Artificial Neural Network-based Maximum Power Point Tracker for the Photovoltaic Application

Oleksandr Veligorskyi [1], Roustiam Chakirov [2], Yuriy Vagapov [3]

[1] Industrial Electronics Department, Chernihiv National University of Technology, 95 Shevchenko Street, Chernihiv, 14027, Ukraine
oleksandr.veligorsky@inel.stu.cn.ua

[2] Department of Electrical and Mechanical Engineering, Bonn-Rhein-Sieg University of Applied Science, 20 Grantham-Allee, Sankt Augustin, D-53757, Germany
roustiam.chakirov@h-brs.de

[3] Department of Engineering and Applied Physics, Glyndwr University, Plas Coch, Mold Road, Wrexham, LL11 2AW, UK

y.vagapov@glyndwr.ac.uk

***Abstract*—This paper proposes a new artificial neural network-based maximum power point tracker for photovoltaic application. This tracker significantly improves efficiency of the photovoltaic system with series-connection of photovoltaic modules in non-uniform irradiance on photovoltaic array surfaces. The artificial neural network uses irradiance and temperature sensors to generate the maximum power point reference voltage and employ a classical perturb and observe searching algorithm. The structure of the artificial neural network was obtained by numerical modelling using Matlab/Simulink. The artificial neural network was trained using Bayesian regularisation back-propagation algorithms and demonstrated a good prediction of the maximum power point. Efficiency of proposed ANN-based MPP tracker has been estimated for linear shadow expanding and constant partial shading of any one PV module.**

Keywords-photovoltaic system, artificial neural network, maximum power point tracker, efficiency, partial-shaded photovoltaic

I. Introduction

The renewable energy sources are considered as essential component of the future energy due to the rises in price of slowly depleting fossil sources and environmental concerns of nuclear power. Photovoltaic (PV) technology has become the fastest growing branch of renewable energy in the recent years. At the beginning of 2013 the total installed capacity of all PV plants have reached milestone 100GW [1], and continued to grow through the latest two year with additional 35GW in 2013 and planned 40GW in 2014.

The expansion of PV technology in power installations across the world restraints by relatively low overall efficiency of conversion of insolation into electricity and its dependence on day time prevent. Therefore the increasing conversion efficiency is the crucial issue of photovoltaic technology attracted attention of researches over the last few decades.

The total efficiency of PV systems can be increased in some ways. The first way is development of new materials able to improve the irradiance conversion. The second approach is the use of PV panel orientation systems (solar trackers) to adjust its position to perpendicular the photosensitive surface to sun rays. Such tracker can partially compensate the irregularity of power production during the day (especially in morning and in evening hours). They can be classified by hanger type as single-axial [2] and bi-axial [3]. The efficiency of solar trackers depends on many conditions, including tracker type, PV system location coordinates, irradiance level, etc. Lorenzo at al shown [4] that the average annual efficiency improvement of PV systems using trackers can reach 40%.

The third way to improve overall efficiency is based on maximum power point tracking (MPPT) on the *V-I* curve of PV panels. Such trackers can adjust a load point on the *V-I* curve of PV to produce a maximum power. The main principle of operation of such devices is changing resistance of the converter (DC/DC, DC/AC) to equal it with PV internal resistance [5], [6], [7], [8], [9].

Maximum power point (MPP) can be searched and determined using different control techniques. Classical methods such as perturb and observe (P&O) [10] or incremental conductance (InC) has been extensively studied in recent years. However, these techniques provide proper operation under uniform irradiance level only. Non-uniform irradiance, such as partial shadowing of some PV modules or even some PV cells can change *P-V* curve (Fig. 1) and make some local MPP, whereas classical MPPT algorithms search one maximum point only. Neither P&O nor other classical algorithms can identify the type of MPP (global or local) has been founded.

However, there are some MPPT techniques which can find the global MPP for partial-shaded PV modules, for example,

INISCom 2015, March 02-04, Tokyo, Japan

DOI 10.4108/icst.iniscom.2015.258313

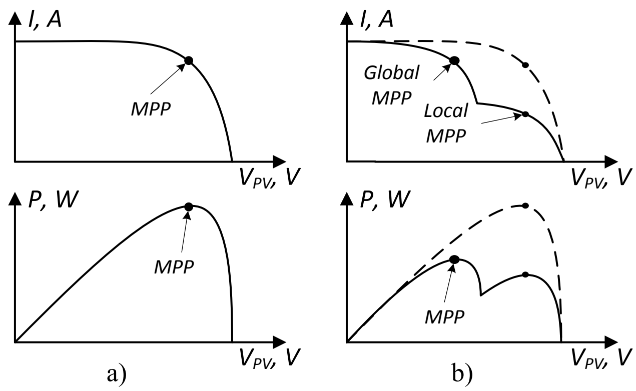


Figure 1. Maximum power point of the series connected PV modules.

two-stage MPPT [11], but these methods are quite complicated. Due to the complexity *V-I* characteristic and dynamic change in time, the methods based on artificial intelligence, such as fuzzy logic and artificial neural network (ANN) [12] demonstrate good results.

