This paper proposes general and specific modeling and simulation for Schott ASE-300-DGF PV panel for Smart Grid applications. This is done, with the aid of MATLAB environment and Artificial Neural Network (ANN). First modeling of PV cell module at nominal conditions at 25°C, and 1KW/m² with I-V curves at (0°C, 25°C, 50°C, 75°C), also power and irradiance. Then, we propose general modeling and simulation at more probable situations for variable values of temperature and irradiance. The simulation results at each irradiance value with various temperature values and corresponding characteristics are well depicted in 3-D figures. Later, the ANN model for the proposed range of irradiance and temperature as model inputs, with the corresponding values of voltages, currents, and power as outputs is presented. Finally, algebraic equations for the ANN model are deduced.

Keywords: Modeling, Simulation, Smart Grid, MATLAB, Neural Network, PV Cell.

1. INTRODUCTION

Due to the importance of PV cell especially in Smart Grid Energy Systems (SGES) this paper is proposed. Smart Grid Energy Systems (SGES) is recently increasing, particularly onsite generation. This interest is because larger power plants are economically unfeasible in many regions due to increasing system and fuel costs, and more strict environmental regulations. In addition, recent technological advances in small generators, Power Electronics, and energy storage devices have provided a new opportunity for distributed energy resources at the distribution level [1-3]. Photovoltaic systems have become increasingly popular and are ideally suited for distributed systems. Many governments have provided the much needed incentives to promote the utilization of renewable energies, encouraging a more decentralized approach to power delivery systems. In spite of their relatively high cost, there has been very remarkable growth in installed Photovoltaic systems. Recent studies show an exponential increase in the worldwide installed photovoltaic power capacity. There is ongoing research aimed at reducing the cost and achieving higher efficiency. Furthermore, new regulatory laws mandating the use of renewable energy have expanded this market around the world. Currently, photovoltaic generation systems are actively being promoted in order to mitigate environmental issues such as the green house effect and air pollution. Solar energy is the world's major renewable energy source and is available everywhere in different quantities. Photovoltaic panels do not have any moving parts, operate silently and generate no emissions. Another advantage is that solar technology is highly modular and can be easily scaled to provide the required power for different loads [4], [5]. The fuel cell was invented by Sir William Grove in 1839, but was not used in a practical application until proton-exchange membrane fuel cells (PEMFCs), made by General Electric, were employed in the National Aeronautics and Space Administration (NASA) Gemini missions in the early 1960s. As a result, the Alkaline Fuel Cell (AFC) was used for a time by NASA, and the use of PEMFCs became almost non-existent. In the 1990s, the PEMFC regained its status as the dominant fuel cell type, and fuel cells in general have received considerable attention as an alternative to fossil fuel combustion. Much of the credit for the revitalization of the PEMFC must be given to Ballard Power Systems and to the Los Alamos National Laboratory. The PEMFC is now seen by many researchers and companies as the only fuel cell type suitable for
vehicular applications, due to a relatively high power density, low operating temperature and solid electrolyte. A significant amount of fuel cell research focuses on fundamental issues of performance and cost [6-9]. And finally, some of recent research advances examples about this topic are introduced in [10-12]. This paper introduces general and specific modeling and simulation for Schott ASE-300-DGF PV panel [13] for Smart Grid (SG) applications as shown in figure [1].

2. PV CELL

A commercial PV panel is constructed from a number of PV cells. A PV cell is constructed from a p-n homo – junction material. The homo – junction is a semiconductor interface that occurs between layers of similar semiconductor material. These materials have equal band gaps and they typically have different doping (semiconductor) which there is a built in electric field. The absorption of photons of energy generates DC power.

The cross – section of a PV cell is shown in figure 2. The most common material used in PV cell manufacture is mono – crystalline or poly – crystalline silicon. Each cell is typically made of square or rectangular wafers of dimensions measuring about 10 cm × 10 cm × 0.3 mm. In the dark, the PV cell’s behavior is similar to that of a diode and the well known Shockley-Read equation can be [1], [14].

