

ANFIS MODEL FOR THE PREDICTION OF GENERATED ELECTRICITY OF PHOTOVOLTAIC MODULES

Mirko Stojčić^{1*}, Aleksandar Stjepanović¹ and Đorđe Stjepanović²

¹ University of East Sarajevo, Faculty of Transport and Traffic Engineering, Doboj, Bosnia and Herzegovina

² University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia

Received: 28 October 2018;

Accepted: 12 February 2019;

Available online: 19 February 2019.

Original scientific paper

Abstract: *The fact that conventional energy sources are exhaustive and limited are increasingly encouraging research in the field of alternative and renewable energy sources. The electricity generated by solar photovoltaic modules and panels occupies an ever greater percentage in total electricity production, so it is clear that photovoltaic systems are increasingly integrating with the existing electricity network into one system or functioning as autonomous systems. The aim of the research is to create a model based on the principles of the fuzzy logic and artificial neural networks that will perform the task of predicting the maximum energy of photovoltaic modules as accurately as possible. The prediction should facilitate work in planning production and consumption, system management, economic analysis. The most important methods used in the research are modeling and simulation. Input and output variables are selected and in the ANFIS (Adaptive Neuro Fuzzy Inference System) model a set of their values is presented. Based on them it comes to the function of dependency. The prediction rating of the created model was performed on a separate data set for testing and a model with the lowest average test error value was selected. The performance of the model was compared with the mathematical model through sensitivity analysis, which led to the conclusion that the ANFIS model gives more accurate results.*

Key words (bold): *prediction, ANFIS (Adaptive Neuro Fuzzy Inference System), photovoltaic modules, artificial neural networks, fuzzy logic, RMSE (Root Mean Square Error).*

1. Introduction

Today, huge attention is paid to the fact that conventional energy sources are exhaustive and limited, and their use is a major source of pollution. Renewable

* Corresponding author.

E-mail addresses: mirko.stojcic@sf.ues.rs.ba (M. Stojčić),
aleksandar.stjepanovic@sf.ues.rs.ba (A. Stjepanović), djoles2014@gmail.com (Dj. Stjepanović)

energy sources, such as sun, wind, waves, etc., are increasingly being promoted. The electricity generated by solar photovoltaic modules and panels occupies an ever greater percentage in total electricity production. Therefore, it is clear that solar systems increasingly integrate with the existing electricity network into one system or function as autonomous systems (Ding et al., 2011). In order to supervise these systems, planning of production and consumption, management, economic analysis, it is necessary to make an accurate prediction of electricity generation. Therefore, the aim of the research is to create a model based on the fuzzy logic and artificial neural networks that will perform the specified task as accurately as possible.

Generated power and energy of photovoltaic systems depend on several factors, and the intensity of the solar radiation and the temperature of the module (Mahmodian et al., 2012), or ambient temperature (Zhu et al., 2017), are indicated as the main sources. Due to the dynamic nature of the energy generated over time and the non-linear dependence of the input and output variables, the prediction is a complex task. Today there are two current prediction methods, physical and statistical. The physical method first predicts meteorological parameters that affect the generated power or energy, and then these same parameters are used in equations. The statistical method is based on a set of data from the past (Zhu et al., 2017; Zhu et al., 2015; Wang et al., 2017). Common statistical methods include SVM (Support Vector Machine) (Zhu et al., 2017), Markov Chains and artificial neural networks (Zhu et al., 2017). Because of the properties that allow them to have a good non-linear approximation and generalization, artificial neural networks are most often used in the prediction of the performance of photovoltaic modules (Antonanzas et al., 2016). In addition, using artificial neural networks avoids complicated mathematical principles, since the network learns from training data. Various types of artificial neural networks are used, some of which are GRNN, FFBR (Feedforward Back Propagation) (Saberian et al., 2014), k-NN (K-nearest neighbors), SVM (Wolff et al., 2016), RBFNN (Radial Basis Function Neural Network), BPNN (Back Propagation Neural Network) (Mandal et al., 2012), recurrent neural networks, etc. (Mellit, 2009). Hybrid approaches that involve a combination of physical and statistical methods are often used (Wang et al., 2017).

The paper presents the materials and methods used, as well as the individual steps during the research process. Theoretical review of the neuro-fuzzy systems is particularly emphasized. The results of the research and discussion also take a special part in the work, where tables and graphs are given. The sensitivity analysis was performed in order to compare the values obtained with the ANFIS model with the mathematical model. Based on the research presented by the work, appropriate conclusions were made.