This paper proposes a new MPP tracker with control scheme based on ANN for global maximum power point detection for partial shading of PV modules. *V-I* characteristic of series, parallel and mixed connection of PV were obtained by modelling in Matlab/Simulink. The optimal structure and size of artificial neural network were obtained after training process. The searching efficiency of proposed algorithm was validated by numerical modelling in Matlab/Simulink.

II. Models of Photoelement

The first step in the design of converter for a photovoltaic application is creating an adequate model of the PV panel. This model must clear depict an *I-V* curve and the MPP position to reflect different temperatures and solar irradiances. Although all PVs have similar *I-V* curves the temperature and irradiance trends of VOC and ISC for various types of PV are different [12].

Many electrical equivalents of PV have been studied in recent decades. Due to the p-n junction of the silicone PV the diode-based models are widely used for the representing solar cells. The simplest equivalent circuit is a single-diode model (Fig. 2a). Such model cannot precise describe a PV cell operation in case of a negative bias. The much better result represents a double-diode model (Fig. 2b) [12]. The second diode D_2 together with the current source $I(V_P)$ needs to show an additional avalanche breakdown current at a high level of negative voltage.

Using the equivalent models presented in Fig. 2b, a current -voltage characteristic describes by the following equations:

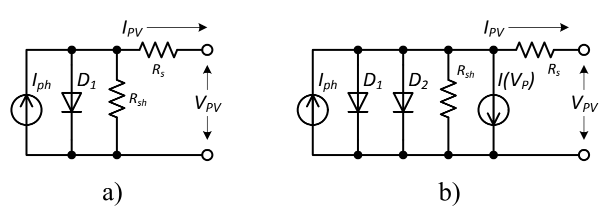


Figure 2. Equivalent circuits of the solar cell.

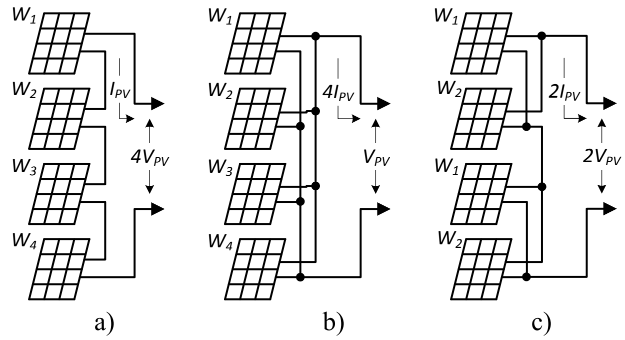


Figure 3. Connection type for the solar cells: serial (a), parallel (b), mixed (c).

$$I_{PV} = I_{ph} - I_{S1}\left(e^{\frac{V_{PV}+I_{PV}R_S}{\varphi_{T1}}} - 1\right) - I_{S2}\left(e^{\frac{V_{PV}+I_{PV}R_S}{\varphi_{T2}}} - 1\right) - \frac{V_{PV}+I_{PV}R_S}{R_{sh}} - \alpha\left(V_{PV}+I_{PV}R_S\right)\left(1-\frac{V_{PV}+I_{PV}R_S}{V_{Br}}\right)^n \quad (1)$$

