Model Identification for Photovoltaic Panels Using Neural Networks

Antonino Laudani, Gabriele Maria Lozito, Martina Radicioni, Francesco Riganti Fulginei and Alessandro Salvini

Department of Engineering, Roma Tre University, Via Vito Volterra 62/b, Rome, Italy

Keywords: Neural Networks, Fully Connected Cascade, Photovoltaic Panels, One-Diode Model.

Abstract: The present work documents the study on the usage of Neural Networks to compute the parameters used in solar panel modelling. The approach followed starts from a dataset obtained by a process of model identification via numerical solution of nonlinear equations. After a preliminary analysis pointing out the intrinsic difficulty in the classic identification of the parameters via NN, by taking advantage of closed form relations, a hybrid neural system, composed by neural network based identifiers and explicit equations, was implemented. The generalization capabilities of the neural identifier were investigated, showing the effectiveness of this approach.

1 INTRODUCTION

The solar energy power industry requires the use of suitable photovoltaic (PV) model for the evaluation of the performance of power plants. Among the available models for electrical representation of a PV panel, the five-parameter one, also known as ”‘one-diode model”’, is the widest adopted and is generally recognized as reference design tool (Blair et al., 2010). This model describes the electrical relation between current and voltage for a PV module (or an array of modules), and may be identified either by employing few experimental data, or by solving a system of five non-linear equations, starting from data provided by manufacturers in datasheets. In both cases, the identification problem is really a complicated task, which must be resolved numerically by means of optimization/inverse problems solving techniques. Indeed, two main issues characterize the model and must be addressed: the transcendental nature of the equations, which leads to the impossibility to solve the problem analytically, and the lack of sufficient informations to take effective initial guess values to be used in the selected optimization/inverse problem technique. For these reasons, almost any possible optimization technique has been adopted in literature: simulated annealing (El-Naggar et al., 2012), genetic algorithm (Zagrouba et al., 2010), differential evolution (Ishaque and Salam, 2011; Jiang et al., 2013), evolutionary algorithm (Siddiqui and Abido, 2013), artificial bee swarm optimization (Askarzadeh and Rezazadeh, 2013), bacterial foraging algorithm (Rajasekar et al., 2013), semi-analytical/deterministic approach and so on. All these techniques, although effective, make the constrained optimization problem with five unknowns rather long and complex to solve without strong computational capabilities. This shortcoming of the model was addressed in (Laudani et al., 2013), where the authors deduced that the model could be reduced, by following algebraic manipulation, to a two only independent parameters model, being three of the original parameters dependent on the other two. The resulting model must be still identified by numerical means, but now using much less complex methods (deterministic algorithms) such as Newton method or steepest descent gradient. In fact, it has been observed that the two-parameter problem is usually convex, also in the case of experimental data (Laudani et al., 2014a). However, regardless of the used model, the PV parameter identification requires a complex software architecture. The five-parameter model needs a high exploration algorithm to isolate candidate solutions, that are later refined by a local search algorithm, to discern local minima from global optimum. The two-parameter reduced form model, even if convex, still requires a local non-linear optimization algorithm to be efficiently identified (Laudani et al., 2014b): this is a serious drawback, which does not allow an easy implementation of a generic solver for the problem outside a suitable computing environment, such as Matlab. This is a serious limitation, since it does not allow the integration of these

Laudani A., Lozito G., Radicioni M., Riganti Fulginei F. and Salvini A..
Model Identification for Photovoltaic Panels Using Neural Networks.
DOI: 10.5220/0005039201300137
In *Proceedings of the International Conference on Neural Computation Theory and Applications* (NCTA-2014), pages 130-137
ISBN: 978-989-758-054-3

identification algorithms in low cost embedded system, based on microncontroller architecture, for the monitoring and the management of PV plants (Carrasco et al., 2013). On the other hand, although many artificial intelligence methods have been used for this problem, the Neural Networks (NNs) were used only to interpolate experimental data, rather than extract the five parameter model. In the PV field, NNs are frequently used for MPPT (Maximum Power Point Tracking) algorithms (Liu et al., 2013), solar irradiance (Mancilla-David et al., 2014) estimation and forecasting (a review on the subject was published by (Yadav and Chandel, 2014)). Nevertheless, at the authors knowledge, in literature the neural approach did not lead to effective results in the PV five parameter model extraction yet. This probably is due to a twofold problem: i) the need of a meaningful dataset for the training of the NN (thanks to which the NN should be able to learn how to solve the respective non-linear system of equations) which involves solving the inverse problem for a high number of different panels; ii) the difficulties in the identification of one of the parameters (R_{SH}), which makes ineffective the neural approach. On the other hand, Neural Networks (NN) are often used in literature to solve efficiently mathematical problems (Capizzi et al., 2004; Xu et al., 2012) involving solution of complex mathematical expression. This paper is aimed at showing the results obtained by the developed neural network in the solution of the identification problem for the five parameter model starting from datasheet information, thanks to the synergy between neural approach and reduced forms.

