FORECASTING SOLAR PHOTOVOLTAIC ENERGY PRODUCTION USING ARTIFICIAL NEURAL NETWORK

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Abstract: A key role in energy management policies is played by the primary resource availability accommodation to the consumption. In such energy system, renewable energy resources play an important role. As these resources are variable in time, their forecast represents a significant issue.

More and more attention is being paid to predicting a possible amount of electricity obtained on the basis of solar radiation on photovoltaic panels, which is influenced by numerous external parameters such as air temperature, amount of clouds and humidity. Numerous previous studies have shown that certain significant techniques which have been used to predict and optimize the performance of various solar energy systems are machine learning and artificial neural networks. Artificial neural networks (ANNs) are widely accepted as a technology that offers a solution to very complex problems, they can handle incomplete data and can perform high-speed prediction. ANNs process can be considered as a black-box modelling with a set of input factors and output variables which are results of input factors treatment through a systematic neural network.

Back-propagation network is a type of multilayer feedforward neural network which achieves an arbitrary nonlinear map from inputs to outputs. In this research the back-propagation learning algorithm is used to construct a prediction model of photovoltaic power generation which can forecast the power outputs of photovoltaic system.

Keywords: Photovoltaic systems, neural network, backpropagation, forecasting

1. INTRODUCTION

On a management level a significant impact on the energy systems is given by the specific renewable resource availability [1]. Since development and utilization of renewable resources is increasing in Bosnia and Herzegovina their forecasting represent a significant issue.

Among renewable resources photovoltaic power generation is the usual for solar energy utilization, where in the recent years the photovoltaic systems have been on the rise and significant financial incentives are even going to be offered for the construction of solar panels on private homes. Such energy is ecologically clean and there is a great possibility of investment profitability. But as uncontrolled energy source its fluctuating also brings new challenges to the stable and economic operation of power grids [2]. So accurate forecasting of the power ouput of PV systems is critical to the proper planning and operation of power system [3].

Photovoltaic power generation is influenced by amount of radiation, cloud cover, temperature, wind velocity etc., thus facing engineers with the difficult task of making reliable predictions. Due to, ANNs based methods are useful tools to model different engineering system under real world conditions without involving in solving complicated mathematical models [4]. In literature there are numerous resources regarding the solar photovoltaic forecast. Also ANNs has been widely used in forecasting solar energy systems. Li et al utilized three neural network algorithms to construct a short-term forecasting model. As inputs they used solar irradiance, environmental temperature, atmospheric pressure, and wind velocity and wind direction. Khatib et al, [5] used ANNs to predict a clearness index which is used to calculate global and diffuse solar irradiations.

This paper is using ANNs as a prediction tool for forecasting energy production in solar photovoltaic systems. The neural network adopted was a feed forward multilayer perception network, among the most used neural networks that learn from examples. Four variables were used as input parameters for the input nodes of the input layer. Input variables are: global horizontal irradiation, direct normal irradiation, monthly average temperature and total monthly precipitation. A single node was at the output layer – monthly power generation.

2. ARTIFICIAL NEURAL NETWORKS

Many researches have proven ANNs to be a powerful tool for modelling, prediction and optimization of the performance of different engineering systems, due to excellent characteristics such as high-speed information processing, mapping capabilities, fault tolerance, adaptively, and generalization [6]. It has ability to learn from examples, recognize a pattern in the data, adapt solutions over time, and process information rapidly [7]. The backpropagation algorithm is the part of the artificial neural network which is the multi-layer perceptron, also known as the Widrow-Hoff learning rule. The network will adjust the weight value, and after that input the data form for the network training once each one is finished. The output value of network is compared with the target value then the error value is calculated. The error - value is returned to the network and used to adjust the next weighted value. The basic structure of the backpropagation neural network is shown in Figure 1.

For each input, the network produces the corresponding output, which is the dependent variable. After each pattern is read, the network uses the input data and produces output, which is than compared to a desired output. If there is a deviation, the connection weights are changed in the direction of reducing the error. As long as there is an error greater than the tolerance, the network will repeatedly go through the input patterns, until the errors are within the required tolerance. When the training reaches a satisfactory level, the network holds the weights constant and uses the trained network to make decisions, identify patterns, or define associations in new input data sets not used to train it. [8]

3. THE MODEL BUILDING

The photovoltaic system for this study consist of polycrystalline solar panels and inverters Danfoss, FLX Pro15. Panels are situated on the rooftop of a building. The panels are fixed and inclined at an angle of 30^{O}. In order to conduct a comprehensive study of the relationship between photovoltaic forecast and climate, the prediction model is relying on data from monthly global horizontal irradiation, direct normal irradiation, monthly average temperature and total monthly precipitation from the July 2015 to December 2020. This data is provided by the Meteorological Information Centre and PVGis software. In Table 1 critical values of input and output data are shown.

