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Neural Network modelling for prediction of energy in hybrid renewable energy systems

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Abstract

When it comes to the expansion of the renewable energy business in today technological age, the ability to predict power and energy output based on shifting weather patterns is crucial. It is possible to support and even improve an economy and quality of life by using renewable energy sources rather than traditional fossil fuels, rather than by using fossil fuels at all. Because global warming and climate change are posing serious challenges to our planet, the findings of this study may be valuable in the development of smart grids that can properly predict future weather conditions. In this study, we develop an artificial neural network (ANN) model to estimate the energy generated at PV and the energy from the hybrid PV and wind energy systems considering several weather factors. The modelling is conducted to potentially predict the energy generation. The results shows that the proposed classifier is efficient in terms of reduced mean squared error with increased accuracy than other methods.

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Keywords: Neural network; Energy prediction; Renewable energy systems

1. Introduction

Energy has become increasingly important as a result of the advent of industrialisation and urbanisation, as well as the expansion of economies worldwide [1,2]. According to a US Energy Information Administration (EIA) briefing [3] global energy consumption is increasing by 2.3% per year on average. According to recent studies [4], an international shortage of petroleum is predicted to arise within the next several years. Carbon dioxide and other greenhouse gases from fossil fuels are the principal sources of environmental contamination, including air and water pollution [5,6]. Consequently, there is considerable interest in the development of renewable energies. The research in [7] revealed that renewable energy sources are abundant, long-lasting, and free of contaminants. Fig. 1 shows some of the fuel sources that account for the vast majority of worldwide energy consumption.

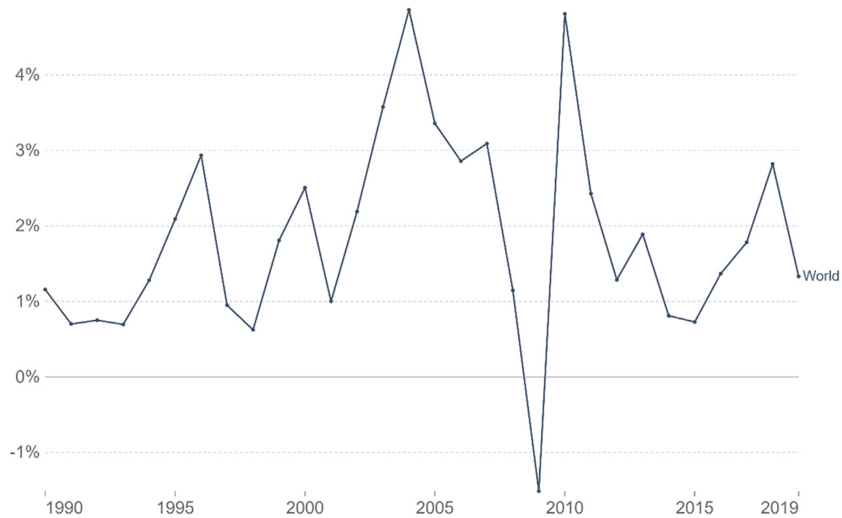

Fig. 1. Global energy consumption.

Because grid power cannot be accessed through distant and rural electrification, it is vital to support the development of other kinds of energy in those areas where grid power cannot be reached [8]. A hybrid renewable energy system, such as the one depicted in Fig. 2, is used to increase electrical power output and provide power to rural areas [9], while RES can produce hydrogen. With its efficiency, dependability, and affordability, a hybrid system has the potential to match or even surpass the limitations of renewable energy sources.

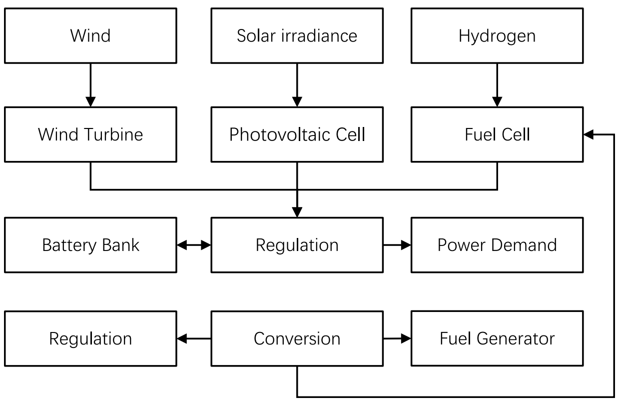

Fig. 2. Schematic of hybrid-renewable-energy system.

