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Research Article

Optimal Placement of Hybrid Wind-Solar System Using Deep Learning Model

Sundeep Siddula,[1] G. K. Prashanth,[2] Praful Nandankar,[3] Ram Subbiah,[4] Saikh Mohammad Wabaidur,[5] Essam A. Al-Ammar,[6] M. H. Siddique,[7] and Subash Thanappan[8]

[1]*Department of Electrical and Electronics Engineering, Vignana Bharathi Institute of Technology, Aushapur, Telangana 501301, India*
[2]*Department of Master of Computer Applications, Siddaganga Institute of Technology, Tumakuru, Karnataka 572103, India*
[3]*Department of Electrical Engineering, Government College of Engineering, Nagpur, Maharashtra 441108, India*
[4]*Department of Mechanical Engineering, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, Telangana, 500090, India*
[5]*Chemistry Department, College of Science, King Saud University, Riyadh 11451, Saudi Arabia*
[6]*Department of Electrical Engineering, College of Engineering, King Saud University, P. O. Box 800, Riyadh 11421, Saudi Arabia*
[7]*Intelligent Construction Automation Centre, Kyungpook National University, Republic of Korea*
[8]*Department of Civil Engineering, School of Civil and Environmental Engineering, Ambo University, Ambo, Ethiopia*

Correspondence should be addressed to Subash Thanappan; subash.thanappan@ambou.edu.et

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In this paper, we develop an optimal placement of solar-wind energy systems using restricted Boltzmann machine (RBM). The RBM considers various factors to scale the process of optimal placement and enables proper sizing and placement for attaining increased electricity production from both wind and solar systems. The multiobjective criterion from both solar and wind energy farms simulated on MATLAB simulator shows an increased number of accuracies with reduced mean average error and computation time during training and testing. The results show that the RBM achieves improved rate of finding the optimal placement with a lesser cost and computation time of lesser than 2 ms than other methods.

1. Introduction

The wind velocity and the intensity of solar radiation are the critical renewable energy source like solar energy. Both factors exhibit strong nonlinearity and are highly dependent on the surrounding environment. Due to the fact that they cut greenhouse gas emissions and are environmentally friendly, accurate forecasts are required for a number of applications. Following accurate forecasting of these factors, researchers discovered that machine learning can predict relative moisture, temperature, wind speed, and solar radiation with high accuracy and predictability. For predicting highly nonlinear variables, artificial neural systems are the most effective method of prediction available.

In recent years, it has become increasingly evident that global warming poses a significant threat to human life, with potentially catastrophic effects. As a result of variable fuel prices and the environmental damage caused by excessive use, experts have shifted their attention away from fossil fuels and toward renewable energy (RE) and other kinds of alternative energy. Renewable energy sources such as photovoltaic (PV) and wind power (WP) have played a significant role in the creation of electricity since they are readily available and environmentally friendly [1, 2]. When renewable

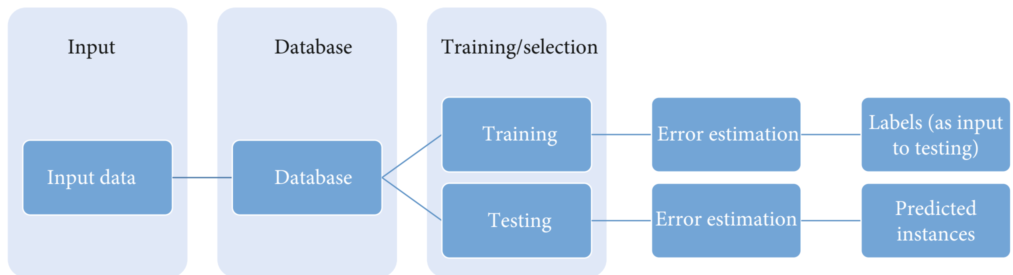

Figure 1: Machine learning approach for optimal placement via features.

energy sources are integrated with power grid, microgrids (MGs) and smart grids (SGs) emerge as a result of the increased use of renewable energy [3–5]. To keep the program costs down, the adoption of greater WT and PV reproduction technologies is encouraged in order to increase the employment of fast-growing renewable sources of energy. In addition, wind turbines and solar photovoltaic technology buildings may be considered to be the most commonly employed and interconnected technologies. Energy derived from renewable sources will soon be more affordable than conventional electricity. Electricity costs are all monetary indicators of power efficiency. The size, features, and WT and PV technology manufacturers can all have a substantial impact on power efficiency.