Table 1: Maximum, minimum and average values of data used for ANNs model

	Temperature (^{o}C)	Global horizontal irradiation	Direct normal irradiation	Precipitation (mm)	Generated energy (kWh)
Maximum	25	235.88	244.65	426.2	44523
Minimum	-3.1	39.66	46.57	0	4043
Average	12.72	128.6	141.1	124.96	27112

The neural network adopted was a feed forward multilayer perceptron network. A schematic flowchart diagram for building model is shown in figure 2 and block diagram of the ANNs topology is shown in Figure 3.

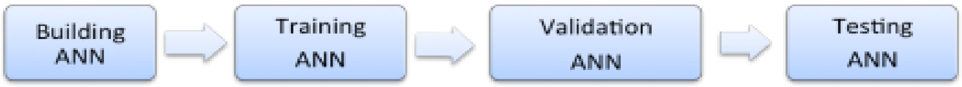

Figure 2: Flowchart diagram for building an ANNs model [8]

Pre-processing of the data is usually required before presenting the data to the network model when the neurons have a transfer function with bounded range [7]. In this study the data was scaled in range of 0 and 1.

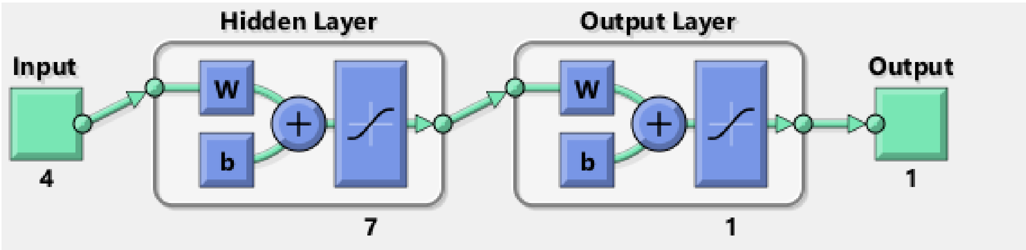

Figure 3: Block diagram of the ANNs topology

Feed forward multilayer ANNs with one hidden layer is chosen. It can approximate any complex nonlinear function provided that a sufficient number of hidden layer neurons are available [8].

The number of neurons in the hidden layer depends on various factors, such as the number of input and output variables, complexity of the activation function, architecture of the neural network and, most importantly, data set used to train the artificial neural network. Guidelines for determining the number of neurons in hidden layers can be found as follows:

- Number of neurons in hidden layer should be 2/3 (70% - 90%) input neurons. In some casses number of neurons in output layer can be added [9].
- Number of neurons in hidden layer shouldn't be greater than twice of number of neurons in input layer [10].
- Number of neurons in hidden layer should be 1/2 (input neurons + output neurons) + $number\ of\ training\ data^{1/2}$[11].

In this paper the optimum neurons number in the hidden layer was determined using trial and error procedure by varying the hidden neuron number from 2 to 11. The best performing network was chosen based on variation of the number of neurons in hidden layer while monitoring the performance criteria, table 2. Bold identifies the number of neurons with the best performance.

Table 2: Results of trained ANNs models

Num. of neurons	Epoch/Iteration	Performance	Gradient	Regression
2	344	0.000733	0.000081	0.99415
3	6	0.000444	0.000179	0.99546
4	18	0.00032	0.000215	0.99422
5	12	0.000345	0.000295	0.99264
6	6	0.000359	0.000211	0.99664
7	**7**	**0.000181**	**0.000573**	**0.99606**
8	6	0.000392	0.000289	0.9964

9	6	0.00056	0.000789	0.99433
10	6	0.00015	0.000542	0.99543
11	6	0.00041	0.000992	0.99179

4. RESULTS AND DISCUSSION

Figure 4 shows a comparison between the measured and predicted monthly energy production of the chosen site. Based on the results the best ANN topology was neural network with one hidden layer and seven neurons in hidden layer.

