ANN solution for increasing the efficiency of tracking PV systems

Duško Lukač and Miljana Milić

Abstract - The purpose of the this research is to build up a system model using artificial neural network (ANN), which should be used to forecast the performance of a tracking solar cell in compare with a fixed positioned cell, by taking into account the outside temperature and light radiation. In this way, one can perform an annual profit comparison as well as the prediction in order to decide whether a tracking PV cell is worthwhile or not. The network was trained using the Cologne weather data collected during one day measurements on a particular Polycristal solar module. The first obtained results have shown that this idea can be considered promising and should be further exploited.

Keywords - Policrystal PV cell, Feed-forward artificial neural networks, Solar cell tracking system.

I. Introduction

The efficiency is one of the most problematic issues in solar cell manufacturing and exploitation. During last few decades, many attempts were made in different scientific disciplines to improve it. Bell Laboratory fabricated the first crystalline silicon solar cells in 1953, achieving the efficiency of 4.5% [1], [2], [3]. Those early PV cell fabrication technologies suffered from high cost, low stability, manufacturability, durability and/or toxicity [4]. Due to constant research effort in this area, these values were changing slowly but unquestionably during many years.

Depending on the production technology, solar cells can be divided into two groups: ones produced from Si wafers i.e., silicon solar cells and others, produced with vacuum technologies i.e., thin-film solar cells. According to the crystalline structure, amorphous, poly-crystalline and mono-crystalline solar cells can be distinguished. In order to build solar modules with power range of two hundred watts or more, solar cells are being connected together. For large PV systems special PV modules are produced with typical power range of up to several hundred watts. The solar module properties depend mainly on the type of the applied solar cell [5].

The improvements in fabrication technology and materials are welcome and expected, since large amounts of money goes for this research. But our aim here is to show that good efficiency improvements can be achieved at the application side of PV modules as well.

Basically one can increase the yield of a solar cell device by actively turning the solar generator to the sun. However, the tracking system increases only the direct radiation component, while the diffuse radiation remains nearly unchanged. As an example Fig. 1 shows the day yields of a tracked solar cell and a fixed one during two different days. During the sunny day the tracked solar cell can increase the energy profit for nearly 60%. Nevertheless, in the case of a cloudy day the yield of the tracked arrangement is approximately 10% less then with the fixed system arrangement. The reason for this lies in the fact that the tracked modules can stand at an acute angle in the morning and in the afternoon and therefore receive vague radiation.

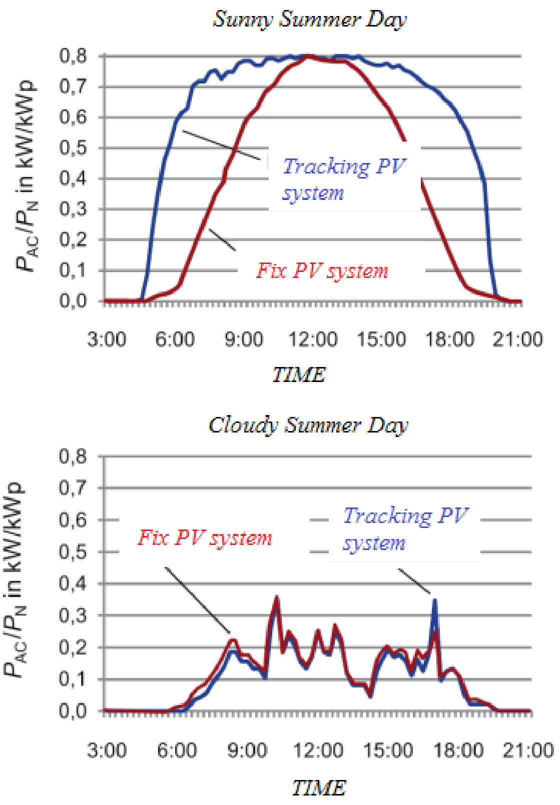

Fig. 1. Yield comparison between fixed and tracked PV cell by different weather conditions