Hybrid renewable energy technologies, which combine multiple renewable energy sources, are quickly becoming the industry standard. Both wind energy and solar energy are currently considered to be viable renewable energy sources. However, solar energy is considered to be more significant due to the large savings that it provides [6–8], whereas wind energy is considered less significant. It may be difficult to maintain stability in a hybrid system because of some of its disadvantages, such as integration difficulties and the fact that renewable sources are often irregular, unmanageable, stochastic, and exceedingly changeable, which may make it difficult to achieve stability. When dealing with power systems, it is possible to run into a range of troublesome scenarios, including load disparity, voltage unpredictability, poor load following, and poor power quality [9–11].

Because of the transient energy characteristics of multi-WT integration and PV power system adjustment, the OPF problem is made more complicated. When attempting to define and address the OPF that develops in WT and PV technology, the following elements must be considered: an estimation of power output based on dependable wind speed and solar radiation characteristics, a choice of goal functions, an outline of the technical issues, an explanation of how to solve the OPF problem, and a conclusion. Recently, some of the aforementioned functions have been the focus of research into the OPF problem [12–14]. Using new and innovative ideas and technology to increase the usage of renewable energy sources in the power system, these issues can be mitigated to a certain extent. Figure 1 shows the machine learning approach for optimal placement via features.

Our discussion of the many scenarios in which RERs and grid-connected applications can be deployed can be found in [15–18]. As a result of this initiative, photovoltaic (PV) energy storage is being integrated into commercial buildings at a faster rate than ever before. A microgrid grid environment, as well as the technologies that go into microgrid applications with energy coordination [19–25], has one of their key purposes, the stability of the flow of energy. Review the worldwide energy situation as well as the integration of renewable energy sources, especially battery energy storage systems (BESS) and solar photovoltaic (PV). By monitoring and correcting power flow in frequency deviations and neutral lines, the model predictive regulator is crucial in maintaining a healthy balance between active electricity generation and active electricity demand in the microgrid. The main contribution of the paper includes the development of an optimal placement of solar-wind energy systems using restricted Boltzmann machine (RBM).

2. Background

The power of the sun and the wind are the most important renewable energy sources in the United States. A long-term source of energy, renewable energy, can endure the effects of changing climate conditions [1] and is becoming increasingly popular. To avoid financial losses, it is vital to forecast wind speeds on a continuous basis [2, 3]. Solar energy systems rely on accurate estimates of solar radiation to function properly. Accurate estimates of wind speed can help to improve both the safety and the economics of wind energy producing operations. Wind energy, which is a variable and nonlinear kind of energy, is not only cleaner than fossil fuels, but it is also safer and more environmentally friendly [4, 5]. It is also more cost-effective than fossil fuels. It is possible to anticipate wind speed in a variety of timeframes. Short-term forecasting, on the other hand, has a higher degree of precision [6–8].

Wind speed, on the other hand, exhibits a significantly higher degree of nonlinearity than temperature. The temperature, solar panels, and wind all have an effect on sun radiation the majority of the time [8]. When it comes to electricity generation, solar energy is an excellent choice because it is both environmentally friendly and reasonably priced [9]. A variety of models can be employed in order to forecast wind energy and solar radiation. For expressing intricate connections between input and output, neural networks are an extremely powerful tool to have at your disposal [10]. Networks of nodes (NN) outperform other types of networks in terms of generalization.

Because wind and solar radiation are nonlinear, artificial neural networks are the best option. In the future, as a result of this planned research, society and the environment will be better equipped to deal with natural calamities. IIT Delhi, India National Institute of Atmospheric Science, is currently engaged in research on climate change in the country. In the design and deployment of artificial neural networks, MPPT control is the key. India has developed a solar energy business in order to meet the country energy requirements. In India, a target of 20 GW of installed capacity has been set for 2022.

In addition, 42 solar power plants have been built across the country to provide electricity. Large-scale data analysis is a demanding task that machine learning can assist with [13]. Solar energy reduces the amount of money that businesses spend on electricity. Energy from coal and natural gas is available at a cost ranging from 7 to 30 cents per kilowatt-hour, whereas solar energy is available at a cost of between 2 and 12 cents per kilowatt-hour. Those interested in investing in commercial solar energy have a wide range of options when it comes to business strategies. Wind turbines and windmills are employed in a number of applications in the local community. In the world electrical supply, renewable energy sources account for around 26% of total supply. There are 80,000 villages in India that must be connected to the electricity grid. [14] There are a total of 2.1 billion people on the planet who do not have access to electricity. Renewable energy sources will account for 95% of our total energy consumption requirements by 2050. The Ministry of New and Renewable Energy has received critical policy support from the Government of India in order to expand the use of renewable energy sources in the country (MNRE).