3. ASE-300-DGF PV MODULE

The ASE-300-DGF/50 is an industrial-grade solar power module built to the highest standards. Extremely powerful and reliable, the module delivers maximum performance in large systems that require higher voltages, including the most challenging conditions of military, utility and commercial installations. For superior performance, quality and peace of mind, the ASE-300-DGF/50 is renowned as the first choice among those who recognize that not all solar modules are created equal [13].
The electrical data applies to standard test conditions (STC): Irradiance at the module level of 1,000 W/m² with spectrum AM 1.5 and a cell temperature of 25°C.

<table>
<thead>
<tr>
<th>Power (max.)</th>
<th>P_{max} (W)</th>
<th>280 W</th>
<th>280 W</th>
<th>300 W</th>
<th>310 W</th>
<th>320 W</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage at maximum-power point</td>
<td>V_{oc} (V)</td>
<td>49.6 V</td>
<td>50.1 V</td>
<td>50.6 V</td>
<td>51.1 V</td>
<td>51.6 V</td>
</tr>
<tr>
<td>Current at maximum-power point</td>
<td>I_{sc} (mA)</td>
<td>5.7 A</td>
<td>5.8 A</td>
<td>5.9 A</td>
<td>6.1 A</td>
<td>6.2 A</td>
</tr>
<tr>
<td>Open-circuit voltage</td>
<td>V_{oc} (V)</td>
<td>0.9 V</td>
<td>0.9 V</td>
<td>0.9 V</td>
<td>0.9 V</td>
<td>0.9 V</td>
</tr>
<tr>
<td>Short-circuit current</td>
<td>I_{sc} (mA)</td>
<td>6.2 A</td>
<td>8.4 A</td>
<td>6.5 A</td>
<td>6.5 A</td>
<td>6.8 A</td>
</tr>
</tbody>
</table>

Table 1: Electrical data [13]

| Length mm (in) | 1,892.3 (74.5") |
| Width mm (in)  | 1,282.7 (50.5") |
| Weight kg (lbs) | 45.6 ± 2 kg (107 ± 5 lbs) |
| Area            | 2.43 sq meters (26.13 ft sq) |

Table 2: Dimensions and weights [13]

<table>
<thead>
<tr>
<th>Solar cells per module</th>
<th>216</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of solar cell</td>
<td>Semi-crystalline solar cell (ETG process), 10x10 cm²</td>
</tr>
<tr>
<td>Connections</td>
<td>10 AWG single conductor, stranded copper with Multi-Contact connector. Junction box comes with 10 built-in bypass diodes</td>
</tr>
</tbody>
</table>

Table 3: Characteristic data [13]

4. MODELING A PV CELL

The use of equivalent electric circuits makes it possible to model characteristics of a PV cell. The method used here is implemented in MATLAB programs for simulations. The same modeling technique is also applicable for modeling a PV module. There are two key parameters frequently used to characterize a PV cell. Shorting together the terminals of the cell, the photon generated current will follow out of the cell as a short-circuit current (I_{sc}). Thus, I_{ph} = I_{oc}, when there is no connection to the PV cell (open-circuit), the photon generated current is shunted internally by the intrinsic p-n junction diode. This gives the open circuit voltage (V_{oc}). The PV module or cell manufacturers usually provide the values of these parameters in their datasheets [14].

The simplest model of a PV cell equivalent circuit consists of an ideal current source in parallel with an ideal diode. The current source represents the current generated by photons (often denoted as I_{ph} or I_{1}), and its output is constant under constant temperature and constant incident radiation of light.

