Solar Panels Modeling Based Design Technique for Distributed Generation Applications

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***Abstract*— Photovoltaic (PV) solar energy has become very important in power systems. PV systems became an affirmative part in power grids. For engineers; it is very important to design and simulate such systems that serve the solar plants. The PV modules are modeled by the use of actual manufacturers' data listed in the lookup table model. The lookup table is performed by the use of MATLAB/Simulink toolbox based. Moreover; Artificial Neural Network (ANN) numerical technique is used to simulate and evaluate the designed modules. The implemented work may help the designer and/or investor in order to elect a specified PV module according to the demanded power load thence; designing the PV fields for many of power applications. The results show a very good matching with the actual commercial data points of the PV systems.**

***Index Terms*— Photovoltaic (PV); MATLAB/Simulink; Artificial Neural Networks (ANN).**

I. Introduction

The renewable energy sources (solar, wind, tidal, geothermal etc.) are attracting more attention as an alternative energy. Among the renewable energy sources, the photovoltaic (PV) energy has been widely utilized in low power applications. It is also the most promising candidate for research and development for large scale users as the fabrication of low cost PV devices becomes a reality. Recently, photovoltaic array system is likely recognized and widely utilized in electric power applications. It can generate direct current electricity without environmental impact and contamination when is exposed to solar radiation. Being a semiconductor device, the PV system is static, quite, and free of moving parts, and these make it have less operation and maintenance costs. Even though the PV system is pushed to its high capital fabrication cost and low conversion efficiency, the increasing oil prices make solar energy naturally viable energy supply with potential long-term benefits. PV module represents the fundamental power conversion unit of a PV generator system. The output characteristics of PV module depends on the solar insulation, the cell temperature and output voltage of PV module. Owing to changes in the solar radiation energy and the cell operating temperature, the output power of a solar array is not constant at all times. Consequently, during the design process of PV powered systems; a simulation must be performed for system analysis and parameter settings. Therefore an efficient user friendly simulation model of the PV is always needed. The PV models that presented by the most of literature are focused on the cell performance, temperature distribution, cell physical, sizing and some applications of an existing technique. Most of these models were implemented according to performance technique of modeling not for the design technique. For cell characteristics modeling example, some literatures [1-6] were implemented for that purpose. The performance issues examples of the PV based on the I-V relation were presented according to references [7-10]. Example of field analysis, sizing and applications of the PV were presented in references [11-17]. The applications focused on the water pumping, water desalination, lighting homes and streets, and some stations to generate electricity, but the card does not exceed 10 MW. Other literatures focus on the optimization based genetic algorithm or neural network simulation tool boxes [18-21]. Such techniques of optimization dealt with the PV matter as a cell, module, or a small system. The common factor between the past works is that their models addressed a performance matter not a design matter. It is obvious from literature for PV systems that the most of presenting mathematical models were performed based on the performance technique not the design technique. Moreover; it was built for special cases and not for a wide range of operating conditions. In This work; a new modeling of the PV modules based on design parameters. ANN algorithm is used to simulate the PV in order to compare the results with the test data from the manufacture manuals. This modular program has great capabilities to overcome previous programming problems and limitations. The units are modeled to present a good example of the proposed modular program. Moreover; the new code may help the user or the designer to select a suitable PV unit based on the power demanded by the application system.

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II. PV Mathematical Models

In order to simulate and predict the characteristics of different types of PV system; a lot of real data are taken from a real manufacture manual of each module type. It is proposed that by identifying the output power from the system application, the design limits would be calculated. The PV system is modeled according to the actual data presented through more than 150 data points from the manufacturing manuals. MATLAB/Simulink [34] browser (as a software tool) is used to model and visualize the PV system program. The design limits that should be calculated are summarized as follows: The open circuit voltage, V and the short circuit current, A; The maximum voltage and current; The cell and module efficiencies; The number of cells and modules of the system; The module and system weights, dimensions and areas; The battery bank capacity; and The total costs of the system. The maximum power per module and the total system power are assigned by the user or by the process modeling to simply calculate the previously mentioned items. MATLAB toolbox [34] is used to predict the characteristics correlations based on a non - linear and Artificial Neural Network (ANN) techniques. The mathematical model that presented in this work is completely differing from any other presented models. The main differences concluded in the actual data that introduced in the core code of the model. Data manuals are fed into the core of the code in order to give a real curve fitting. Two methods are utilized in this study; the first is the use of lookup tables of Simulink toolbox, where the second is the use of Artificial Neural Network (ANN) tool box.

