Enhanced Hybrid Global MPPT Algorithm for PV Systems Operating under Fast-Changing Partial Shading Conditions

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Abstract- A global maximum power point tracking algorithm including an artificial neural network and a hill climbing method is combined. The proposed solution is suitably designed for handling fast changing partial shading conditions in photovoltaic systems. Through only a limited number of preselected current measurements, the proposed algorithm is capable to automatically detect the global maximum power point of the photovoltaic array, also minimizing the time intervals required to identify the new optimal operating condition. The method does not require any information on the environmental operating conditions and it is cost-effective, with no additional hardware requirements. The analysis of different artificial neural network structures has pointed out that a simple network can be used when the not-uniform shading conditions change slowly. On the other hand, in the case of solar electric vehicles moving in a city it is necessary the use of more complex structures to reach satisfactory performance.

Keywords Artificial neural networks; maximum power point tracking; solar energy; partial shading; photovoltaic characteristics.

1. Introduction

In recent years, solar cells have become more and more energy efficient, as well as the technology to manufacture them [1], [2]. Both trends had a positive effect on the sustainability of solar photovoltaic (PV) systems in terms of greenhouse gas emissions. In fact, nowadays electricity generated by PV systems is considerably less carbon-intensive than electricity generated by natural gas plants or by coal plants. Moreover, recent advances in material technology could soon lead to high-performance solar cells that can be applied onto flexible surfaces, such as that of a car roof, in order to produce enough power for small onboard electric loads in a very cost-effective manner.

Although the above considerations reveal how efficiently is possible to produce electrical energy from the sun by exploiting a well-proven technology, on the contrary, the photovoltaic technology still faces efficiency limits. Hence, the capability to extract the maximum power from PV modules independently on the array temperature, solar irradiation, shading conditions and PV cell ageing plays an essential role, especially when the photovoltaic array is installed on a vehicle or boat, thus continuously subjected to variable operating conditions.

Ever since the first studies on this technology it became evident that suitable control techniques named as Maximum Power Point Tracking (MPPT) algorithms were necessary to optimally exploit the available power at the PV field terminals. Basically, these algorithms are tracking controls employed to extract the maximum power from PV modules and they are implemented in the control units of the power converters used to interface the PV field with the grid or electric loads.

The most widely used MPPT methods can be grouped into two different categories: hill climbing methods (HCMs), such as Perturb and Observer (P&O) and Incremental

Conductance, and constant voltage methods [3]-[6]. Many such implementations have been proposed over the years to improve the accuracy and dynamic behavior of the tracking controls [7]-[19]. They differ in many aspects such as complexity, sensors required, convergence speed, range of effectiveness and investment cost. Most of them neglect that MPPT is a multimodal optimization problem [20] since there are local optima in the P-V characteristic curve when not uniform irradiance occurs over the photovoltaic system. In fact, partial shading has a strongly non-linear effect on the power output and the electrical response of a PV array. Depending on the shading pattern, multiple local maximum power points may arise, compromising the effective tracking of the optimum operating point by means of traditional approaches, thus leading to suboptimal operation, as well as to hot spot condition and fast deterioration of the shaded cells.

In order to overcome such limitations, considerable research efforts have been dealt with the implementation of more sophisticated algorithms able to identify the Global Maximum Power Point (GMPP) in order to extract the maximum available power from the PV system whatever the shading pattern are [21]-[42]. Even for those algorithms, the computational burden, range of effectiveness and convergent speed is strictly dependent on the adopted theoretical methodology. Among the numerous solutions presented in literature, metaheuristic approaches such as the particle swarm optimization [21] and Artificial Neural Networks (ANNs) [27] are expected to provide satisfying results especially in the case of well-defined PV array configurations. The Evolutionary Algorithms [43], e.g. genetic algorithms [44], applying niching strategies [45] are designed to properly address multimodal functions occurring during partial shading conditions.

Most of the MPPT methods proposed in past have been designed for PV system placed in fixed installation, where the shading phenomena does not suddenly and frequently change as in case of installations on the roof of electric vehicle; moreover, some approaches require the measurement of solar radiation over the panel and/or their temperature and/or the scansion of a large portion of the PV characteristic to suitably determine the GMPP.

The research activity proposed in this paper is specifically focused to PV installations onboard of vehicles, in which a very accurate and fast GMPP tracking (GMPPT) is imperative to maximize the extracted electric energy, considering that solar irradiance on the panel is often not uniformly distributed due to the presence of other vehicles, buildings and any other obstacles that block or refracts the solar rays impacting the PV modules. The paper aims to study the effectiveness of an ANN based MPPT approach whose goal is to quickly and accurately estimate the GMPP when no information about the solar irradiance distribution over the modules and their temperature is given, and when the PV system is subjected to continuously and rapidly changing shadowing patterns.

Few measures are used to esteem the GMPP by means of the ANN, and they are set at priori. Consequently, the estimation time is small and fixed. In this work, the solution provided by the ANN, esteemed maximum power point (EMPP), is given, as starting point, to a HCM to improve the accuracy of EMPP.

2. Photovoltaic Array Model

A PV array can be analytically represented by its current-voltage characteristic, achieved by combining the solar cells in series and parallel. In the following analysis a single diode model representation of each solar cell is considered since it can be assumed a good compromise between simplicity and accuracy. In fact, the identification of the single diode model's parameters can be also obtained starting from datasheets values, avoiding experimental measurements. The single diode model can be represented as:

$$I_{PV} = n_p \left(I_{ph} - I_0 \left[e^{\frac{q(V_{PV}+R_s I_{PV})}{AkTn_s}} - 1 \right] - \frac{(V_{PV} + R_s I_{PV})}{n_s R_{sh}} \right) \quad (1)$$

$$I_{ph} = I_{ph\_STC} + K_I (T - T_{STC}) \frac{G}{G_{STC}} \quad (2)$$

$$I_0 = \frac{I_{SC\_STC} + K_I (T - T_{STC})}{e^{(V_{oc\_STC} + K_V (T - T_{STC})/V_T - 1)}} \quad (3)$$

where the description of the quantities is given in Table 1. Relationships (1)-(3) underline the dependence of the model on the solar radiance and temperature conditions. Model parameters are affected by the degradation of the cells due to the outdoor conditions. Starting from this mathematical representation, the power curve associated with the PV array is obtained by considering the series and parallel connection of the PV modules.