2 THE FIVE-PARAMETER MODEL AND ITS REDUCTION TO TWO PARAMETERS

The five parameter model is based on the circuit representation of a PV module by the means of an independent current source, an anti-parallel diode and two output resistances, one in parallel with the diode and one in series with the output branch (see fig. 1). The current-voltage relation expressed by the model is shown in 1.

$$I = I_{Irr} - I_0 \left[e^{\left(\frac{q(V+IR_S)}{N_S nkT} \right)} - 1 \right] - \frac{V + IR_S}{R_{SH}} \qquad (1)$$

This equation can represent a PV module composed by an arbitrary number N_S of cells in series. The parameters of equation (1) are the ideality factor n, the shunt resistance R_{SH}, the series resistance R_S, the saturation reversal current of the diode I_0 and the irradiation current I_{Irr}. The other physical quantities involved are: the electron charge q ($q = 1.602 \times 10^{-19}$ C); the Boltzmann constant k ($k = 1.3806503 \times 10^{-23}$ J/K); the cell temperature T. Apart from the ideality factor n and the series resistance R_S, the three other parameters are temperature and/or irradiance dependent. Among the different version of the five parameter models, which describe these dependences, the one proposed and validated in (Desoto et al., 2006) is one of the most successfully adopted, and, for this reason, is the one used in this work. Unfortunately, manufacturers of PV panel do not report these five parameters on the datasheet, so they must be derived by actual available data: the open circuit voltage V_{OC}, the short circuit current I_{SC}, the voltage and current at the maximum power point I_{MPP} and V_{MPP}, and the temperature coefficient of both I_{SC} and V_{OC}, respectively α_T and β_T at Standard Reference Conditions (SRC), that is in correspondence of a solar irradiance S_{REF} of 1000 W/m^2 and a temperature T_{REF} of 25°C. By using these data, five implicit non-linear equations in the unknowns of n, R_{SH}, R_S, I_0, and I_{Irr} can be formulated in order to achieve the values of the five parameters at SRC: the first equation is achieved by writing the (1) at open circuit condition; the second equation by imposing short circuit condition; the third and forth equation by using maximum power point condition; the last equation by exploiting the condition on open circuit at not SRC condition. The solution of this system of trascendental equations by numerical techniques gives the parameters of the model (Laudani et al., 2014b). A schematization of this identification problem approach is illustrated in Fig. 2. From this figure it is also to worth noticing that in order to avoid passing the number of cells in series, N_S, as input, the product $a = N_S n$ was used as output, thus reducing the input parameters. Then, once the parameters are extrapolated at SRC, they can be modulated by the means of simple relations to obtain an $I-V$ characteristic for any condition of temperature and irradiance. This identification process, although being complete and effective, is far from being computationally efficient: and this essentially because of the trascendental

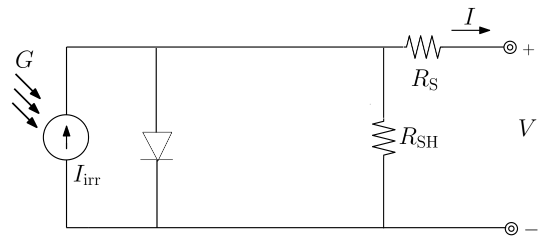

Figure 1: Circuit representation of a PV module by means of the five-parameter model .