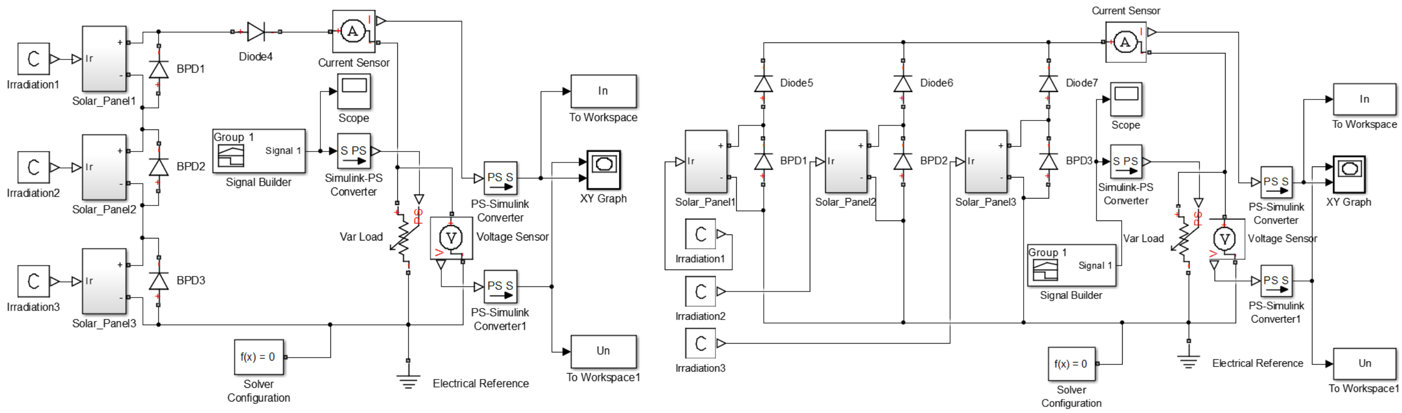
where I_{ph} is the photocurrent, A; I_{PV} is the PV output current, A; V_{PV} is the PV output voltage, V; $\varphi_T = kTA/q$ is the temperature coefficient (k is the Boltzmann's constant; A is the p-n junction ideality factor; T is the temperature of the cell, K); I_{S1} and I_{S2} are diodes D_1 and D_2 reverse saturation currents, A; V_{br} is the breakdown voltage, V.

Output current and voltage (1) can be calculated numerically because it is not given in the explicit form, and I_{PV} is presented in both side of equation. On the other hand, *I-V* characteristic of PV cell can be found by modelling in numerical computing software such as Matlab.

PV modules contain an array of unit solar cells, which can be connected in series, parallel, or mix (Fig. 3). A connection type defines output characteristics of the PV module. Output voltage and current can be multiplied by using a series (Fig. 3a) or parallel (Fig. 3b) connection, respectively. A mixed connection (Fig. 3c) allows reaching a necessary level of output power if required voltage level is achieved. In further research PV modules YH116*116-12A was used. The main parameters of such modules are presented in the Table I. A model of one module has been created in Matlab/Simulink where the basic element of this structure is Simulink model *Solar Cell*, connected in series 12 times.

Table I. Parameters of the PV Module YH116*116-12A for Standard Test Conditions AM 1.5, 1000 W/m^2, 25°C [13].

Symbol	Term	Value
P_{MAX}	Maximum output power	1.5W
I_{SC}	Short-Circuit Current	0.275A
V_{OC}	Open-Circuit Voltage	7.2V
n_s	Number of cells connected in series	12
n_p	Number of column connected in parallel	1
k_T	Short-circuit current temp. coefficient	0.065%/°C
k_V	Open-voltage temp. coefficient	-0.027V/°C



(a) (b)

Figure 4. Matlab model for analysing characteristics of three series-connected (a) and parallel connected (b) PV modules.

III. Connection Type Influence on PV Array Characteristics

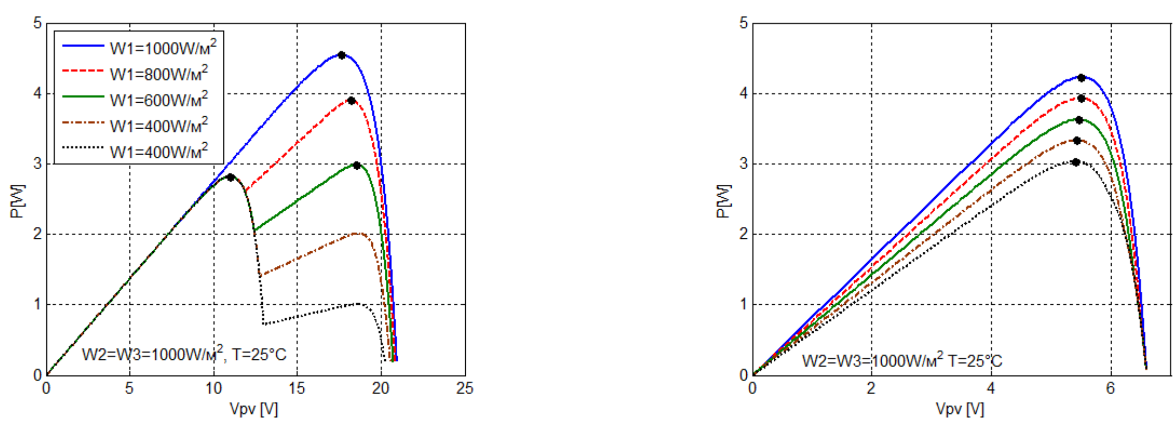
According to equivalent model parameters presented in Table I, array of three PV modules has been analysed in Matlab for three different connection types (serial, parallel, mixed) and different shading patterns. The first model for analysis of partial-shading influence on PV array with series connection is represented in Fig. 4a. The irradiance level for every module was set up by external m-file operated constants *Irradiation1*…*Irradiation3*. Elements *BPD1*…*BPD3* act as bypass diodes for prevention of hot spots and potential damage of some PV modules in case of their shading [14]. These bypass diodes play a crucial role in the analysis of partial shading performance for PV array. The *P-V* characteristics for PV series connection for non-uniform solar irradiances are presented in Fig. 5a. The irradiance of the first PV module has been changed at a step of 200W/m^2 during the numerical modelling.

