Journal of Solar Energy Research (JSER)

Journal homepage: www.jser.ut.ac.ir

Forecasting of PV Output Power in Cloudy Conditions by LOLIBEE, MLP-ABC and MLP Algorithms

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ARTICLE INFO

Received: 16 October 2016
Received in revised form: 28 January 2017
Accepted: 30 January 2017

Keywords:
PV; LOLIBEE Algorithm; MLP-ABC Algorithm; MLP Algorithm

A B S T R A C T

Forecasting PV power generated by photovoltaic panels (PV) in cloudy conditions is of great importance. The aim of this paper is to forecast the produced power by PV using LOLIBEE (Local Linear Bee Model), MLP-ABC (Multi-layer perceptron - Artificial Bee Colony) and MLP algorithms. Experimental data (ambient temperature, solar radiation, speed of wind and relative humidity) are collected at a five-minutes interval from Tehran University's PV laboratory from September 22nd, 2012 to January 14th, 2013. Upon validation of data gathered from the lab, 10665 data which are equivalent to 35 days are used in the analysis. The output power of PV was forecasted by constructing three models for different parts of a day using LOLIBEE, MLP-ABC and MLP algorithms (three models for each algorithm), which resulted in better precision by LOLIBEE with about 95% and 1.9 in terms of R^2 (Co-relation Co-efficient) and MBE (Mean bias error) respectively. The accuracy gained by our proposed model for dividing the day into three durations is also increased by about 1.5 percentage in comparison with the model which is covering the whole day.

1. Introduction

Most renewable energy forms originated either directly or indirectly from the sun. Solar energy can be used directly for heating and lightening homes and other buildings, for generating electricity, hot-water heating, solar cooling and a variety of commercial or industrial uses [1].
The energy consumption through the world is increasing rapidly to almost double from 2004 to 2030. In other words, in the next four decades, the world will consume as much energy as in the whole of human history up to now**.**
Consequently, the uses of renewable energy forms such as solar energy are increasing around the world [2] .
As a pioneer, Germany is widely considered global leader in solar power, with over a third of the world's solar cells.
Ernsting sees the rise of wind power and solar power as serving the corporate agenda rather than human needs. She examines Germany's real energy mix, which puts solar and wind in perspective. Most "renewable" energy in Germany is from bio-fuels, bio-gas and wood pellets, none of which are innocent of causing serious environmental impacts. These three prime renewable energy supplies, and dependency on them, means that the "24,000 wind turbines and 1.4 million solar panels have scarcely made a dent in Germany's fossil fuel burning and carbon emissions"[3].
China, the largest energy consumer in the world and due to air pollution in large cities, the country remains one of the main concerns of the Beijing government, will follow the path of expanding the use of renewable energy sources. Accordingly, China is the world's largest investor in renewable energy also allocated**.**
Photovoltaic cells collect sunlight and convert it to electrical energy, which is the most convenient way of utilizing solar energy. The performance of a PV panel is strongly dependent on the availability of solar irradiance at the required location, PV panel temperature and other environmental conditions [4-8].
In recent years, numerous researches have been done for predicting solar PV system's efficiency and optimizing the effective parameters by using artificial intelligence techniques[9-14]. There are some studies have been done in order to investigate the environmental factors which affect the current–voltage (I–V) characteristics of PV modules based on simultaneous measurement of the open-circuit

voltage Voc as a function of a slowly varying light intensity[15].
The main objective of this study is to pursue a simplified simulation model with acceptable precision to estimate the output power of a PV module under different operation conditions. The sunny part duration is divided into 3 parts and three models are employed to compute the output instead of using a model for the whole day.
In this paper, LOLIBE, MLP-ABC, and MLP algorithms are used to predict the output energy of PV solar panels. The obtained results showed that these methods can be used to determine the PV panel's outputs instead of time consuming experimental tests, with a reasonable accuracy.

2. Materials and Method Data
Data is related to Tehran university photovoltaic power plant, located in Tehran at a longitude of N 37.51, latitude E 47.35 and an altitude of 1548 meters, which are measured and registered by data loggers at five-minute intervals.