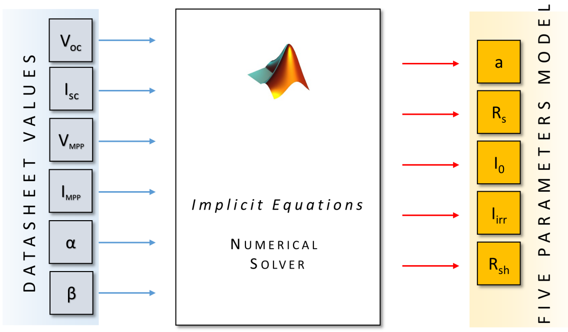

Figure 2: Identification of the five-parameter model by means of numerical solution of implicit equations system.

nature of the involved equations. Recently, it has been observed (Laudani et al., 2013) that the five implicit equations used in the five-parameter model identification can be manipulated algebraically to reduce the number of unknowns. In particular, the unknowns of I_{Irr}, I_0 and R_{SH} can be expressed as a function of the unknown $n = a/N_S$ and R_S by means of closed forms expressions, like:

$$R_{SH} = h(n, R_S) \quad (2)$$

$$I_0 = f(n, R_S) \quad (3)$$

$$I_{irr} = g(n, R_S) \quad (4)$$

where the function $f(n, R_S)$, $g(n, R_S)$ and $h(n, R_S)$ are respectively given by the formulae reported in the Appendix together with a table summarizing the nomenclature. This reduction has two benefits. First, the problem of model identification is reduced to the extraction of only two unknown parameters (n and R_S), allowing simpler optimization techniques to be used. Second, differently from the five-parameter problem, this is generally a convex unimodal problem. Another important advantage of the two-parameter model lies in the search domain. Consider the five-parameter model: while a lower bound for the five parameters is apparent (i.e. they must be positive to be physically sensible) the upper bound is undefined. An exception can be made for the n parameter, defined by solid-state physics lower than 2 (although often amorphous silicon modules have higher ideality factor), according to the transport mechanism for charges inside the junction. The remaining four parameters, however, must be searched in the positive semi-space of solutions. By using the reduced closed forms model, the R_S unknown is related to I_{Irr}, $I_0$and R_{SH} by means of the above cited implicit equations. By imposing the non-negativity of I_{Irr}, I_0 and R_{SH}, it is possible to formulate an upper bound for R_S itself. Thus the resulting equations with the relative constraints constitutes an optimization problem easier to address and solve than the original one inherent in the five-parameter

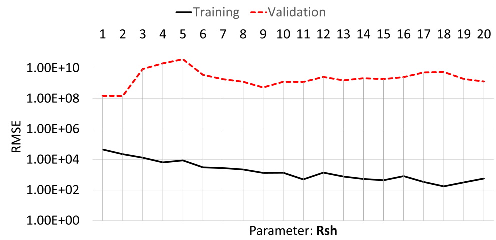

Figure 3: Mean error on training and validation for MLP estimating R_{SH} parameter (hidden layer size up to 20 neurons).

model identification (Laudani et al., 2014a; Laudani et al., 2014b). Nevertheless, the system of the reduced model still cannot be solved easily outside a suitable computing environment, such as Matlab, Mathcad, etc. This drawback has not allowed the development of suitable management software of PV plants in low cost computational system (such as microncontroller based architecture), which is of interest for the photovoltaic system industry. On the other hand, it allowed the identification of thousands of modules from database in few minutes giving the possibility to constitute a valid dataset for the training of a NN able to deal with this kind of problem.

3 SET-UP OF THE PV MODEL NEURAL IDENTIFIER

Different possibilities arises when choosing for a NN architecture. Firstly, the nature of the problem must be examined: static or dynamic problems influence our choice in the direction of feed forward or recurrent networks. In this case, the problem is a static identification problem which can be solved by a feed forward approach. Another point to take into account is the complexity of the implementation in low cost/performance system. Starting from these considerations the Multi-Layer-Perceptron (MLP) architecture is surely the clear choice for this kind of problems. In the MLP architecture the neurons are organized in subsequent layers, and the connections are made using a feed forward configuration: no connection exists between neurons of the same layer, but each neuron communicates via weighted connections to all the neurons of the successive layer. The number of layers in a MLP is variable, with a minimum of three. In this case, the Input layer performs no operations. The Hidden layer is composed by neurons with a non-linear activation function. The Output layer is analogous to the second, but with a simple linear activation function. Indeed, the hidden layer re-maps the inputs so that they are linearly separable, and the out-

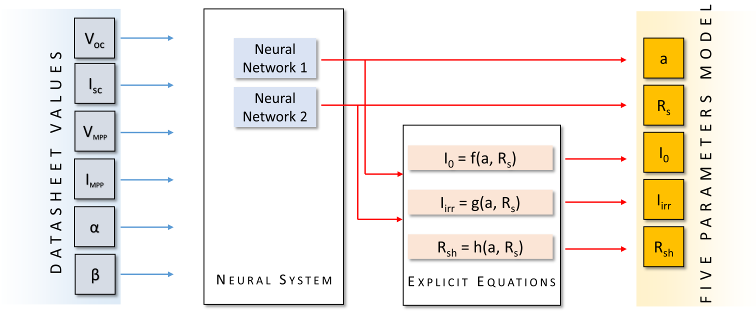

Figure 4: Identification of the parameters by means of a neural system and explicit equations.