The major issue of partial shading can be seen from analysis of these curves for irradiance W_1 less than 600 W/m^2. Due to the conductance of diode *BPD1* in such conditions the position of the global maximum power point was changed to V_{PV} = 11V instead 17-18V. Further decreasing of irradiance of shaded panel does not lead to relocation of the MPP position.

Matlab model for analysis of partial-shading influence on parallel-connected PV modules is shown in Fig. 4b. This model has no significant changes in presented blocks versus series-connected model except of blocking diodes *Diode5*…*Diode7*. Blocking diodes are usually used for prevention of the reverse current flowing from loaded battery to PV modules in cloudy weather or at night. For the parallel connection of PV modules the blocking diodes also prevent current flowing from the PV string under higher irradiance level to the string under lower irradiance level. Therefore, they can minimise additional losses for non-uniform PV modules insolation. The *P-I* curves for this model obtained by numerical modelling are presented in Fig. 5b. It can be seen that the shading of any one PV module does not affect on another modules generation.

IV. MPP Tracker Based on Artificial Neural Network

A diagram of proposed MPP tracker for photovoltaic application is shown in Fig. 6. Three PV modules YH116*116-12A connected in series are used as electricity generation elements. A voltage from these PV's goes to the buck DC/DC convertor which act as power part of MPP tracker. PWM signal from *MPPT Controller* adjusts the input resistance of the DC/DC convertor equating it to the output resistance of PV at MPP point. The control system of the convertor is operating under classical P&O algorithm based on V_{PV} and I_{PV} values. In addition to voltage and current sensor signals the algorithm uses PWM reference bias, calculated by the AAN based on data of



(a) (b)

Figure 5. *P-V* curve for three PV modules with bypass diodes and non-uniform irradiance levels in case of series-connection (a) and parallel-connection (b).

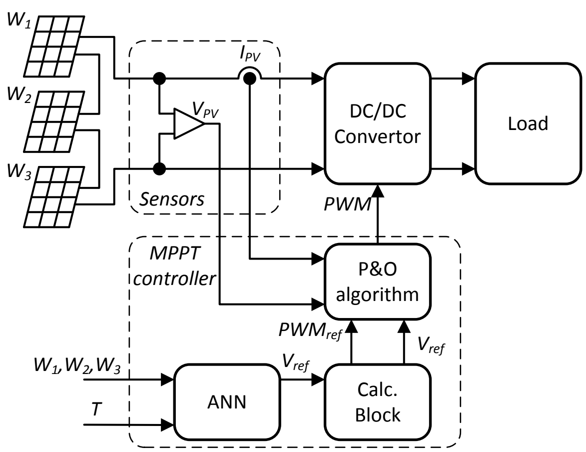


Figure 6. Proposed diagram of MPP tracker based on ANN for the PV application

irradiance levels W_1, W_2, W_3 and temperature T. The main aim of the ANN is a prediction of PV voltage corresponding to the maximum power point of the *P-V* curve. Predicted PV voltage goes to the *Calculation* block where it converted into the PWM reference control signal PWM_{REF} for conventional P&O algorithm.

V. Structure and Training process of Artificial Neural Network

The basic issue for the creation of ANN is a training process based on training set. The elements of training set must be distributed evenly on possible range of input data. Moreover, the data in the training set have to be without sharp discontinuities in the output responses for the close input elements. This rule is not performed for the photovoltaic systems because voltage corresponding to the MPP is changed under partial shading, as shown in Fig. 1. Due to such irregularity the structure of ANN becomes much complex.

Matlab model of three series connect PV modules represented in Fig. 5 has been used to form a training set. The input data contains an array of irradiances in the range from 25 to 1000W/m^2 and seven temperature levels (–15, 0, 15, 25, 35, 50, 75°C, respectively). Because the position of MPP is independent on sequence of irradiance levels and number of shaded PV panels, training set has been reduced to 9443 input-output pairs. An additional training data were implemented for the most complex area where the position of MPP could be moved due to the partial shading (e.g. curves $W_1 = 600$W/m^2, $W_2 = 1000$W/m^2 and $W_1 = 400$W/m^2, $W_2 = 1000$W/m^2 in Fig. 5). Eventually, the final size becomes 10510 pairs for the training set and 2935 pairs for the testing set.