In this research, ambient temperature, relative humidity, incoming radiation and output power of PV, between September 22nd, 2012 and January 14th, 2013 were used. Validation test was done for data due to the inaccurate data registration. To accomplish this, incoming radiations were compared with extraterrestrial radiation. The measured power was integrated to calculate the total obtained energy within a day and then the nominal power of PV modules was compared to each other.

Figure1. University of Tehran's photovoltaic Plant Complex

3. METHOD
Three different networks are used to calculate the output of the panel. The first of them is Multi-layer perceptron which is a basic neural network. The second is MLP-ABC, which is a MLP trained by ABC algorithm, and the last one is LOLIBEE, which is a Neuro-fuzzy algorithm consisting of a single-layer neural network with fuzzy activator trained by ABC algorithm.[16]

3.1.MLP
Multi-layer perceptron is the basic form of neural network. It often has three to four layers (an input, two hidden and an output), each containing several neurons that are connected to other neurons in adjacent layers. It usually employs a feed-forward approach for calculating the output. Input layer that represents the input values of a given pattern (a neuron for each dimension), will pass its values to the next layer, which is a hidden layer. The values are multiplied by a pre-defined weight (that might be assigned randomly), representing the connection strength between each neuron. The values then are added together and will continue passing to other layers until reaches the output layer.

3.2.MLP-ABC

Fundamentally, MLP-ABC is a form of MLP network. In basic form, weight between neurons computed through a gradient-descent technique. Since the calculation of weight is an optimization problem (finding the best weight that minimize or maximize the output) in MLP-ABC, the computation is carried out by ABC algorithm.

Artificial Bee Colony proposed by Karaboga [17] is an optimization algorithm used for solving many optimization problems [18, 19]. It was inspired from behavior of honey bees in finding and storing honey in their nest and the way they communicate with each other. Both employee and scot bees work together to find the best solution to the problems. The first one works on the current solution and those around it hoping for improve the result. In case of no acceptable result, an employed bee becomes a scot and try to look for another solution in areas far away. In general, the ABC algorithm is as follows:

```
Initialization Phase
REPEAT
    Employed Bees Phase
    Onlooker Bees Phase
    Scout Bees Phase
    Memorize the best solution achieved so far
UNTIL(Cycle=Maximum Cycle Number)
```

MLP-ABC employs the ABC algorithm as a mechanism to calculate the best weight between neurons, so the error between the computed output and desired output becomes minimum. All weights are represented in a string, considered as solution, to the problem.

3.3.LOLIBEE
Local Linear Neuro-fuzzy model (LLNF) is a type of neuro-fuzzy algorithm that employs local linear models to compute the final output. It divides the problems into sub-problems and by applying the divide-and conquer strategy tries to solve them to finally solve the whole one. Each local linear estimates part of the problem and a fuzzy validity function is used to define the portion that the model is active and can be used to compute the whole output. By utilizing a partitioning approach the LLNF model can accurately calculate the result. Since it is a neural network with a hidden layer, implicitly its structure is based on the neural network method. Three layers with neurons and weights between them as well as fuzzy validity functions $\varphi 1(\mu)$ for indicating the portion of the local linear in solving the problem (As shown in figure 2).

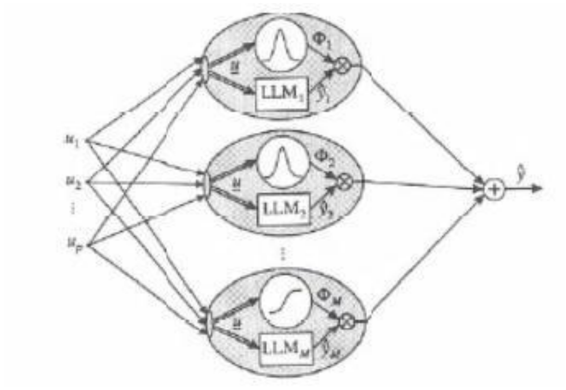

Figure 2. Network structure of a LLNF model

The output of each LLM is computed as follows:

$$\varphi_1 = w_{i0} + w_{i1} u_1 + w_{i2} u_2 + \cdots \quad (1)$$

The output of a local linear Neuro-Fuzzy model simply becomes the weighted sum of the output of locally linear models and becomes:

$$\varphi = \sum_{i=1}^{M} (w_{i0} + w_{i1} u_1 + w_{i2} u_2 + \cdots + w_{ip} u_p) \quad (2)$$