put layer performs linear combination. By the Universal Approximation Theorem (Cybenko, 1989; Hornik et al., 1989) a feed forward neural network with a single hidden layer containing a finite number of neurons can interpolate any continuous function. In addition, the single hidden layer MLP is a standard architecture, where the only parameter is the number of neurons in the hidden layer. The advantage of this architecture lies in its univocal determination by the number of neurons: given the hidden layer size, the number of inputs and the number of outputs, the NN architecture is completely defined. Another important issue is that the relation between training performance and layer size has been investigated thoroughly in literature (Ilonen et al., 2003; Rawat et al., 2013; Hunter et al., 2012; Teoh et al., 2006; Kim and Lee, 2008). However, complex problems may require a very high number of neurons, making the training of a single hidden layer MLP difficult: that is, even if the MLP could approximate any function, it may not be the most efficient way to do it (Wilamowski, 2009). On this behalf, different architectures arose in literature. Nevertheless, it usually is the first typology of NN to try when a new problem is addressed for the first time. For the implementation of the neural identifier of the PV five parameter model we have investigated the use of MLP architectures, since we have already successfully used it for other PV related problems: in particular for the solution of maximum power point identification (Carrasco et al., 2013) and for the prediction of solar irradiance from PV voltage and current measurements (Mancilla-David et al., 2014). The approach pursued in this paper is to use a neural network to estimate the parameters of the one diode model starting from datasheet value, as explained in section 2. The simplest strategy would be to substitute the block shown in figure 2 with a MLP composed by multiple inputs and outputs, train it on the training set and validate the results obtained. It has been observed, however, that by using a MIMO architecture, an effective estimation with NN cannot be achieved for the addressed problem. To understand the reasons behind this behavior, the MIMO was split in multiple MISO networks (Parodi et al., 2012), one for each of the five parameters figuring in the model. By trying to compute the parameters individually, the problem became apparent: the parameter R_{SH} could not be estimated by the NN, at least by using a low/medium number of neurons, and consequently neither by the MIMO network (the performance of the MISO network up to 20 neurons can be seen in figure 3). This parameter, by itself, was the cause of the NN approach failure. This justifies as well the lack of PV model neural identifiers. By taking advantage of the closed forms proposed in Section 2, the calculation of parameters I_0, R_{SH} and I_{Irr} is not necessary to identify the model. Indeed, as can be seen in figure 4, the NN approach can be used to evaluate the two independent parameters R_S and a, while the remaining three can be calculated by using the closed forms $f(n, R_S)$, $g(n, R_S)$ and $h(n, R_S)$ ($n = a/N_S$). Thus, two MISO NN have been implemented: both NNs receive as inputs the six datasheet values (the open circuit voltage of the cell V_{OC}, the short circuit current I_{SC}, the voltage and current at the maximum power point I_{MPP} and V_{MPP}, and the temperature coefficient of both I_{SC} and V_{OC}, respectively α_T and β_T.), and returns as output either R_S or a.

3.1 Dataset and Training Procedure Description

The dataset used to train the neural networks in the present work was acquired from a large database of panels (California Energy Commission, 2013). The database collects all the relevant datasheet informations for about 10000 photovoltaic panels. By using the techniques illustrated in (Laudani et al., 2014b) for each module of the database a five-parameter model was identified. In order to verify the generalization capabilities of our neural network, we decided to use the modules with Monocrystalline Silicon (mono-Si) technology available on CEC database as training set, and the modules with multicrystalline Silicon (multi-Si) technology as test set. Choosing the mono-Si modules should also guarantee a training dataset capable of representing an acceptable diversity of panels with different characteristics. In addition, in this way we can assume that the neural identifier has learnt to solve this system of trascendental equations, since the two technologies differ significantly in the reference parameters. The resulting training set consists of about 4000 entries, whereas the test set has more than 6000 modules. The interpolation capabilities of a NN can be correlated to the number of neurons composing the network itself. On the other hand, an relationship can be achieved for each kind of problem, which links for a data generalization measure the number of neurons with the size of the training set (more explanations can be found in (Fulginei et al., 2013) and are out of the scope of this work). In our case training set is very large with respect to the number of neurons adopted and consequently it is improbable to run into over trained networks. Finally, in our investigation, we adopted the following principles: *i*) we use a NN with a number of neurons in the hidden layer variable from 20 down to 1; *ii*) each NN with a fixed number of neurons is trained 10 times for 1000 epochs in order to perform a statistical analysis of the results (minimum, average, median and standard deviation are computed); *iii*) No validation set has been used for early stopping techniques. One of the reasons behind the choice of not using the early stopping mechanism with a validation set is the low number of epochs adopted with respect the size of the training set. As stated, each single NN was trained multiple times, changing the characteristic size and making a statistic analysis of the training and validation performances for both sets (training and test data set). A total of 2x10x20 MLP were trained and validated. The performance was evaluated using as metric the MSE on training (or test) set and the NNs output. The discussion on the results is reported in the next section.

