Artificial Neural Networks in Renewable Energy: Forecasting, Prediction, and Optimization

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Abstract

Artificial neural networks have received a vast amount of research in the past two decades, much of which has observed the use of how intelligent technology is used in the renewable energy sector as a tool for predicting, optimizing, and forecasting energy storage and utilization. Within the scope of this article will be an exploration into how neural networks are used to develop renewable energy for sustainability and advancement of society. A specific focus will be placed into how the use of AI prediction models in society has an overwhelming effect on economic and social prosperity, and how attention has shifted towards the regulation of these technologies to promote the globally defined near-future shift towards green energy practices.

1 Introduction

The ongoing increase in global population has a detrimental effect on resource availability as it relates to sustainable energy consumption and production. Conventional energy sources such as fossil fuels like coal and natural gas have limited resources, which puts them in danger of depletion in our lifetime. Additionally, the demand of fossil fuels has noticeable and extreme effects on the planet—greenhouse gasses (GHG) and carbon dioxide (CO2) emissions being the biproduct of their usage. In reaction to the overwhelming amount of data on global warming, there has been substantial usage of and research about the development of green energy from renewable energy sources (RES) that are both more cost-effective and more powerful than fossil fuel powered plants.

Wind, hydraulic, and solar energy are sustainable, nondestructive options that have been leading the renewables market for the past few decades: in 2020, wind and solar energy production costs dropped significantly, while solar photovoltaic (PV) costs decreased by 85% and wind power by 56% since 2010 [35]. Aside from their sustainable benefits, power plants fueled by

RES have the heightened advantage of functioning autonomously and uninterrupted using intelligent control systems. Artificial intelligence (AI) is often used as a controller for these power plants by means of innovative machine learning (ML) algorithms. AI can also be utilized in various ways to increase the output and efficiency of the power plants. Because RES often depend on dynamic parameters that cannot easily be predicted using ML strategies, engineers and researchers have been building a body of knowledge around using artificial neural networks (ANN) to predict, control, and optimize RES.

ANN are advantageous because they can be trained using open, publicly available datasets, and they can focus on predicting power output and forecasting physical trends, which, in the example of solar power, provides an abstraction layer between the conversion from solar radiation to solar power [3]. This abstraction layer affords a properly trained ANN to make predictions of correlations quickly and accurately between complex, nonlinear input and output variables, exclusive of human understanding. Without needing explicitly defined mathematical delineations of the variables, they can reproduce the behavior of intricate datasets even if the data is noisy or insufficient. Furthermore, they are cost-effective and easy to develop in comparison to physical models; they can be developed using historical data, they are fast and efficient, and do not possess the same boundary limitations as physical models [34]. While most learning methods rely on a graphical representation to demonstrate nonlinear relationships of input and output training data, ANN outperforms with its generalization capabilities by using a mathematical function to approximate the relationship, thereby reducing the magnitude of the degree of nonlinearity [21].

This article will provide an in-depth focus on the link between neural networks and renewable energy production—how ANN are applied to modern RES technologies, and the impact that ANN and RES can provide for society when they are properly comprehended and utilized by appropriate decision-makers. The paper will first look at how ANN is used by specialists in the renewable energy sector—how they are beneficial to the field for their prediction, optimization, and forecasting power. Next, it will explain the greater social and economic impacts on society and what some countries are doing to implement their use. Finally, the article will highlight the developmental needs of ANN and RES technology as it pertains to a wider global reach in developing and rural communities.

2 Uses of ANN in Renewable Energy

Neural networks are one form of AI, used by engineers in various fields, that mimic how the human brain is coded. ANN attempt to replicate the network structures and response mechanisms of the brain that provide for learning from complex data and pattern recognition. The system is abstracted into three main layers: an input layer, output layer, and a variable number of hidden layers [14]. Data are stored in nodes, which represent neurons in the biological simulation. The input layer serves as the gateway for noisy, uncorrelated data. The hidden layers utilize an activation function, which is an explicitly defined function that connects input nodes to output nodes by finding nonlinear characteristics in the data. The final predictions are made after computation of the activation function, and the output layer stores these final correlations. The connection between two nodes in a neural network carries a weighted value. This weight is used during the training stages to influence the connection between nodes and is evaluated during the testing stage [14]—like the linking of neurons, which consists of a synaptic weight that records the amplitude of the connection between two neurons and corresponds the influence one neuron has over another when firing [25].