Selecting a neuron activation function is the next step in ANN controller design. The type of an activation function for neurons depends on its goals. The types mainly used in activation are represented in Fig. 7. Linear activation function (Fig. 7c) is a simplest type, it used for narrow range of the input neuron signal. This function does not need high computing challenges and can be implemented into any microprocessor or microcontroller. Logistic activation function (Fig. 7b) has some additional benefits, for example, a nonlinear gain coefficient. The small signals has a high gain, while as for the

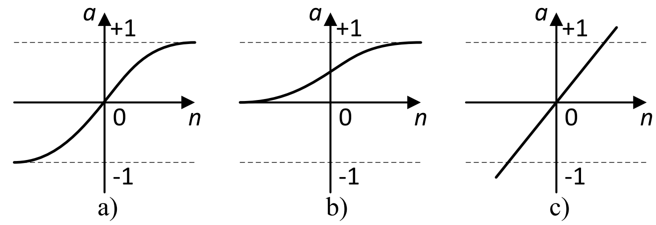


Figure 7. Neuron activation functions.

big input signals gain will decrease. Therefore, such neuron will works well under wide range of input signals. Hyperbolic tangents activation function (Fig. 7a), in addition to benefits of previous one, has a bipolar output and ANN with such neurons will train faster.

Due to the benefits described above the hyperbolic activation function has been used for all hidden layers. In contrary, the linear function has been used for the output layer because of no scale of the output signal of the ANN. The scheme of the ANN is shown in Fig. 8a. The final structure of the feedforward ANN for the MPP solar tracker has been obtained by modelling in Matlab. The error teaching of ANN has been used as performance factor during modelling process by *trainlm* and *trainbr* algorithms. The final structure of ANN is 4-8-7-7-1 and has 4 inputs, 1 output, 3 hidden layers with 8, 7 and 7 neurons, respectively.

The next step in the ANN design is a training process. All training procedures for the ANN use a back-propagation learning (BPL) algorithm. BPL iteration technique is based on gradient descent trying to minimize the network rot-mean square error. In this paper two Matlab training algorithms was studied for the MPP tracking. The first training function *trainlm* (Levenberg-Marquardt back-propagation) due to the complex input-output characteristic with big gaps showed unsatisfactory results. The second function *trainbr* (Bayesian regularisation back-propagation) demonstrated much better results. The main characteristics of training process depicted in Fig. 9 and Fig. 10. Fig. 9 represents targeted and ANN-predicted values of MPP for different shading patterns and temperatures. It can be seen that the predicted by ANN values are close to calculated data. Proposed ANN has the best efficiency in case of higher irradiance level, while prediction of lower MPP voltage

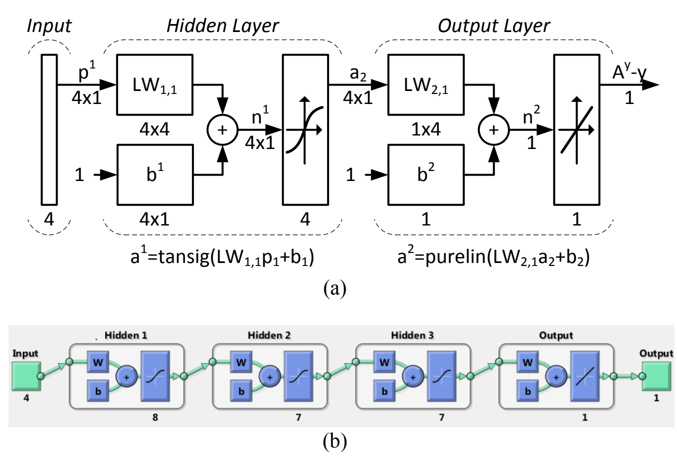


Figure 8. Schematic (a) and final (b) structure of the feedforward ANN for the MPP tracker.

