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# Using artificial neural network for solar energy level predicting

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**Abstract** One of the problems with the use of renewable energy sources is the determination of the optimal location of a wind or solar power station on the earth's surface. The paper suggests a model for predicting the solar energy level in the region, which allows choosing the most effective location for the location of a solar power plant. The forecast of the solar energy level is made by means of an artificial neural network, trained at the data of meteorological stations, using the backpropagation algorithm. Comparison of results of the solar energy level forecast made by the artificial neural network with the actual values shows a good correlation. This confirms the possibility of using artificial neural networks for modeling and forecasting in regions where there is no data on the level of solar energy, but there are other data from meteorological stations.

**Keywords:** *s*olar energy, artificial neural network, multilayer perceptron, backpropagation.

## 1. Introduction

The solar power represents one of the perspective directions of renewable power based on direct use of sunlight heating, power supply and hot water supply. The significance of solar power constantly grows because solar energy is environmentally friendly. In 10 minutes, Earth receives more energy from the Sun, than the humanity makes for all year.

Now maps of solar resources are created and widely available to determination of potential of a certain area in solar energy. These maps created based on satellite images and data of meteorological stations. However, the big scale of maps of the resources, which are in free access, differences in a microclimate and topography, do not allow to make the decision on the choice of the optimum project of solar power station. The mistake in the choice of the location of solar power station can significantly reduce the possible number of sunny days in a year [1].

Exact data on the solar illumination of the Earth's surface are necessary for effective systems of solar power creation. The traditional way of monitoring of solar energy consists in arrangement of the pyranometers system over a large area and their service that considerably increases the cost of data collection.

For this reason, the problem of developing of a method of the collecting of information about solar energy using the climatic data registered by stationary meteorological stations is important.

The aim of this work is to develop a neural network useable to forecast level of solar energy based on indirect data of meteorological stations.

Artificial neural networks the instrument of modeling and forecasting which gained wide recognition as a method of the solution of hardly formalizable tasks with independent parameters. Neural networks trained on test cases, have high fault tolerance for noisy and incomplete data. The trained neural network can used for forecasting in a particular subject area [2-6].

The artificial neural network is one of approaches of technology of the intellectual systems based on imitation of behavior of a human brain. Neural networks divided into two categories: feed-forward and feedback. In feed-forward neural nets, the signal extends only in one direction from inputs to output. In feedback neural nets the output signal from neuron transmitted to an input of other neuron, at the same or previous layer. In feed-forward networks neurons are divided into groups with the general output signal - layers, to each neuron of the first layer an external output signal is applied, and all outputs of neurons of the i-th layer are applied to each layer neuron (i + 1).

Multilayered perceptron - the general case of feed-forward network. It contains three types of layers of neurons: input, hidden and output. Multilayered perceptron possesses high degree of connectivity realized by means of synaptic connections. Each neuron of network has smooth nonlinear function of activation. Multilayered nonlinear neural networks allow to form more difficult connections between inputs and outputs,



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than single-layer linear. The three-layer neural network with one hidden layer can trained to approximate with certain accuracy any continuous function [7].

## 2. Data collection

Meteorological data on weather conditions from fifteen meteorological stations of North Caucasus region during 2000 - 2010 were obtained from “Aisori” database of All-Russia Research Institute of Hydrometeorological Information - World Data Centre (RIHMI-WDC) [8]. The following geographical and meteorological parameters were considered: latitude, longitude and altitude above sea level of observation points, duration of light day, temperature, relative humidity, and solar illumination. Data from seven meteorological stations were used for neural network training, data of four meteorological stations for testing, and data of four meteorological stations for validation.

## 3. Development of artificial neural network

Development of neural network demands several stages (fig. 1).

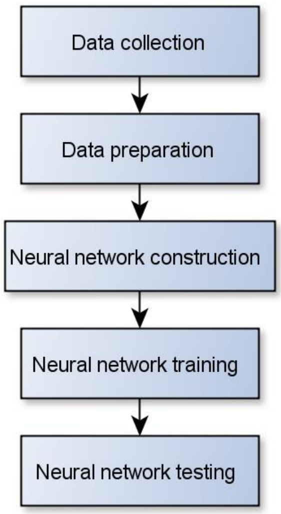


Fig. 1. Development stages of artificial neural network.

Preparation of data include data normalization and addition of the absent data (boundary averaging).

At the training stage, the neural network restores the target function, based on a training set of data, i.e. solves a problem of interpolation. At the forecasting stage, trained neural network will use the restored dependence for obtaining the predicted value, i.e. solves a problem of extrapolation [9].

The sequence of stages of creation of neural network in shown in fig. 2.