ANN are commonly used by energy specialists in the renewables sector as a prediction tool to measure energy output generation. A group of researchers conducted a literature review and found 40% of studies concerning energy output prediction were related to ANN models [9]. A few different strategies involving ANN have been employed in the aforementioned studies, Peiris et al. (2021) examined the wind power generation of a wind farm in Sri Lanka using ANN models to calculate prediction error, concluding that the Levenberg-Marquardt-based ANN model was a robust choice for future energy predictions of wind power; Kalogirou and Bojic (2000) used ANN to model the thermal characteristics of a solar building and predict its energy consumption—achieving an exceptional correlation coefficient of 0.9991; Mellit et al. (2005) accurately predicted global solar radiation data using radial basis function (RBF) networks with just sunshine duration and air temperature as inputs.

2.1 Prediction

Having the ability to learn from past trends to make predictions about the future is an exclusive advantage of data-driven models over physical models, shown by researchers Prasad et al. (2020) in their case study of wind speed forecasting, where ANN was proven to have better generalization capabilities than a multiple linear regression (MLR) model; and shown once again by Deo and Şahin (2015), who used the extreme learning machine (ELM) algorithm as a tool to predict drought duration and severity in Australia, concluding that the ELM algorithm can even outperform an ANN model in speed and accuracy for the prediction of drought and its complex properties.

Being able to predict multifaceted variables is equally advantageous to energy specialists and engineers as it is to investors of clean energy. Majority stakeholders in the energy industry have the need to understand how much their investment into green energy will be profitable; therefore, the more sufficient data that is accumulated to make these decisions about investing, the higher the probability will be of leaders making the decision to invest. When it comes to relying on resources that will turn into profitable ventures, it is difficult to depend on environmental factors to achieve these profits. For example, solar energy is influenced by factors such as temperature, wind speed and direction, and the quality of solar panels used, which adds an extra layer of complexity to the process of solar radiation storing electricity into PV batteries. As a result, engineers do not have a clear idea of how much solar energy output can be expected on any given day, and investors do not know how much capital to invest in an installation because the location and the characteristics of the solar panel may have a key influence in the decision [3]. With this in mind, it is appropriate to use ANN as a prediction tool when making the decision to convert traditional power sources into renewables. One case study that used ANN to predict energy sales for the initial penetration of RES into the market was conducted, where the researchers found both PCA and ANN improved the quality of electricity revenue estimation when used together [24]. Due to the modularity of ANN and ML algorithms, it is possible to utilize different techniques and technologies together to optimize the incentives of an intelligent system.

2.2 Optimization

Intelligent systems controlled by neural networks possess the ability to use predictions to optimize functionality of energy systems. In the context of renewable energies in the residential sector, the energy consumption of buildings are in need of intelligent optimization, as the consumption of energy by buildings alone has been estimated at 40% of the world's energy supply while generating 33% of total carbon dioxide emissions [12]. Argiriou et al. (2000) introduced the idea of controlling the indoor temperature of a solar building using ANN to optimize the conditions, showing a 7.5% decrease in annual heating energy consumption can be achieved in the weather conditions of Athens, Greece. They demonstrated how ANN has the ability to forecast current weather patterns and compare the impact of future patterns on the thermal behavior of the building, reducing the required energy in maintaining proper living conditions and minimizing the carbon footprint of the residential energy source.

Additionally, neural networks can use time series data to 'learn' behaviors by analyzing seasonal patterns and optimizing the systems according to the trained model's predictions. The predicted behavior of solar radiation as time series data can be processed to control the heating system of a building to prevent afternoon overheating, as one example. Researchers raised an optimization algorithm to deal with residential energy scheduling of a smart grid and to minimize the energy consumption cost for users, finding a new method of optimization that is more efficient than conventional methods in terms of total energy cost [20]. Hybrid renewable energy systems' (HYRES) control logic can dramatically lower operating costs of energy systems by reducing temperature swings outside the comfort zone by as much as 22%, while increasing unmet comfort hours ("underheating" in the spring, "undercooling" in the fall months) by a maximum of 48%; optimizing the full potential of energy usage by enhancing their efficiency, raising the revenues of exported electricity, and reducing total operational heating costs for energy systems by a substantial 81% [18].

2.3 Forecasting

Forecasting nonlinear physical variables such as wind speed and solar radiation is a powerful means to collect imperative data in the energy industry, which would be highly sought after information in the hands of engineers. In order to design efficient renewable energy systems for residential purposes, it is important to understand the daily and hourly energy consumption of a typical household. Rodrigues et al. (2014) showed how ANN can be a reliable and accurate tool for creating load forecasts to predict daily and hourly consumption of electricity in residences by researching real case data of 93 households in Portugal.