Assuming a PV array consisting of identical photovoltaic cells, under uniform solar irradiation, the typical P-V curve

Table 1. Description of parameters and electrical quantities used in the considered PV Array Model

V_{PV}, I_{PV}	PV array output voltage and current
R_s	resistance of the metallic contacts and ohmic resistance of the material
R_{sh}	resistance associated to the leakage of the current across the p–n junction or at the cell edges
q	electron charge
I_{ph_STC}, I_{ph}	photo-generated current in Standard Test Conditions (STC) and operating conditions
I_o	dark saturation current in STC
T_{STC}, T	temperature at STC and operating conditions
I_{SC_STC}	short circuit current measured at STC
A	diode quality (ideality) factor
k	Boltzmann's constant
n_p, n_s	number of cells connected in parallel and series
V_{oc_STC}, V_{oc}	open circuit voltage at STC and operating condition
G_{STC}, G	irradiance at STC and operating condition
V_T	thermal voltage
K_I, K_V	temperature coefficient of short-circuit current and temperature coefficient of open-circuit voltage

of the array includes a single peak. When partial shading occurs in one of the cell composing the PV module, the last reduces the current circulating through the unshaded cells, causing the so-called hot-spot heating and thus the crack of the shaded cell [30].

This drawback is overcome by using an external bypass diode conducting every time the solar cell is reversed biased, allowing the current of unshaded cells to flow externally to the shaded cell, thus preventing hot-spot damages. A similar approach is applied at module level. Although the impact of shaded cells can be mitigated by inserting bypass diodes, partial shading still significantly impairs the energy produced from the PV system due to two reasons: P-V curve presents multiple peaks and the position and amplitude of the global maximum change as the shading conditions change.

3. Enhanced Hybrid GMPPT Algorithm

3.1. Coupling ANN and standard hill climbing method

The proposed method is able to extract the GMPP from a PV array frequently subjected to fast changing partial shading conditions; such an approach does not require any irradiance measurement neither temperature sensors. The GMPPT algorithm acts whenever the variation of the extracted power from the PV array exceeds a preset threshold because of a change in the environmental conditions [46].

The GMPPT approach described hereafter is a two-stages MPPT control solution in which at the first stage, an ANN [47] is adopted to provide a first estimation of the GMPP (defined as EMPPA). Then, a HCM is adopted to further improve the estimated GMPP and to find the esteemed optimal one (i.e. the EMPP). Basically, the HCM performs a local optimization starting from the EMPPA obtained by the ANN at the first stage.

The proposed method has been developed assuming that:

- there is not any relation among the irradiance level among the modules (i.e. the worst case is considered);
- there is not any change in the shading pattern and temperature during the global method application;
- the temperature is uniform in the PV system;
- the temperature is in the range [10, 55] °C.

The first assumption is necessary to account for solar electric vehicles moving in a city where many different shadowing shapes due to buildings, trees and many other obstacles are present.

The input of the ANN is a set of currents acquired by forcing the array to operate at different voltage points for a brief period; the voltages set is established by means of a DC/DC power converter and the voltage values VPV are chosen a priori according to the following relation:

$$V_{PV}(i) = i\frac{V_{OC10}}{N_S+1} \quad (4)$$
$$i = 1\ldots, N_S$$

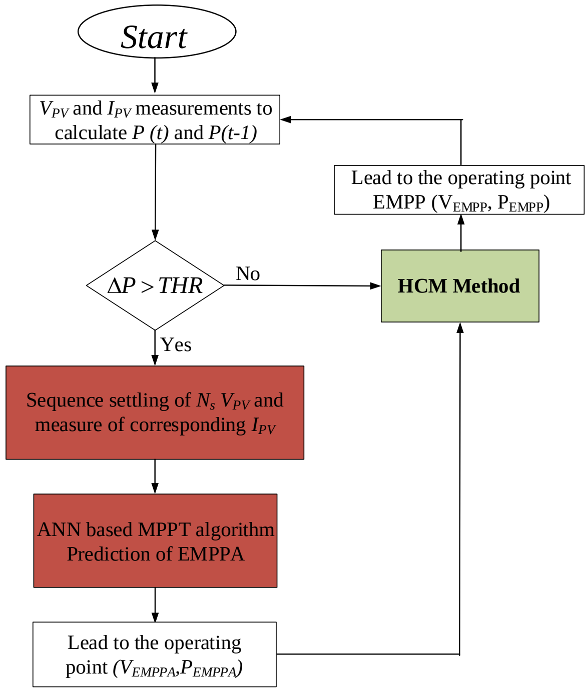

Fig. 1. Flowchart of the method coupling ANN with HCM.

where V_{OC10} is the open-circuit voltage of the PV panel at 10°C, and NS is the number of the PV modules connected in series.

The output of the ANN is the voltage corresponding to the EMPPA, which is imposed by the power converter to the PV system. Then, the HCM is started to continuously track the EMPP. HCM runs until a new scanning of the P-V curve will be performed because the DC bus of the power converter has detected that a certain threshold of power variation is again exceeded. Figure 1 shows a flowchart of the overall method.