More than half of the annual global radiation in Germany can be categorized as the vague. That's why the

Duško Lukač is with Rheinische Fachhochschule Koeln gGmbH, Schaevenstr. 1 a/b, 50676 Koeln, Germany, E-mail: dusko.lukac@rfh-koeln.de.
Miljana Milić is with the Department of Electronics, Faculty of Electronic Engineering, University of Niš, Aleksandra Medvedeva 14, 18000 Niš, Serbia, E-mail: miljana.milic@elfak.ni.ac.rs.

profit win of tracking solar cell systems is limited to approximately 30%. Hence, the application of tracking solar cell systems should be considered with respect to additional mechanical and electric expenditures. One example of the tracking PV system is shown in Fig. 2.

Fig. 2. 2-axis PV tracking system (Mover M100)
Source: http://www.pv-mover.com/tl_files/pv_mover/images/PVMover%202010/ MG_9663kl.jpg

To realize a comparison of yields with and without construction of the tracking solar arrangement, an artificial neural network will be trained. The network should perform the prediction of the profit win when tracked solar arrangements are observed, in order to decide, whether they should be used or not.

II. Preparation of Input Data and Calculation of Outputs

The feed-forward ANN model, which is to be developed using the principles of the supervised learning, needs a large number of input-output data pairs in order to represent the required function. The number of all possible input-output data pairs can be calculable, since the large amount of data for ANN training would last unacceptably long, regardless of the used arithmetic system. For modelling of the artificial network, the sufficient number of training pairs can be calculated according to various criteria. For example, the number of training pairs (TP) as reported by [6], depends on the number of neurons in input, hidden and output layer of the ANN. On the other hand, the number of TP, according to [7] depends on the number of weights (W) and acceptable testing errors (ε) and is calculated as: $N > \frac{W}{\varepsilon}$. This rule is not used in our study because of the lack of necessary data. In order to obtain required value for TP, the number of the hidden neurons must be considered. For the calculation of the number of hidden neurons different criteria can be tested, such as those described in [8] and [9]. Because of relatively small number of input and output neurons for our purpose, criteria by [9] appear to be more fitting. The number of hidden neurons taking into account 4 input and 3 output neurons, according to chosen criterion is therefore shown in the following table:

TABLE I
Calculation of the Number of the Hidden Neurons and Training Pairs

Reference	Number of hidden neurons	Minimal number of training pairs (TP), by [6]
[9]	H = 1 ... 3 * 4 = 4 ... 12	TP = 5 * ((4*4)+(4*3)) = 140 → minimal case 900 → maximal case

The number of TP, which is calculated as described in [6], is also shown in the table. As stated in [6] there should be at least 5-times more training pairs than weights. Therefore the following minimal and maximal TP values arise:

- Minimal = 140
- Maximal = 900

With the calculation of training pairs, confirming to chosen expert's criteria, we plan to reach at least the minimal number of TP, while in the optimal case, the maximal number of TP. With total amount of 658 available training pairs in this work, it can be assumed that we are in the good middle. The preparation of the input values is carried out with the help of the Excel programme.

III. Data Normalisation

Dependent and independent variables, as well as the criteria of their goodness, are defined with respect to values that may differ numerically and in meaning. If these values were fed into an ANN without normalisation, the net would be wrongly trained considering its weights because such weights could not represent the input and output (result) relations, neither numerically nor by the meaning. The weight's change depends on the "height" of the derivation of the neuron activation function and for the case of very small and very large input values of logistic function behaves in the same way, i.e., is constantly equal to zero. Consequently, no weight change arises during the training process, which leads to failure in learning. Therefore, ranges of input values should be made narrower, while the appropriate input connection weights should also be kept small. Hence, the input beside small initial weights and learning rates should also have small span. Such a phenomenon is called "Saturation" of the ANN [10].