2. Materials and methods

The most important methods used in the research are modeling and simulation. The task of the model, represented by this paper, is the prediction of the generated electricity of the photovoltaic modules at the daily level. It is necessary to first select the input and output variables and present the set of their values (obtained by simulation) on the basis of which the model itself will come to the function of dependance. The model represents the integration of the principle of fuzzy logic and artificial neural networks into an ANFIS (Adaptive Neuro Fuzzy Inference System). Assessment of the ability of the prediction of the created model is done on a separate data set for testing and a model with the lowest average test error is chosen.

2.1. Selection of variables and data collection

The solar cell represents a PN coupling of a semiconductor which, on the basis of the photovoltaic effect, under the influence of the Sunlight, releases the charge carriers, resulting in current in a closed circuit. More interconnected cells comprise a module, and more modules, a photovoltaic panel.

According to its structure, the solar cell is most often constructed from semiconductor materials (Si, Ge, GaAs), and represents a pn compound that absorbs photons from solar radiation and uses their energy to create electron-cavity pairs. The internal electric field that exists on an impoverished area of the pn junction separating couples holders that are created within or near the pn junction. From the front and back of the solar cell, contacts are collected that collect separate energies, and an electromotive force appears at the ends of the cell. The electrons and cavities in the semiconductor tend to move from a higher density region to a less-density region. When multiple solar cells transmit to a serial or parallel connection, a photovoltaic panel with the desired output voltage or current is obtained. Due to the effect of solar radiation on the surface of the solar cell or panel, there are changes in several important parameters of the solar cell (photovoltaic panels), the concentration of free carriers and the width of the energy gap between the semiconductor. The change in these parameters is conditioned by the intensity of the radiation and the influence of the outside temperature. The increase in temperature on the panel affects the output parameters of the photovoltaic panel, the output current and voltage, and thus the power. A solar cell model based on two semiconductor diodes was selected to create a photovoltaic panel model. Figure 1 shows the solar cell model (Castaner & Silvestre, 2002):

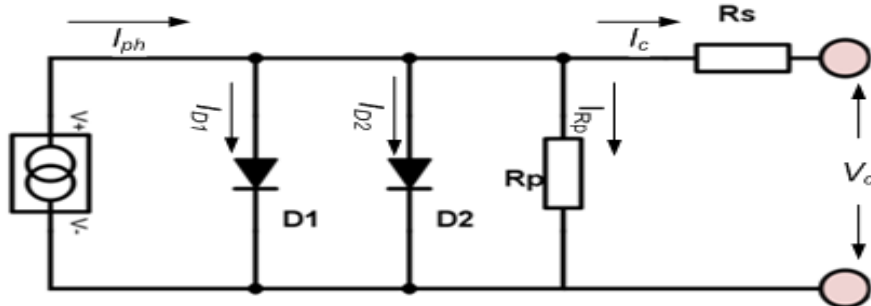


Figure 1. Solar cell model with two diodes (Castaner & Silvestre, 2002)

The dependence of the short-circuit current on the intensity of the incident solar radiation and the temperature of the environment and the module can be represented by the following pattern (Castaner & Silvestre, 2002; Sharma & Jain, 2014; Guo et al., 2014):

$$I_{scM} = \frac{I_{scMr}}{1000} \cdot E + \left(\frac{dI_{scM}}{dT} \right) \cdot (T_c - T_r) \quad (1)$$

and the open-circuit voltage is given by the approximate relation (Castaner & Silvestre, 2002; Sharma & Jain, 2014):

$$V_{ocM} \approx V_{ocMr} + \left(\frac{\partial V_{ocM}}{\partial T} \right)_E \cdot (T_c - T_r) + V_T \cdot \ln \frac{I_{scM}}{I_{scMr}} \quad (2)$$

where: I_{scMr} - short-circuit current of the photovoltaic module at the reference temperature, E - intensity of the solar radiation V_{ocM} - the open-circuit voltage of the photovoltaic module, the V_{ocMr} - the open-circuit voltage of the photovoltaic module at the reference temperature, T - ambient temperature, T_c - temperature of the module, T_r - reference temperature.

The output performance of photovoltaic modules depends to a large extent on the intensity of radiation and temperature. Therefore, for the input variables of the model, the daily amount of solar radiation (measured in kWh/m²/day) and the average temperature of the module (in °C), are chosen. As the output variable is observed the virtual maximum energy that the photovoltaic modules can supply at the maximum power point for one day, measured in kWh/day.