3.2. Structure and training of the ANN

ANN is a computational model aiming to emulate the behavior of nervous system when dealing with problem-solving. The neurons and the synapses of the biological systems become, respectively the core processing units and the weighted links connecting these units of an ANN [48]. Therefore, as the brain learns by experience, the ANN is trained to deal with the problem it is designed for. More specifically, learning an ANN means estimating the parameters of a model by means of given data [49]. When supervised learning is adopted, some sets of input data (patterns) are provided to the ANN and for each pattern the desired/expected output is used as reference to train the network, that is to iteratively adjust the weights [48].

Multi-layer perceptron is a feedforward neural network able to deal with non-linear problems [50] like finding the voltage position of the GMPP in the P-V curve when different partially shading conditions occur. Figure 2 shows an example of an ANN structure used in this work for GMPPT and a common neuron whose computational model is [51]:

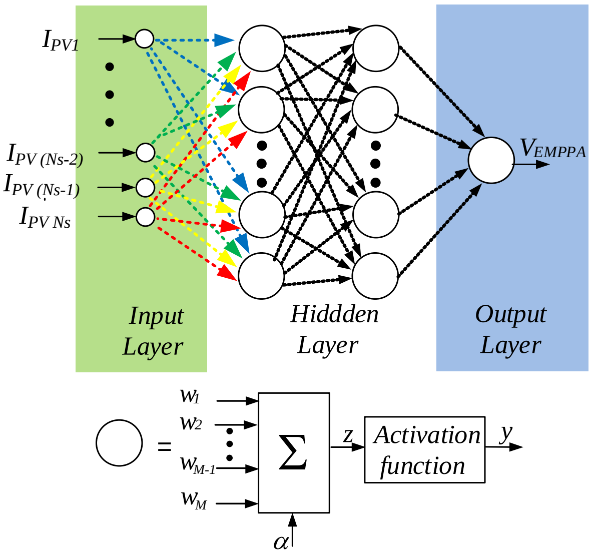

Fig. 2. Multi-layer feed forward neural network used for GMPPT.

$$y = f(z) \tag{5}$$

with

$$z = \sum_{m=1}^{M} w_m x_m + \alpha \tag{6}$$

where:

- y is the output of the neuron;
- f is the activation function [51];
- M is the number of neurons in the previous layer (M is equal to N_s for a neuron in the first hidden layer);
- w_m is the weight related to the incoming x_m signal;
- α is an offset.

The ANN structure can be trained by considering as input pattern a set of measured currents (or currents estimated via the PV system model) at the voltage points established a priori by using (4); the ANN desired output is the voltage value corresponding to the true GMPP location. Various pairs of input pattern - desired output need to be created by simulating the P-V curves of the array for different configurations of shading condition and temperature in order to let the ANN properly learning the underlying model. To this aim Back-propagation method [52] is adopted to adjust the weights.

4. ANN Design for a Given Case Study

In order to validate the aforementioned Global MPPT algorithm, a case study has been considered in which the PV system consists of one string composed by five modules series connected. The technical specifications of PV modules under standard test conditions are reported in Table 2.

Various ANN structures with different number of hidden layers and number of neurons for hidden layer have been trained using 100000 couples of input pattern - desired output that have been obtained by randomly emulating

Table 2. Specification of PV modules.

Parameter	Value
V_{oc}	21.06 V
I_{sc}	3.80A
Current at P_{max} (I_{MPP})	3.50 A
Voltage at P_{max} (V_{MPP})	17.10 V
Maximum Power (P_{MPP})	59.90 W
V_{oc} *coeff. of temperature* (K_V)	-0.084 V/°C
I_{sc} *coeff. of temperature* (K_I)	3.3e^{-4} A/°C

possible operative conditions. More specifically, for each module an irradiation level is randomly generated in the range [0; 1000] W/m2 and a random temperature for the overall system is generated in the range [10, 55] °C.

Two quality indicators (QIs) are considered to compare the performance of various ANN structures. To compute the value of the two QIs for the ANN structures under test, N_T=1000 operative conditions are randomly generated by using the same procedure adopted to carry out the pairs *input pattern - desired output*.

The former, QI1, provides information about the ability of the ANN to predict the MPP:

$$QI1 = 1 - \frac{1}{N_T}\sum_{t=1}^{N_T}\frac{EMPPA_t}{GMPP_t} \tag{7}$$

The greater the value of QI1 the greater the average wasted power exclusively due to the ANN inaccuracy and, consequently the worse the ANN performance.

The latter, QI2, provides information about the ability of the ANN in discovering the "hill" where the actual GMPP is located:

$$QI2 = 1 - \frac{1}{N_T}\sum_{t=1}^{N_T} h_t \tag{8}$$

where h_t is equal to 1 when the EMPPA is located in the "hill" of the true GMPP, otherwise it is equal to 0. The greater the value of QI2 the worse the ANN performance.

It is worth to note that QI1 is essential for understanding the suitability of an ANN structure in a scenario where continuous rapidly variable not-uniform shading conditions occur. In this situation, it could happen that the HCM is not activated because a change in the shading conditions over the PV system occurs immediately after the voltage has been set by the power converter according to the ANN. Therefore, QI1 is more important than QI2 in any application where this kind of scenario is frequent, as in the case of solar electric vehicles moving in a city. On the other hand, in any application where this kind of scenario is improbable, the identification of the right "hill" is the most important target and, consequently QI2 assumes more relevance than QI1. As an example, QI2 is the most significant indicator when the time interval between the occurrences of two different not-uniform shading conditions is greater than the time spent by the overall method to reach the EMPP.

Notwithstanding, the value of QI1 is correlated to the value of QI2. More specifically, when the ANN does not discover the "hill" where the actual MPP is located, the ratio between the EMPPA and the GMPP is less than 1.

