



IJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 Issue: VI Month of publication: June 2022

DOI: <https://doi.org/10.22214/ijraset.2022.44099>

www.ijraset.com

Call:  08813907089

E-mail ID: ijraset@gmail.com

Optimized ANN using GA for Solar Power Prediction

Prajesh Jain¹, Rejo Roy², Albert John Varghese³

^{1, 2, 3}Department, Department of Electrical Engineering, Rungta College of Engineering and Technology, Bhilai (C.G.), 490024

Abstract: Renewable energy sources are not widely adopted due to their variability. Solar Power prediction is one such technique that can predict the solar power to be generated in the near future. Artificial Intelligence-based techniques are also used widely for power prediction. Short-term prediction is of much interest nowadays as it can help in scheduling activities. In this paper, a solar power prediction is done using Genetic Algorithm with ANN to help better understand the various concepts involved in power prediction. Artificial Neural Networks has shown much progress in the field of prediction. Power prediction proves to be beneficial for users who want to reduce their dependence on grid power.

Keywords: Genetic Algorithm, Solar Power, Backpropagation, Solar Power Prediction, ANN.

I. INTRODUCTION

It is widely acknowledged by power producers, utility companies and independent system operators that it is only through advanced forecasting, communications and control that renewable energy resources can collectively provide a firm, dispatchable generation capacity to the power systems [1][2]. Power prediction is one key tool in this regard, which directly supports in better operation and management of electric network [3]. The variability of power production in a solar PV plant is one of the pressing issues which hinders its widespread acceptance as a major source of power production [4]. In the proposed method Genetic algorithm with ANN is used. A description is given in the third section and follows on to demonstrate and analyze the review of the findings we received by using the MATLAB programs.

II. OBJECTIVE

The objectives identified to carry out the proposed work are as listed below:

- 1) To develop a Solar Power Prediction model this can predict power production within shorter periods of time [5].
- 2) To provide an optimized solution for the model using artificial intelligence techniques and evolutionary algorithms [6][7].
- 3) To compare various models and improve the performance parameters in order to suggest a better prediction model [8].

III. PROPOSED METHOD

The training of a neural network results in a matrix that holds the weight values between the neurons. Once a neural net is trained correctly, it will probably be able to find the desired output to a given input that had been learned, by using these matrix values. There are various methods for neural network training such as supervised / unsupervised, forward propagation, back propagation, self-organization etc.

A. Back Propagation

The essence of neural network training is back propagation. It's a technique for fine-tuning the weights of a neural network based on the previous epoch's error rate (i.e., iteration). By fine-tuning the weights, you can lower error rates and improve the model's generalisation, making it more dependable. The basic structure of a back propagation-based ANN is depicted in Figure 1 below.

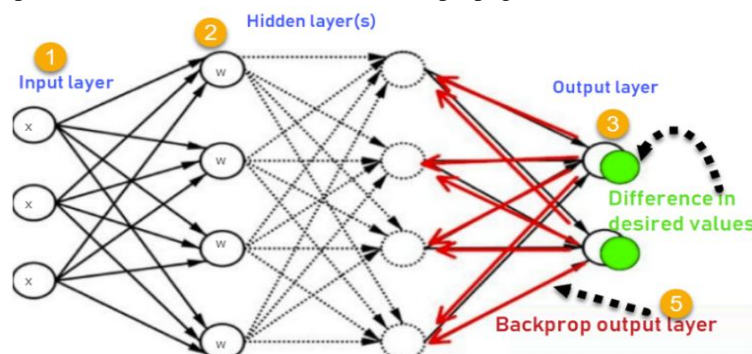


Fig. 1: Basic Structure of Back Propagation ANN

1) Steps for Implementation of Back propagation

A basic Artificial Neural Network using Back Propagation can be implemented on the basis of steps given below:

- a) X inputs enter via a pre-connected path.
- b) Real weights W are used to simulate the input.
- c) The weights are normally chosen at random.
- d) From the input layer to the hidden layers to the output layer, calculate the output for each neuron.
- e) Determine the amount of error in the outputs.
- f) Actual Output – Desired Output = Error
- g) Return from the output layer to the hidden layer to change the weights in order to reduce the error.

B. Genetic Algorithm

The genetic algorithm lays forth a method for performing heuristic search in which the fittest are chosen to fulfil a specific goal. This algorithm mimics natural selection, in which the fittest individuals are chosen for reproduction in order to create the following generation's children.

Genetic Methods (GAs) are adaptive heuristic search algorithms that fall under the evolutionary algorithms umbrella. Natural selection and genetics are the foundations of genetic algorithms. These are clever applications of random search aided by previous data to lead the search to a solution space region with superior performance.