The goal of this work is to offer a methodology for power forecasting for a hybrid renewable energy system based on artificial neural networks (ANNs). This research also demonstrates how artificial intelligence approaches can be applied at various stages of the life cycle of a renewable energy-integrated system. This article covers several artificial neural network (ANN) models in order to appropriately manage hybrid energy systems and renewable energy generation.

In this study, we develop an artificial neural network (ANN) model to estimate the energy generated at PV and the energy from the hybrid PV and wind energy systems considering several weather factors.

2. Related works

When operating in grid-connected modes, a number of studies developed HRES models that included renewable energies [6,10–12]. In recent years, the use of machine learning (ML) methodologies in renewable energy applications has exploded, particularly in the fields of solar and wind energy.

Error back-propagation algorithm [13] attempted to estimate the maximum energy demand based on the root-mean-squared-error based on GDP, population, import and export amounts, and the scaled FF–back-propagation method. It was decided to use the Harmony Search Estimation [14] model in order to anticipate future energy demand till 2025, and a heuristic model was applied to it.

Fig. 3 depicts the results of research in energy systems and other fields that has made use of ML [15] over the previous two decades. Given the uncertain nature of renewable energy supply and the ANN ability to handle massive volumes of data, this technology is rapidly being used to predict the future of renewable energy sources.

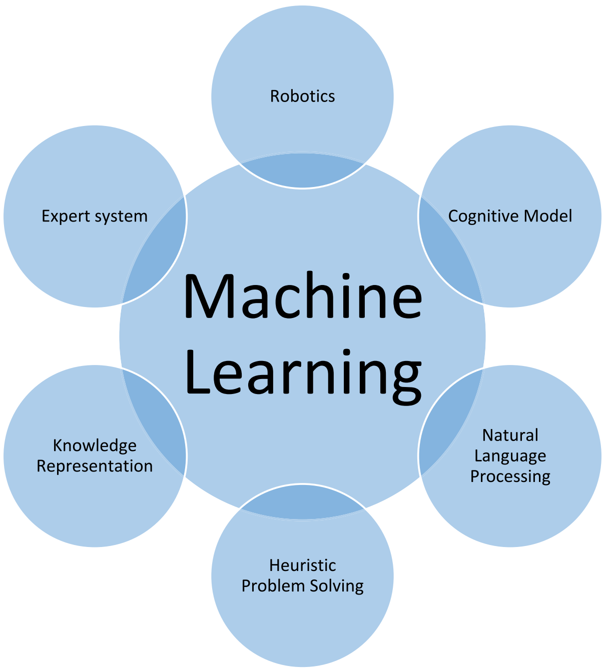

Fig. 3. Areas of machine learning.

Using an artificial neural network, Mubiru [16] was able to predict solar radiation in the field of meteorology (ANN). When Ahmad et al. [17] wanted to predict hourly sun irradiation, they used autoregressive recurrent neural networks. For the computer to provide hourly predictions regarding the intensity of the sun beams, just two variables were required: temperature and relative humidity. Long–short-term memory (LTSM) served as the foundation for the development of an innovative deep learning model for predicting PV generation by researchers in [18].

Senthil Kumar [19] pioneered the use of back-propagation networks (BPNs), nonlinear auto-regressive with exogenous inputs (NARX), and radial basis function (RBF) models for wind speed prediction, respectively (RBF). In this study, LSTM optimisation techniques in conjunction with recurrent neural networks (RNNs) [20] were used to anticipate wind speed on a daily and monthly basis.

Finally, for wind speed forecasting, a univariate single-layer RNN was proposed as an alternative. Jaime et al. [21] developed deep learning algorithms for wind speed prediction that incorporated ANN architectures, among other techniques. In their analysis, the researchers found that the deep-learning model was the most accurate in estimating air speed and power, and they came to this conclusion.

Thanks to machine learning, it is now possible to estimate hydroelectric generation. On a daily, monthly, annual, and average basis, it is capable of measuring the amount of hydroelectric energy produced. It was discovered by Ali [22] that, by utilising a feed-forward network and a back propagation mechanism, ANN-based models were utilised to estimate hydropower energy. According to [23], an irrigation dam annual hydroelectric energy output was accurately predicted using a single hidden-layer MLP and the Levenberg–Marquardt method. The approach that has been planned

3. Proposed method

In the field of energy forecasting, the practice of projecting the quantity of energy that will be created by diverse sources is referred to as energy estimation. Similarly, as the general public perception of advanced technology improves, the role of energy forecasting in today power system increases. Bottom-up forecasting is the process of creating predictions at the lowest levels of the forecasting hierarchy and then building those predictions to the highest levels of the forecasting hierarchy, as shown in the diagram. In a hybrid system, a bottom-up approach is preferred for determining the individual value of the anticipated components since it is more accurate. Fig. 4 displays a high-level overview of a bottom-up approach to determining the quantity of energy provided by different energy sources.