The simplest ANN structure under test presents only one hidden layer with 3 neurons. The number of neurons in the hidden layer has been chosen as the average of inputs (i.e. 5, the currents at the voltage points established *a priori*) and outputs (i.e. 1, the voltage related to the EMPPA) according to [53]. This ANN has been trained and tested firstly, then other structures obtained by adding each time a neuron in the hidden layer have been analyzed, until an ANN with 6 (i.e. the sum of inputs and outputs) neurons in the hidden layer was trained and tested. To deeper analyze the effects on the ANN performance of the number of neurons in the hidden layer, two further structures obtained, respectively, by doubling and tripling the number of neurons in the hidden layer have been considered. Finally, the effects on the ANN performance of the number of hidden layers has been studied. Each time a new layer was added, the related number of neurons has been chosen by averaging the number of neurons in the previous hidden layer and the number of outputs.

Figure 3-6, show four different P-V curves among the 1000 randomly generated. In each figure are also marked: the power points corresponding to the 5 voltages points chosen *a priori*; the EMPPA obtained by means of the simplest ANN structure (i.e. 1 hidden layer with 3 neurons); the EMPP obtained by the overall method (ANN and HCM) and the true GMPP. In particular, Fig 3 shows a poor case in which the ANN fails in discovering the "hill" where the GMPP is located, and both the EMPPA and the EMPP yield to a very large wasted power (respectively, 34% and 33%). Fig 4 shows a similar situation (i.e. correct "hill" not discovered), but in a more favourable case in which the EMPPA and especially the EMPP entails a little percentage of wasted power (respectively, 7% and 4%). In the case shown in Fig 5 the ANN identifies the correct "hill" but provides a poor EMPPA (wasted power 17%). Finally, the ANN provides very good results when the case of Fig 6 occurs (wasted power by EMPPA less than 1%).

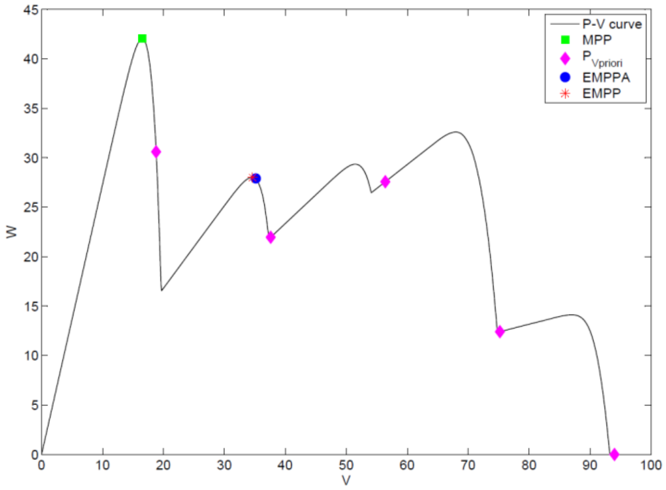

Fig. 3. The ANN fails in discovering the "hill" and the amount of wasted power is large.

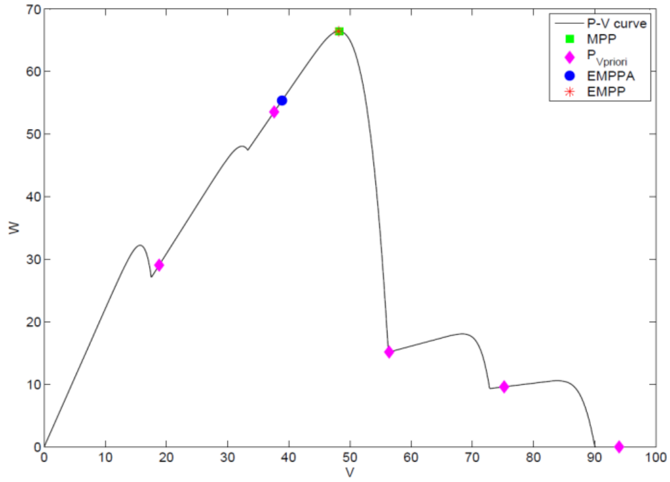

Fig. 5. The ANN discovers the correct "hill" but the amount of power wasted by EMPPA is not negligible.

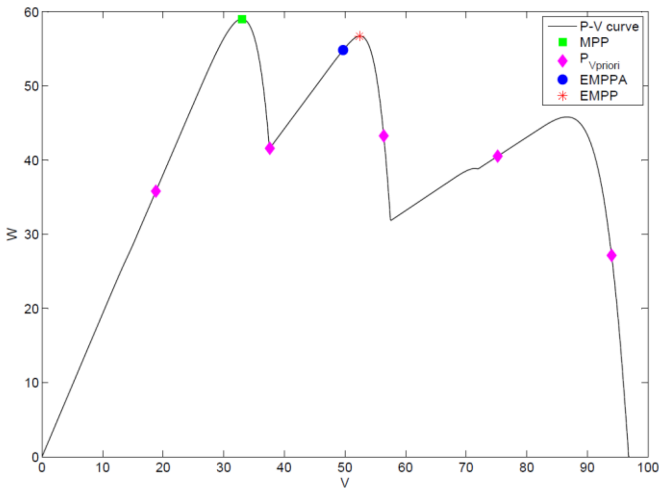

Fig. 4. The ANN fails in discovering the "hill" but the amount of wasted power is not large.