The model of a multilayer perceptron with three layers was chosen: seven neurons in the input layer, five neurons in the hidden layer and one neuron in an output layer (fig. 3). The input layer of neural network performs distributive functions. Neurons of the hidden layer have threshold function of activation and they make information processing. The output layer is necessary for information processing (definition of an error) and conclusion of result. For prevention of neural network overtraining, dimension (neurons number) of the hidden layer have to be lower than dimension of the training set. For activation of the hidden and output layer logistic and linear functions was used correspondingly.



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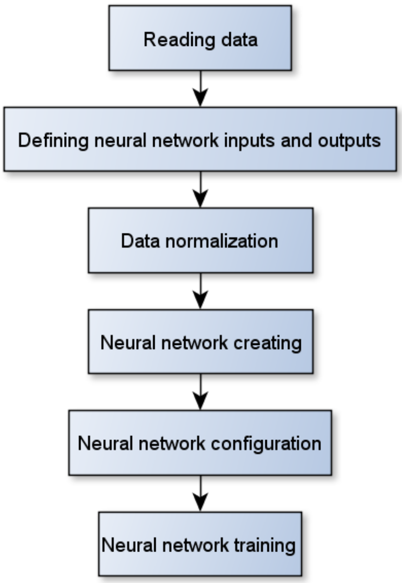


Fig. 2. Stages of neural network creation in MATLAB.

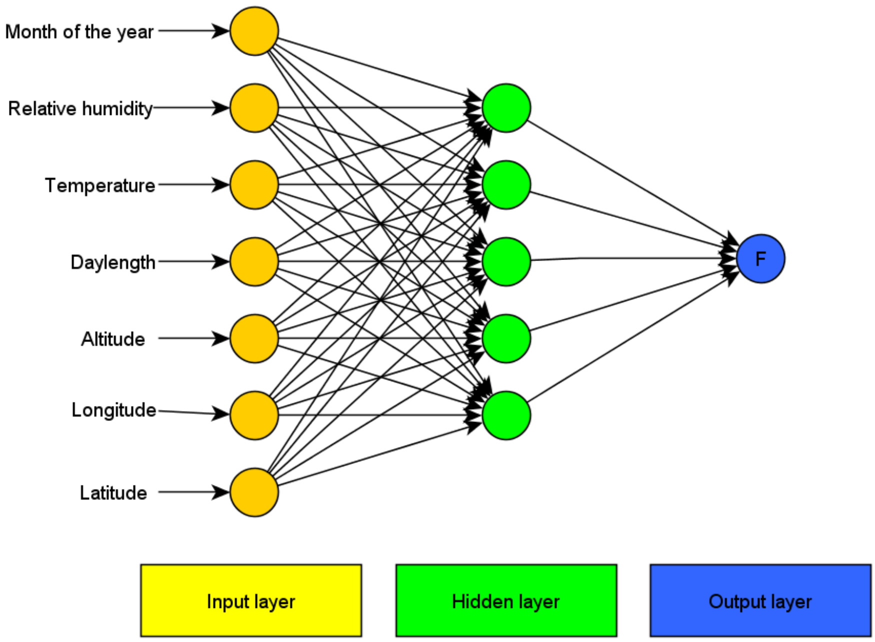


Fig. 3. Architecture of neural network.

For construction of neural network with the good generalizing ability, it is necessary to define Vapnik–Chervonenkis dimension for topology of neural network [10]:

$$2\left[\frac{K}{2}\right]N \le VC_{dim} \le 2N_w(1+\log N_n),$$

where N - dimension of input data; K - number of neurons in the hidden layer; $N_w$ – total number of weights of network; $N_n$ – total number of neurons in network.

To prevent neural network overtraining the dimension of the training data has to be more or is equal to number of neurons of the hidden layer.

There is no way to accurately define $VC_{dim}$ and as the approximate value of $VC_{dim}$ the total number of network weights is used. In [11] established that correct generalization results achieved when the number of training examples is several times greater than the number of network weights.



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Training of network was made by method of the backpropagation which general scheme is described as follows:

1. Initialize the synaptic weights of neurons by small random values;
2. Select the next data from the training sample and submit it to the network input;
3. Calculate result at the output of neural network;
4. Determine the difference between the current output of the network and the required output (target value);
5. Adjust the synaptic weights of the neural network to minimize the error;
6. Repeat steps 2 through 5 for each training data until the error on the entire set has reached an acceptable level.

After the neural network was trained and tested, it used to predict the level of solar energy based on the validation data (fig. 4).

