

Machine Learning in Renewable Energy

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The volume of energy produced and consumed from renewable sources increases by a significant rate both in absolute value and also as a proportion of the total energy produced and consumed. As a result, scientific interest and research in forecasting various aspects of the renewable-energy sector is very keen, and the results of this research are invaluable to both academics and stakeholders in terms of the industry or national and local governments. At the same time, researchers are now able to use a rich arsenal of empirical methodologies in forecasting these markets. Apart from the traditional econometrics and statistical forecasting techniques, recent developments in the area of artificial intelligence and machine learning methodologies have proven to be very efficient for this task as it has been demonstrated, also, in other scientific fields such as finance, macroeconomics, meteorology, medicine, language, etc. Thus, there are many fascinating developments in the relevant research that combine the state-of-the-art empirical methodologies in artificial intelligence and machine learning with forecasting problems that are related to renewable energy. A selection of some interesting and innovative research works is discussed below.

The abundance of energy is of great importance in today's world for both the industry and household users. The wide availability of power is not only defined by the quantity produced per unit of time but also by its pricing—by being affordable to all users. This is because energy has now become what economists call a “public” or “social” good in the sense that it is highly significant for modern society and the readily available and affordable energy benefits the society. The fabric of the society overall—and not only of the industry—is now dependent on the production and supply of affordable and renewable energy.

Over the 20th century, the majority of the energy produced globally was derived from oil and gas, i.e., the exploitation of hydrocarbons. A significant shift in the production of energy away from fossil fuels has underway over the last two decades. There are two reasons for this: (a) existing fossil fuel sources cannot be considered as renewable as they are depleting since the rate of discovering of new fossil fuel sources cannot match the increased modern energy needs, and (b) society is moving away from hydrocarbons due to their significant negative impact on the environment that leads to global warming from carbon dioxide emissions and greenhouse gases in general. Thus, research on this scientific field is very interesting and with real-world consequences and applications.

The energy derived from resources that can be regenerated naturally over a short period of time—usually as compared to the human lifetime—are defined as renewable. Such sources include solar rays, atmospheric wind, the currents and waves of the sea, the potential energy created by river systems or naturally or artificially created volumes of water in lakes, geothermal energy from the earth's crust, etc. Even nuclear energy, which may not strictly be considered as renewable by some definitions, in terms of carbon dioxide emissions and the production and release of greenhouse gases in the atmosphere, may be included in this extended list of renewable energy sources (<https://www.energy.gov/ne/articles/3-reasons-why-nuclear-clean-and-sustainable> (accessed on 10 September 2022)).

Moreover, the sources of renewable energy can be strictly defined as “public good” as they satisfy both requirements, in economics, for such a good. First, they are non-excludable as, for example, all of us can use the solar rays and the wind to generate energy without



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restricting or inhibiting their use for the others. Second, there is a practically unlimited amount of these energy sources to be used over time.

Most renewable energy sources (RES) suffer from seasonality and climatic variations that significantly affect the generated electric power. These problems inhibit the continuous production and supply of electricity to the power grid. Moreover, electricity has an intrinsic characteristic that differentiates it from other types of goods: the inability to be massively and efficiently stored. These disadvantages create a significant problem for the power grid operator, who must have a reliable estimate of the RES-based energy load to the system in order to produce or buy the rest of the required energy from hydrocarbons-based power plants. Thus, forecasting the factors affecting the production of the RES has attracted the attention of many studies. In this review, we present five papers that investigated the problem of directly or indirectly forecasting the RES-based electric power production using tools taken from the arsenal of machine learning. This is an obvious choice if we consider that the timing of recent technological advances and the inception of new ML structures ideally coincide. Cost-effective parallel computing allowed the use of complex and demanding ML architectures such as recurrent neural networks and convolutive neural networks. Simultaneously, algorithms such as support vector machines and random forests and techniques such as kernelization, bagging and boosting allowed, for the first time, the application of ML to relatively small datasets. In addition, researchers have access to free open-source deep learning libraries such as TensorFlow and PyTorch, making the algorithmic part of their studies uncomplicated.

Here, we present and briefly discuss a selection of some recent and innovative approaches to RES forecasting where state-of-the-art machine learning structures are employed.

Bodke et al. in [1] studied the problem of forecasting wind power and wind speed using a hybrid approach mixing econometrics and machine learning (ML). Their basic idea is to decompose the wind power and wind speed time-series in its components using ensemble empirical mode decomposition (EEMD) and then forecast the sub-series using ARIMA or pattern-sequence-based forecasting (PSF) depending on the stationarity or not of the component. The scheme seems successful since it outperformed the competition, yielding a more than 14% accuracy increase in wind power forecasting and 20% accuracy increase in wind speed forecasting.

Mendonça de Paiva et al. in [2] investigated the forecasting of intraday solar irradiance in photovoltaic power generation. They case-studied six locations around the world, using two machine learning algorithms: multigene genetic programming (MGGP) and the multilayer perceptron (MLP) neural network. The authors tested these methods in forecasting horizons varying from 15 to 120 min. The results revealed that the MLP network is more accurate for short horizons, while the MGGP is more accurate for longer forecasting horizons.

In a similar framework, Vier et al. in [3] developed two hybrid systems for the forecasting of wind power of a wind power plant in Vietnam using double optimization. The systems combine particle swarm optimization (PSO) or the genetic algorithm (GA) with MLP in two set-ups: PSO-PSO-MLP and GA-PSO-MLP. Both the proposed systems outperformed the selected benchmark methods. The juxtaposition of the forecasted wind power against the ground truth marks the effectiveness of the GA-PSO-MLP system on a day and on a week horizon.

Bochenek et al. in [4] followed the same idea on a larger scale: they created a set of ML models to forecast the day-ahead wind power generation on a national level for Poland. The authors tested the following models: simple NN, deep neural networks (DNN), random forest (RF), and extreme gradient boosting (XGB). XGB outperformed the competition on the hourly forecasting horizon, while NN achieved the more accurate forecasting on the daily horizon. The authors also noted that the variability in the trained model performances was affected by seasonality: the lowest accuracy variability was found during the winter months and the highest one during the summer.

The study of Bae et al. [5] investigates the distortion on the calculation of the electric load in South Korea produced by the behind-the-meter (BTM) solar photovoltaic generators.

The electric load of these small photovoltaic generators is not measured in real time, creating a source of error in the calculation of the national electric load. This is a source of errors that affects the performance of any attempt to forecast the electric load. Attacking the problem, the authors first estimate the BTM electric load and use it to correct the measured electric load, and then they forecast the corrected electric load on a daily horizon using the XGB methodology. The corrected dataset improved the forecasting accuracy by more than 20%.

The selected papers, which were briefly discussed above, demonstrate that these advanced ML architectures, when applied to RES data, can significantly improve the forecasting efficiency of traditional competing methodologies. Moreover, we can draw an additional significant conclusion: the traditional empirical methodologies (from statistics and econometrics), despite the great advancements in ML, are still not outdated or irrelevant. They can be combined with ML techniques in hybrid empirical pipelines and enhance the efficiency of the results.

Conflicts of Interest: The authors declare no conflict of interest.

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