1) Genetic Algorithm for Renewable Power Prediction

The selection of the fittest individuals from a population begins the natural selection process. They generate offspring who inherit the parents' qualities and are passed down to the next generation. If parents are physically active, their children will be fitter than they are and have a better chance of surviving.

This procedure will continue to iterate until a generation of the fittest individuals is discovered. This method can be used to solve an optimization problem.

Genetic Algorithm is an approach for global searching and optimization. Unlike other traditional searching or optimization techniques, such as hill-climbing methods, which rely solely on local information to determine the best direction in which the next step should move, GAs use global information, perform parallel search, and do not require local gradient information to find globally optimal or near globally optimal solutions. Genetic algorithms (GA) and other optimization techniques have also been utilized to determine relevant parameters for extremely efficient, accurate, and reliable prediction.

2) Flowchart of the Genetic Algorithm

Genetic Algorithm is used to produce an offspring with the best characteristics of the parents. This concept can be used for optimizing the weights and bias of the neural network designed. This process keeps on repeating and at the end, a generation with the fittest individuals (i.e., neural network model with the best performance) will be obtained.

The flowchart for the genetic algorithm is as shown below in Figure 2. The steps involved in Genetic algorithm are as illustrated below:

- a) Step 1 - Initial Population: a group of people defined by their genes (set of parameters). Chromosomes are made up of genes strung together like a string (solution).
- b) Step 2 - Fitness Function: Giving a fitness score to a person to determine how fit they are.
- c) Step 3 – Selection: selecting the fittest individuals and let them pass their genes to the next generation
- d) Step 4: Crossover: Creating kids by exchanging the genes of parents to be added to the population by picking a crossover point at random from within the genes.
- e) Step 5 – Mutation: Offspring are formed by exchanging the genes of parents among themselves until the crossover point is reached and by flipping bits in select offspring to maintain variety within the population and prevent early convergence.

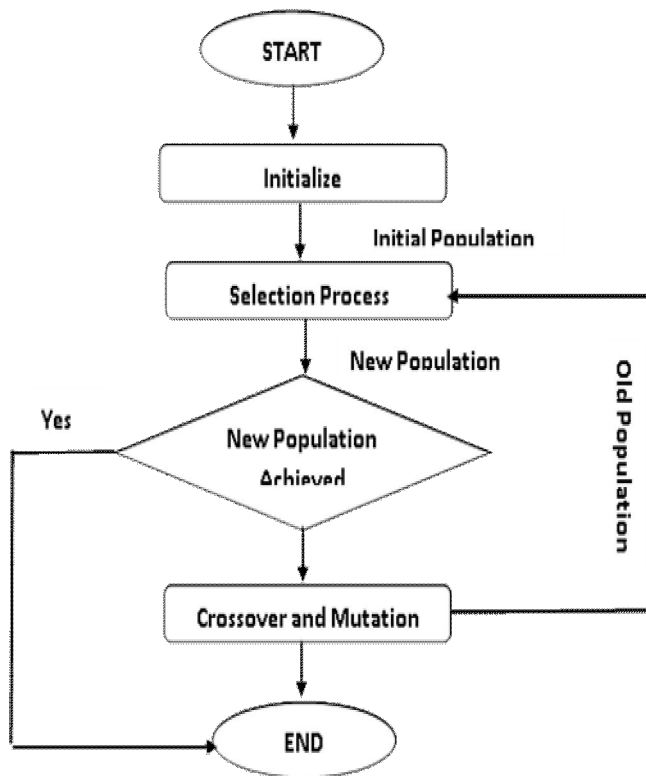


Fig. 2: Flowchart of Genetic Algorithm

IV. RESULT

A. Predicted PV Power Plot

On completion of training of neural network for GA optimized ANN model a graph showing PV power versus time at hourly duration is obtained. Figure 3 shows the Predicted PV Power for hourly duration for a period of 12 hours.