Data collection for model training is carried out by the simulation method in PVsyst software, which is intended for engineers, architects and researchers involved in the analysis and construction of photovoltaic systems, i.e. systems that convert Solar radiation into electricity. PVsyst is an industrial standard, but it is also very useful as an educational software. A simulation model of an autonomous photovoltaic system has been created which supplies consumers with electricity exclusively generated by solar modules, independent of the public electricity network. The selected location is in Banja Luka (RS, BiH), and the model envisages a daily electricity consumption of 915 Wh/day. The real components are available, so that two photovoltaic modules are specified (two modules are the panel) of LG Electronics with a maximum power of 300 Wp and a total area of 3 m², batteries have a total capacity of 400 Ah. Once the system is defined, its block diagram can be seen in Figure 2. It is important to point out that the regulator, belonging to this system, contains a maximum power point tracker (MPPT - Maximum Power Point Tracker) because of the low degree of conversion of solar radiation into electricity. The MPPT is implemented as a microcontroller which, together with the DC-DC converter, transmits the maximum power from the module to the system.

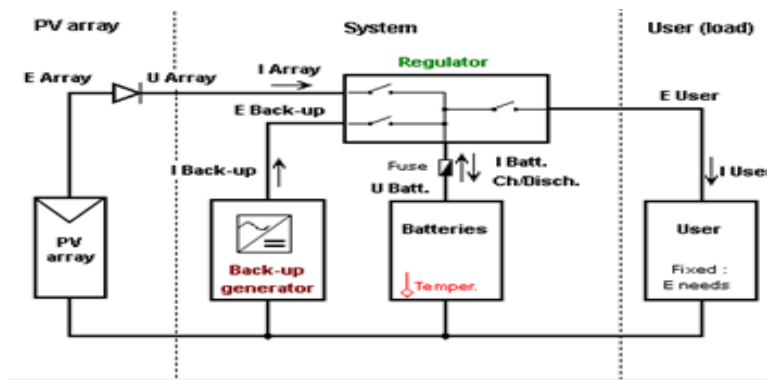


Figure 2. Block diagram of the photovoltaic autonomous system in the PVsyst program

ANFIS model for the prediction of generated electricity of photovoltaic modules

Figure 3 shows the general block diagram of the photovoltaic system. The A/D converter provides an input signal for the MPPT that is connected to a pulse width modulator (Pulse Width Modulator - PWM). In PW modulation, the mean value of the signal changes depending on the length of the period and the duration of the rectangular pulse. A modulated signal represents an input signal for a DC-DC converter that transforms the DC voltage of one value to the DC voltage of the second value.

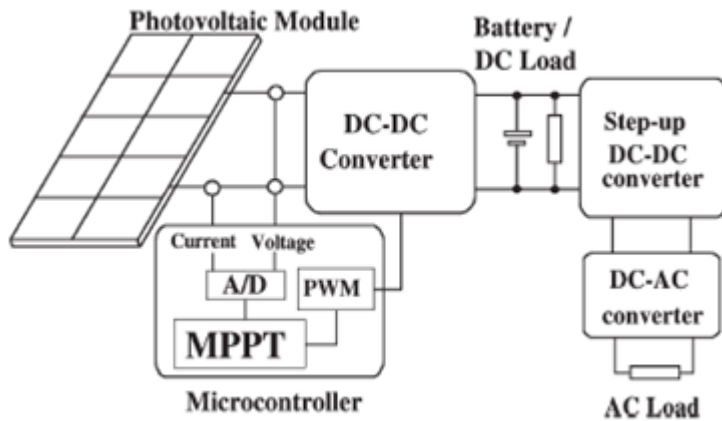


Figure 3. Block diagram of photovoltaic system (Gules et al., 2008)

Training data for the ANFIS model is obtained by performing simulations on the model of the photovoltaic system for a period of one year. The values of the input and output variables are selected for five days each month, which makes a total of 60 training vectors. In addition, a special set of data for testing and testing of the ANFIS model has been created, which consists of realized values of the variables for one day during each month - 12 vectors.

2.2. Artificial neural networks and fuzzy logic

Artificial neural networks represent an attempt to model the human brain. Similarity with the work of the human brain is reflected through the structure, function and method of processing data and information. No matter what network it is, their common feature is the ability to learn. Therefore, their main application is to look for dependencies between data that are not in a strict linear relationship. The training process is based on adjusting the weight of network connections. However, the network can be trained structurally, i.e. the correct choice of the number of neurons, layers, etc. (Bašić et al., 2008).

Fuzzy logic is an extension of classical logic, allowing the work with uncertainties to make the computer adapt to the human way of thinking. The word fuzzy implies something unclear, indeterminate, but that does not mean that there is something unclear with the fuzzy logic itself, but that it has enabled the presentation of uncertainty.

By applying the fuzzy logic in various fields, it was difficult to create a fuzzy-inference system with good performance. Tasks such as finding adequate membership functions and the fuzzy inference rules pose problems to experts in a

particular field. Hence the idea that the principles of the fuzzy logic and neural networks are combined in a unique system called the neuro-fuzzy system, combining both the ability to learn and logical conclusion. ANFIS is one of the most commonly used architectures of the neuro-fuzzy system (Figure 4).