The PV panel is usually represented by the single exponential model or the double exponential model. The single exponential model is shown in fig. 6. The current is expressed in terms of voltage, current and temperature as shown in equation 1 [1].

\[
I = I_{ph} - I_0 \left\{ \exp \left[ \frac{q(V + IR)}{AKT} \right] - 1 \right\} - \frac{V + IR}{R_p} \tag{1}
\]

Where \(I_{ph}\): the photo generated current; \(I_o\): the dark saturation current; \(I_{s1}\): saturation current due to diffusion; \(I_{s2}\): is the saturation current due to recombination in the space charge layer; \(I_{np}\): current flowing in the shunt resistance; \(R_s\): cell series resistance; \(R_p\): the cell (shunt) resistance; \(A\): the diode quality factor; \(q\): the electronic charge, \(1.6 \times 10^{-19}\) C; \(k\): the Boltzmann’s constant, \(1.38 \times 10^{-23}\) J/K; and \(T\): the ambient temperature, in Kelvin.

Eq.1 and Eq.2 are both nonlinear. Furthermore, the parameters (I_{ph}, I_0, I_{s1}, I_{s2}, R_s, R_p, and A) vary with temperature, irradiance and depend on manufacturing tolerance as shown in figure 8. Numerical methods and curve fitting can be used to estimate [1], [14].
There are three key operating points on the IV curve, \( V = V_{oc} \) and \( I = 0 \). After substituting these circuit point. At the open – circuit point on the IV curve of a photovoltaic cell. They are the short

We can estimate the diode quality factor as:

\[ A = \frac{V_{app} + I_{mpp} R_s - V_{sc}}{V_T \ln(I_{sc} - \frac{V_{mpp}}{R_{sh}}) - \ln(I_{sc} - \frac{V_{mpp}}{R_{sh}}) + I_{mpp} \left( \frac{V_{mpp}}{R_{sh}} - V_{sc} \right)} \]

And

\[ R_p = R_{sho} \]

\[ I_o = \left( I_{sc} \frac{V_{sc}}{R_p} \right) \exp \left( -\frac{V_{sc}}{A V_T} \right) \]

\[ R_s = R_{so} - \frac{A V_T}{I_o} \exp \left( -\frac{V_{sc}}{A V_T} \right) \]

\[ I_{ph} = I_{sc} (1 + \frac{R_s}{R_p}) + I_o (\exp \left( \frac{I_{sc} R_s}{A V_T} - 1 \right) \]

As a very good approximation, the photon generated current, which is equal to \( I_{sc} \), is directly proportional to the irradiance, the intensity of illumination, to PV cell [15]. Thus, if the value, \( I_{sc} \), is known from the datasheet, under the standard test condition, \( G_0=1000W/m^2 \) at the air mass (AM) = 1.5, then the photon generated current at any other irradiance, \( G(W/m^2) \), is given by:

\[ I_{sc}[G] = \left( \frac{G}{G_0} \right) I_{sc}[G_0] \]

It should be noticed that, in a practical PV cell, there is a series of resistance in a current path through the semiconductor material, the metal grid, contacts, and current collecting bus [16]. These resistive losses are lumped together as a series resistier \( (R_s) \). Its effect becomes very conspicuous in a PV module that consists of many series-connected cells, and the value of resistance is multiplied by the number of cells. Shunt resistance is a loss associated with a small leakage of current through a resistive path in parallel with the intrinsic device [16]. This can be represented by a parallel resister \( (R_p) \). Its effect is much less conspicuous in a PV module compared to the series resistance so it may be ignored [16] [17]. The ideality factor denoted as \( A \) and takes the value between one and two (as to reach the nominated characteristics) [17].