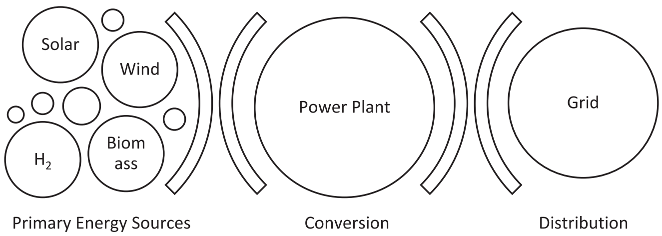

Fig. 4. Forecasting using Bottom-up energy generation.

3.1. Data processing

The major purpose of this project is to develop data-driven models that can be used to accurately anticipate wind and solar electricity generation. In the field of renewable energy forecasting, data collection and interpretation are the most important aspects to consider. When making an accurate energy estimate, it is required to perform several procedures, such as normalisation, outsourcing of unneeded or incorrect information, data aggregation, and correlation analysis. It is not necessary to employ the first two steps in all data training approaches; in fact, they are more typically used for data preprocessing than for training. However, data clustering is required in order to construct a training dataset. When it comes to forecasting models, correlation analysis provides a clearer view of how they deal with delays than other methods of investigation.

The altitude of the sun, the latitude and longitude of the earth, the time, the air pressure and temperature, the humidity and wind speed are only a few of the variables that are considered in solar energy forecasting. The predicted solar irradiance is the average solar irradiance for the year. Wind power forecasting was similar to weather forecasting in that it was based on local wind speed and direction, as well as temperature. It is compiled using hourly data, and variables such as wind speed and temperature are used to determine the mean, and standard deviation of these variables, in addition to their respective current pressure, humidity, and solar radiation. Temperature, humidity, and pressure are all required for hydropower forecasting. Time and temperature are the most important variables. It has long been popular to use image-based algorithms to anticipate the output of biomass power plants, particularly in the field of energy forecasting.

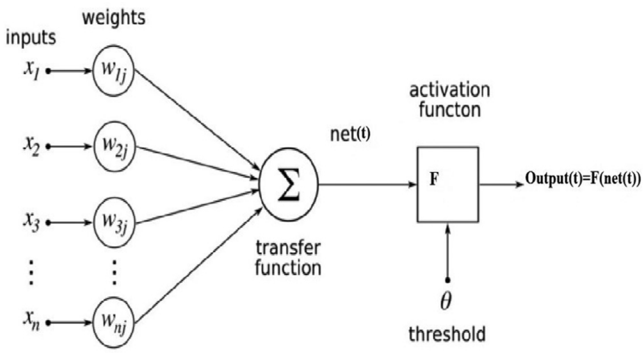

Fig. 5. Schematic diagram of an artificial neuron.

3.2. Modelling of neural network

ANNs are mathematical functions that are designed to imitate the fundamental functions of biological neurons. ANNs are composed of numerous neurons that work together to solve a given problem by using training data that is composed of inputs, weights of input, and output data.

The inputs to this neuron are all labelled with X1, X2, ... X_n, after a final summation of the weights W_1, W_2...W_n of the inputs is performed, the result is the output NET, which is represented by the letter NET. It is then compared to this threshold number to see if it falls inside or outside of the range of the threshold as shown in Fig. 5.

$$\text{net} = \sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{Wi} * \mathbf{Xi} \tag{1}$$

Then the result is compared to the predetermined threshold.

When neurons in a neural network are triggered, the transfer function acts as a squeezing function, limiting the range of values that can be output by a neuron to a specified range of values. The output of the transfer function is responsible for converting input signals into output signals. Fig. 6 shows a number of different activation functions, including linear transfer, hard-limit transfer, and logistic function.

The Hard-limit function can return either 0 or 1 depending on the threshold value. Because of the discontinuity in this function, an artificial neural network with more than one layer has concluded that it is insufficient and an activation algorithm has been devised to convert neuron activation levels (weighted inputs) into an output signal.