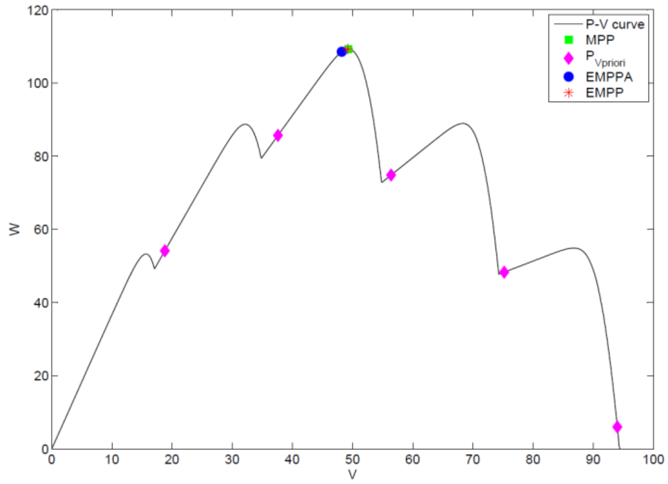

Fig. 6. The ANN provides a very good result.

Table 3 reports the value of the QIs related to the ANN structures considered in this study. The results show that it is profitable the use of ANN structures with large size in order to obtain satisfactory values (wasted power less than 10%) of QI1. Similar considerations can be done for the values of QI2. The worst value in term of QI1 and QI2 is obtained when the simplest ANN structure is adopted, while the best ANN design in term of both QIs is the one featuring the most complex structure (ANN with 3 hidden layers: 18-9-5 neurons).

In view of ANN design considering conflicting targets, that is performance vs. structure size, two further indicators have been defined. The first one provides information about the ability of a given ANN structure to reduce the power wasted by the simplest ANN structure:

$$RWP_s = 1 - \frac{QI1_s}{QI1_3} \tag{9}$$

where: RWPs is the reduction of wasted power of structure s (s=”3”, “4”, …, “18-9-5”, see 1st column of Table 3) with respect to the ANN with a hidden layer having 3 neurons; QI1s is the value of the first quality indicator computed for structure *s*.

An additional indicator has been adopted to compute the improvement in the matching of the EMPP with the GMPP. Obviously, such a performance improvement depends on the ability of an ANN structure in discovering the "hill" where the true GMPP is located. Consequently, the second indicator is computed as:

$$IDRH_s = 1 - \frac{QI2_s}{QI2_3} \tag{10}$$

where: IDRHs is the improvement in discovering the correct "hill" when the structure s is adopted instead of the worst one (QI23); QI2s is the value of the second quality indicator computed for structure s.

Figure 7 and Figure 8 show the two indicators evaluated for each ANN structure under test. The indicator RWP is based on the quality indicator QI1 while IDHR is based on QI2; consequently, hold the previous considerations about the relevance of them in different scenarios.

Table 3. Performance of the trained and tested ANNs.

ANN structure (s) neurons for layer	QI1 in percentage	QI2 in percentage
3	14.26	4.66
4	14.12	4.52
5	12.56	3.70
6	12.44	3.00
6-3	11.43	2.61
6-3-2	11.38	3.27
12	11.13	2.86
12-6	10.32	2.87
12-6-3	9.36	2.70
18	10.84	3.05
18-9	9.03	2.74
18-9-5	8.96	2.39

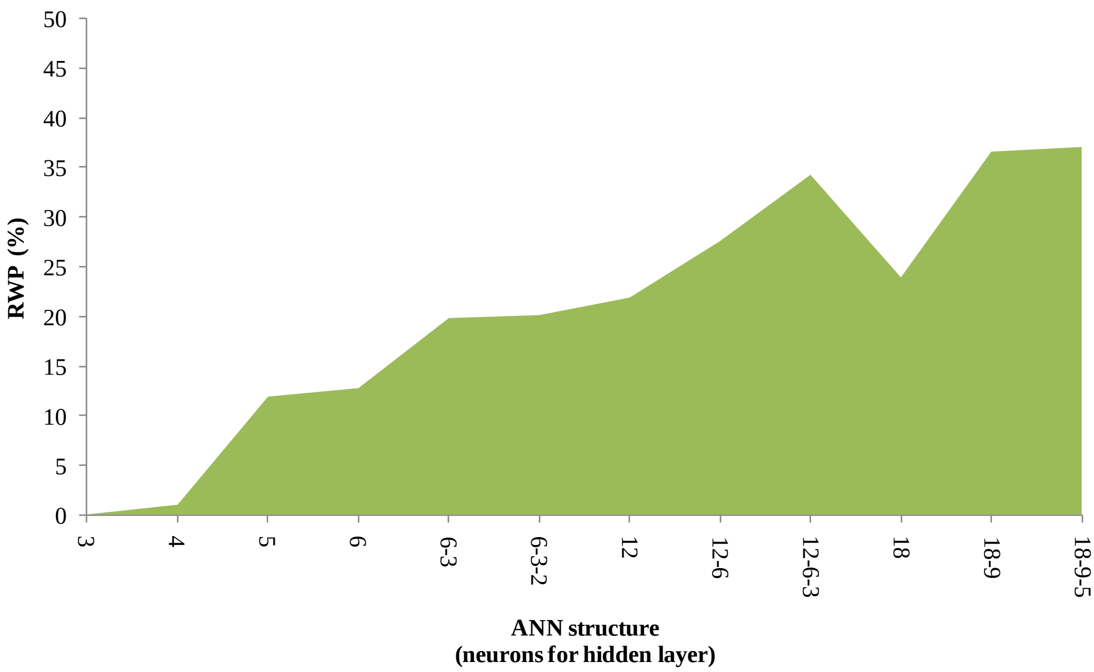

Fig. 7. Reduction of wasted power (RWP) vs. ANN complexity.