A wind turbine may be used to create power by harnessing the speed of the wind. Wind turbines provided electricity to the country to the tune of 11% of total electricity use. According to [16], that ratio will increase to 16.5% in 2020 and 27% in 2030. Wind speed and solar radiation may now be predicted with high accuracy using a range of artificial neural network (ANN) approaches, including different architectures and adjustments to the rules of learning that are currently being researched. Predictions for wind turbines and solar panels can be produced with the help of an energy management system (EMS) [17].

3. Proposed Method

In this study, many methodologies for data visualization were studied as in Figure 2. The study involves data extraction, data preprocessing, feature selection, model training and testing, and evaluation. This project purpose was to identify important patterns that would allow statistical learning models to learn from their own usage patterns. This technique selects the suitable feature (in this case, weather factors) for the procedure in order to develop a robust model. It is vital to remember that in this situation, power or energy may be the ideal characteristic to have.

3.1. Preprocessing. The manipulation of data was used and not used in the processing of the data that was collected. Data adjustments were carried out with the help of RFECV. To study the data, RBM prediction algorithms were utilised, and correlations between various dataset features were established through the investigation. It was the primary purpose of this study to identify meaningful trends in usage that might be exploited to train statistical learning models.

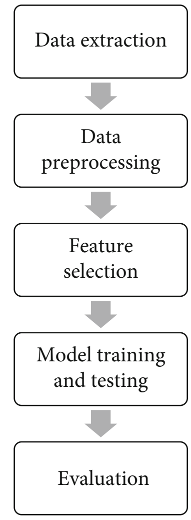

Figure 2: Proposed model.

In step 2, we apply preprocessing and feature engineering to the raw data in order to remove any trash values that could interfere with our model performance. Feature selection is an option in stage 3 in order to reduce computing time and errors, and it is used to do this. Its properties are further refined, and zero padding is applied where necessary to make the model more durable and efficient. During step 4, RFECV is used to separate and train the data in order to remove the repetitive features that could have an impact on the model outputs. Furthermore, the data obtained is evaluated using the seven most commonly used regression models, which are listed below.

3.2. Learning Model. When the estimator runs through each iteration, it takes into account all of the data and all of the features in order to build a set of scores. Each of the scores in this collection will be associated with a characteristic. Consider the following scenario: so we have a total of 20 characteristics to choose from, and we need to select the top five characteristics that will have the greatest impact on the accuracy of the model. Each iteration of the algorithm begins deleting features if and only if the obtained score is less than that predicted by the algorithm in the previous iteration. Cross-validation can be used as an alternative, in which the training and test sets are separated from one another using a k-fold cross-validation procedure. The process of learning and evaluating takes place at the conclusion of every fold.

3.3. Restricted Boltzmann Machine. RBMs are constructed by layering stochastic hidden units on top of visible units, on top of hidden stochastic units, and on top of visible units. RBM bipartite graphs, which can be used to display them, do not contain any visible-visible or hidden-hidden links, respectively. The illustration of proposed RBM model is given in Figure 3.

The joint distribution function in RBM is represented as $\boldsymbol{p}(\boldsymbol{v}, \boldsymbol{h}\,; \boldsymbol{\theta})$ that consists of hidden units $\boldsymbol{h}$ and visible units $\boldsymbol{v}$ that takes into consideration the model parameters $\boldsymbol{\theta}$, which is measured as an energy function $\boldsymbol{E}(\boldsymbol{v}, \boldsymbol{h}\,; \boldsymbol{\theta})$ as given below:

$$p(v, h\,; \theta) = \frac{\exp\ (-E(v, h\,; \theta))}{Z}, \tag{1}$$

where

$\boldsymbol{Z}$ is the partition function,

$$Z = \sum_{v}\sum_{h} \exp(-E(v, h\,; \theta)). \tag{2}$$

The study enables the computation of the marginal probability density function that gets aligned with the visible vector $\mathbf{v}$ as below:

$$p(v\,; \theta) = \frac{\sum_h \exp(-E(v, h\,; \theta))}{Z}. \tag{3}$$

For a Bernoulli-Bernoulli relation between the hidden and visible RBM, the study computes the energy function as below:

$$E(v, h\,; \theta) = -\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij} v_i h_j - \sum_{i=1}^{I} b_i v_i - \sum_{j=1}^{J} a_j h_j, \tag{4}$$