For creating a LLNF model, we need to compute the number of partitions (number of neurons), the weights and φ1(μ). Since these parameters must be chosen in a way that the error between output and desired value becomes minimum, it is an optimization problem. Therefore, for computing the parameters of LLNF, the artificial bee colony is utilized. LOLIBEE algorithm is as follows [20]:

3.4.LOLIBEE Algorithm

Initialize population Popij ← randij [with boundary constrains]
Evaluate fitness Fitj ← f(Popj)
While the termination criteria (number of LLMS)
For i = 1 to iteration (stopping criteria) do
For j = 1 to NP (employed bee) do
Produce new solution (Parameters of LLM)

Calculate the fitness (Best Model)
Select by a greedy process
End for
Compute the probability values for each solution
For k = 1 to NP (employed bee) do
Select a solution si based on computed probability
Produce new solution (Parameters of LLM)
Calculate the fitness (Best Model)
Select by a greedy process
End for
Store the best solution so far
End for
Repeat

The proportionality factor k_σ is usually chosen as $\frac{1}{3}$ for LOLIMOT. In LOLIBEE, the factor k_σ depends on the input data. In case of unwell distributed data, k_σ must be chosen as it helps the local linear models (partitions) to cover the input space completely and properly.

4. MODELS STRUCTURE

Since the radiation of the sun in various hours of the day is different, to calculate the output power of solar panel efficiently, we employed three networks for each model. Each network covers specific hours of the day including beginning of it (7-10), middle of it (10-14), and end of the day (14-17). Using this approach, each network was responsible for computing the output power of its own duration – learning the changing patterns - and therefore, it can be fitted better to the duration. Figure shows the structure of the models:

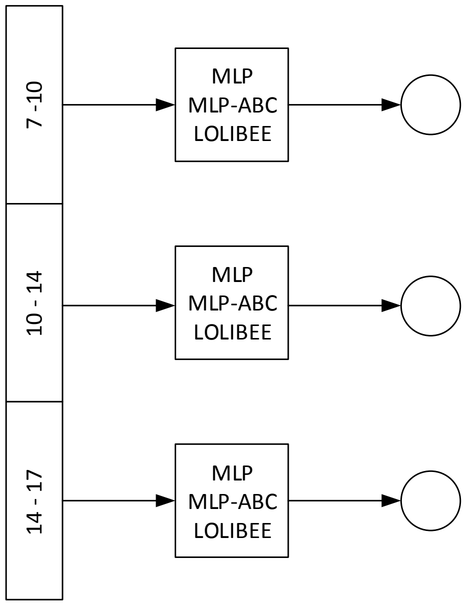

Figure 3. The Structure of the networks for computing the power

5. Result and Discussion

The research investigates the effect of using more than one network for computing the output power of a solar panel. It also utilized three different methods to see the difference in accuracy and performance in computing the output by them. MLP, MLP-ABC and LOLIBEE were employed for computing the output in three different duration. Beginning of the day and end of the day where the radiation is not high as well as the middle of the day where the radiation is usually higher than the others. The result of the experiment is depicted in Tables 1 and 2 as well as figures 4 and 5.