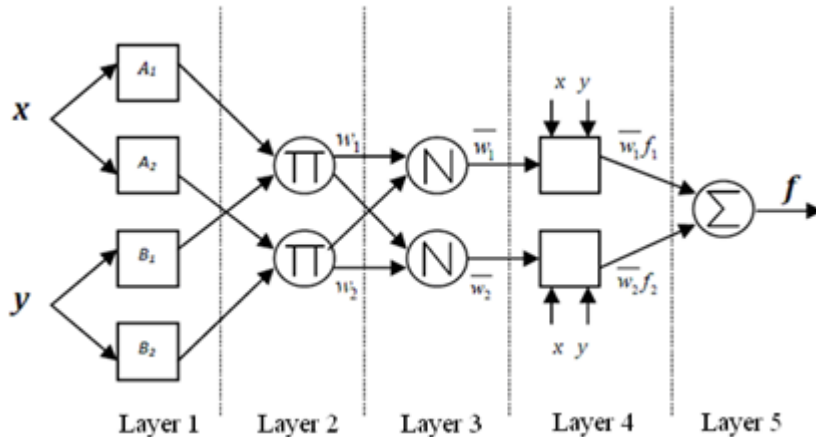


Figure 4. Architecture of the ANFIS model

Nodes of the first hidden layer define the fuzzy sets, i.e. fuzzy membership functions corresponding to the input variables. The nodes of this and the fourth layer are adaptive, which means that their parameters change during the training process. Therefore, in Figure 4 they have a rectangular shape in contrast to the fixed, circular nodes. The nodes of the second hidden layer are fixed and perform an operation of multiplying the input signals (operation AND), which determines the degree of consistency of the premise (IF part) of each rule - w_i , which has a general shape:

IF x is A **AND** y is B , **THEN** $z=f(x,y)$,

where A and B are fuzzy sets corresponding to the input variable, and $z = f(x, y)$ function that is a consequence of the rule (Raja & Pahat, 2016; Rasit, 2009). The function $z = f(x, y)$, can be a polynomial of zero or first order, i.e. constant or linear function. The third hidden layer normalizes the values obtained at the output of the nodes of the second hidden layer. In the case shown in Figure 4, with two nodes in the second layer, the normalized value at the output of the node of the third hidden layer has the following mathematical form:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \tag{3}$$

Each node of the fourth hidden layer is an adaptive node with a function it realizes, which can be written as follows:

$$\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{4}$$

ANFIS model for the prediction of generated electricity of photovoltaic modules where p_i , q_i and r_i conclusion parameters. The fifth layer calculates the output as the sum of all input signals:

$$f = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (5)$$

The ANFIS model for the prediction of generated electricity of photovoltaic modules was created in the MATLAB software package. The ANFIS editor, thanks to the graphical user interface, allows easy definition and work with the model. The algorithm describing the process from creation to model evaluation can be written in the following steps:

1. Loading data for training, checking and testing (60 training vectors, 12 for checking and testing),
2. Defining the number and shape of the fuzzy membership functions of the input variables and the form of the membership function of the output variable,
3. Model training (Hybrid training algorithm, tolerance error=0, epoch number=60),
4. Testing the ANFIS model, RMSE (*Root Mean Square Error*).
5. Testing data allow you to evaluate the ability of the ANFIS model to execute a prediction of the value of the output variable.

The outputs of the ANFIS model are compared with already known values and, based on this, RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^N [n(k) - \hat{n}(k)]^2} \quad (6)$$

where N is the number of individual observations (the number of data vectors for testing, $N = 12$), $n(k)$ is the expected value (obtained by the simulation in the PVsyst program), $\hat{n}(k)$ - the value obtained by the model. The verification data is primarily aimed at preventing the occurrence of *overfitting*.

3. Results and Discussion

Table 1 shows the different values of the average testing error, depending on the shape of the membership function of the input variables, their number, and the output form of the ANFIS model. The model with the lowest value of the average testing error or RMSE=0.209 is chosen. Such an error value is achieved with the triangular form of the fuzzy membership functions (two of them for each input variable) and the linear function of the output of the model.