3.2.1. Logistic function

In neural networks, the use of a logical function can be used to achieve nonlinearity and/or signal clamping, respectively. There are two forms of log-sigmoid functions: the linear sigmoid function and the log-sigmoid function, which is a nonlinear curved s-shape function with a nonlinear curved s-shape function. It is common practise to transform neuron activation levels (weighted sum of inputs) into output signals using sigmoid functions, as these functions are the most frequently encountered activation functions. In mathematical terms, it is a well-behaved function that is differentiable everywhere and always increases in value. The following is an example of how to express a sigmoid transfer function mathematically:

$$\mathrm{Y(x)} = (1 + \exp(-\alpha \mathrm{x}))^{-1} \tag{2}$$

where

Y(x) - weighted sum of input and bias

y - neuron output.

α - slope parameter. where "α" = 1

When compared to neurons in the output layer, neurons in the hidden layers do not have access to the target vectors. It would be possible for a hidden neuron to malfunction, and the following error message would be

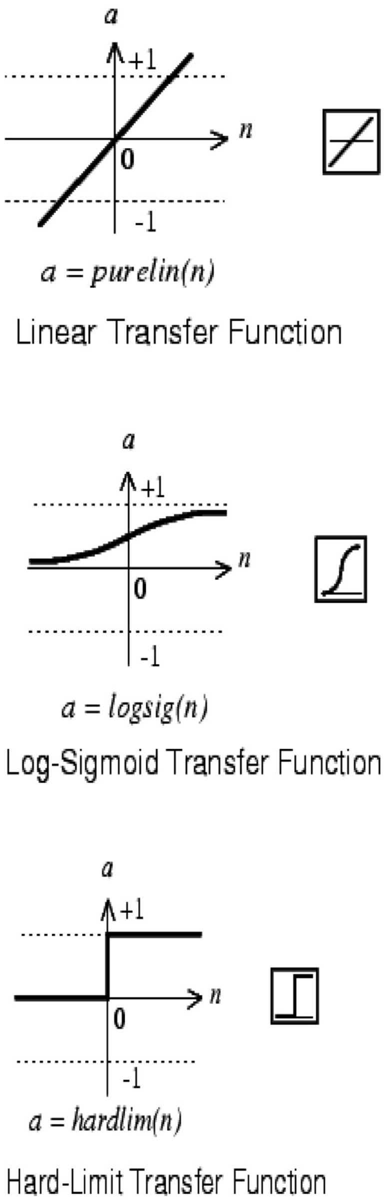

Fig. 6. Types of transfer functions.

displayed:

$$\Delta_h = \dot{F}(I_h) * \sum_{\mathbf{j=o}}^{\mathbf{Nj}} \mathbf{W_{jh}} * \Delta_{\mathbf{j}}$$

$$\Delta_h = O_h * (1 - O_h) * \sum_{\mathbf{j=o}}^{\mathbf{Nj}} \mathbf{W_{jh}} * \Delta_{\mathbf{j}}$$

When determining how frequently the weights between the input layer and the hidden layer should be updated, the following formula is used:

$$W_{hi}\ (new) = W_{hi}\ (old) + \eta * \Delta_h * O_i + \alpha * [\delta W_{hi}\ (old)]$$

A similar set of weights were changed in the output layer as in the input layer.

4. Results and discussions

A variety of meteorological conditions are used to generate the data for the output power and weather factor datasets, respectively. To get the energy required, we simply multiply the power by a changing value, as shown below. The amount of power and energy that the PV–wind system can generate in a given number of hours is determined by weather factors and measured readings from calibrated sensors. The levels of power and energy fluctuate in response to changes in weather conditions. Specifically, the projected values of the regressor models are compared to the calculated values of power and energy in this study.

The datasets contained in the prediction model are divided into two different sets for the purposes of training and testing the prediction model. Once the data has been normalised, the final findings must be de-normalised in order to obtain the expected values. The training dataset is then divided into two subsets: one for training and the other for validation, with the training dataset being used for both. It is necessary to fine-tune model constraints in order to avoid overfitting during the training phase of an ANN model, and this is accomplished through the use of training and validation datasets. In order to determine the accuracy of a model, the cross-validation procedure is the most effective way. Before final testing against an unlabelled dataset, the trained model is evaluated for its accuracy at making predictions.

