediction studies use machine learning,[7] such as Mellit et al. analysing hybrid, deep learning, machine learning, and AI photovoltaic power forecast literature. H. Wang et al. (2019) examined deep learning renewable energy projection models, using deep recurrent neural networks, stack auto-encoders, and deep belief networks. Bermejo et al. (2019) used artificial neural networks to anticipate energy and reliability in wind, hydroelectric, and solar energy. Mousavi et al. (2019) assessed energy system machine learning taxonomy and use, finding hybrid models outperform machine-learning models.[8][9]

Ahmed & Khalid (2019) examined renewable power system forecasting models from dispatching, storage, reliability, optimum reserve capacity, energy policy and markets, and power perspectives. SVMs were found to be the most accurate solar and wind energy forecasting methods, and hybrid models can outperform single support-vector machine models. Pérez-Ortiz et al. (2016) suggested that renewable energy categorization algorithms may help academics and practitioners.[10] Kare et al. (2016) studied renewable-energy

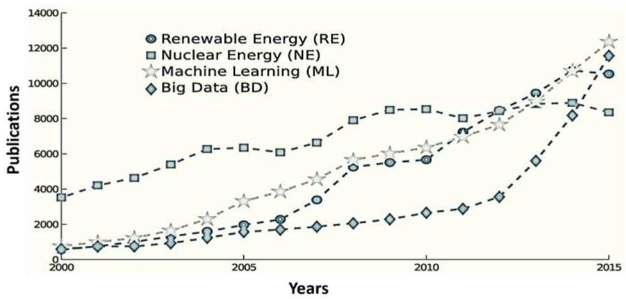

Fig. 1. Publication patterns for various fields of study

hybrids, examining applications of evolutionary technique, game theory, optimal sizing, modelling, control, and dependability in hybrid renewable-energy systems.[11]

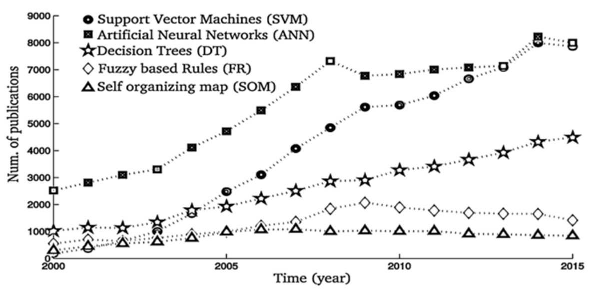

Fig. 2. Predictions of Renewable Energy Using Machine Learning Models

III. Analysis

Renewable energy is a crucial eco-friendly and carbon-free technology for replacing petrochemical energy sources and combating climate change. However, renewable energy power systems are uncertain due to their variable features. To address this issue, data-driven machine learning models can provide smart solutions. Machine learning relies on data preparation, feature extraction and selection, model selection, and model validation. Solar and wind power make up 40% of renewable energy sources, while the other five make up less than 5%.[12] Classification issues are an essential aspect of machine learning (ML), with data scientists playing a crucial role in identifying patterns and insights in vast datasets. Unsupervised learning analyses unlabelled data structures, helping to identify clusters or groupings in data analysis like

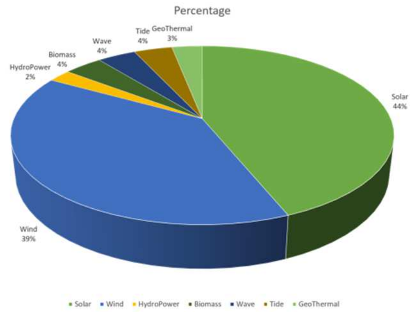

Fig. 3. the pie chart in terms of seven renewable energy sources with percentage of renewable energy source in literature

segmentation. Supervised algorithms teach models to accurately identify and forecast data, leading to the existence of categorization algorithms. Semi-supervised learning is a prominent topic in machine learning research, supplementing labelled sample knowledge with labelled and unlabelled data.