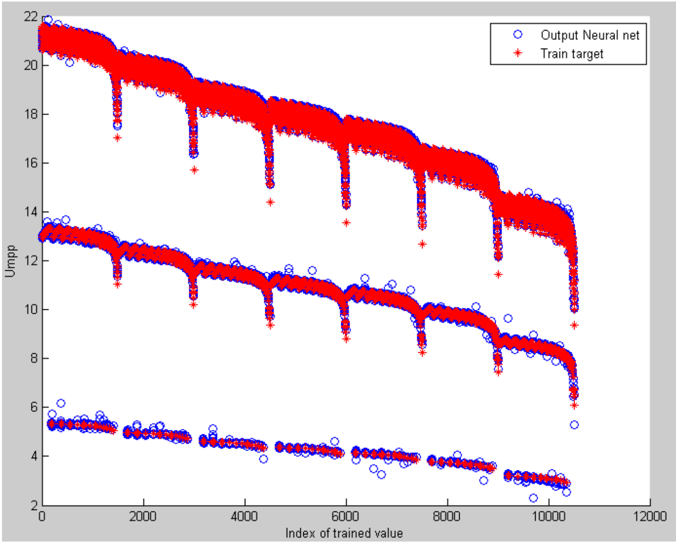


Figure 9. Target and Output values of V_{MPP} for ANN

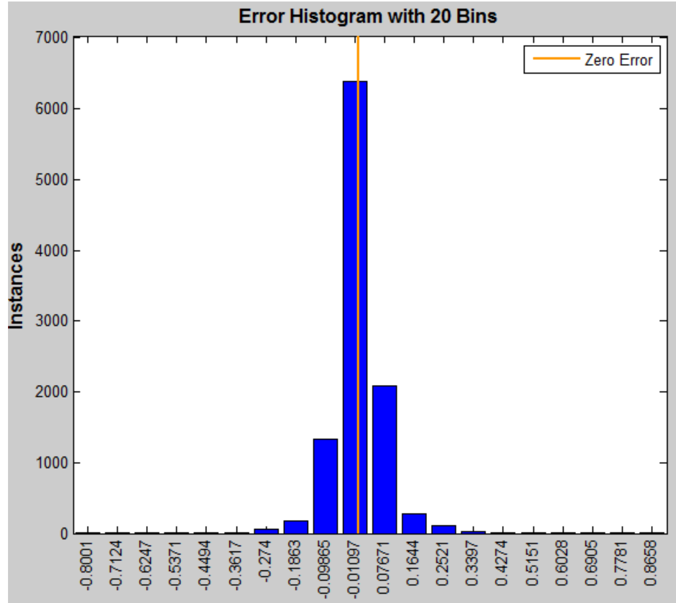
contains insignificant errors. The effect of these errors will be negligible due to classical P&O algorithms.

Error histograms for training and testing sets, depicted in Fig. 10a and Fig. 10b respectively, show relative amount of V_{MPP} prediction errors. According to the validation data, relative number of V_{MPP} prediction errors is 0.94% in range of ±0.01V and 0.05% in range of ±0.2V. It can be seen in Fig. 10b that there are a few significant prediction errors up to 20V. In fact, these errors do not bring substantial power loses. Such type of errors arises at the edge of shading mode change, when local and global MPPs are close to each other. Therefore, PV modules tuned on local MPP produces almost the same amount of electricity as under global MPP operation.

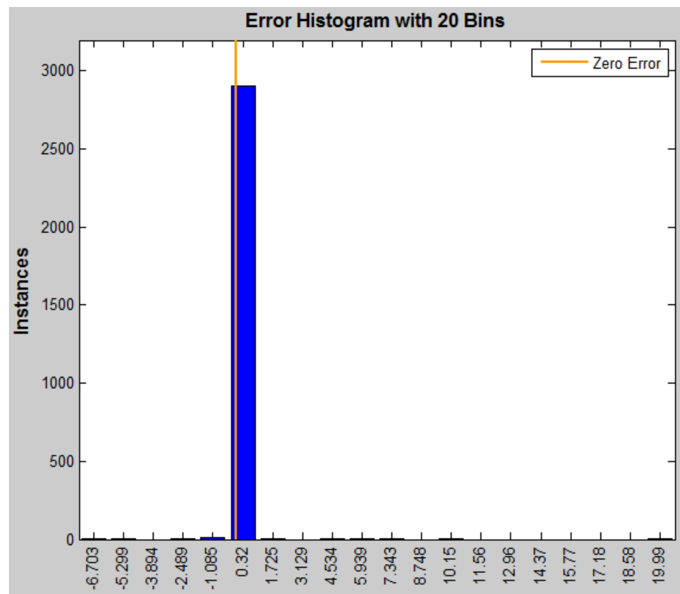
VI. ANN-BASED MPP TRACKER EFFICIENCY ESTIMATION

Efficiency of proposed ANN-based MPP tracker has been estimated by numerical calculation for two typical cases, represented in Fig. 11a and Fig. 11b. Each example contains irradiance level on PV panel diagrams (*W1-W3*), maximum power point voltage V_{MPP} and PV array output power (P_{PV}) for classical MPP algorithm (red dashed line), proposed ANN-based algorithm (green line) and the maximum possible power (black line). In addition, operation period of the ANN-based algorithm T_{ANN} represented at the bottom. This period influences on speed of searching a global maximum power point: the longer T_{ANN} the less speed.

