Machine Learning For Optimization Of Renewable Energy Systems

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Abstract
The use of renewable energy sources (RESs) at the distribution level has become increasingly appealing in terms of costs and technology, expecting a massive diffusion in the near future and placing several challenges to the power grid. Since RESs depend on stochastic energy sources —solar radiation, temperature and wind speed, among others they introduce a high level of uncertainty to the grid, leading to power imbalance and deteriorating the network stability. In this scenario, managing and forecasting RES uncertainty is vital to successfully integrate them into the power grids. Traditionally, physical- and statistical-based models have been used to predict RES power outputs. Nevertheless, the former are computationally expensive since they rely on solving complex mathematical models of the atmospheric dynamics, whereas the latter usually consider linear models, preventing them from addressing challenging forecasting scenarios. In recent years, the advances in machine learning techniques, which can learn from historical data, allowing the analysis of large-scale datasets either under non-uniform characteristics or noisy data, have provided researchers with powerful data-driven tools that can outperform traditional methods.
This research investigates the application of machine learning models to optimize renewable energy systems and contribute to achieving Net Zero emissions targets. The primary objective is to evaluate how machine learning can improve energy forecasting, grid management, and storage optimization, thereby enhancing the reliability and efficiency of renewable energy sources. The methodology involved the application of various machine learning models, including Long Short-Term Memory, Random Forest, Support Vector Machines, and ARIMA, to predict energy generation and demand patterns.

Keywords: Machine learning, Renewable energy net zero energy forecasting, Grid optimization, CO_2 emissions reduction, Renewable energy sources, Machine learning, RES power output forecasting.

In particular, since RESs depend on stochastic energy sources, they introduce a high level of uncertainty to the grid, leading to power imbalance and deteriorating its stability. In this scenario, managing RES uncertainty is vital to successfully integrate them to the grid.
The pressing imperative to tackle climate change has dominated global discourse, with growing acknowledgement of the need to shift toward sustainable practices in all societal sectors. A primary objective arising from these conversations is attaining Net Zero emissions. This objective is essential for alleviating the detrimental impacts of climate change, representing the equilibrium of greenhouse gas emissions with removal technologies to guarantee that net emissions to the atmosphere are effectively zero. Countries, industries, and individuals strive to achieve Net Zero ambitions, with breakthrough technologies like machine learning recognized as essential facilitators in attaining these objectives. Machine learning, a branch of artificial intelligence (AI), offers robust tools for analyzing extensive information, generating precise predictions, and optimizing intricate systems, elements that are essential in the energy sector.

This study examines the role of machine learning in expediting the attainment of Net Zero emissions through optimizing renewable energy systems. Machine learning enables energy generation, storage, and management transformation, diminishing dependence on fossil fuels and decreasing overall carbon footprints. In climate change mitigation, machine learning facilitates the development of highly efficient energy systems, enables precise forecasts of energy demands and generation, and ultimately enhances the integration of renewable energy sources into the global grid. The subsequent sections examine Net Zero's significance and machine learning's revolutionary potential in renewable energy systems.

Net Zero denotes the equilibrium between the quantity of greenhouse gases emitted and the volume extracted from the atmosphere. This equilibrium is essential for curbing global warming and alleviating its consequences, including elevated sea levels, heightened occurrence of extreme weather phenomena, and biodiversity loss. The Net Zero concept has garnered substantial global attention since the Paris Agreement was signed in 2015, wherein almost every government pledged to restrict global warming to below 2 °C, with aspirations to limit the rise to 1.5 °C.

Discussion

Governments, corporations, and organizations are pledging to achieve Net Zero emissions. Over 140 nations, accounting for over 90% of worldwide emissions, have established Net Zero objectives. Achieving these targets necessitates substantial alterations in energy production, including transitioning from a reliance on fossil fuels to renewable energy sources such as wind, solar, and hydropower. These modifications are both essential and urgent as the impacts of climate change intensify each year. The shift to renewable energy is vital to attaining Net Zero, as it directly targets the primary source of global greenhouse gas emissions: the energy sector.