5. PHOTOVOLTAIC MODULE MODELING

A single PV cell produces an output voltage less than 1V, thus a number of PV cells are connected in series to achieve a desired output voltage. When series-connected cells are placed in a frame, it is called as a module. When the PV cells are wired together in series, the current output is the same as the single cell, but the voltage output is the sum of each cell voltage. Also, multiple modules can be wired together in series or parallel to deliver the voltage and current level needed. The group of modules is called an array. The panel construction provides protection for individual cells from water, dust etc, as the solar cells are placed into an encapsulation of flat glass. Our case here depicts a typical connection of 216 cells that are connected in series [13]. The strategy of modeling a PV module is no different from modeling a PV cell. It uses the same PV cell model. The parameters are the all same, but only a voltage parameter (such as the open-circuit voltage) is different and must be divided by the number of cells. An electric model with moderate complexity [18] is shown in figure 9, and provides fairly accurate results. The model consists of a current source \( (I_{sc}) \), a diode \( (D) \), and a
series resistance ($R_s$). The effect of parallel resistance ($R_p$) is very small in a single module, thus the model does not include it. To make a better model, it also includes temperature effects on the short-circuit current ($I_{sc}$) and the reverse saturation current of diode ($I_o$). It uses a single diode with the diode ideality factor set to achieve the best $I$-$V$ curve match.

Figure 9: Equivalent circuit used in the simulations

The equation (13) describes the current-voltage relationship of the PV cell.

$$I = I_{sc} - I_o \left( \exp\left( \frac{V + IR}{AKT} \right) - 1 \right)$$

(13)

Where: $I$ is the cell current (the same as the module current); $V$ is the cell voltage = {module voltage} ÷ {No. of cells in series}; $T$ is the cell temperature in Kelvin (K).

First, calculate the short-circuit current ($I_{sc}$) at a given cell temperature ($T$):

$$I_{sc} = I_{sc}\left[T_{ref}\left(1 + a\left(T - T_{ref}\right)\right) \right]$$

(14)

Where: $I_{sc}$ at $T_{ref}$ is given in the datasheet (measured under irradiance of 1000W/m$^2$), $T_{ref}$ is the reference temperature of PV cell in Kelvin (K), usually 298K (25°C), $a$ is the temperature coefficient of $I_{sc}$ in percent change per degree temperature also given in the datasheet.

The short-circuit current ($I_{sc}$) is proportional to the intensity of irradiance, thus $I_{sc}$ at a given irradiance ($G$) is introduced by Eq. 12.

The reverse saturation current of diode ($I_o$) at the reference temperature ($T_{ref}$) is given by the equation (15) with the diode ideality factor added:

$$I_o = \frac{I_{sc}}{\left( \exp\left( \frac{qV_{oc}}{AKT} \right) - 1 \right)}$$

(15)

The reverse saturation current ($I_o$) is temperature dependant and the $I_o$ at a given temperature ($T$) is calculated by the following equation [18].

$$I_{oT} = I_{oTref} \left( \frac{T}{T_{ref}} \right)^{3/2} \exp\left( -\frac{qE_g}{AK} \left( \frac{1}{T_{ref}} - \frac{1}{T} \right) \right)$$

(16)

The diode ideality factor ($A$) is unknown and must be estimated. It takes a value between one and two; however, the more accurate value is estimated by curve fitting [18] also, it can be estimated by try and error until accurate value achieved. $E_g$ is the Band gap energy (1.12 V (Si); 1.42 (GaAs); 1.5 (CdTe); 1.75 (amorphous Si)).

The series resistance ($R_s$) of the PV module has a large impact on the slope of the $I$-$V$ curve near the open-circuit voltage ($V_{oc}$), hence the value of $R_s$ is calculated by evaluating the slope $dV/dI$ of the $I$-$V$ curve at the $V_{oc}$ [18]. The equation for $R_s$ is derived by differentiating the $I$-$V$ equation and then rearranging it in terms of $R_s$ as introduced in equation (17).

$$R_s = -\frac{dV}{dI}\bigg|_{sc} = \frac{AKT / q}{I_o \exp\left( \frac{qV_{oc}}{AKT} \right)}$$

(17)

Where: $\frac{dV}{dI}\bigg|_{sc}$ is the slope of the $I$-$V$ curve at the $V_{oc}$ (using the $I$-$V$ curve in the datasheet then divide it by the number of cells in series); $V_{oc}$ is the open-circuit voltage of cell (Dividing $V_{oc}$ in the datasheet by the number of cells in series).