When scoring a large number of features, the approach of cross-validation is used to choose the best-scoring group of features for further investigation. A graph is often used to represent cross-validated test scores and feature variety; the number of features that will be included in the model is calculated based on this data. The MSE is kept, and fewer features are lost as a result. The amount of time it takes to train the learning model is also reduced as a result.

The goal levels of power and energy can be predicted independently of one another. As a result, when energy has been removed from the equation, power can be employed as a target variable. According to the results of the linear regression analysis, the variables temperature, humidity, air pressure, wind direction, and precipitation had the least amount of influence on PV production. The connection between solar radiation and wind speed is substantial, as shown in Figs. 7–10, with R2 values of 0.79 and 0.74, respectively, indicating a strong relationship between power and energy.

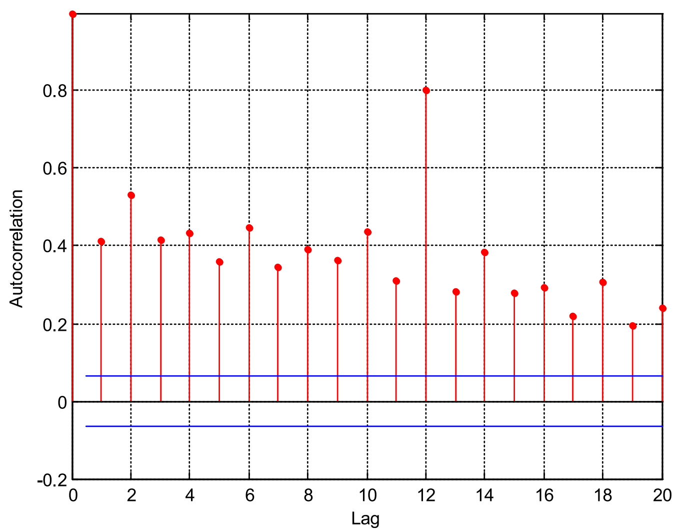

Fig. 7. Autocorrelation of PV output from small farms.

As a result, it is evident that these factors will have a significant impact on the variables that are produced as output. When the amount of solar radiation and the speed of the wind fluctuate, the amount of PV output power changes as well. When running forecast models and regulating the electricity system, the controller should take these factors into consideration in order to ensure grid stability, maximum unit commitment, and compliance

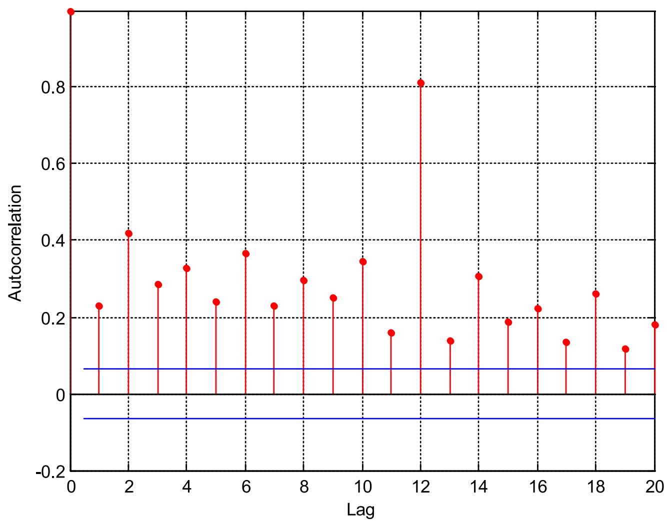

Fig. 8. Autocorrelation of PV output from large farms.

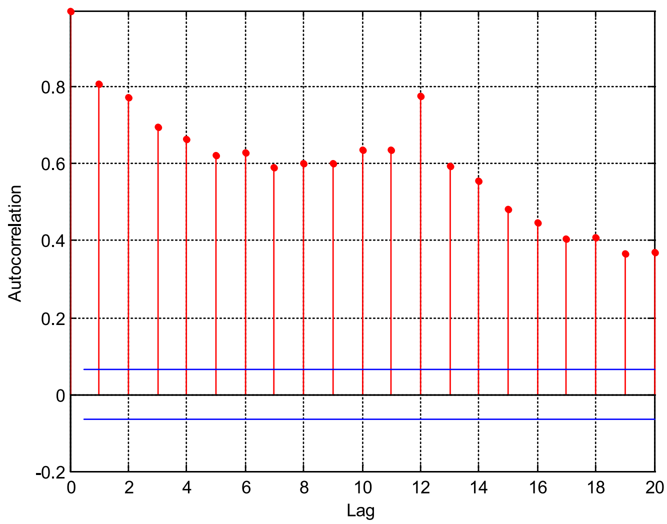

Fig. 9. Autocorrelation of PV output from small farms.

with applicable legislation. There was also a significant relationship identified between solar irradiance, relative humidity, temperature, and wind speed. As a result, it is feasible to create a new feature by combining many linear combinations.