4 RESULTS AND DISCUSSION

The performance of the Neural identifier are summarized in the tables 1 and 2 where the minimum MSE for both training and test set are reported for parameters a and R_S, respectively. As it is possible to notice the MSE reaches extremely low values (under 1E-7) giving an accurate estimation of these two parameters. It is worth to remind that the training set is made of mono-Si modules whereas the test set is made of multi-Si modules: the low MSE achieved on test set allows us to confirm the generalization capabilities of the Neural networks. In addition, the MSE decreases by adding further neurons, and this trend should continue for a number of neurons higher than 20 in the

Table 1: Result for parameter a.

Neurons	min MSE on training set	min MSE on test set
1	5.129E-02	4.133E-02
2	2.827E-04	2.947E-04
3	9.733E-06	5.271E-05
4	2.987E-06	1.461E-05
5	5.597E-07	3.566E-05
6	2.168E-07	3.079E-05
7	1.218E-07	1.312E-05
8	2.657E-08	3.103E-07
9	7.755E-08	5.162E-06
10	2.305E-08	1.233E-05
11	5.416E-09	9.532E-06
12	9.227E-09	9.425E-06
13	1.280E-08	3.649E-06
14	9.672E-09	5.569E-06
15	8.046E-09	1.073E-05
16	1.341E-08	8.131E-06
17	4.077E-09	2.652E-06
18	1.733E-08	6.063E-06
19	1.619E-09	5.078E-07
20	1.218E-09	9.606E-07

Table 2: Result for parameter R_S.

Neurons	min MSE on training set	min MSE on test set
1	7.033E-04	4.903E-04
2	6.979E-05	2.619E-05
3	3.844E-06	7.508E-06
4	1.444E-06	1.734E-06
5	3.914E-07	7.847E-07
6	5.802E-08	3.084E-07
7	2.049E-08	1.468E-07
8	5.303E-09	6.925E-08
9	5.316E-09	3.302E-08
10	1.679E-09	2.223E-08
11	1.266E-09	4.499E-08
12	6.415E-10	1.685E-08
13	5.282E-10	1.275E-08
14	3.045E-10	6.508E-09
15	4.748E-10	1.266E-08
16	1.715E-10	9.018E-09
17	1.789E-10	6.829E-09
18	1.919E-10	5.594E-09
19	8.278E-11	2.025E-09
20	1.100E-10	1.096E-08

hidden layer as well. However accurate results are already achived with less than 20 neurons and consequently it is not necessary to further add neurons. In figures 5 and 6 the comparison between the values of a and R_S parameters and NN output of the best NNs trained, are shown for the first 1000 modules of the test set. Practically the values returned by NN are superimposed to the exact values (a maximum difference of the order of 1E-4 is achieved, which is surely satisfactory since the input data have a precision lower than this). This gap is clearly due to the precision of the trained NN. This could be reduced if we further train the network by using a high number of epochs. But, in every case, it is already quite acceptable, considering that the state of the art approach for this computation used often approximated formulae introducing error of the order of 1% (see (Cubas et al., 2014; Li et al., 2013) for reviews of these approaches). At the same time, from these accurate values, the other dependent parameters R_{SH}, I_0 and I_{Irr} can be computed precisely by using the respective closed forms, confirming that the use of NN in conjunction with reduced closed forms allows to identify quickly the one diode model. The suggested sizes in both cases is 19 neurons in the hidden layer: this choice is done considering the MSE complessively obtained for all the 10000 PV modules constituting the training and test set. Indeed the aim is also to use this NN for the solution of the problem in a real application and to implement it in embedded systems, and consequently we are interested in the best performance available on all modules with a low computational cost. In this sense, if we accept a higher error, the NNs with 8 neurons allows to achieve a good accuracy estimation as well (MSE about 1E-7) with a lower computational cost. Lastly, it is worth noticing that the comparison with the other approaches must be done in terms of both computational cost/environment of implementation and precision; thus we have: exact methods, such as those proposed in (Laudani et al., 2014b), which although efficient cannot be implemented in low cost microcontroller based system (Mancilla-David et al., 2014); other high accuracy approaches (such as those reported in (Li et al., 2013) or based on cluster analysis (Sandrolini et al., 2010)), which have prohibitive computational cost; approximated methods, such that one reported in (Cubas et al., 2014) which introduce errors in the calculation of the parameters and have a low computational cost. The approach herein proposed is efficient from the computational cost point of view and enough correct in the estimation of the five-parameter model and thus it is a good trade-off with respect the approaches presented in literature. Although the MLP architecture could be not so efficient, we have verified that an implementation of the same problem by using a Full Connected Cascade NN (Wilamowski, 2009) did not give significative improvement in the results and showed an equivalent computational cost.