In order to achieve equal level of weights accommodation for different ANN layers, a pre-processing of all used values of the input vector is necessary. This process is called normalisation or standardisation, and it guarantees the comparability of the data. There are many different suggestions for the standardisation of the input or output values. Some of the standardisation methods are described in [11], [12] where normalisation procedure can be calculated as (1):

TABLE II

SYSTEMATIZATION OF THE ANN TRAINING DATA

Input1	Input2	Input3	Input4	Output	Output1>10%	Output2>30%	Output3>50%
I [mA]	U [V]	Outside temperature	Weather/ Light	Pn [W]/ P [W]			
fixed (normalized)	fixed (normalized)	°C (normalized)	sunny (0,9); cloudy (0,5), raign/dark (0.1) (normalized)	tracked in % (normalized)	Efficiency increase with a tracked module > 5%	Efficiency increase with a tracked module > 10%	Efficiency increase with a tracked module > 20%
0.389473684	0.9375	0.48	0.5	0.07998908	0.07998908	0	0
0.392982456	0.943181818	0.48	0.5	0.063898451	0.063898451	0	0

$$SV_{VV} - TF_{min} + (TF_{max} - TF_{min}) \cdot \frac{D - D_{min}}{D_{max} - D_{min}} \cdot V \quad (1)$$

Description of the abbreviations:

- *SV* - Scaled Value
- TF_{min} and TF_{max} - minimal and maximal value of the transfer function
- *D* - observed values
- D_{min} and D_{max} = minimal and maximal values of the observation

The highest value can therefore be at least 1, and the lowest value 0. Besides, the absolute value is the one to be followed. The addition of the negative TF_{min} value occurs in the form of the reverse array of the values. Therefore the values of input and output vectors are normalised taking into account the use of the logistic function. The normalisation of input or output values can be carried out by applying the framework used at Rheinische Fachhochschule-Koeln, for example. In this research, training pairs are standardised before the net training.

IV. DESIGN OF THE ANN, TARGET NET ERROR AND RESULTS

Designed ANN is presented in Fig. 3. The selected topology represents a feed-forward ANN cell with one hidden layer, containing four input, eight hidden and tree output neurons.

A small part of training data obtained after normalization can be systematized in the Table 2.

Before the net training, the TPs have been separated into the training, test and validation set according to ration 70:20:10. The net learning has been carried out conforming to Resilient Backpropagation (RPROP) algorithm defined in [13]. Target net error for “auto teacher” has been set to 2%. Training has been performed with Intel Pentium 2020M, 2.4 GHz processor PC, and took 45min till the target values have been reached. The target net error graph is shown in Fig. 4. The target net error is satisfied after the training.

When the ANN training is complete, it has been tested with the test set and validated with the validation set. Definition of the test set is presented in Fig. 5.

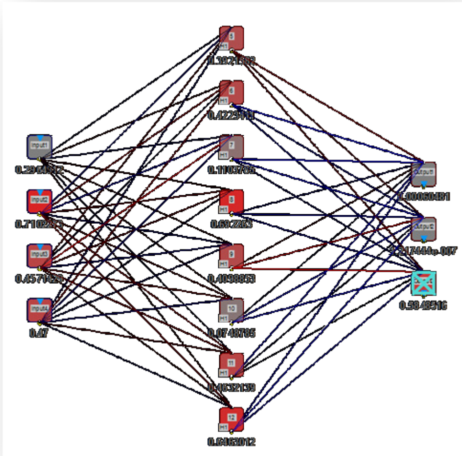

Fig. 3. Architecture of the used ANN

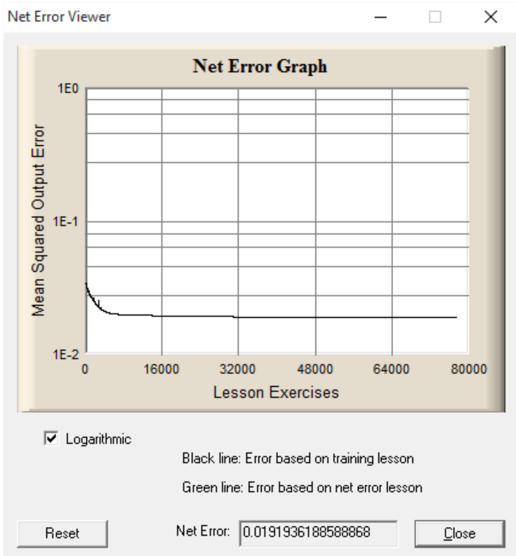

Fig. 4. Target net error graph

In the particular case of the input values, the Output 3 has to be activated (increase of the performance > 20%).