Because of the fluctuating nature of solar energy, the output power of a hybrid photovoltaic power plant is scaled up and down as needed. Ramping is a method of displaying how much energy has been generated over a specific amount of time. The mismatch between actual and predicted power production, which might result in a sudden loss in power, has a negative impact on end users, particularly network controllers. As a result, the ramp event is crucial for both short- and long-term solar forecasting, depending on the situation. When dealing with large ramps, accurate forecasting of time and rate is essential in order to assure the safety of the electrical systems.

The application of artificial neural networks (ANN) in renewable energy forecasting is moving toward newer forms. This has the potential to improve model topologies, forecasting results, and data optimisation, among other things. Artificial intelligence-based prediction models are being used in real estate forecasting because they have

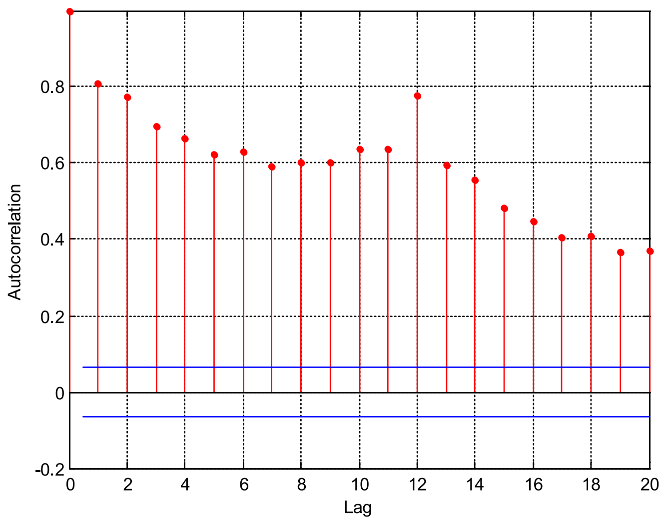

Fig. 10. Autocorrelation of PV output from large farms.

improved accuracy, are easier to use, use less data, and perform better. MLP outperforms linear techniques in the works examined, though linear time-series data may allow it to outperform them even more in the future.

When compared to SVM and KNN, the ANN showed huge performance gains in the same studies, indicating that they are significantly more promising. It is possible that RMSE or MAE are not the optimal metrics to use to communicate the results, but that standard error measurements such as RMSE are more appropriate.

It is evident that having fewer characteristics is advantageous, as demonstrated by the data. Finding the most appropriate features to use for machine learning model training can be a difficult task. The feature selection model has been employed by a number of researchers. When it comes to reducing computational complexity, FCME has been found to be less efficient than the proposed strategy. Techniques for improving energy detection in cognitive radio systems and spectrum sensing techniques have also been developed using machine learning technologies. Limiting variables such as multipath fading and shadowing are responsible for the occurrence of errors. When compared to the previous results, weighted KNN improved total accuracy by nearly 92% with feature deletion at various SNR levels. Thus, feature selection has been shown to improve the overall computing efficiency of a model.

5. Conclusions

The overall purpose of this research is to develop an artificial neural network (ANN) model that can forecast the amount of energy created by solar panels as well as the amount of wind energy generated by hybrid solar and wind energy systems, among other things. Ideally, the modelling will aid in the prediction of the amount of energy created. The datasets contained in the prediction model are divided into two different sets for the purposes of training and testing the prediction model. Once the data has been normalised, the final findings must be de-normalised in order to obtain the expected values. The training dataset is then divided into two subsets: one for training and the other for validation, with the training dataset being used for both. It is necessary to fine-tune model constraints in order to avoid overfitting during the training phase of an ANN model, and this is accomplished through the use of training and validation datasets. In order to determine the accuracy of a model, the cross-validation procedure is the most effective way. Before final testing against an unlabelled dataset, the trained model is evaluated for its accuracy at making predictions. The results show that the proposed classifier is more accurate and efficient than previous approaches in terms of reducing mean square error than the previous approaches used.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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