Table 1. Different values of the average testing error (RMSE) for model

Shape of the membership functions of input variables	Form of output function of ANFIS model					
	Linear			Constant		
	Number of membership functions of the input variables					
	2 2	3 3	4 4	2 2	3 3	4 4
trimf	0.209	0.321	6.321	0.243	0.211	0.361
trapmf	0.245	0.938	0.442	0.483	0.292	0.981
gbellmf	0.223	1.047	39.464	0.348	0.220	0.396
gaussmf	0.212	0.642	36.433	0.288	0.215	0.335
gauss2mf	0.252	1.141	46.554	0.383	0.225	0.573
pimf	0.256	1.206	0.508	0.609	0.351	3.229
dsigmf	0.254	0.620	11.073	0.578	0.302	0.498
psigmf	0.254	0.620	11.073	0.578	0.302	0.498
	5 5	2 3	3 2	5 5	2 3	3 2
trimf	10.450	0.221	0.240	0.335	0.217	0.256
trapmf	1.141	0.244	0.418	1.060	2.289	0.439
gbellmf	8.447	0.286	0.535	0.530	0.216	0.331
gaussmf	19.091	0.252	0.665	0.272	0.213	0.291
gauss2mf	280.229	0.399	0.296	16.590	0.245	0.344
pimf	3.839	0.240	0.727	6.537	0.330	0.558
dsigmf	34.961	0.226	0.661	6.608	0.307	0.518
psigmf	34.961	0.226	0.661	6.608	0.307	0.518

The graphical results of the prediction of the selected model are given in Figure 5. Red stars represent the values given by the model, while the blue points are known values (data for testing). From Figure 5 it is evident that the generated daily electricity has the greatest value in the summer months, because it is presented on the apsis one day for each month of the year.

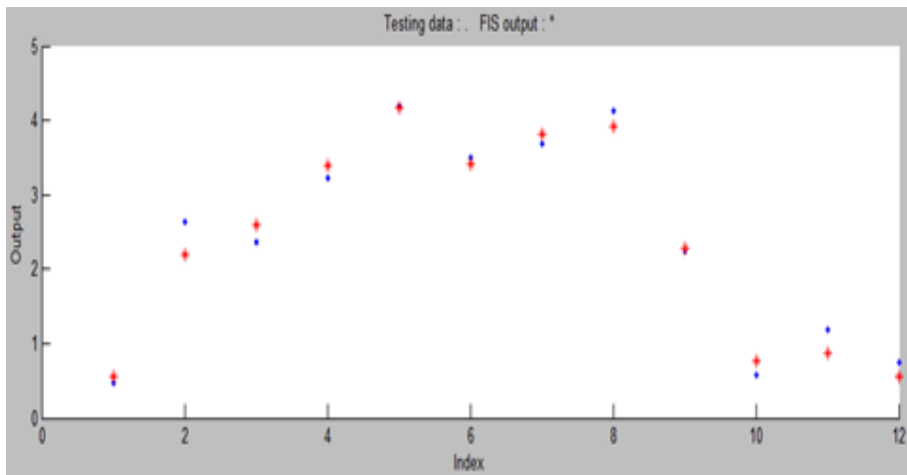


Figure 5. Graphical representation of the prediction for the selected ANFIS model

ANFIS model for the prediction of generated electricity of photovoltaic modules

Figure 6 shows the shape of the membership functions of the input variables. As can be seen from Table 1, membership functions have a triangular form.

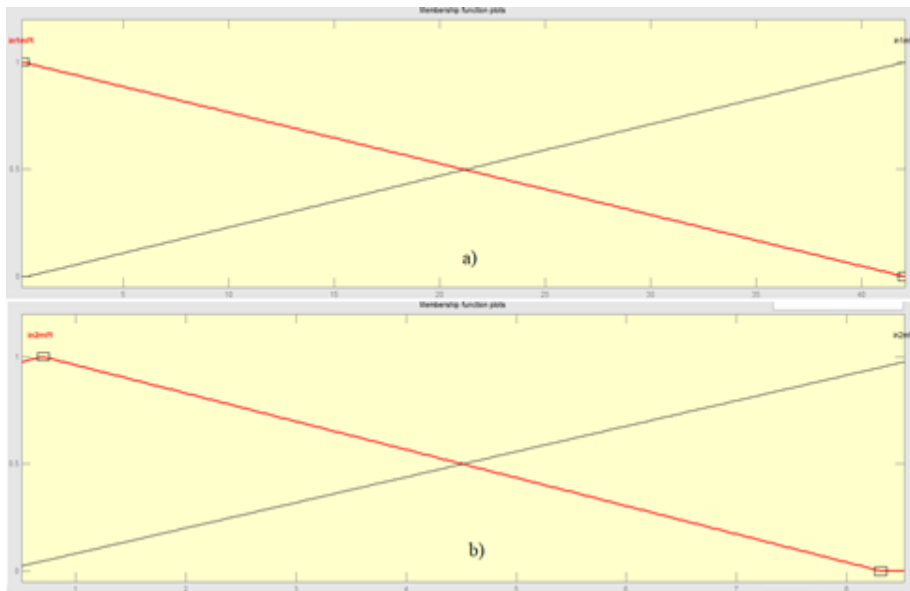


Figure 6. Forms of the membership functions of the input variables: a) Average temperature of the module; b) Daily amount of solar radiation

Figure 7 shows the structure of the selected ANFIS model where the number of nodes in each layer of the network is visible.