where

$\boldsymbol{v_i}$: visible unit
$\boldsymbol{h_j}$: hidden unit
$\boldsymbol{b_i}$ and $\boldsymbol{a_j}$: bias
$\boldsymbol{I}$: total hidden units
$\boldsymbol{J}$: total hidden units
$\boldsymbol{w_{ij}}$: symmetric interaction between $\boldsymbol{v_i}$ and $\boldsymbol{h_j}$. Finally, the study computes the conditional probabilities as below for hidden unit and then the visible unit:

$$\begin{aligned} p(h_j = 1 | v\,; \theta) &= \sigma\left(\sum_{i=1}^{I} w_{ij} v_i + a_j\right), \\ p(v_i = 1 | h\,; \theta) &= \sigma\left(\sum_{j=1}^{J} w_{ij} h_j + b_i\right), \end{aligned} \tag{5}$$

where

$$\sigma(x) = \frac{1}{(1 + \exp\ (x))}. \tag{6}$$

4. Results and Discussions

The assessment is conducted in MALTAB environment, where the ANN was used to compare the mean squared error (MSE), the coefficient of determination (R^2), and the mean absolute error (MAE) of RBM for the annual datasets, with the results being presented below. Weather conditions and the output of the hybrid power system were used to collect and analyse the 77,000 samples that were collected and analysed. RBMs are trained, tested, and verified using the data that has been collected. Outliers, typographical errors, and missing values were removed from the datasets to make them more representative. The validation procedure was employed in order to simplify the network to the point where no more improvement could be detected. Finally, the developed model is put to the test in order to determine its overall effectiveness.

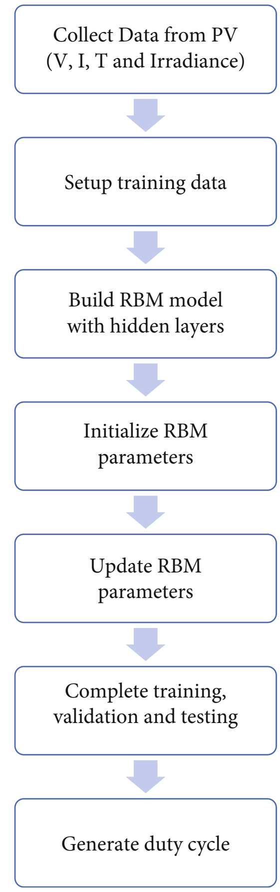

Figure 3: Proposed RBM model.

Specifically, three groups of datasets were created: one for training and validating models, and another for testing models. It is estimated that around 75% of the data was utilised for training, with the remaining 15% being used for testing and validation. Through network training, the output values of MSE and $\boldsymbol{R}$ were tested for the input datasets, and the results were reported. The presence of an error is not shown if the MSE is zero, and the $\boldsymbol{R}$-value is close to one, because zero indicates a weak correlation as in Figure 4.

The dataset was cleaned up at the start of the experiment, and then, the values were scaled between 0 and 1 as the experiment went on. Following the data purification procedure, classifiers were evaluated using the MSE, MAE, R^2, among other metrics as in Figure 5.

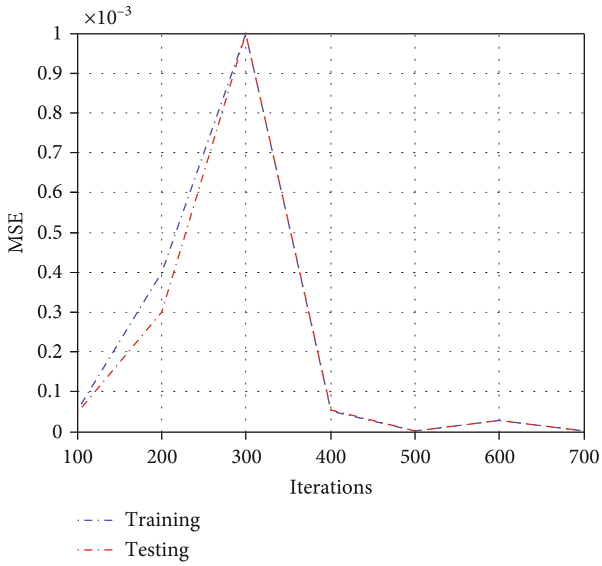

Figure 4: MSE.