This situation is shown in the Fig. 6.

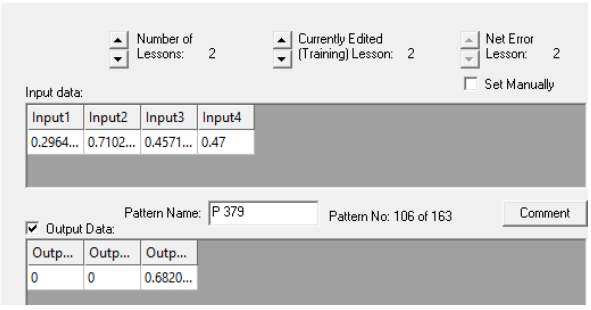

Fig. 5. Definition of the test set

In Figs. 7, 8, and 9, the target and current output activation of the output neurons 1, 2 and 3, respectively are presented. By observing the following figures, it can be concluded that the training of the output neuron 2 is optimal, while trainings of output neurons 1 and 3 are very good, but may sporadically have some values which can be optimised. This can be done, by optimising the architecture of the ANN or/and using additional representative TPs.

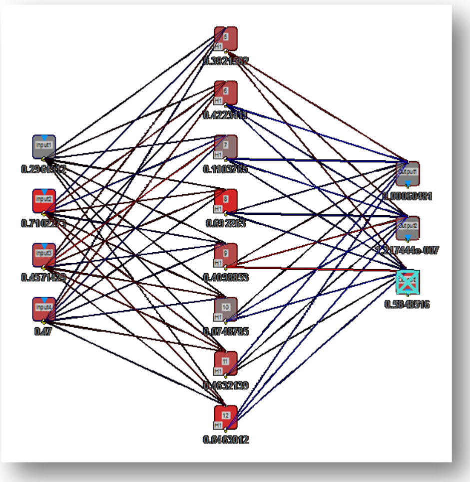

Fig. 6. Test results and expected activation of Output 3

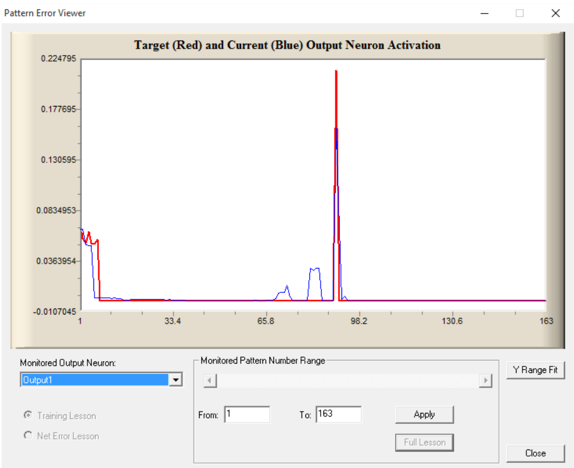

Fig. 7. Pattern error graph of the Output neuron 1

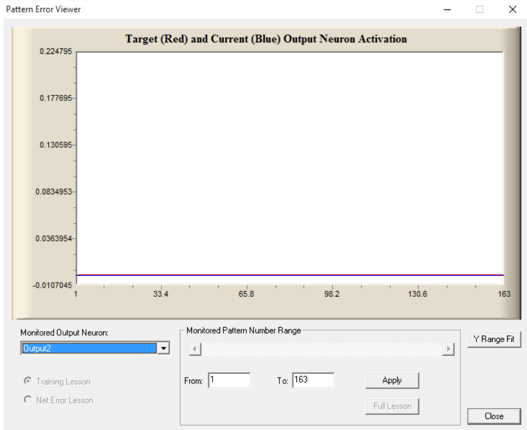

Fig. 8. Pattern error graph of the Output neuron 2

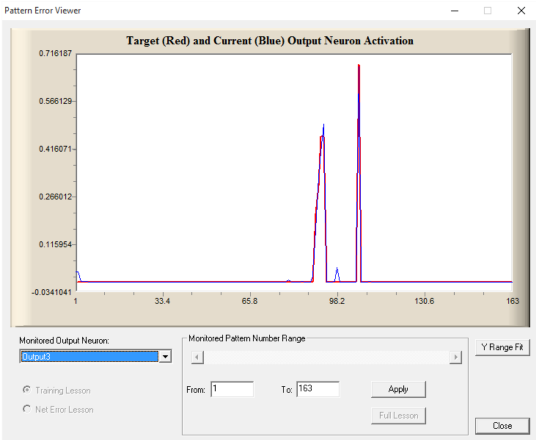

Fig. 9. Pattern error graph of the Output neuron 3

Limitations of the work

Main limitation of the work is the lack of data, since the net was trained by taking into consideration data which represent only partially annual behaviour and whether data for the Cologne area. In order to build up usable ANN, the annual data should be used for the net training.

V. Conclusion

Regardless of the limitations of this research, the architecture, the way how to train it, and training results of the ANN used for the comparison of the yield increases with and without construction of the tracking solar arrangement, have been presented in this paper. Further work will be oriented to net optimization by using the representable annual set of training pairs.

References

[1] Saga, T., "*Advances in crystalline silicon solar cell technology for industrial mass production*", Asia materials, Vol. 2, July 2010, pp. 96-102.