Unsupervised classification is more common in machine learning research, but Renewable Energy has also encountered difficulties in unsupervised, semi-supervised, and nagana than approaches. Classification methods can be categorized by learning[13] type (supervised, unsupervised, or semi-supervised), model type (probabilistic, non-probabilistic, generative, or discriminative), reasoning type (induction or transduction), task type (classification, segmentation, or regression), and learning process type (batch or online). Data scientists must understand data structure and aim to solve issues using machine learning, a science and art.[14]

Machine learning-based renewable energy forecasting has been extensively studied since 2017-2018. Early wind energy estimates were statistical, but AI and machine learning have enabled the development of wind energy forecast systems such as SVMs, GBDTs, ANFIS, ANNs, and LSMs.[15] These models have improved quickly using hybrid algorithms that integrate optimization and data processing. ELM has been used to forecast wind power,hile WD, WPD, and EEMD have improved wind speed estimates.[16] The Bayesian model has been found to be most accurate in hybrid wind production projections.[17]

TABLE I. DECOMPOSITION APPROACH

Data Pre-Processing Techniques	Number of Papers Used	References
Data splitting	3	(G. Wang et al., 2020), (Elmaz et al., 2020), (Rohani et al., 2018)
KWMD	1	(Zambrano & Giraldo, 2020)
Decomposition	21	(Zambrano & Giraldo, 2020)
Discretization	4	(Aly, 2020), (McCandless et al., 2020), (Sun et al., 2018)
Encoding categorical features	1	(Kim et al., 2019)
Feature selection	2	(Zhang et al., 2019)
Imputation of missing values	2	(Atique et al., 2019), (Majidpour et al., 2018)
Normalization	8	(G. Wang et al., 2020)
Standardization	2	(Manero et al., 2019)
Transformation	1	(Hocaoglu & Serttas, 2017)

TABLE II. SOURCES OF ENERGY

	Sources of Energy					
Pre-Processing Techniques	**Solar**	**Wind**	**Biomass**	**Wave**	**Tidal**	**Total**
Data splitting	1	1	1			3
kWMD	1					1
Decomposition	6	13		1	1	21
Discretization	3				1	4
Encoding categorical features	1					1
Feature selection	1	1				2
Imputation of missing values	2					2
Normalization	2	6				8
Standardization	1	1				2
Transformation	1					1
Total	19	22	1	1	2	45

Table-2: Methods for preparing machine learning models to make predictions about renewable energy from a variety of sources.

TABLE III. VARIOUS METHODS OF PRE-PROCESSING THAT MACHINE-LEARNING MODELS USE FOR MAKING PREDICTIONS ABOUT RENEWABLE ENERGY SOURCES.

Pre-processing Method\Sources of Energy	Solar	Wind	Biomass	Wave	Tidal
Data splitting	V3, V5, V6, V7	V1, V2, V3	V18, V19, V20, V21, V22		
Data Validation	V3, V4, V5, V7				
KWMD	V1, V3, V4, V5, V7	V1, V2, V3, V7, V10		V23	V16, V17
Discretization	V1, V2, V3, V4, V5, V7, V8, V9				V16, V18
Encoding categorical features	V1, V2, V3, V7, V13, V14, V15				
feature selection	V3, V4, V5, V7	V1			
Imputation of missing values	V6				
Normalization	V1, V2, V3, V5, V7, V8, V10, V11	V1, V2, V3, V10, V12			
Standardization	V6	V2, V3, V10, V12			
transformation	V5				

V1 = wind speeds; V2 = wind directions; V3 = temperatures; V4 = global horizontal irradiation; V5 = solar irradiation; V6 = sunshine; V7 = humidity; V8 = cloud cover; V9 = clearness index; V10 = air pressure; V11 = precipitation; V12 = air density; V13 = sky type; V14 = rainfall type; V15 = elevation; V16 = tidal speeds; V17 = tidal directions; V18 = CO; V19 = CO_2; V20 = CH_4; V21 = higher heating value; V22 = H_2; V23 = wave heights.