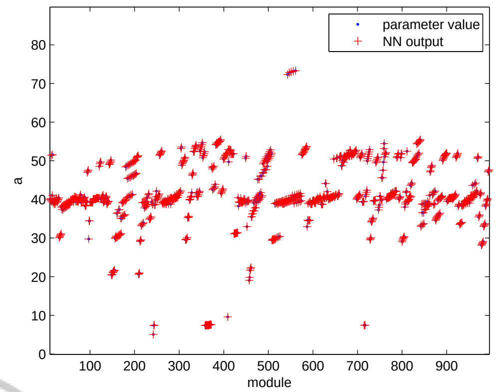

Figure 5: a parameter values versus estimated by Neural Networks for 1000 modules of the test set.

5 CONCLUSIONS

A neural network approach to identify PV one diode model was proposed. The work started from the preliminary analysis of the CEC database, which collects the datasheet parameters of about 10000 PV panels. For each panel in the database, the five parameters for the classical one-diode model were determined via numerical approach, creating a training and validation dataset. A first approach, consisting of a direct computation of parameters via MIMO NN was found unsuccessful. Further analysis suggested to avoid predicting all the parameters, and instead, use the NN approach just on the independent ones. Then, two MLP were used to interpolate the two parameters. From the obtained results, it is obvious that

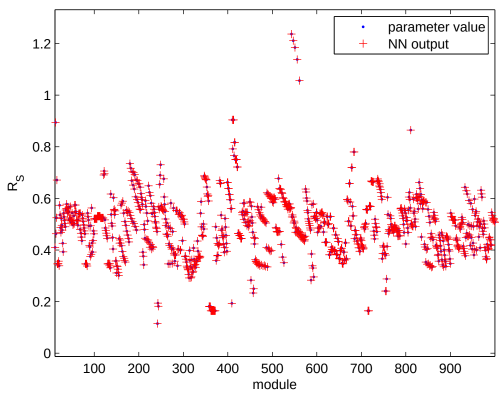

Figure 6: R_S parameter values versus estimated on by Neural Networks for 1000 modules of the test set.

in literature the neural network approach was often overlooked because of the hard obstacle encountered in the prediction of the shunt resistance. The solution of switching to closed forms for the identification of the model, shifts the problem of the shunt resistance calculus to the solution of an explicit non-linear equation. In conclusion, NNs can identify the R_S and a parameters correctly, making the NN approach viable for model identification in conjunction with the adoption of reduced forms for the computation of the three remaining unknown parameters of the one diode model. The so achieved NN for the estimation of the series resistance R_S and the modified ideality factor a, and the closed form for the computation of the remaining dependent parameters constitute a complete tool extremely easy to be implemented in a microcontroller based architecture: this is another successful step made thanks to Soft Computing techniques in the development of intelligent systems for the monitoring and the management of renewable generation plants.

REFERENCES

Askarzadeh, A. and Rezazadeh, A. (2013). Artificial bee swarm optimization algorithm for parameters identification of solar cell models. *Applied Energy*, 102(0):943 – 949.

Blair, N. J., Dobos, A. P., and Gilman, P. (2010). Comparison of photovoltaic models in the system advisor model. In *Solar 2013*, Baltimore, Maryland.

California Energy Commission (2013). CECPV calculator version 4.0. [Online]. Avialable: http://www.gosolarcalifornia.org/tools/nshpcalculator/.