Notwithstanding the high objectives and substantial global commitments, the journey to Net Zero has obstacles. Numerous nations face challenges expanding and assimilating renewable energy systems into current infrastructure. The sporadic characteristics of renewable energy sources, like wind and solar power, pose further difficulties in ensuring a reliable energy supply. Moreover, economic and political impediments and the necessary extensive infrastructural modifications provide significant challenges. Nonetheless, the emergence of new technologies, such as machine learning, enables the resolution of these difficulties.

The renewable energy market can be revolutionized by machine learning, a subset of artificial intelligence, which provides advanced analytical skills to maximize energy generation, delivery, and consumption. The core idea of machine learning is its ability to analyze large datasets, identify patterns, and produce predictions or recommendations based on that analysis. These capabilities can enhance energy systems through energy generation forecasting, demand management, and grid operation optimization of renewable energy.

Variability constitutes a fundamental challenge to renewable energy. Wind turbines function only in the presence of wind, and solar panels produce electricity exclusively during sunlight exposure. The sporadic nature of the energy supply makes it difficult to ensure a stable and reliable provision. This is the domain in which machine learning is utilized. By analyzing climatic patterns, machine learning algorithms can predict the volume and time of energy renewable sources produce. This information is crucial for grid operators since it allows them to balance supply and demand more efficiently, ensuring grid stability and optimizing renewable energy generation. This Special Issue focuses on reviewing severe challenges, cutting-edge contributions, and trends in ML for ESs. Such an ES requires not only higher reliability and security but also the smooth integration of distributed ESs into the existing grid, without losing high functional improvement. This article summarizes the major findings and discussions of the Special Issue, which includes 13 research articles on ML techniques for ESs.

Currently, ML approaches, including supervised, unsupervised, reinforcement, online, transfer, deep learning, support vector machines, and decision trees, have been utilized to enhance conventional optimization models and to develop new robust and adaptive ML models. These two approaches are expected to become more complementary to each other to reliably, robustly, adaptively, and flexibly solve the optimization problem of ESs. Although different technologies, such as the ones based on energy storage, can be used to support the integration of RESs, they usually demand a huge investment. To avoid the installation of expensive devices in the network, RES uncertainty can be managed by a more proactive distribution system operator (DSO) that is capable of taking advantage of RES flexible resources for the provision of ancillary services (ASs). This approach requires efficient coordination between transmission systems operators (TSOs) and DSOs. On the one hand, TSOs should support voltage in the transmission network, maintaining the overall system security via frequency control and congestion management across borders and on the TSO level. On the other hand, DSOs should manage voltage stability and congestion on the distribution grid, being responsible for providing data about consumers and distributed generation behavior to the TSOs.

On the one hand, physical methods are computationally expensive since they rely on solving complex mathematical models of the atmospheric dynamics. In addition, they are not able to handle unexpected errors, making them not suitable for short-term horizon applications. On the other hand, statistical methods are focused on modeling the mathematical relationship between the online time series associated with RESs. Unfortunately, although they outperform physical methods in terms of high spatio-temporal resolution forecasting, they usually consider linear models, which prevents them from addressing challenging prediction time horizons, such as long-term ones.

In recent years, the continuous development of artificial intelligence (AI) techniques has provided researchers with powerful data-driven tools that can outperform physical and statistical methods. Among them, machine learning (ML)-based techniques, which are non-linear, non-parametric models that can learn from historical data, allowing the analysis of large-scale datasets, even under non-uniform characteristics or noisy data, deserves special attention. According to, ML-based methods are suitable for RES behavior forecasting applications since they can adapt themselves to changing trends inside datasets. Recent state-of-the-art reviews of ML-based RES behavior forecasting approaches can be found. They agree that artificial neural networks (ANNs), support vector machines (SVMs), deep learning (DL) and ensembles significantly outperform traditionally used statistical methods in terms of accuracy, robustness, precision and generalization capability.