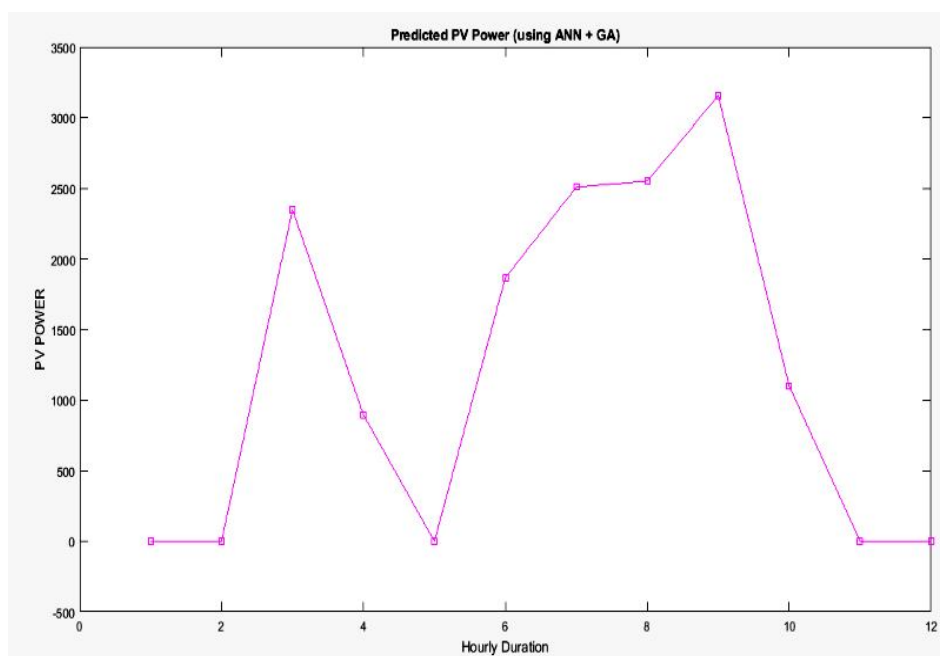


Fig. 3: Predicted PV power using GA optimized ANN

B. Training State Plot

The whole optimization process training state validation check graphs illustrate the data training progress and gradients with each passing epoch. Where one complete iteration is utilized to update the weight values, and epoch is one complete iteration. This graph can be used to assess network performance and evaluate whether any changes to the training procedure, network architecture, or data sets are required. The training state map for a GA optimized ANN model is shown in Figure 4.

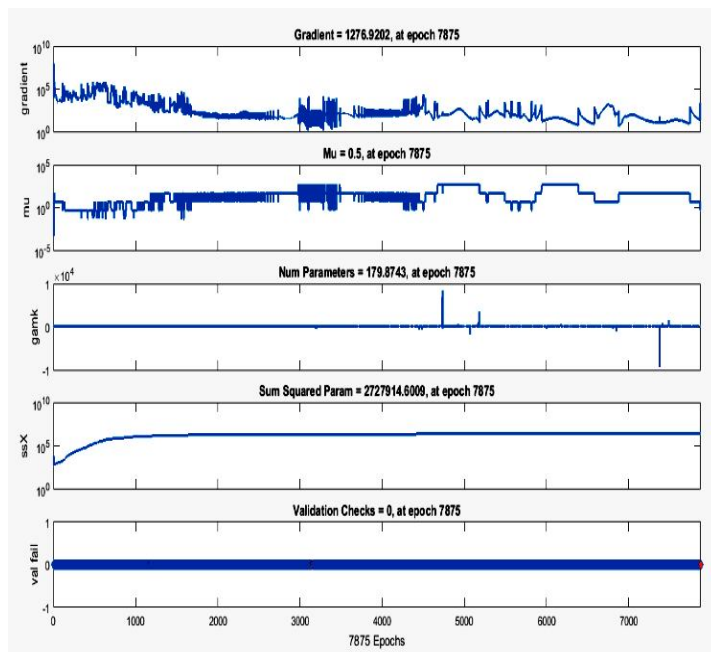


Fig. 4: Training State Plot for GA optimized ANN

C. Regression Plot

A Scatter plot is a great way of exploring relationships or patterns in data. But adding a regression line can make those patterns stand out. Figure 5 shows the Regression plot for model using GA optimized ANN model. The value of R approximately equals 1 in this case.

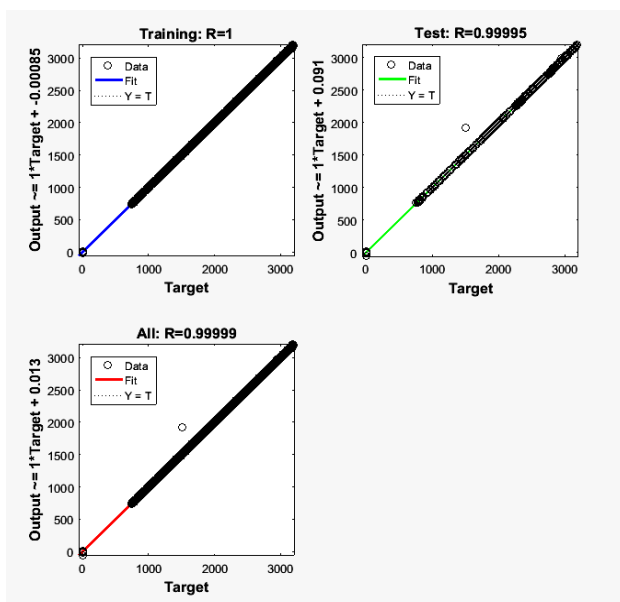


Fig. 5: Regression Plot for GA optimized ANN

D. Performance Plot

MSE is a risk function, corresponding to the expected value of the squared error loss. Ideally the value of MSE should be zero. A model with less error produces more precise predictions. Figure 6 shows the MSE error values with every iteration for a GA optimized ANN model.