A. *Lookup table method for PV*

The n-D Lookup Table block evaluates a sampled representation of a function in N variables y=F(x1, x2, x3 …xn) where the function F can be empirical. The block maps inputs to an output value by looking up or interpolating a table of values you define with block parameters. The block supports flat (constant), linear, and cubic-spline interpolation methods. The user can apply these methods to a table of any dimension from 1 through 30. In the following block, the first input identifies the first dimension (row) breakpoints; the second input identifies the second dimension (column) breakpoints, and so on. The numbers of table dimensions specify the number of dimensions of your lookup table. Breakpoints specify a breakpoint vector that corresponds to each dimension of your lookup table. Table data defines the associated set of output values.

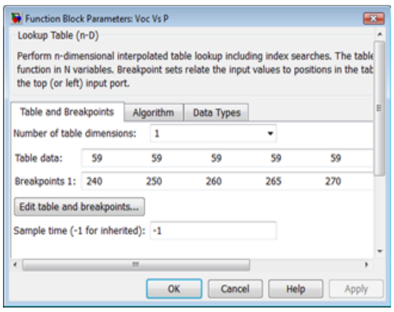

Fig. 1. Schematic diagram of the n-D lookup table

Lookup table block under Simulink toolbox is allowed to insert the actual data as a matrix. The data can be arranged as row, column and page. The figure shows the data row versus the break points row. The n-D Lookup Table block generates output by looking up or estimating table values based on the input values. In case of matching the values of indices in breakpoint data sets, the outputs the table value at the intersection of the row, column, and higher dimension breakpoints. In case of do not match the values of indices in breakpoint data sets, but are within range, interpolates appropriate table values, using the interpolation method that the user select. In case of do not match the values of indices in breakpoint data sets, and are out of range, extrapolates the output value, using the extrapolation method that the user select. In this work, the range of the operating module type is from 5-280Watt. Each module watt type can calculate the module specification based on the data fed in the table. Table 1 illustrates the inputs and outputs of the developed lookup table model block.

Table 1: Known inputs to calculate desired outputs based on the design model methodology

Inputs:	*Outputs:*
1-Operating hours (*OH*), h. 2-Solar flux (G_b), W/m^2. 3-Number of cloudy day's factor. 4-System total power (P_t), kW. 5-Module power (P_m) (5-280Watt). 6-Battery depth of discharge (*DOD*). 7-Battery voltage (V_b), Volt. 8-Battery efficiency, %. 9-Battery unit price (C_b), $.	1-Open circuit voltage (V_{oc}), Volt. 2-Short circuit current (I_{sc}), A. 3-Maximum voltage (V_m), Volt. 4-Maximum current (I_m), A. 5-Cell & Module efficiencies, %. 6-Net weight, kg. 7-The dimensions, m^2. 8-Module price, $/Watt. 9-Number of cells (*NOC*). 10-Cell area (A_c), cm^2. 11-Module area (A_m), m^2. 12-Total system area (A_t), m^2. 13-Battery storage, Wh. 14-Battery capacity, Ah. 15-Number of batteries (*NOB*). 16-Full over board cost (FOB_c), $.

When calculating the main specifications (Table 1: parameters from 1 to 9) based on the module power the following code can be easily calculated. The number of modules (*NOM*) could be calculated based on total power and module power:

$$\mathrm{NOM} = \mathrm{P_t} / \mathrm{P_m} \tag{1}$$

And the module area in m^{2}is then calculated:

$$\mathrm{A_m} = 100\,\mathrm{P_m} / (\mathrm{G_b}\eta_m) \tag{2}$$

Then the total area in m^2 can be calculated:

$$\mathrm{A_t} = \mathrm{A_m}\ NOM \tag{3}$$

The cell area in cm^2 based on the number of cells (*NC*) that's been calculated from the lookup table.

$$\mathrm{A_c} = 1000\,\mathrm{A_m} / NC \tag{4}$$

The battery storage in Wh based on the operating hours (*OH*), number of cells (*NC*), the total power (P_t), battery efficiency and depth of discharge (*DOD*):

$$\mathrm{BS} = \mathrm{OH\ NOC\ P_t} / (\mathrm{DOD}\eta_b) \tag{5}$$

If a 24 V system is chosen, the required (*AH*) of batteries=16 585/24700 AH.

$$AH = BS/V_m \tag{6}$$

Number of batteries can be calculated as follows based on the maximum voltage and the battery voltage:

$$NOB = V_m \,/\, V_b \tag{7}$$

The system total costs in (C_t, *$*) are then calculated based on the full over board costs of the modules (FOB_c) and the battery costs (C_b):

$$C_t = P_t \; FOB_c + C_b \, NOB \tag{8}$$

Where; the FOB_c includes the cables, connections, workers' time, inverter unit, and the maintenance costs. The presented model associated with the above method has some important features such as: Easy model constructing: it can be easily built by the use of the lookup table block where the hard part is to collect and arrange the needed data vector. The main specifications are easily calculated based on one parameter (the identification of the module power can drive out nine parameters). However; in the other modeling techniques, it is not found that one parameter can result out nine parameters. Such technique of modeling is not used before.