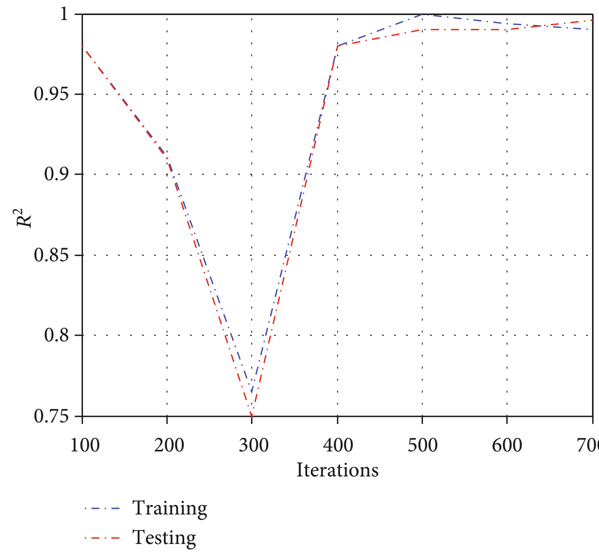

Figure 6: Coefficient of determination.

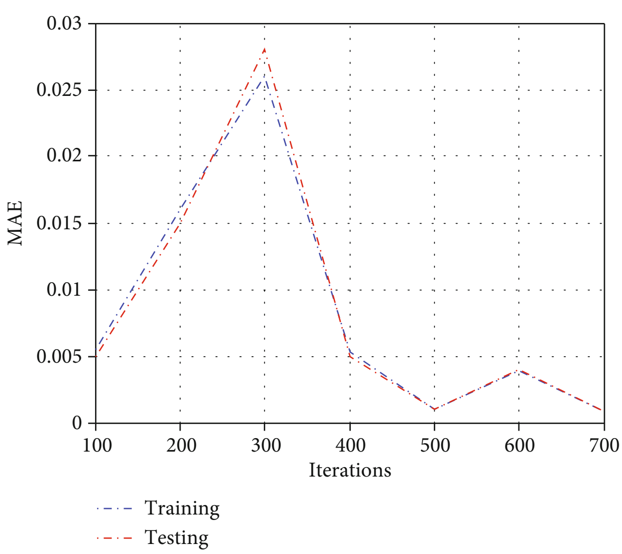

Figure 5: MAE.

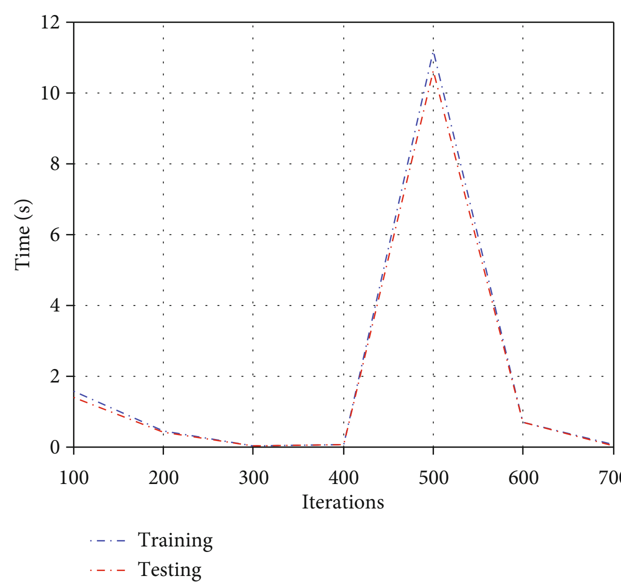

Figure 7: Computational time.

Cross-validation is a technique that is used to score a huge number of features and then select the set of features that scored the highest. The MSE is kept, and fewer features are lost as a result. In addition, the amount of time necessary to train the learning model is significantly decreased as a result of this.

The goal levels of power and energy can be predicted independently of one another. As a result, once the energy has been eliminated, it is possible to regard power as a variable to be targeted. Once the linear regression investigation was done, the researchers found that humidity, temperature, wind direction, air pressure, and precipitation all had relatively small associations with PV production. Although the R^2 values for power and energy were 0.79 and 0.74, respectively, they were significantly linked with solar irradiation and wind, as illustrated in Figures 6 and 7. According to this knowledge, these elements will have an impact on the ability to forecast output variables. It is directly related to changes in solar irradiation and wind speed that the output power of a PV system varies.

5. Conclusion

The results of the simulation are analysed, and the effectiveness of the proposed controller is tested under a variety of weather conditions. A computer programme called MATLAB was used to design and simulate the projected wind and hybrid PV/wind energy systems, which were then connected to a microgrid for operation. The goal is to implement the proposed RBM via a number of simulations of the proposed system to determine how it would operate in a variety of real-world settings. In the future, the study enables assessment of statistical and deep learning models for predicting the values of optimal nature.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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