The first case represented in Fig. 11a is a linear shadow expanding, when big shadow (e.g. big cloud) spreads from the one side of PV array to another. This pattern is common for partly cloudy weather. In this case, classical P&O algorithm will work well till the first global MPP become local (Fig. 5a, curve $W_1 = 400\text{W/m}^2$). At some moment of time power provided by P&O and ANN-based proposed algorithms become less than maximum possible (black line P_{PV} on Fig. 11). At the time t_1 ANN-based algorithm estimates a new position of global MPP and changes duty cycle of the control PWM signal for DC/DC convertor according to V_{MPP}. So, starting from this point proposed algorithm will provide maximum possible



(a)



(b)

Figure 10. Error histograms for the training set (a) and testing set (b).

generated power, while classical method will work at the local MPP. The energy loss for those two algorithms is depicted light blue (for ANN-based, ΔE_{ANN}) and pink (for P&O, $\Delta E_{P\&O}$) filled regions (Fig.11). Therefore, the proposed algorithm will provide a better efficiency comparing to a classical MPPT algorithm in case of linear shadow expanding only in dynamic mode (when shadow spreads across all PV modules).

The second case is a shading of any one PV module (partial shading), represented in Fig. 11b. This is a typical pattern for a constant shading, such as chimney shadow, shadow from tree branches, etc. Speed of such shadow is relatively low and depends on sun movement. It can be seen in Fig. 11b that the efficiency of the proposed method is much higher comparing to classical P&O algorithm. The beginning of process is quite similar to previously discussed, but effi-

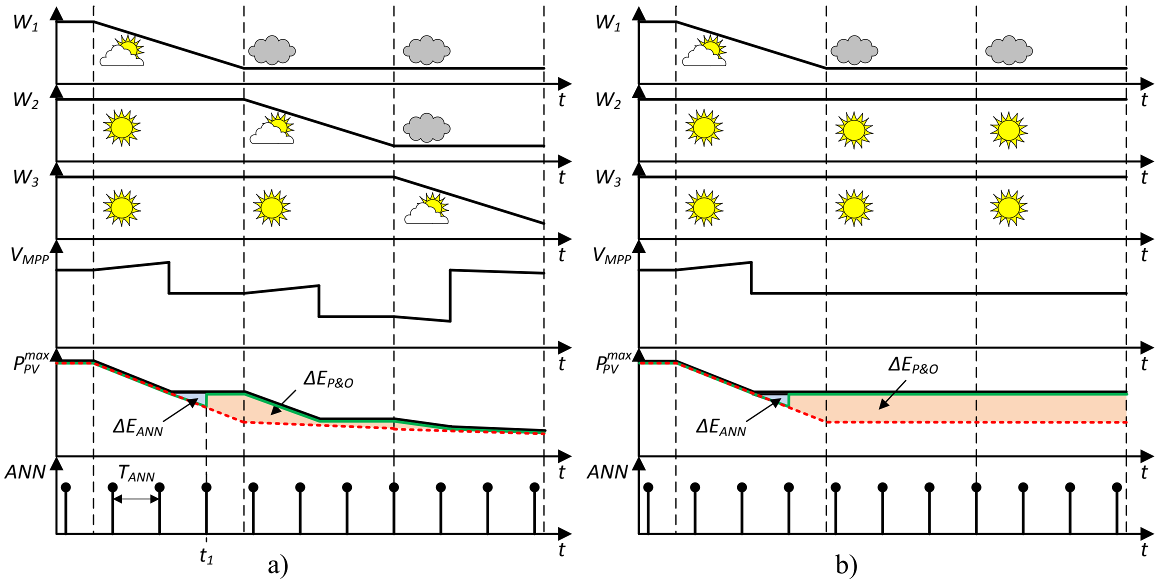


Figure 11. Comparison of classical P&O and proposed ANN-based MPPT algorithms for linear shadow expanding (a) and partial shading (b).

ciency for the proposed algorithm will be much higher under static mode rather than for linear shadow expanding. Increase in efficiency depends on ratio between irradiance levels of shadowed and lit PV modules. Given above example shows an increase in efficiency around 70%.