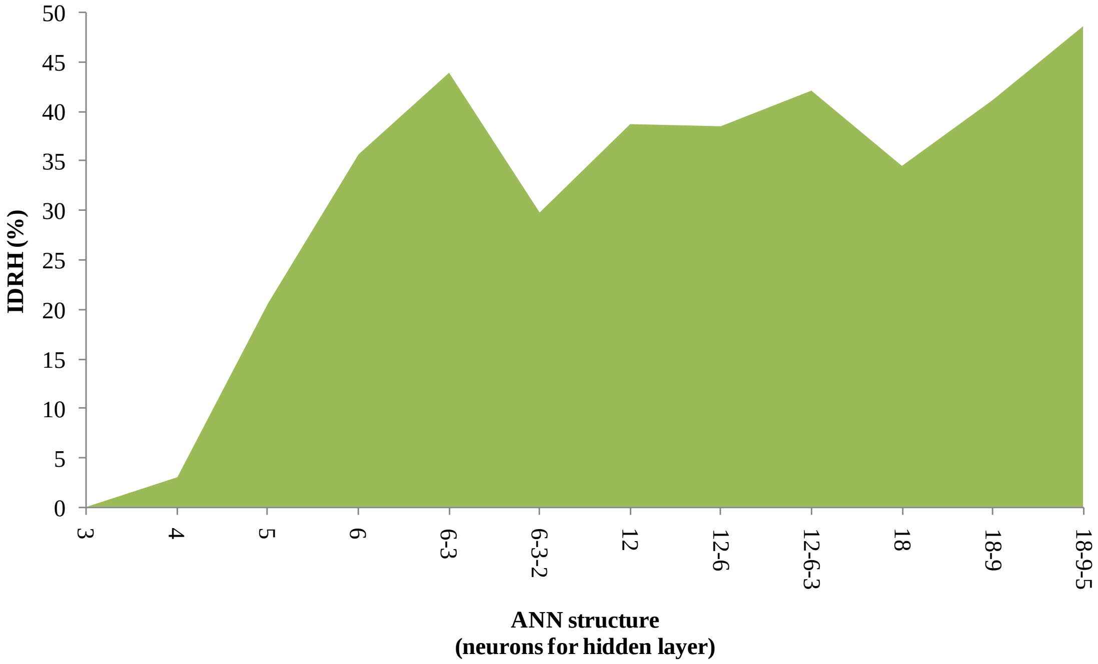

Fig. 8. Improvement in discovering the "hill" (*IDRH*) where the GMPP is located vs. ANN complexity.

Therefore, when continuous rapidly variable not-uniform shading conditions occur the wasted power that can be recovered increases as the ANN size increases as shown in Figure 7. On the other hand, when the not-uniform shading conditions change slowly, it is not necessary the use of a large sized ANN structure to greatly improve the ability of the ANN in discovering the correct "hill". In fact, Figure 8 highlights that an ANN having one hidden layer with 6 neurons obtains performance (in terms of IDHR) comparable with the ANN structures having more hidden layers and/or neurons. In other words, the ability of this ANN in discovering the correct "hill" is similar to more complex ANN structures (comparable IDHR), then it is suitable for fixed PV installations. On the other hand, more complex structures provide an EMPPA closer to the GMPP, which is an essential requirement for PV system installed on vehicles.

5. Conclusion

This paper has dealt with the analysis of a maximum power point tracking algorithm capable of handling very fast changing environmental conditions. This goal has been achieved by combining artificial neural networks and hill climbing methods. Firstly, the artificial neural network estimates the maximum power point in absence of any information about the shading conditions and panels temperature, then the hill climbing method further improve the result. The computational burden is greatly reduced thanks to a suitable design of the artificial neural network structure as well as to its training process. Numerical simulations have validated the effectiveness of the proposed method on a relevant case study and meaningful design criteria have been obtained.

References

[1] Soohyun Kim, Jin-Won Chung, Hyun Lee, Jinhee Park, Younho Heo, Heon-Min Lee, "Remarkable progress in thin-film silicon solar cells using high-efficiency triple-junction technology", Solar Energy Materials & Solar Cells, vol. 119, pp. 26 – 35, 2013.

[2] By Mariusz Malinowski, Jose I. Leon, and HaitHaM Abu-Rub, "Solar Photovoltaic and Thermal Energy Systems: Current Technology and Future Trends," IEEE Proceedings of the, vol. PP, n. 99, April 2017.

[3] T. Esram, P.L. Chapman, "Comparison of Photovoltaic Array Maximum Power Point Tracking Techniques," IEEE Transactions on Energy Conversion, vol. 22, n. 2, pp. 439–449, June 2007.

[4] M.A.G. De Brito, L. Galotto, L.P. Sampaio, G. de Azevedo e Melo, C.A. Canesin, "Evaluation of the Main MPPT Techniques for Photovoltaic Applications", IEEE Transactions on Industrial Electronics, vol. 60, n.3, pp. 1156 – 1167, March 2013.

[5] K. Ishaquea, Z. Salamb, "A review of maximum power point tracking techniques of PV system for uniform insolation and partial shading condition", Renewable and Sustainable Energy Reviews, vol. 19, pp. 475 – 488, march 2013.

[6] S. Jain, V. Agarwal, "Comparison of the performance of maximum power point tracking schemes applied to single-stage grid-connected photovoltaic systems", IET Electric Power Applications, vol.1, n. 5, pp. 753 – 762, 2007.

[7] N.Femia, D.Granozio, S. Petrone, G. Spagnuolo, M. Vittelli, "Predictive & adaptive MPPT perturb and

observe method", IEEE Transactions on Aerospace and Electronic Systems, vol. 43, n.3, pp. 934-950, July 2007.

[8] Abdelhakim Belkaid, Ilhami Colak, Korhan Kayisli, "Implementation of a modified P&O-MPPT algorithm adapted for varying solar radiation conditions", Electrical Engineering, pp. 1 – 8, october 2016.