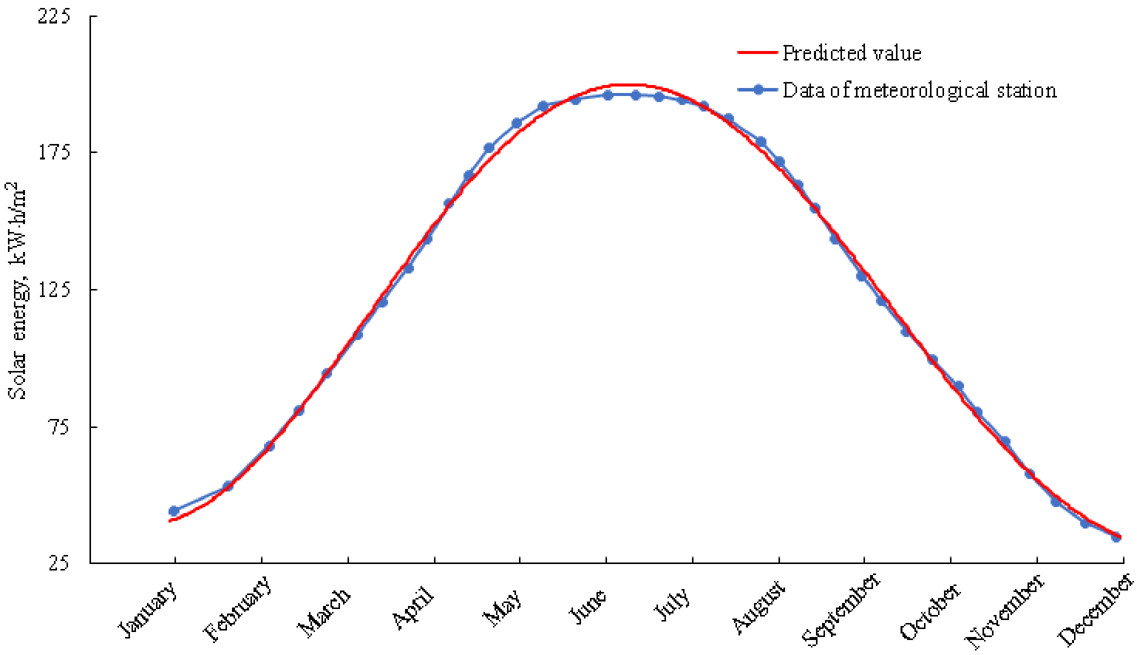


Fig. 4. The measured and expected values of average daily solar energy in Makhachkala.

## 4. Conclusion

Comparison of forecasting results of the level of solar energy given by artificial neural network with relevance show good correlation. It confirms a possibility of use of artificial neural networks for modeling and forecasting in regions where there are no data on the level of solar energy, but there are other data of meteorological stations.

## 5. References

[1] *Measurement of sunlight in solar power*, Available at: http://www.kippzonen.com/ProductGroup/3/Pyranometers (accessed 13.01.2018).

[2] A. Sozen, E. Arcaklioglu, M. Ozalp, and E.G. Kanit, *Use of Artificial neural network for mapping of solar potential in Turkey*, Applied Energy, vol. 77(3), 2004, pp. 273-286.

[3] M. Ahmed, F. Ahmad, and M. Wasim, *Estimation of global and diffuse solar radiation for Hyderabad, Sindh, Pakistan*, Journal of Basic and Applied Sciences, vol. 5(2), 2009, pp. 73-77.



DOI https://doi.org/2024-JICS-22441 | Generated on 2025-04-05 22:12:03
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[4] M. Rumbayan, A. Abudureyimu, and K. Nagasaka, *Mapping of Solar Energy Potential in Indonesia Using Artificial Neural Network and Geographical Information System*, Renewable and Sustainable Energy Reviews, vol. 16(3), 2012, pp. 1437-1449.

[5] S. Rehman, *Artificial neural network estimation of global solar radiation using air temperature and relative humidity*, Energy Policy, vol. 36(2), 2008, pp.571-576.

[6] L. Hontoria, J. Aguilera, and P.J. Zufiria, *Generation of hourly irradiation synthetic series using the neural network multilayer perceptron*, Solar Energy, vol. 72(5), 2002, pp.441-446.

[7] V.V. Kruglov, and V.V. Borisov, *Artificial neural networks. Theory and practice*, Moskow, Goryachaya liniya – Telekom, 2001, (in Russian).

[8] *Scientific and applied reference book "Climate of Russia"*, Available at: http://aisori.meteo.ru/ClspR (accessed 14.02.2018).

[9] A.N. Gorban, Ye.M. Mirkes , and V.G. Tsaregorodtsev, *Generation of explicit knowledge from empirical data through pruning of trainable neural networks, Neural Networks, IJCNN '99*, Washington, vol. 6, 1999, p.4393–4398.

[10] S. Osovskiy, *Neural networks for information processing*, Moskow, Finansy i statistika, 2002, (in Russian).

[11] A.I. Galushkin, Neural Networks Theory, Springer, 2007



DOI https://doi.org/2024-JICS-22441 | Generated on 2025-04-05 22:12:03

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