Research has found that the forecasting of meteorological information by the use of ANN can optimize HYRES as they are used autonomously in energy plants [13]. Researchers in this study preferred the use of a recurrent neural network (RNN) for it's favorability in time series data—due to the nature of meteorological information having a high degree of nonlinear variables, and to the dynamic layers and cyclic structure of RNN. Work has also been done to propose new methods of forecasting solar PV energy using long short-term memory recurrent neural networks (LSTM-RNN); where the researcher further minimized error in comparison with three other PV forecasting methods [1].

3 Renewable Energy's Impact on Society

As the carbon footprint of civilization grows into a terminal ailment for the planet, it is appropriate to observe the trends that are counteracting it effectively. In 2020, global energy demand dropped by 4% due to the COVID-19 pandemic—demand for energy had not seen a decline as big since World War II. Noting the potential of carbon reduction when fossil fuels are restricted, more renewable energy is being generated by countries such as China, the United States, European Union and India, with China accounting for about half of the global increase in production. Is is highlighted that renewable energy production will expand by more than 8% in 2021—solar and wind energy will contribute nearly two-thirds of the growth [22]. As renewable energy expands, countries will be in need of policies and action to eradicate fossil fuel production in order to phase in the new energy systems, which will come at a cost for society and global economies. As best stated in IEA (2018), "…the world's energy system is at a crossroads, current global trends in energy supply and consumption are patently unsustainable—environmentally, economically and socially".

3.1 Economic Impact

Governments and governing bodies that are able to bear the expenses of transitioning to solar or wind powered energy sources have immense control over the impact to their respective countries. One study showed the correlation between renewable energy usage and economic growth in Iran, by using GDP as a metric. [32]. In Afghanistan and Nepal, rural electrification models using ANN are being developed by researchers to predict the economic impact of increasing energy expansion into unelectrified communities [28].

Meanwhile, researchers in India have developed an energy-economic model to confront the need of improving energy access to rural areas of the country in order to minimize the socio-economic impacts of poverty on the region [26]. Expanding the reach of energy to rural communities is a resource-full and economically demanding task, but there are sustainable advantages to using RES that could lead to economic prosperity for countries. In context, Myanmar was used as a case study in an exploration of the availability of PV energy to developing countries. In order to meet the growing demands of energy output and increasing methods of energy consumption in the global South, researchers assessed the ability of ANN models to forecast load profiles of renewable energy systems, focusing on the variations of output in the timeframe of a single day as opposed to months or years—noting that PV is a significant source of energy for countries such as Myanmar [2].

As more focus on penetration into the renewables market is being researched, benefits other than those of an ethical nature are being discovered by policy makers. Renewable energies are blossoming as a significant source of employment growth, as reaching climate neutrality by 2050 is a main focus of the European Union's climate and energy policy [29]; which is a similar goal shared by the country of Sri Lanka [33].

3.2 Regulation by Countries

The highest level of responsibility in the development of sustainable energies, not belonging to investors and stakeholders in the energy sector, belongs to the leaders and policy makers of countries. Accordingly, much progress in the light of developmental goals has already been made through projected political moves. The idea that renewable energies will not simply replace fossil fuels overnight is a reasonable assumption held by authorities, and it has led to a series of actions taken to phase out fossil fuels while incentivizing renewable energy production. A 100% renewable energy model by 2050 for the European Union (EU) has been proposed with the idea that renewable energy will simply not take over the energy industry, but rather it will be intertwined with conventional energy until a full replacement is possible [15]. Additionally, Germany has started implementing feed-in tariffs that promote green energy by regulating a fixed price and giving feed-in priority to renewable energy sources over conventional ones [10]. The feed-in process implemented by Germany is an important example of how intelligent technology like ANN can be used to assess and predict the potential of the renewables market as a policy maker.

In variation to approaching the increase of sustainable power, researchers conducted a case study of Croatia in order to develop legislature to decrease GHG emissions. By using ANN to model future policies in-line with EU and United Nations Framework Convention on Climate Change (UNFCCC) directives, they intended to create a generalizable model that can be transferred to other countries for use. They used ANN to test energy consumption strategies adopted by Croatia, finding that an ANN structured approach reduced GHG emissions significantly [11].