[9] A. Belkaid, I. Colak, O. Isikc, "Photovoltaic maximum power point tracking under fast varying of solar radiation", Applied Energy, vol. 179, pp. 523 – 530, october 2016

[10] D. Casadei, G. Grandi, C. Rossi, "Single-phase single-stage photovoltaic generation system based on a ripple correlation control maximum power point tracking", IEEE Transactions on Energy Conversion, vol. 21, n. 2, pp. 562-568, June 2006.

[11] A.K. Abdelsalam, A.M. Massoud, S. Ahmed, P. Enjeti, "High-Performance Adaptive Perturb and Observe MPPT Technique for Photovoltaic-Based Microgrids", IEEE Transactions on Power Electronics, vol. 26, n.4, pp. 1010 – 1021, 2011.

[12] M. Qiang, S. Mingwei, L. Liying, J.M. Guerrero, "A Novel Improved Variable Step-Size Incremental-Resistance MPPT Method for PV Systems", IEEE Transactions on Industrial Electronics, vol. 58, n. 6, pp. 2427 – 2434, 2011.

[13] D. Sera, R. Teodorescu, J. Hantschel, M. Knoll, "Optimized Maximum Power Point Tracker for Fast-Changing Environmental Conditions", IEEE Transactions on Industrial Electronics, vol. 55, n. 7, pp. 2629 – 2637, July 2008.

[14] X. Weidong, N. Ozog, W.G. Dunford, "Topology Study of Photovoltaic Interface for Maximum Power Point Tracking", IEEE Transactions on Industrial Electronics, vol. 54, n. 3, pp. 1696 – 1704, June 2007.

[15] A.D. Karlisa, T.L. Kottasb, Y.S. Boutalisb, "A novel maximum power point tracking method for PV systems using fuzzy cognitive networks (FCN)", Electric Power Systems Research, vol.77, n° 3-4, pp. 315 – 327, March 2007.

[16] A.A. Kulaksız, R. Akkaya, "A genetic algorithm optimized ANN-based MPPT algorithm for a stand-alone PV system with induction motor drive", Solar Energy, vol. 86, n. 9, pp. 2366 – 2375, September 2012.

[17] A.B.G. Bahgata, N.H. Helwab, G.E. Ahmadb, E.T. El Shenawyb, "Maximum power point traking controller for PV systems using neural networks", Renewable Energy, vol. 30, n. 8, pp.: 1257 – 1268, July 2005.

[18] T. Hiyama, K. Kitabayashi, "Neural network based estimation of maximum power generation from PV module using environmental information", IEEE Transactions on Energy Conversion, vol. 12, n.3, pp. 241 – 247, 1997.

[19] C.B. Salah, M. Ouali, "Comparison of fuzzy logic and neural network in maximum power point tracker for PV systems", Electric Power Systems Research, vol. 81, n.1, pp. 43 – 50, January 2011.

[20] J.H. Seo, C.H. Im, C. G.Heo, J.K. Kim, H.K. Jung, C.G. Lee, "Multimodal function optimization based on particle swarm optimization", IEEE Transactions on Magnetics, vol. 42, n. 4, pp. 1095-1098, 2006. DOI: 10.1109/TMAG.2006.871568.

[21] M. Miyatake, M. Veerachary, F. Toriumi, N. Fujii, H. Ko, "Maximum Power Point Tracking of Multiple Photovoltaic Arrays: A PSO Approach", IEEE Transactions on Aerospace and Electronic Systems, vol. 47, n.1, pp. 367 – 380, 2011.

[22] E. Koutroulis, F. Blaabjerg, "A New Technique for Tracking the Global Maximum Power Point of PV Arrays Operating Under Partial-Shading Conditions", IEEE Journal of Photovoltaics, vol. 2, n.2, pp.: 184 – 190, April 2012.

[23] T. L. Nguyen, K.-S. Low, "A Global Maximum Power Point Tracking Scheme Employing DIRECT Search Algorithm for Photovoltaic Systems," IEEE Transactions on Industrial Electronics, vol. 57, n. 10, pp. 3456–3467, October 2010.

[24] Y.H. Ji, D.Y.Jun, J.G. Kim , J.H. Kim, T.W. Lee, C.Y. Won, "A real maximum power point tracking method for mismatching compensation in PV array under partially shaded conditions", IEEE Transactions on Power Electronics, vol. 26, n.4, pp. 1001-1009, 2011.

[25] H. Patel, V. Agarwal, "Maximum power point tracking scheme for PV systems operating under partially shaded conditions," IEEE Trans. Ind. Electron., vol. 55, n. 4, pp. 1689–1698, Apr. 2008.

[26] M. Boztepe, F. Guinjoan, G. Velasco-Quesada, S. Silvestre, A. Chouder, E. Karatepe, "Global MPPT Scheme for Photovoltaic String Inverters Based on Restricted Voltage Window Search Algorithm", IEEE Transactions on Industrial Electronics, vol. 61, n.7, pp. 3302 – 3312, 2014.

[27] Syafaruddin, E. Karatepe, 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, n. 2, pp.:239 – 253, 2009.

[28] B.N. Alajmi, K.H. Ahmed, S.J. Finney, B.W. Williams, "A Maximum Power Point Tracking Technique for Partially Shaded Photovoltaic Systems in Microgrids", IEEE Transactions on Industrial Electronics, vol. 60, n. 4, pp. 1596 – 1606, 2013.

[29] M. Boztepe, F. Guinjoan, G. Velasco-Quesada, S. Silvestre, A. Chouder, E. Karatepe, "Global MPPT Scheme for Photovoltaic String Inverters Based on Restricted Voltage Window Search Algorithm", IEEE Transactions on Industrial Electronics, vol. 61, n.7, pp. 3302 – 3312, 2014.

[30] L. Peng, L. Yaoyu, J.E. Seem, "Sequential ESC-Based Global MPPT Control for Photovoltaic Array With

Variable Shading", IEEE Transactions on Sustainable Energy, vol. 2, n. 3, pp.: 348 – 358, 2011.