[2] Pearson, G., J., "*PV for founders award luncheon*", 18th IEEE Photovoltaic Specialists Conference,

Las Vegas, 1995.
[3] Chapin, D., M., Fuller, C., S., Pearson, G., L., "*A New Silicon p-n Junction Photocell for Converting Solar Radiation into Electrical Power*", J. Appl. Phys. 25, No. 5, May 1954, pp. 676—677.
[4] Green, M., A., "*Recent developments in photovoltaics*", Solar Energy 76, 2004, pp. 3-8.
[5] http://www.pvresources.com/Introduction/Technologies.aspx
[6] Klimasauskas, C., C., *"Neural Network Technicques*", in Trading on the Edge: Neural, Genetic, and Fuzzy Systems for Chaotic Financial Markets by Deboeck, G., J., pp. 3-27, New York City: John Wiley & Sons, 1994.
[7] Baum, E., B., Haussler, D., "*What size net gives valid generalization?*", Neural Computation 1, pp. 151-160 M. P. Cambridge, Hrsg, November 1989.
[8] Ersoy, O., "*Tutorial at Hawaii International Conference on Systems Sciences*, 1990.
[9] Katz, J., O., "*Developing neural network forecasters for trading*", Technical Analysis of Stocks and Commodities, Vol. 10, No. 4., April 1992, pp. 160-168.
[10] Zander, A., *Neuronale Netze zur Analyse von nichtlinearen Strukturmodellen mit latenten Variablen*, Wiesbaden: Deutscher Universitäts-Verlag, 2001.
[11] Scherer, A., "*Neuronale Netze: Grundlagen und Anwendungen (Computational Intelligence)*". Wiesbaden: Vieweg Verlagsgesellschaft, 1997, pp. 148-149.
[12] Kaastra, I., Boyd, M., "*Designing a neural network for forecasting financial and economic time series*", Neurocomputing, Vol. 10, Issue 3, March 1995, pp. 215–236.
[13] Riedmiller, M., Braun, H., "*Rprop - A Fast Adaptive Learning Algorithm*", Proceedings of the International Symposium on Computer and Information Science VII, Turkey, March 1992.