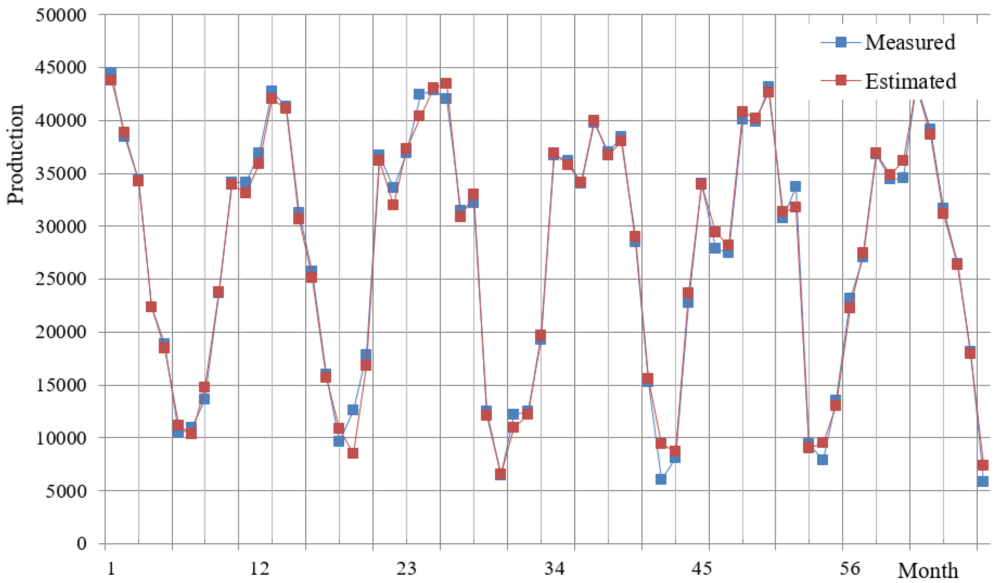

Figure 4: Comparison between the predicted and measured energy power production

Figure 5 presents the results from the ANN model for different stages, including training, validation, test and together.

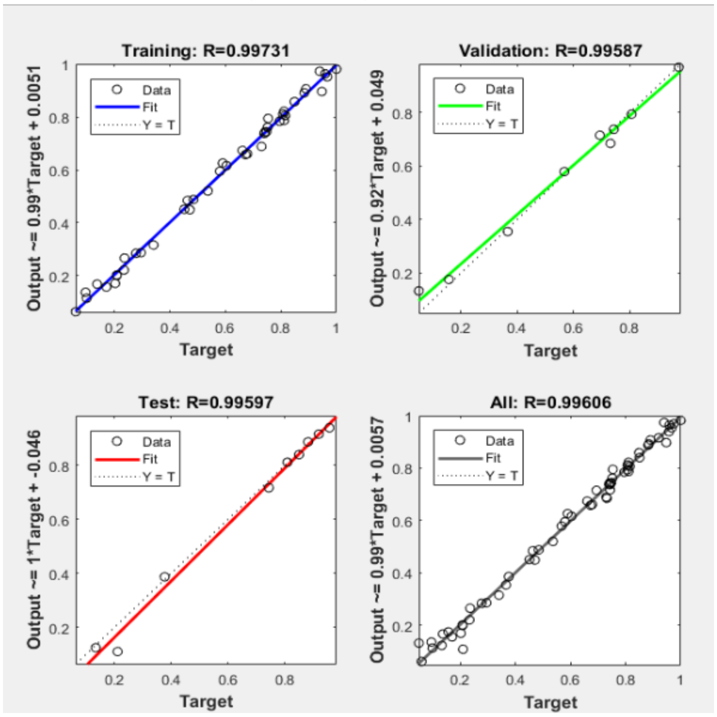

Figure 5: ANN results under the multi-layer training algorithm: for training, for validation, for test and for all

The overall acceptability is very good. Results show that ANNs are able to predict the power output of a PV panel. It can be observed that the most accurate prediction results were obtained in July and August probably due to the weather conditions were stabile while the worst accurate prediction results were in December.

5. CONCLUSION

The main target in this study has been a prediction of monthly power generation using ANNs in the perspective of climate variability. For this purpose, a single hidden layered feed forward neural network model is used.

Global horizontal irradiation, direct normal irradiation, monthly average temperature and total monthly precipitation are used as inputs. The monthly production in the solar power plant has been taken as the output. The input and output data is taken for the period 2015-2020. Developed model have correlation coefficient (R) 0,99606.

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