Literature Review

The literature was searched based on the database search methodology. Since the use of different databases allows covering as many evidence as possible, generic sources, such as Science Direct and Google Scholar, as well as a specialized source, such as the IEEE Xplore, were used. Science Direct, which has more than 15 million records, was used as the principal search database, whereas Google Scholar, which allows retrieving a large amount of free-access articles, was used as the complementary one. Finally, the IEEE Xplore database, which provides access to a great amount of high quality engineering articles, was used as the specialized search database. In recent years, the use of RESs, including geothermal, biomass, hydro, tidal, wind and solar ones, has gained great popularity since they are more sustainable than fossil fuels. In particular, wind turbines and photovoltaic (PV) cells have been installed worldwide, making it crucial to efficiently integrate them into the distribution grid. In this scenario, the SLR conducted in this paper focuses on ML-based forecasting of solar and wind energy systems' power output.

The initial phase in employing machine learning to optimize renewable energy involves collecting and preparing high-quality data. This procedure entails identifying, cleansing, and transforming data to ensure its readiness for analysis by machine learning models. Weather data, encompassing historical and real-time information on factors such as solar irradiance, wind speed, and temperature, is essential for predicting energy production from renewable sources like solar panels and wind turbines. Sources comprise national meteorological services, satellite data, and weather stations. Data on energy consumption from residential, commercial, and industrial sectors offer insights into usage trends and aids in formulating demand-side management strategies. Data regarding energy flow, load distribution, and grid efficiency are crucial for enhancing grid operations. Historical data from renewable energy systems, such as solar and wind farms, are used to train machine learning models to forecast future energy generation. Financial information about energy generation, storage, and grid operations aids in the economic assessment of renewable energy initiatives.

Future Work

Several works in the literature have compared the performance of different ML algorithms. In, a comparison between ANNs, SVMs, multiple linear regressions (MLR) and random forest (RF) for PV power output prediction was conducted. Results of showed that RF achieved better performance for 5-min to 3-h-ahead predictions. In, a comparison between ANNs, support vector regression (SVR) and Gaussian progressive regression (GPR) to predict PV power output, wind power output and electricity demand was proposed. The best results for wind and PV power outputs were obtained with SVR, whereas the best results in terms of electricity demand were the ones corresponding to the ANN-based model.

The use of machine learning techniques in renewable energy systems is a crucial component of this research. The process encompasses gathering and processing pertinent data, selecting suitable machine learning models and algorithms, and assessing these models to evaluate their efficacy in attaining Net Zero objectives. In particular, they are evaluated in terms of the ML technique, the predicted time horizon, the data collection, the model parameters and the obtained results. In addition, the main implementation steps of the ML-based model – data pre-processing, feature extraction and selection, hyper-parameter optimization and validation – are studied in detail. The SLR results provide valuable insights into the best ML-based RES power output forecasting strategies to facilitate their integration into the grid, giving stakeholders useful tools to design – and implement – them according to their needs. In addition, the feasibility of actually using the prediction within the context of different decision-making problems, enabling an efficient TSO-DSO coordination capable of managing RESs – and their ASs –, to address economic, operational and managerial grid challenges, is discussed.

Conclusion

After data collection, it must be sanitized to guarantee consistency and reliability. Missing values in the dataset are managed by interpolation, imputation, or eliminating incomplete entries. Variables such as energy demand, temperature, and wind speed are standardized to ensure comparability, enhancing machine learning models' efficacy. New attributes are extracted from the existing dataset to improve model precision. Temporal characteristics such as seasonality or time of day are essential for predicting energy demand. The dataset is partitioned into three subsets: a training set for model training, a validation set for hyper parameter tuning, and a testing set for ultimate performance evaluation.

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