Capizzi, G., Coco, S., Giuffrida, C., and Laudani, A. (2004). A neural network approach for the differentiation of numerical solutions of 3-d electromagnetic problems. *Magnetics, IEEE Transactions on*, 40(2):953–956.

Carrasco, M., Mancilla-David, F., Fulginei, F. R., Laudani, A., and Salvini, A. (2013). A neural networks-based maximum power point tracker with improved dynamics for variable dc-link grid-connected photovoltaic power plants. *International Journal of Applied Electromagnetics and Mechanics*, 43(1).

Cubas, J., Pindado, S., and Victoria, M. (2014). On the analytical approach for modeling photovoltaic systems behavior. *Journal of Power Sources*, 247:467 – 474.

Cybenko, G. (1989). Approximation by superpositions of a sigmoidal function. *Mathematics of control, signals and systems*, 2(4):303–314.

Desoto, W., Klein, S., and Beckman, W. (2006). Improvement and validation of a model for photovoltaic array performance. *Solar Energy*, 80(1):78–88.

El-Naggar, K., AlRashidi, M., AlHajri, M., and Al-Othman, A. (2012). Simulated annealing algorithm for photovoltaic parameters identification. *Solar Energy*, 86(1):266 – 274.

Fulginei, F. R., Laudani, A., Salvini, A., and Parodi, M. (2013). Automatic and parallel optimized learning for neural networks performing MIMO applications. *Advances in Electrical and Computer Engineering*, 13(1):3–12.

Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural networks*, 2(5):359–366.

Hunter, D., Yu, H., Pukish, M. S., Kolbusz, J., and Wilamowski, B. M. (2012). Selection of proper neural network sizes and architectures - A comparative study. *Industrial Informatics, IEEE Trans. on*, 8(2):228–240.

Ilonen, J., Kamarainen, J.-K., and Lampinen, J. (2003). Differential evolution training algorithm for feed-forward neural networks. *Neural Processing Letters*, 17(1):93–105.

Ishaque, K. and Salam, Z. (2011). An improved modeling method to determine the model parameters of photovoltaic (PV) modules using differential evolution (de). *Solar Energy*, 85(9):2349 – 2359.

Jiang, L. L., Maskell, D. L., and Patra, J. C. (2013). Parameter estimation of solar cells and modules using an improved adaptive differential evolution algorithm. *Applied Energy*, 112(0):185 – 193.

Kim, C.-T. and Lee, J.-J. (2008). Training two-layered feed-forward networks with variable projection method. *Neural Networks, IEEE Trans. on*, 19(2):371–375.

Laudani, A., Fulginei, F. R., and Salvini, A. (2014a). High performing extraction procedure for the one-diode model of a photovoltaic panel from experimental I–V curves by using reduced forms. *Solar Energy*, 103:316 – 326.

Laudani, A., Fulginei, F. R., Salvini, A., Lozito, G. M., and Coco, S. (2014b). Very fast and accurate procedure for the characterization of photovoltaic panels from datasheet information. *International Journal of Photoenergy*, 2014. Article ID 946360.

Laudani, A., Mancilla-David, F., Riganti-Fulginei, F., and Salvini, A. (2013). Reduced-form of the photovoltaic five-parameter model for efficient computation of parameters. *Solar Energy*, 97(0):122 – 127.

Li, Y., Huang, W., Huang, H., Hewitt, C., Chen, Y., Fang, G., and Carroll, D. L. (2013). Evaluation of methods to extract parameters from currentvoltage characteristics of solar cells. *Solar Energy*, 90(0):51 – 57.

Liu, Y.-H., Liu, C.-L., Huang, J.-W., and Chen, J.-H. (2013). Neural-network-based maximum power point tracking methods for photovoltaic systems operating under fast changing environments. *Solar Energy*, 89:42–53.

Mancilla-David, F., Riganti-Fulginei, F., Laudani, A., and Salvini, A. (2014). A neural network-based low-cost solar irradiance sensor. *Instrumentation and Measurement, IEEE Trans. on*.

Parodi, M., Fulginei, F. R., and Salvini, A. (2012). Learning optimization of neural networks used for mimo applications based on multivariate functions decomposition. *Inverse Problems in Science and Engineering*, 20(1):29–39.

Rajasekar, N., Kumar, N. K., and Venugopalan, R. (2013).

Bacterial foraging algorithm based solar {PV} parameter estimation. *Solar Energy*, 97(0):255 – 265.

Rawat, R., Patel, J. K., and Manry, M. T. (2013). Minimizing validation error with respect to network size and number of training epochs. In *Neural Networks (IJCNN), The 2013 International Joint Conference on*, pages 1–7. IEEE.