B. *ANN method for PV*

ANN consists of very simple and highly interconnected processors called neurons. The neurons are connected to each other by weighted links over which signals can pass. Each neuron receives multiple inputs from other neurons in proportion to their connection weights and generates a single output which may propagate to several other neurons. Among the various kinds of ANNs that exist, the Back-propagation learning algorithm has become the most popular used method in engineering application. It can be applied to any feed-forward network with differentiable activation functions, and it is the type of network used in this paper. The ANN modeling is carried out in two steps; the first step is to train the network, whereas the second step is to test the network with data, which were not used for training. It is important that all the information the network needs to learn is supplied to the network as a data set. When each pattern is ready, the network uses the input data to produce an output, which is then compared to the training pattern. If there is a difference, the connection weights are altered in such a direction that the error is decreased. After the network has run through all the input patterns, if the error is still greater than the maximum desired tolerance, the ANN runs through all the input patterns repeatedly until all the errors are within the required tolerance. Because networks with two hidden layers can represent functions with any kind of shapes, there is no theoretical reason to use networks with more than two hidden layers. In general, it is strongly recommended that one hidden layer is the first choice for any feed-forward network design. The quality, availability, reliability, repeatability, and relevance of the data used to develop and run the system is critical to its success. Data processing starts from the data collections and analysis followed by pre-processing and then feeds to the neural network. The Back-propagation is the most commonly used methods for training multi-layer feed-forward networks. For most networks, the learning process is based on a suitable error function, which is then minimized with respect to the weights and bias. The algorithm for evaluating the derivative of the error function is known as back-propagation, because it propagates the errors backward through the network. This technique is used in many renewable energy systems applications [22-33].

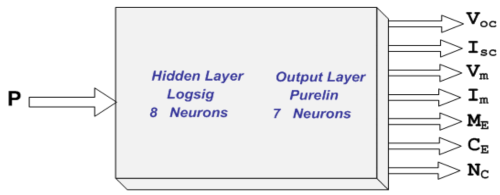

Fig. 2. A schematic diagram of PV ANN model

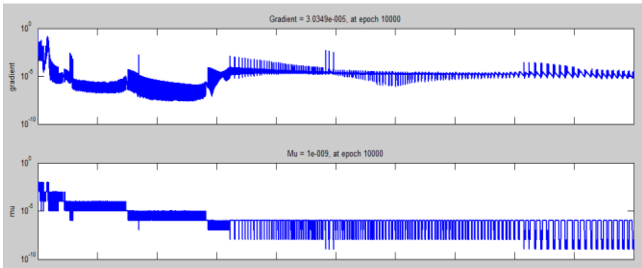

Fig. 3. The training results for the proposed PV ANN model

The ANN generated code is developed based on the following equations. The normalized power Pn equation is obtained as; Equation (9) presents the normalized input for the power and the following equations lead to the required derived equation. Where; n: Subscript denotes normalized parameters, Ei: Sum of input with input weight and input bias for each node in a hidden layer in a neural network, Fi: Output from each node in a hidden layer to output layer according to transfer function here is logsig [35-46].

$$Pn = (P_m - 154.1228) / 86.9785 \tag{9}$$

$$Pn = (P_m - 154.1228) / 86.9785 \tag{10}$$

$$F1 = 1/(1 + \exp(-E1)) \tag{11}$$

$$E2 = 292.1159\, P_n - 307.4633 \tag{12}$$

$$F2 = 1/(1 + \exp(-E2)) \tag{13}$$

$$E3 = 47.5094\, P_n - 35.5277 \tag{14}$$

$$F3 = 1/(1 + \exp(-E3)) \tag{15}$$

$$E4 = 1.825\, P_n + 1.7837 \tag{16}$$

$$F4 = 1/(1 + \exp(-E4)) \tag{17}$$

$$E5 = 142.7159\, P_n + 75.2497 \tag{18}$$

$$F5 = 1/\,(1 + \exp(-E5)) \tag{19}$$

$$E6 = -55.6915\, P_n - 89.3902 \tag{20}$$

$$F6 = 1/\,(1 + \exp(-E6)) \tag{21}$$

$$E7 = 131.8635\, P_n + 176.6258 \tag{22}$$

$$F7 = 1/\,(1 + \exp(-E7)) \tag{23}$$

$$E8 = -56.1527\, P_n - 90.14 \tag{24}$$

$$F8 = 1/\,(1 + \exp(-E8)) \tag{25}$$

The normalized outputs relations from ANN:

The normalized open circuit voltage is obtained as;

$$V_{ocn} = 0.2603\,F1 - 0.8646\,F2 + 1.5262\,F3 - 0.7479\,F4 + 1.6856\,F5 - 27.716\,F6 + 0.1945\,F7 + 27.5989\,F8 - 1.2466 \tag{26}$$

The normalized short circuit current is obtained as follows;

$$I_{SCn} = -0.3577\,F1 + 0.4036\,F2 - 0.6836\,F3 + 6.0477\,F4 - 1.4217\,F5 + 29.7807\,F6 - 0.4409\,F7 - 29.7082\,F8 - 2.7748 \tag{27}$$

The normalized maximum current and voltage are obtained as follows;

$$V_{mn} = 1.6336\,F1 - 0.9422\,F2 + 1.577\,F3 - 0.5747\,F4 + 1.4615\,F5 - 33.4875\,F6 + 0.1497\,F7 + 33.352\,F8 - 2.484 \tag{28}$$

$$I_{mn} = -0.4981\,F1 + 0.4071\,F2 - 0.6475\,F3 + 5.4252\,F4 - 1.1416\,F5 + 9.683\,F6 - 0.3647\,F7 - 9.6696\,F8 - 2.4307 \tag{29}$$

The normalized efficiencies of the module and the cell are

$$\eta_{Cn} = -0.0523\,F1 + 0.1946\,F2 - 0.4488\,F3 + 3.5823\,F4 - 0.6633\,F5 - 945.6335\,F6 - 1.7534\,F7 + 943.8266\,F8 - 0.4238$$

obtained respectively as follows;

$$\eta_{mn} = 0.0193\,F1 - 0.5307\,F2 + 0.1383\,F3 + 1.2274\,F4 - 1.5651\,F5 - 963.6758\,F6 + 0.6763\,F7 + 962.8663\,F8 - 0.104 \tag{30}$$

(31)

The normalized number of cell parameter is obtained as follows;

$$NOC_n = 0.0194\,F1 - 1.2485\,F2 + 1.6434\,F3 + 3.1176\,F4 + 0.1489\,F5 - 64.457\,F6 - 0.8867\,F7 + 64.9028\,F8 - 2.0399 \tag{32}$$

The un-normalized output relations from ANN related to the open circuit voltage, short circuit current, maximum voltage and current, module and cell efficiencies; and number of cells are listed in Table II:

Table 2: The un-normalized correlations for the desired output parameters

Output parameter:	Correlation:
Open circuit voltage	$V_{OC} = 11.0323 \times V_{OCn} + 35.0009$
Short circuit current	$I_{SC} = 2.785 \times I_{SCn} + 5.4497$
Maximum voltage	$V_m = 9.3979 \times V_{mn} + 27.2772$
Maximum current	$I_m = 2.6309 \times I_{mn} + 5.0547$
Module efficiency	$\eta_m = 0.0059 \times \eta_{mn} + 0.1350$
Cell efficiency	$\eta_c = 0.0116C \times \eta_{cn} + 0.1675$
Number of cells	$NOC = 18.9866 \times NOC_n + 58.7895$

III. The Models Validation

The PV models (ANN and Lookup table) are presented in this section. The normalized data fit shows a very good agreement corresponding to the actual data. It has become easy for the users and designers to simulate and model such units or systems without involving with any other complicated equations or models. Fig. 4 shows the variations of open circuit voltage versus the variations of the module power. It is clear from Fig. 4 that the ANN and lookup table data match with the actual data fed to the model. The model varies from 0.5watts up to 300watt. The behavior shows that the increase of power is followed by the increase of the open circuit voltage parameter. The same behavior is noticed in Fig. 5. The short circuit current is increasing with the increase of module power. Moreover; the ANN and lookup table data show a very good agreement corresponding to the actual data. The behavior of the cell efficiency and number of cell parameters is shown in Fig. 6 and 7. Fig. 6 indicates that the cell efficiency is variation between the range of 14~17%. Fig. 7 shows a constant line correlation corresponding to the module power. The number of cells per module is nearly between 35~80 cells per module according to 0.5 to 300watt respectively. The manufacture deals with the number of cell parameter as a constant line because of the frame, the structure, the weight, and the power from the module panel. Such example from the Figures (4-7) represents a very good recognition to the designers in order to understand the PV design without any complicated calculations or extra equation with generality and simplicity depending on one parameter, the power.