[31] J. Ahmed, Z. Salam, "A Maximum Power Point Tracking (MPPT) for PV system using Cuckoo Search with partial shading capability", Applied Energy, vol. 119, n°15, pp. 118 – 130, april 2014.

[32] E. Mamarelis, G. Petrone, G. Spagnuolo, "A two-steps algorithm improving the P&O steady state MPPT efficiency", Applied Energy, january 2014, vol. 113, pp. 414 – 421.

[33] K. Punitha, D. Devaraj, S. Sakthivel, "Artificial neural network based modified incremental conductance algorithm for maximum power point tracking in photovoltaic system under partial shading conditions", Energy, vol. 62, n. 1, pp. 330 – 340, December 2013.

[34] Lian Lian Jiang, D.R. Nayanasiri, Douglas L. Maskell, D.M. Vilathgamuwa, A hybrid maximum power point tracking for partially shaded photovoltaic systems in the tropics, Renewable Energy, Volume 76, April 2015, Pages 53-65.

[35] K. Ishaque, Z. Salam, A. Shamsudin, M. Amjad, "A direct control based maximum power point tracking method for photovoltaic system under partial shading conditions using particle swarm optimization algorithm", Applied Energy, vol. 99, pp. 414 – 422, april 2012.

[36] M. Saadsaoud, H. Abbassi, S. Kermiche, and M. Ouada, "Study of Partial Shading Effects on Photovoltaic Arrays with Comprehensive Simulator for Global MPPT Control", International Journal of Renewable Energy Research. Turkey, vol. 6, no. 2, pp. 413-420, 2016

[37] Sayed Farzad Hosseini, Behnam Mostajeran Goortani, Mehdi Nirooman, "Instantaneous Responses of on-grid PV Plants to Changes in Environmental and Weather Conditions", International Journal of Renewable Energy Research. Turkey, Vol 6, No 4 (2016), pp 1296 - 1306, 2016

[38] Mouna Ben Smida, Anis Sakly, "A comparative study of different MPPT methods for grid-connected partially shaded photovoltaic systems", International Journal of Renewable Energy Research. Turkey, Vol 6, No 3, 1082-1090, 2016

[39] Ngo Ngoc, T., Phung, Q.N., Tung, L.N., Riva Sanseverino, E., Romano, P., Viola, F. "Increasing efficiency of photovoltaic systems under non-homogeneous solar irradiation using improved Dynamic Programming methods" (2017) Solar Energy, 150, pp. 325-334.

[40] Sanseverino, E.R., Ngoc, T.N., Cardinale, M., Li Vigni, V., Musso, D., Romano, P., Viola, F. "Dynamic programming and Munkres algorithm for optimal photovoltaic arrays reconfiguration" (2015) Solar Energy, 122, pp. 347-358.

[41] Caruso, M., Di Noia, L.P., Romano, P., Schettino, G., Spataro, C., Viola, F. "PV reconfiguration systems: A technical and economic study", (2017) Journal of Electrical Systems, 13 (1), pp. 55-73.

[42] Viola, F., Romano, P., Miceli, R., Spataro, C., Schettino, G. "Technical and economical evaluation on the use of reconfiguration systems in some EU countries for PV plants"(2017) IEEE Transactions on Industry Applications, 53 (2), art. no. 7736973, pp. 1308-1315.

[43] A. Ghosh, S. Dehuri, "Evolutionary Algorithms for Multi-Criterion Optimization: A Survey", International Journal of Computing & Information Sciences, vol.2, n.1, pp.38-57, 2004.

[44] S. Daraban, D. Petreus, C. Morel, "A novel global MPPT based on genetic algorithms for photovoltaic systems under the influence of partial shading", 39th Annual Conference of the IEEE Industrial Electronics Society, IECON 2013.

[45] B. Sareni, L. Krahenbuhl, "Fitness Sharing and Niching Method Revisited", IEEE Transactions on Evolutionary Computation, vol. 2, n. 3, 1998, pp 97-106. DOI: 10.1109/4235.735432.

[46] Hassan Fathabadi, Novel solar powered electric vehicle charging station with the capability of vehicle-to-grid, Solar Energy, Volume 142, 15 January 2017, Pages 136-143.

[47] Y. Singh, A. S. Chauhan, "Neural networks in data mining", Journal of Theoretical and Applied Information Technology, vol. 5, n. 6, pp. 36–42, 2009.

[48] Leandro Nunes de Castro, Fundamentals of natural computing: an overview, Physics of Life Reviews, Volume 4, Issue 1, March 2007, Pages 1-36.

[49] Alberto Prieto, Beatriz Prieto, Eva Martinez Ortigosa, Eduardo Ros, Francisco Pelayo, Julio Ortega, Ignacio Rojas, Neural networks: An overview of early research, current frameworks and new challenges, Neurocomputing, Volume 214, 19 November 2016, Pages 242-268.

[50] W. S. McCulloch, W. Pitts, "A logical calculus of the ideas imminent in nervous activity", Bulletin of the Mathematical Biophysics, vol. 5 pp. 115-133, 1943. DOI: 10.1007/BF02478259

[51] A. K. Jain, J. Mao , K. M. Mohiuddin, "Artificial Neural Networks: A Tutorial", Computer, vol. 29, pp.31-44, 1996. DOI: 10.1109/2.485891

[52] D.E. Rumelhart, G.E. Hinton, R.J. Williams, "Learning representations by back-propagating errors", Nature, vol. 323, pp. 533–536, 1986. DOI:10.1038/323533a0

[53] S. Piramuthu, M.J.Shaw, J.A. Gentry, "A classification approach using multi-layered neural networks", Decision Support Systems, vol. 11, n. 5, pp. 509-525, 1994.