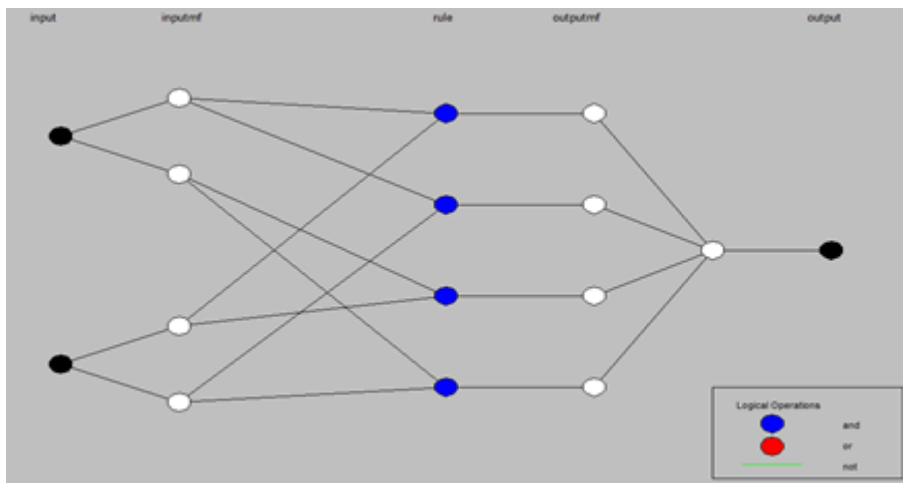


Figure 7. The structure of the selected ANFIS model

The surface that represents the dependence of the output variable of the two inputs in the selected ANFIS model is shown in Figure 8. It can be concluded that

when the energy of the solar radiation increases, the maximum virtual energy of the photovoltaic modules increases. In contrast, the average temperature adversely affects the output variable, as its increase results in a slight decrease in the maximum virtual energy of the photovoltaic modules.

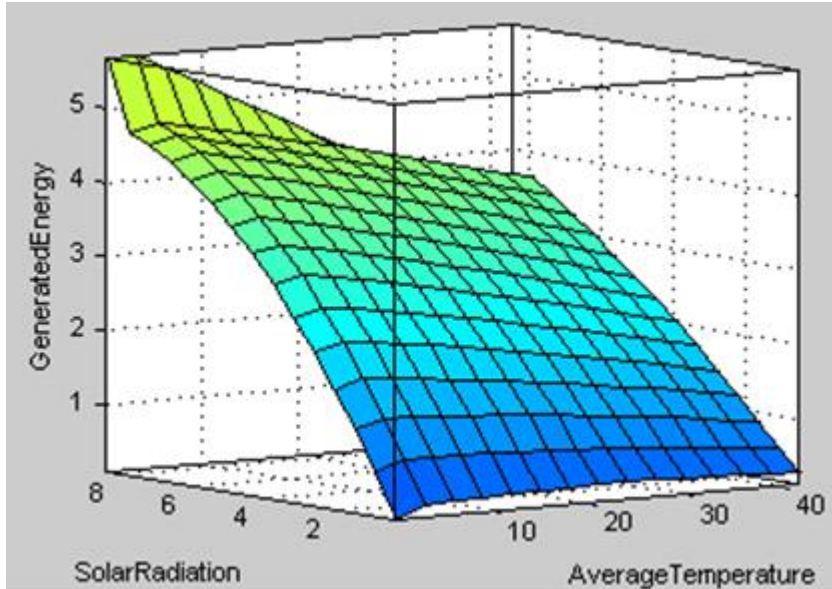


Figure 8. The surface of the dependence of the maximum virtual energy from the solar radiation and the average temperature of the module

4. Sensitivity analysis

In order to perform the sensitivity analysis, in this section will be compared the values of the prediction created by the ANFIS model and the regression mathematical model. The regression was performed on a data set for training the ANFIS model. Table 2 shows 15 different mathematical models together with the corresponding prediction correlation indexes. For simpler presentation, the selected variables carry the following tags:

- Daily amount of solar radiation - E
- Average temperature of the module - T
- Virtual maximum generated energy – Electricity.