Table1. Generated error in PV panels' power prediction in terms of R^2 using all the networks

R^2	7 – 10	10 - 14	14 – 17	7 – 17
LOLIBEE	95.1	95.8	95.5	94.3

MLP-ABC	91.5	91.4	91.3	90.5
MLP	89.2	88.9	89.1	88.4

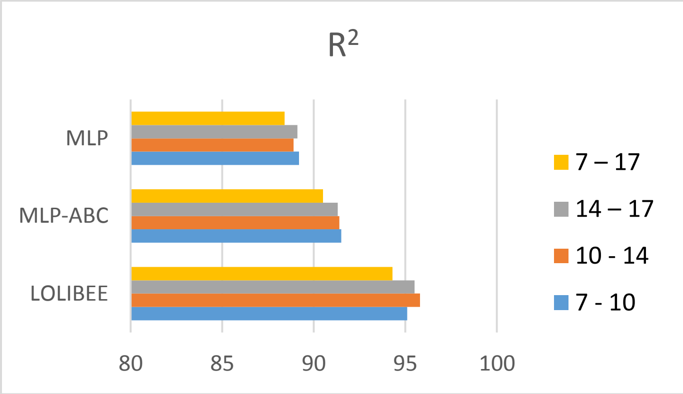

Figure 4. Comparison of output of different network in different time in terms of R^2

Table3. Generated error in PV panels' power prediction in terms of MBE using all the networks

MBE	7 - 10	10 - 14	14 – 17	7 - 17
LOLIBEE	1.9	1.7	2.0	1.95
MLP-ABC	2.3	2.1	2.3	2.7
MLP	3.1	2.9	2.9	3.2

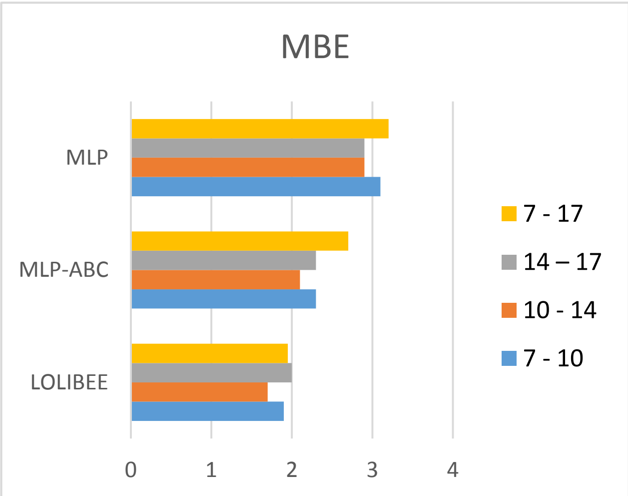

Figure 5. Comparison of output of different network in different time in terms of MBE

Using a separate model for each duration, we tried to only focus on that duration and let the network learn the behavior of solar panel at that time regardless of what happens in other hours. Our experiment showed the better accuracy in results when they were used separately for shorter duration than whole the day (about 1.5 percent more accurate). Since we divide the whole day into three parts, each model needed only to work with one-third of the data and therefore, it can learn faster.

Employing three different network showed that since the parameters, affecting the output of the solar panel is dependent on uncertain factors, a neuro fuzzy model (LOLIBEE) provides the better results in computing the output power (because of its fuzzy nature), following by MLP-ABC and MLP. However, we must indicate that tuning the parameter of the networks models has a great effect on performance of them.

6. Conclusions

In this paper, the output of a photovoltaic solar panel was forecasted with LOLIBEE, MLP-ABC and MLP and the results compared with the experimental data. The ambient temperature, irradiance on the horizontal surface, PV power (by multiplying current and voltage) were collected in the photovoltaic laboratory of Tehran University between September 22nd, 2012 and January 14th, 2013. 10665 data were measured at five-minutes intervals (during approximately 35 days) after pre-processing. The data were divided into three parts covering the whole day (7-10, 10-14, and 14-17). We employed three different methods to compute the power, including LOLIBE, MLP-ABC and MLP. For all methods, a model was constructed for each duration. Final results showed that LOLIBEE gained the better accuracy by about 95% and 1.9 for R^2 and MBE respectively. Dividing the data into three parts and creating a separate model for each duration also resulted in an increase in accuracy by 1.5% in contrast to using a model covering the whole day.

For the future work, it is possible to divide the day to more parts and employ other methods for computing the output.

ACKNOWLEDGMENTS

The authors would like to thank the research council of the Islamic Azad University South Tehran Branch (contract No. 812) for supporting this research.

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