Finally, the equation of $I$-$V$ characteristics is solved using the Newton’s method for rapid convergence of the answer, because the solution of current is recurvise by inclusion of a series resistance in the model [18]. The Newton’s method is described as:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$$

(18)

Where: $f'(x)$ is the derivative of the function, $f(x) = 0$, $x_n$ is a present value, and $x_{n+1}$ is a next value.

$$f(I) = I_{sc} - I - I_o \left( \exp\left( q(V + IR) / AKT \right) - 1 \right) = 0$$

(19)

By using the above equations the following output current ($I$) is computed iteratively.

$$I_{sc} = I_{sc} - I - I_o \left( \exp\left( q(V + IR) / AKT \right) - 1 \right)$$

(20)

6. SIMULATION RESULTS

The figures of $I$-$V$ characteristics at various module temperatures are simulated with the MATLAB model for our PV module are shown. Also, the $P$-$V$ relations at various module temperatures are presented. All of these are done at various irradiance values are introduced.
Finally, a set of 3 D figures are proposed to cover the most probable situations at various irradiance, various temperature with the current, the voltage, and the power. These surface faces relations will be considered later as the learning or training data for the general neural network simulation.

Figure 10: I-V curves at (1KW/m²; 0, 25, 50, 75°C)

Figure 11: I-V curves (0.75 KW/m²; 0, 25, 50, 75°C)

Figure 12: I-V curves (0.50 KW/m²; 0, 25, 50, 75°C)

Figure 13: I-V curves (0.25 KW/m²; 0, 25, 50, 75°C)

Figure 14: P-V curves at (1KW/m²; 0, 25, 50, 75°C)

Figure 15: P-V curves (0.75KW/m²; 0, 25, 50, 75°C)

Figure 16: P-V curves (0.50KW/m²; 0, 25, 50, 75°C)

Figure 17: P-V curves (0.25KW/m²; 0, 25, 50, 75°C)

Figure 18: Voltage & Temp.& (1KW/m²) Irradiance
Figure 19: Power & Temp.& (1KW/m²) Irradiance

Figure 20: Current & Temp.& (1KW/m²) Irradiance

Figure 21: Voltage & Temperature&(0.75KW/m²)

Figure 22: Power & Temperature&(0.75KW/m²)

Figure 23: Current & Temperature&(0.75KW/m²)

Figure 24: Voltage & Temperature&(0.50KW/m²)

Figure 25: Power & Temperature&(0.50KW/m²)

Figure 26: Current & Temperature&(0.50KW/m²)

Figure 27: Voltage & Temperature&(0.25KW/m²)
The neural network has the ability to deal with all previous relations as surface or mapping face, due to this technique ability for interpolation between points with each other and also curves.

7. ARTIFICIAL NEURAL NETWORKS (ANN) TECHNIQUE

An 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 [19]. 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 [20], and it is the type of network used in this paper.

A. Fundamentals of Neural Network

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 read, 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 [21], [22].

B. Data Collection, Analysis and Processing

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.

C. Network Structure Design

Though theoretically there exists a network that can simulate a problem to any accuracy, there is no easy way to find it. To define an exact network architecture such as how many hidden layers should be used, how many units should there be within a hidden layer for a certain problem is a painful job.

1) Number of Hidden Layers

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 be the first choice for any feed-forward network design [19-22].

2) Number of Hidden Units (node)

Another important issue in designing a network is how many units to place in each layer. Using too few units can fail to detect the signals fully in a complicated data set, leading to under fitting. Using too many units will increase the training time, perhaps so much that it becomes impossible to train it adequately in a reasonable period of time. The best number of hidden units depends on many factors – the numbers of input and output units, the number of training cases, the amount of noise in the targets, the complexity of the error function, the network architecture, and the training algorithm. The best approach to find the optimal number of hidden units is trial and error.
3) Initializing Back-Propagation feed-forward network

Back-propagation is the most commonly used method 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.