The use of artificial intelligence in the form of ANN as well in the form of a hybrid structure using ANN and evolutionary algorithm proved to be useful for the problem at hand. Both the MATLAB models were run successfully for the provided dataset and both the models were capable of providing the values of solar power prediction for hourly durations.

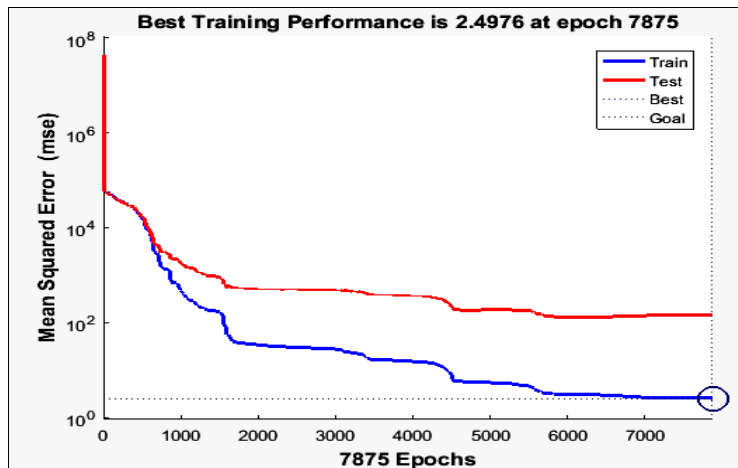


Fig. 6: Performance Plot for GA optimized ANN

The model proved to be better as it could complete without waiting for all the iterations to complete. The parameters obtained after successfully running the GA optimized ANN model are summarized in Table 1.

Table 1: Parameters for Model using GA optimized ANN

Parameters	ANN (After Training Completed)
Hidden Layer	50
Error (MSE)	4.53
Iterations	7875
ANN	Neural Network Training tool
Optimization	Genetic Algorithm (weights and bias)
Data Initialization	done randomly
Execution Time	36:48 minutes

V. CONCLUSION

Solar PV power prediction was successfully implemented using a basic Artificial Neural Network and a Genetic Algorithm optimized Artificial Neural Network. Neural Network Training tool available in MATLAB helped with the implementation of the proposed idea. These techniques help in reducing the variability of solar resource by giving proper predictions for shorter durations which will be helpful for power system operators. This will also help in better utilization of solar PV power generated.

Some of the major contributions of the proposed work carried out as a simulation study can be highlighted as given below:

- 1) GA optimized ANN model gave faster results when compared with ANN based Model. It can be said because GA optimized ANN model took:
- 2) Lower Time
- 3) Lower Number of Iterations



REFERENCES

- [1] Fatih Serttas, Fatih Onur Hocaoglu, Emre Akarslan, "Short Term Solar Power Generation Forecasting: A Novel Approach", International Conference on Photovoltaic Science and Technologies (PVCon), IEEE, 2018.
- [2] Musaed Alrashidi, Massoud Alrashidi, Manisa Pipattanasomporn, Saifur Rahman, "Short-Term PV Output Forecasts with Support Vector Regression Optimized by Cuckoo Search and Differential Evolution Algorithms", IEEE International Smart Cities Conference, 2018.
- [3] Astha Singh, Kishan Bhushan Sahay, "Short-Term Demand Forecasting By Using ANN Algorithms", IEECON 2018, Krabi, Thailand, 2018.
- [4] Badia Amrouche, Xavier Le Pivert, "Artificial neural network based daily local forecasting for global solar radiation", Applied Energy 130 (2014) 333–341, 2014.
- [5] Gabriele Mosaico, Matteo Saviozzi, "A hybrid methodology for the day-ahead PV Prediction exploiting a Clear Sky Model or Artificial Neural Networks", IEEE EUROCON 2019 -18th International Conference on Smart Technologies, 2019.
- [6] Hamed H.H. Aly, "A proposed intelligent short-term load Prediction hybrid models of ANN, WNN and KF based on clustering techniques for smart grid", Electric Power Systems Research (Elsevier), 2020.
- [7] Vikas Pratap Singh, Vivek Vijay, M. Siddhartha Bhatt, "Generalized neural network methodology for short term solar power forecasting", 13th International Conference on Environment and Electrical Engineering (EEEIC), 2013.
- [8] Hanmin Sheng, Jian Xiao, Yuhua Cheng, Qiang Ni, Song Wang, "Short-Term Solar Power Forecasting Based on Weighted Gaussian Process Regression", IEEE Transactions on Industrial Electronics, 2018.



10.22214/IJRASET



45.98



IMPACT FACTOR:
7.129



IMPACT FACTOR:
7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089  (24*7 Support on Whatsapp)