VII. Conclusion

This paper has introduced a design of ANN-based MPP tracker for the photovoltaic application. Different connection type of PV array and their influence on *P-V* characteristics has been studied using Matlab/Simulink. Results of the modelling shown that the series connections of PV modules leads to a complex *P-V* curve with some maximum power point for non-uniform irradiance pattern. These data were used in the ANN-based controller for the prediction of MPP. The final structure of ANN has 4 inputs, 1 output layer with linear activation function and 3 hidden layers (hyperbolic activation function) with 8, 7 and 7 neurons, respectively. Bayesian regularisation back-propagation algorithm was used for the ANN training procedure. Training has shown a good prediction of the MPP, the relative number of V_{MPP} prediction errors in range ±0.01V is 0.94%, in range ±0.2V is 0.05%. Efficiency of proposed ANN-based MPP tracker was estimated for two typical cases. Proposed controller provides a better efficiency comparing to classical MPPT algorithm in dynamic mode under linear shadow expanding. The proposed solution has also demonstrated much higher efficiency in static mode under constant partial shading of any one PV module.

References

[1] (2013) Renewables Global Status Report 2013 [Online]. Available: http://www.ren21.net/REN21Activities/ GlobalStatusReport.aspx

[2] I. Sefa, M. Demirtas, and I. Colak, "Application of one-axis sun tracking system," *Energy Conversion and Management*, vol. 50, no. 11, pp. 2709 –2718, 2009.

[3] A. Şenpinar, and M. Cebeci, "Evaluation of power output for fixed and two-axis tracking PV-arrays," *Applied Energy*, vol. 92, pp. 677–685, 2012.

[4] E. Lorenzo, M. Perez, and A. Ezpeleta, "Design of tracking photovoltaic systems with a single vertical axis," *Progress in Photovoltaics: Research and Applications*, vol. 10, no. 8, pp. 533–543, 2002.

[5] T. Esram, and P.L. Chapman, "Comparison of Photovoltaic Array Maximum Power Point Tracking Techniques," *IEEE Transaction on Energy Conversion*, vol. 22, no. 2, pp. 439–449, 2007.

[6] C. Roncero-Clemente, S. Stepenko, O. Husev, V. Minambres-Marcos, E. Romero-Cadaval, and D. Vinnikov, "Three-level neutral-point-clamped quasi-Z-source inverter with maximum power point tracking for photovoltaic systems," in *Technological Innovation for the Internet of Things*, L. Camarinha-Matos, S. Tomic, and P. Graca, Eds. Berlin, Heidelberg: Springer, 2013, pp. 334–342.

[7] C. Roncero-Clemente, O. Husev, V. Minambres-Marcos, E. Romero-Cadaval, S. Stepenko, and D. Vinnikov, "Tracking of MPP for three-level neutral-point-clamped qZ-source off-grid inverter in solar applications," *Journal of Microelectronics, Electronic Components and Materials*, vol. 43, no. 4, pp. 212–221, 2013.

[8] O. Veligorskyi, and Y. Vagapov, "Improvement of perturb and observe MPPT method for photovoltaic systems: case of study," *International Journal of Renewable Energy Technology*, vol. 4, no. 2, pp. 141–156, 2013.

[9] O. Veligorskyi, R. Kosenko, and S. Stepenko, "High-efficiency solar tracker development and effectiveness estimation," in *Proc. 2014 IEEE Int. Conf. on Intelligent Energy and Power Systems*, Kiev, pp. 153–158.

[10] N. Femia, G. Petrone, G. Spagnuolo, and M. Vitelli, "Optimization of perturb and observe maximum power point tracking method," *IEEE Transactions on Power Electronics*, vol. 20, no. 4, pp. 963–973, 2005.

[11] K. Kobayashi, I. Takano, and Y. Savada, "A study on a two stage maximum power point tracking control of a photovoltaic system under partially shaded insolation conditions," in *Proc. IEEE Power Engineering Society General Meeting*, Toronto, Canada, 2003, vol. 4, pp. 2612–2617.

[12] S. Syafaruddin, T. Hiyama, and E. Karatepe, "Feasibility of artificial neural network for maximum power point estimation of non crystalline-Si photovoltaic modules," in *Proc. 15th Int. Conference on Intelligent System Applications to Power Systems*, Curitiba, Brazil, 2009, 6p.

[13] (2009) PV Module based on Polycrystalline Silicon YH116*116-12A/ B250-P [Online]. Available: http://www.kosmodrom.com.ua/pdf/ S1194.pdf

[14] V. Quaschning, and R. Hanitsch, "Numerical simulation of current-voltage characteristics of photovoltaic systems with shaded solar cells," *Solar Energy*, vol. 56, no. 6, pp. 513–520, 1996.

[15] S. Syafaruddin, E. Karatepe, and T. Hiyama, "Artificial neural network-polar coordinated fuzzy controller based maximum power point tracking control under partially shaded conditions," *IET Renewable Power Generation*, vol. 3, no. 2, pp. 239-253, 2009.