4) Training the network

Training occurs according to any training function as previous and we must decide the training parameters with their default values: The order used for training is for example 
\[ [\text{net}, \text{tr}] = \text{train} (\text{net}, \text{pn}, \text{tn}) \]
where \( \text{pn}, \text{tn} \) is the input and output which are normalized

5) Network simulation

To obtain the output of the network, we must simulate it the order, which can be used, is
\[ \text{an} = \text{sim} (\text{net}, \text{pn}) \]
where \( \text{an} \) is the network but normalized so if we want to un-normalize it we use this order
\[ \text{an} = \text{unstd} (\text{an}) \]
To performs a linear regression between the network response the target, and computes the correlation coefficient use the order
\[ \text{[m, b, r]} = \text{postreg} (\text{an}, \text{meant}, \text{stdt}) \]
where, \text{m}, \text{b} are the network output and desired or actual output and returns, M - Slope of the linear regression; B - Y intercept of the linear regression; R - Regression R-value. R=1 means perfect correlation.

6) Weights and Bias

The weights and bias, can be obtained from training data by the orders; \( \text{Net.iw}\{1,1\} \ldots \) for the weight from input layer to hidden layer; \( \text{Net}\{b1\} \) \ldots bias to a hidden layer
\( \text{Net.lw}\{2,1\} \ldots \) for the weight from hidden layer to output layer; \( \text{Net}\{b2\} \ldots \) bias to output layer from a hidden layer

7) Testing the network

At first the data for testing mainly the input and the output from the network is prepared and then is compared with the desired or actual output to test the ability of the network by using the same initialized network.
\[ [\text{p1n, meanp1, stdp1}, \text{t1n, meant1, stdt1}] = \text{prestd} (\text{p1}, \text{t1}) \]
\[ \text{net} = \text{train} (\text{net}, \text{p1n}); \text{an1} = \text{sim} (\text{net}, \text{p1}); [\text{a1}] = \text{poststd} (\text{an1}, \text{meant1}, \text{stdt1}); [\text{m, b, r}]=\text{postreg} (\text{a1}, \text{t1}) \]
where: \( \text{p1}, \text{t1} \) are testing data, \text{an1}: is normalized output, \text{a1}: un-normalized output

8) Derived mathematical equations

Finally mathematical equations can be derived [23], in order to be used in future to calculate the output from the input data without needing to construct a neural network by using the weights and bias according to activation and transfer functions as when using \{logsig 'purelin}\}: as in this paper, the next sequences have to be followed
1- Normalize the input data as shown previous .
2- Calculate sum of \( \sum \text{xi} * \text{w} \{i, j\} + \text{b} \{i\} = \text{hi} \) for each node in hidden layer
where: \text{xi}: is the input variable, \text{hi}: is a hidden layer input from input layer \( \text{w} \{i, j\} , \text{b} \{i\} \) are obtained before, \text{Net.iw}\{1,1\} \text{Net.b}\{1\}
3- Calculate the output from each node in hidden layer to output layer (Fi) according to transfer function here is logsig so \( \text{Fi} = 1/(1+\exp(-\text{hi})) \)
4- Calculate the sum of output from hidden layer to output layer \( \text{hi} = \text{Fi} * \text{Net.lw}\{2,1\} + \text{Net.b}\{2\} \)
5- Calculate the required output according to transfer fun. here is purelin [Matlab/toolbox] so output
\[ \text{yi} = \text{hi} \]
6- Un normalized \text{yi} to obtain the output \( \text{y} = \text{yi} \text{stdt} + \text{meant} \)
7- to obtain the actual values