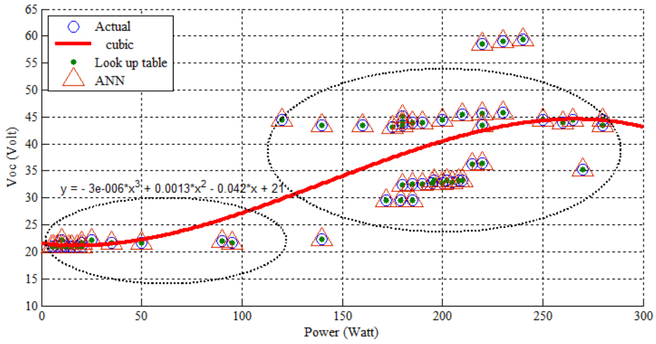

Fig. 4. Open circuit voltage vs. the power variations

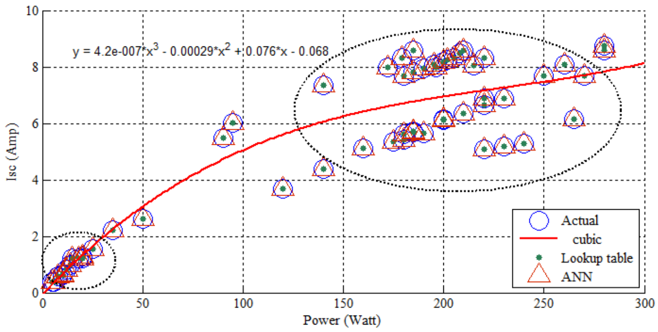

Fig. 5. The variation of short circuit current vs. the power variation

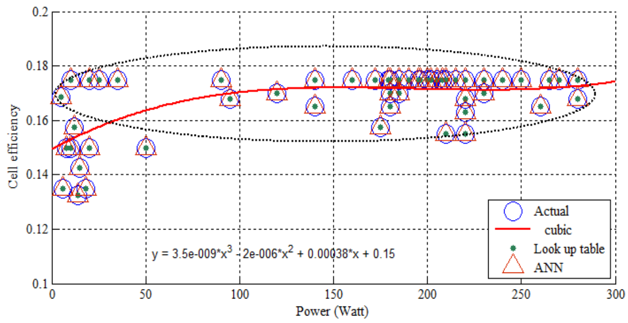

Fig. 6. The PV cell efficiency vs. the power variation

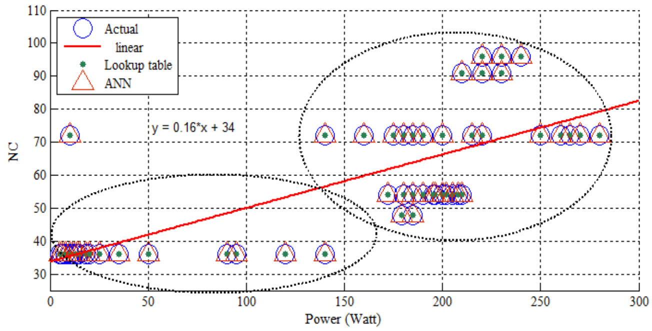

Fig. 7. The Number of cells parameter vs the variation of power parameter

IV. CONCLUSION

The modeling technique and the proposed circuit model are useful for power electronics designers who need a simple, fast, accurate, and easy-to-use modeling method for using in simulations of PV systems. PV model is validated with experimental data of commercial PV arrays. Traditional modeling techniques are too difficult for the investor/designer to specify accurately the specific point of design (power, module efficiency, wind speed, design limits, etc.). Thence; the need for an accurate software programming package to make a selection based design and simulation of different types. Therefore; two techniques of modeling (GUI with lookup table and ANN) are used in this work in order to design and simulate Photovoltaic (PV) systems.

The neural network units are implemented, using the back propagation (BP) learning algorithm due to its benefits to have the ability to predict values in – between learning values, also make interpolation between learning curve data. This is done with suitable number of network layers and neurons at minimum error and precise manner. The ANN regression function for each unit is introduced to be used directly without operating the neural model each time. The required models are investigated and compared with the actual data from the manufacturer's manuals of the turbines. Results reveal that the actual data are matched with the model data results. The models have many features such as; Easy model construction. Covering a wide range of power. Easy of combination with other technologies such as desalination and/or photovoltaic. Ease of converting the model codes into C++ or Visual Basic software programming. It becomes very easy for the designer to specify the power point and simply elect the PV module from the market based on the model data results. The developed model is very easy to be used instead of the using the complicated correlations for the PV systems.

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