Table 2. Regression mathematical models

Number	Model	R ² pred (%)
1	Electricity = 0.386 - 0.00128 T + 0.5045 E	87.90
2	Electricity = 0.049 + 0.0446 T + 0.5027 E - 0.001189 T ²	88.60
3	Electricity = -0.146 + 0.0144 T + 0.882 E - 0.000764 T ² - 0.0407 E ²	90.78
4	Electricity = -0.164 + 0.0186 T + 0.882 E - 0.00101 T ² - 0.0407 E ² + 0.000004 T ³	90.53

ANFIS model for the prediction of generated electricity of photovoltaic modules

Number	Model	R ² pred (%)
5	Electricity = -0.184 + 0.0163 T + 0.923 E - 0.00091 T ² - 0.0522 E ² + 0.000003 T ³ + 0.00089 E ³	90.26
6	Electricity = -0.065 + 0.842 E - 0.0502 E ² + 0.00130 E ³	89.75
7	Electricity = -0.046 - 0.01682 T + 1.032 E - 0.0769 E ² + 0.00250 E ³	90.29
8	Electricity = 0.039 - 0.01639 T + 0.920 E - 0.0447 E ²	90.50
9	Electricity = -0.020 + 0.7851 E - 0.0336 E ²	90.01
10	Electricity = 0.6886 + 0.1767 E ² - 0.01552 E ³	87.75
11	Electricity = 0.170 - 0.01507 T + 0.7518 E - 0.003306 E ³	90.30
12	Electricity = -0.122 + 0.986 E - 0.000454 T ² - 0.0649 E ² + 0.00167 E ³	90.66
13	Electricity = 0.069 + 0.7538 E - 0.000437 T ² - 0.003279 E ³	90.75
14	Electricity = 0.7324 - 0.000275 T ² + 0.1913 E ² - 0.01704 E ³	87.87
15	Electricity = -0.174 + 0.0134 T + 0.925 E - 0.000744 T ² - 0.0531 E ² + 0.00095 E ³	90.52

As can be concluded from Table 2, the largest correlation index has a model numbered at number 3, 90.78%. It is a second-degree model that has the following form:

$$\text{Electricity} = -0.146 + 0.0144 T + 0.882 E - 0.000764 T^2 - 0.0407 E^2$$

Table 3 gives an overview of the expected values of the generated photovoltaic module energy (test data), as well as the values obtained by ANFIS and the regression model, for the same input values. Values are expressed in kWh/day.

Table 3. The expected values of the generated energy and the values obtained by the prediction of ANFIS and the mathematical model

Expected value of generated energy	Value obtained by an ANFIS model	Value obtained by the regression mathematical model
0.48	0.56	0.57
2.64	2.19	2.09
2.36	2.60	2.49
3.23	3.39	3.41
4.19	4.17	4.22
3.50	3.41	3.42
3.68	3.81	3.83
4.12	3.93	3.92
2.24	2.28	2.28
0.58	0.76	0.71
1.19	0.88	0.76
0.75	0.56	0.56

In addition to a tabular display, these values can also be represented graphically, as shown in Figure 9

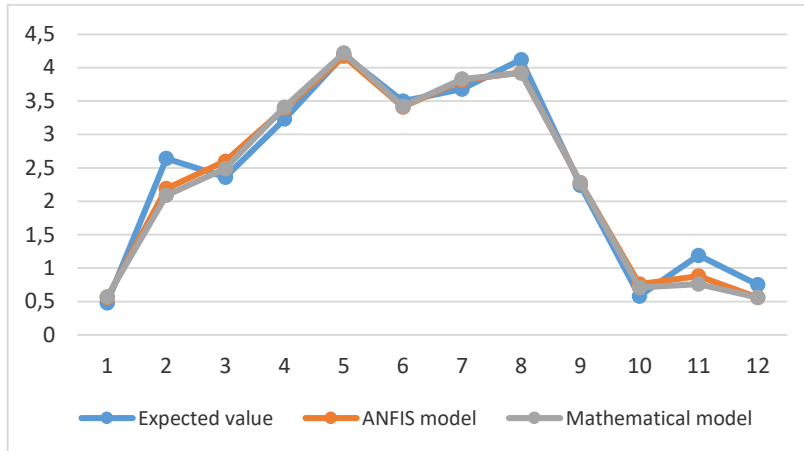


Figure 9. Diagram of expected values, values obtained by ANFIS and mathematical model

By comparing the output variable from the test data with the values obtained by the specified mathematical model, the RMSE = 0.235 value is obtained, which is more than the selected ANFIS model (0.209). Therefore, it is clear that the ANFIS model shows better performance.