4 Shortcomings of ANN in Renewable Energy

The biggest obstacle in development is that there is an inherit "black box" approach to the ANN model that severely limits problem solving capacities. In many instances, it is important to be able to understand the parameters that are most meaningful to the model in order to eliminate the variables acting as obstacles in the model prediction; however, there is an innate disadvantage to artificial neural networks that makes their outputs entirely cryptic in the explanation of how the decisions were obtained [4]; and the computational complexity of explaining how an ANN arrived at a certain conclusion can be more expensive than the solution itself. In comparison with other ML models in use such as support vector machines (SVM), a supervised learning technique used for classification and regression analysis [16], ANN is difficult to train. For example, ANN is more accurate than an SVM model in solar radiation modeling, but requires a large time to train for a proportionally-sized dataset; while ANN accuracy varies when a new simulation is required, and requires a longer length of dataset to be properly trained [31]. The correct ANN needs to be selected for the proper task as well—traditional neural networks are not able to retain information learned at a previous step, which is the problem that the technique of RNN attempts to improve, and ultimately succeeds [1].

Inconsistency in environmental parameters is one of the most capricious shortcomings that need to be monitored by those who design renewable energy systems for commercial and residential use. Due to the variability of solar irradiance in relation with time and space, and the fact that not all weather patterns have the same impact on a building's energy consumption, HYRES controlled by ANN algorithms are limited by having one controller to prevent overheating and overcooling [5]. Only having one focal point that is vulnerable to fluctuations in prediction is disadvantageous when reliant on something as volatile as weather. Additionally, RES tend to rely too heavily on their fuel sources to keep large amounts of energy production, unlike fossil-fuel energy sources, that can stay on schedule to produce a consistent output regardless of environmental conditions—solar power requires UV radiation to charge PV battery cells, and wind turbines rely on wind to generate power.

From an economic point of view, there is little to discuss about the disadvantages of developing AI technology to monitor RES. There is, however, one major bridge that must be gapped in terms of using technology to support renewable energy, which is the access to green energy in low-density rural areas and developing countries. In order to support highly advanced RES with ANN-centered intelligence, there must be enough capital to support its development, and enough interest at a government level to support its capacity. Unfortunately, there is not enough access to these technologies globally to be able to use AI as the standard for energy control—renewable energy options such as biomass stoves and solar cookers do not require as advanced systems in order to operate. For the purpose of having fully automated manufacturing and maintenance of renewable energy systems built with intelligent ANN models, specific factories need to be designed with the capabilities to allow the intelligent systems to monitor and control them, which is not just expensive financially, but logistically as well [8]. Also, the copious amounts of data needed to forecast marketability and train advanced models is not publicly available in developing countries as it is in the west, something that supplementary research could help mitigate.

4.1 Further Research

As the quantity of useable data becomes more common throughout time, it is worthy to focus on the development of AI prediction models for the renewable energy sector. The research could be focused on the combination of ML tools and techniques (PCM, SVM, deep learning, etc.) that could be used in combination with ANN to increase the quality of understanding of the data. Although there is plentiful data on how ANN models can provide an overall increase in economic and social progress, there is still more research that could be focused on how to implement these structures into a society that is tied to conventional ways of storing energy. To improve the efficiency of intelligent systems for renewable energy, there must be more effort to understand how to build these systems in an economic way that make them more approachable to diverse markets. As it stands, many, if not all, countries would switch to 100% renewable energy if they had the resources to create, control, store, and disperse energy for communities. When we discuss the use of ANN as a tool for RES, more research can be centered towards the effects that intelligent systems have on low-density and rural populations, and how ANN can help bridge the gap between sustainable energy and these communities.

5 Conclusion

There is an expansive amount of data available to train ANN models that makes the renewable energy sector a flourishing field when used in conjunction with these intelligent tools. Models that simulate biological learning capabilities of humans are an intelligent technology only being used at a fraction of their potential. Because ANN are relatively easy to train, they have a high ceiling in terms of prediction accuracy and quality. They can also be used in production plants to optimize RES to produce at a maximum efficiency, in control centers to forecast meteorological data, and in smart grids to control energy output of residential buildings, all while maximizing profits of investors and states. The current body of research has done overwhelmingly well to promote the development of ANN models for the renewable energy sector, and there is still more potential yet. The global population is turning to renewable energy as the contamination from fossil fuels is becoming an observable development worldwide. GHG and pollutants aside, there are limited resources in conventional energy production that will cause an eventual necessary turn towards RES. To accelerate the evolution of sustainable energy utilization, AI and ML algorithms together with ANN as a strategic resource will help lead the way to an innovated future.

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