Machine learning models use data pre-processing methods for renewable energy sources and variables, with decomposition being the most common wind energy forecasting technique. Parameter selection is influenced by parameter selection, often containing multiple parameters and trial-and-error methods being unrealistic. Metaheuristics are used to establish parameters, with error prediction as the goal. Machine learning models generate new predictive parameters each iteration, and validation datasets are isolated from the training dataset to reduce overfitting.[18] Techniques like GWO and ANFIS models, extreme-learning machines, multi-objective grey wolf optimization, Firefly approach, PSO, ABC algorithms, dragonfly approach, genetic algorithm, deep belief network, wind speed prediction, coral reef algorithms, and ELM are used to predict hydropower production, wind, and solar radiation.[19] In requirements engineering (RE) applications, various strategies for handling categorization issues in renewable energy applications are discussed. Wind speed prediction is crucial for wind farms, kernel-based classifiers and neural networks have been explored for long-term wind speed prediction, while SVMs classify tornadoes. Smart grid fault detection and power quality are critical concerns in renewable energy systems, and decision trees, fuzzy decision trees, and fuzzy expert systems have been effective in classifying power quality issues. Ion-intrusive Appliance Load Monitoring (NIALM) techniques have been researched, but load disaggregation remains a challenge.[20]

IV. FINDINGS

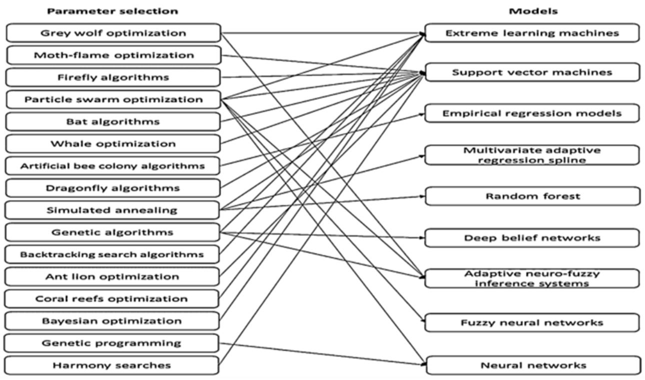

Fig. 4. using meta heuristics to choose machine learning parameters for renewable energy projections.

The research emphasizes the importance of renewable energy as a sustainable alternative to petrochemical energy sources in combating climate change. It highlights the need for accurate forecasting to address uncertainties in renewable energy power systems due to the varied properties of different sources. The study also explores the use of machine learning as a data-driven approach for forecasting, focusing on data preparation, feature extraction, model selection, and validation. The research categorizes machine learning models into statistical models, artificial intelligence approaches,[21] and hybrid methods. Solar and wind power account for approximately 40% of all renewable energy sources, while the remaining five categories account for less than 5%, indicating their dominance in the current renewable energy landscape.[22]

V. CONCLUSION

Renewable energy is a significant topic due to concerns about climate change and global warming, leading to increased research on accurately predicting electricity output from renewable sources. Machine learning algorithms have become increasingly used in energy prediction, with potential avenues for further study.[23] Most machine learning research has focused on solar and wind power, but future research may explore hydraulic, tidal, wave, biomass, and geothermal energy predictions. Hybrid models and artificial intelligence approaches may also be beneficial for renewable energy forecasting. Data pre-processing procedures affect the performance of machine-learning models, [24] and future studies could explore using machine learning and data pre-processing methods to forecast renewable energy sources' performance. Parameter selection heavily impacts machine learning models' accuracy in renewable energy projections, so exploring novel metaheuristics like coronavirus optimization algorithms could enhance their performance in renewable energy projections. This article provides an overview of prominent categorization algorithms and their applications to various forms of renewable energy. [25]Data cleansing, pre-processing, model building, and assessment or interpretation of model and results are typical workflows for predictive analysis. Support vector machines and artificial neural networks are notable classification approaches, as they can handle noisy and non-linear data with ease. These learning approaches can be useful for various real-estate problems, such as wind farm management, power quality disturbance detection in the grid, fault diagnosis, solar energy facility management, maritime energy, and wind speed prediction and turbine diagnosis. The article also analyses the most crucial uses of renewable energy systems with classification issues as its foundation.[26]

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