Sandrolini, L., Artioli, M., and Reggiani, U. (2010). Numerical method for the extraction of photovoltaic module double-diode model parameters through cluster analysis. *Applied Energy*, 87(2):442 – 451.

Siddiqui, M. and Abido, M. (2013). Parameter estimation for five- and seven-parameter photovoltaic electrical models using evolutionary algorithms. *Applied Soft Computing*, 13(12):4608 – 4621.

Teoh, E., Tan, K., and Xiang, C. (2006). Estimating the number of hidden neurons in a feedforward network using the singular value decomposition. *Neural Networks, IEEE Trans. on*, 17(6):1623–1629.

Wilamowski, B. M. (2009). Neural network architectures and learning algorithms. *Industrial Electronics Magazine, IEEE*, 3(4):56–63.

Xu, C., Wang, C., Ji, F., and Yuan, X. (2012). Finite-element neural network-based solving 3-d differential equations in mfl. *Magnetics, IEEE Transactions on*, 48(12):4747–4756.

Yadav, A. K. and Chandel, S. (2014). Solar radiation prediction using artificial neural network techniques: A review. *Renewable and Sustainable Energy Reviews*, 33:772 – 781.

Zagrouba, M., Sellami, A., Bouacha, M., and Ksouri, M. (2010). Identification of PV solar cells and modules parameters using the genetic algorithms: Application to maximum power extraction. *Solar Energy*, 84(5):860 – 866.

APPENDIX

In this appendix we summarize the main symbols and formulae useful for understanding the one-diode model and its reduced form. In particular table 3 reports the nomenclature used and the definition of parameters. With the aim to simplify the notation and the expressions, the shunt conductance $G_{\mathrm{SH}} = R_{SH}^{-1}$ will be used instead of R_{SH}, and the following quantities are defined:

Table 3: List of the technical parameters used in this work.

Name	Value or Description
S	Irradiance
T	Cell temperature
n	Ideality factor
a	$N_S n$
N_s	Number of series modules/cells
T_{ref}	$25°C$ at SRC
S_{ref}	$1000\frac{W}{m^2}$ at SRC
R_S	Series resistance at SRC
I_{Irr}	Photocurrent at SRC
I_0	Reverse saturation current at SRC
R_{SH}	Shunt resistance at SRC
G_{SH}	R_{SH}^{-1}
V_{OC}	Open circuit voltage at SRC
I_{SC}	Short circuit current at SRC
V_{MPP}	Maximum power voltage at SRC
I_{MPP}	Maximum power current at SRC
α_T	Temperature coeff. for I_{SC}
β_T	Temperature coeff. for V_{OC}

$$EXP_{OC} = exp\left(\frac{V_{OC}}{aV_T}\right) \tag{5}$$

$$EXP_{MPP} = exp\left(\frac{V_{MPP} + R_S I_{MPP}}{aV_T}\right) \tag{6}$$

$$EXP_{SC} = exp\left(\frac{I_{SC}}{aV_T}\right) \tag{7}$$

The formulae (2),(3) and (4), which express R_{SH}, I_0 and I_{irr} as function of R_S and modified ideality factor a are respectively (8), (9) and (10).

$$R_{SH} = \frac{(R_S I_{MPP} - V_{MPP})\left[EXP_{MPP}(I_{MPP}R_S + V_{MPP} - V_{OC} - aV_T) + EXP_{OC}aV_T\right]}{I_{MPP}\left[(V_{MPP} + aV_T - I_{MPP}R_S)\,EXP_{MPP} - aV_T EXP_{OC}\right]} \tag{8}$$

$$I_0 = \frac{I_{MPP}(V_{OC} - 2V_{MPP})\,aV_T}{(R_S I_{MPP} - V_{MPP})\left[EXP_{MPP}(I_{MPP}R_S + V_{MPP} - V_{OC} - aV_T) + EXP_{OC}aV_T\right]} \tag{9}$$

$$I_{irr} = \frac{I_{MPP}\left[V_{OC}(V_{MPP} - I_{MPP}R_S + a)\,EXP_{MPP} + aV_T(2V_{MPP}(1 - EXP_{OC}) - V_{OC})\right]}{(R_S I_{MPP} - V_{MPP})\left[EXP_{MPP}(I_{MPP}R_S + V_{MPP} - V_{OC} - aV_T) + EXP_{OC}aV_T\right]} \tag{10}$$