5. Conclusion

The research presented by the paper focuses on the development of a model for the prediction of maximum energy generated photovoltaic modules based on neuro-fuzzy principles. The model represents a simple solution that requires the value of the output variable for the given values of the energy of the Sun's radiation and the average temperature of the module. Model training was performed according to the data obtained by the simulation, so that it is possible to deviate if the values obtained by the prediction were compared with the actual measured values. Nevertheless, PVsyst is a widely used software, so that data obtained by simulating the performance of photovoltaic modules can be considered relevant for the training of the ANFIS model. It is obvious that the selected model yields better results than mathematical model, although it has a high percentage of adequacy. The maximum energy generated depends to a large extent on the energy of the Sun's radiation, while the influence of the temperature is considerably smaller and negative. Future research may take into account other factors that influence the generation of energy in order to increase accuracy.

Author Contributions: Each author has participated and contributed sufficiently to take public responsibility for appropriate portions of the content.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- Antonanzas, J., Osorio, N., Escobar, R., Urraca, R., Martinez-de-Pison, F. J. & Antonanzas-Torres, F. (2016). Review of photovoltaic power forecasting. *Solar Energy*, 136, 78-111.
- Bašić, B. D., Čupić, M., & Šnajder, J. (2008). *Umjetne neuronske mreže*. Zagreb: Fakultet elektrotehnike i računarstva.
- Castaner, L., & Silvestre, S. (2002). *Modelling Photovoltaic Systems using PSpice*. England: John Wiley & Sons Ltd, The Atrium, Southern Gate, Chichester West Sussex.
- Ding, M., Wang, L., & Bi, R. (2011). An ANN-based approach for forecasting the power output of photovoltaic system. *Procedia Environmental Sciences*, 11, 1308-1315.
- Gules, R., Pacheco, J. D. P., Hey, H. L., & Imhoff, J. (2008). A maximum power point tracking system with parallel connection for PV stand-alone applications. *IEEE transactions on industrial electronics*, 55(7), 2674-2683.
- Guo, G., Wu, X., Zhou, S., & Cao, B. (2014). Modeling of solar photovoltaic cells and output characteristic simulation based on Simulink. *Journal of Chemical and Pharmaceutical Research*, 6(7), 1791-1795.
- Mahmodian, M. S., Rahmani, R., Taslimi, E., & Mekhilef, S. (2012). Step by step analyzing, modeling and simulation of single and double array PV system in different environmental variability. In *Proceedings of International Conference on Future Environment and Energy* (pp. 37-42).
- Mandal, P., Madhira, S. T. S., Meng, J., & Pineda, R. L. (2012). Forecasting power output of solar photovoltaic system using wavelet transform and artificial intelligence techniques. *Procedia Computer Science*, 12, 332-337.
- Mellit, A. (2009). Recurrent neural network-based forecasting of the daily electricity generation of a Photovoltaic power system. In *Ecological Vehicle and Renewable Energy (EVER)*, Monaco, March, 26-29.
- Raja, P., & Pahat, B. (2016). A review of training methods of ANFIS for applications in business and economics. *International Journal of u-and e-Service, Science and Technology*, 9(7), 165-172.
- Rasit, A. T. A. (2009). An adaptive neuro-fuzzy inference system approach for prediction of power factor in wind turbines. *IU-Journal of Electrical & Electronics Engineering*, 9(1), 905-912.
- Saberian, A., Hizam, H., Radzi, M. A. M., Ab Kadir, M. Z. A., & Mirzaei, M. (2014). Modelling and prediction of photovoltaic power output using artificial neural networks. *International Journal of Photoenergy*, ID 469701, <https://doi.org/10.1155/2014/469701>
- Sharma, C., & Jain, A. (2014). Solar panel mathematical modelling using simulink. *International Journal of Engineering Research and Applications*, 4(5), 67-72.
- Wang, J., Ran, R., & Zhou, Y. (2017). A short-term photovoltaic power prediction model based on an FOS-ELM algorithm. *Applied Sciences*, 7(4), 423.

Wolff, B., Lorenz, E., & Kramer, O. (2016). Statistical learning for short-term photovoltaic power predictions. *Computational sustainability*, 31-45.

Zhu, H., Li, X., Sun, Q., Nie, L., Yao, J., & Zhao, G. (2015). A power prediction method for photovoltaic power plant based on wavelet decomposition and artificial neural networks. *Energies*, 9(1), 11. <https://doi.org/10.3390/en9010011>

Zhu, H., Lian, W., Lu, L., Dai, S., & Hu, Y. (2017). An improved forecasting method for photovoltaic power based on adaptive BP neural network with a scrolling time window. *Energies*, 10(10), 1542.



© 2019 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license

(<http://creativecommons.org/licenses/by/4.0/>).