8. ANN PV MODULE MODEL WITH ITS REGRESSION FUNCTION

This model uses the previous technique which used and verified before in the field of renewable energy like in [24-27]. This model uses the previous 3D graphs illustrated before as training or learning data for input and desired target. The inputs in this model are the Irradiance and Temperature; the outputs are: Module Voltage, Current, and Power. This model with its hidden and output layers’ suitable neurons numbers is depicted in figure 30. Also, the general neural network, and training state are presented in figures 31, and 32 respectively.
The normalized inputs \( G_n \): (Normalized Irradiance); \( T_n \): (Normalized Temperature) are as follow:

\[
G_n = \frac{(G - 0.6250)}{0.2797} \quad (21)
\]

\[
T_n = \frac{(T - 37.5000)}{27.9683} \quad (22)
\]

Equations (21) and (22) present the normalized inputs for irradiance and temperature, also the following equations lead to the required derived outputs equations.

\[
E1 = -0.3884G_n - 0.8968T_n + 2.8411 \quad (23)
\]
\[
F1 = 1/(1 + \exp(-E1)) \quad (23)
\]
\[
E2 = 10.8336G_n - 0.1120T_n - 4.7062 \quad (24)
\]
\[
F2 = 1/(1 + \exp(-E2)) \quad (24)
\]
\[
E3 = -0.3773G_n - 9.6071T_n + 7.2495 \quad (25)
\]
\[
F3 = 1/(1 + \exp(-E3)) \quad (25)
\]
\[
E4 = -0.0696G_n - 9.4705T_n - 5.0369 \quad (26)
\]
\[
F4 = 1/(1 + \exp(-E4)) \quad (26)
\]

\[
E5 = 6.3252G_n + 0.3523T_n + 4.6963 \quad (27)
\]
\[
F5 = 1/(1 + \exp(-E5)) \quad (27)
\]
\[
E6 = -0.1062G_n + 3.4660T_n + 8.7149 \quad (28)
\]
\[
F6 = 1/(1 + \exp(-E6)) \quad (28)
\]
\[
E7 = 0.1802G_n + 4.0327T_n + 3.7157 \quad (29)
\]
\[
F7 = 1/(1 + \exp(-E7)) \quad (29)
\]
\[
E8 = 11.6503G_n - 1.1094T_n + 11.1433 \quad (30)
\]
\[
F8 = 1/(1 + \exp(-E8)) \quad (30)
\]
\[
E9 = 0.2372G_n - 0.8735T_n + 0.7613 \quad (31)
\]
\[
F9 = 1/(1 + \exp(-E9)) \quad (31)
\]

The normalized outputs are:

\[
V_n = 0.0466F1 + 0.0080F2 + 0.0661F3 - 0.2311F4 - 0.0071F5 + 2.5608F6 + 0.0771F7 + 0.0091F8 - 0.0021F9 + 2.7656 \quad (32)
\]
\[
I_n = 6.2907F1 + 1.5501F2 + 0.2881F3 + 1.8330F4 - 1.1986F5 - 0.6123F6 - 1.2526F7 + 1.6547F8 - 2.6831F9 - 6.1682 \quad (33)
\]
\[
P_n = 7.2249F1 + 1.7820F2 + 1.0262F3 + 5.1377F4 - 0.9574F5 + 3.4515F6 + 1.8830F8 - 6.9036F9 - 7.3615 \quad (34)
\]

The normalized outputs are:

\[
V = 25.2226V_n + 42.6563 \quad (35)
\]
\[
I = 2.1788I_n + 2.3181 \quad (36)
\]
\[
P = 57.5303P_n + 81.4030 \quad (37)
\]

9. CONCLUSIONS

This paper presents a simple but efficient photovoltaic modeling trial for both specific and general one. It models each component and simulates them using MATLAB. The result shows that the PV model using the equivalent circuit in moderate complexity provides good matching with the real PV module. Simulations are based on Schott ASE-300-DGF PV panel as a practical one. A non-specific modeling and simulation at more probable situations for variable values of temperature and irradiance are presented. The simulation results at each irradiance value with various temperature values and corresponding characteristics are well depicted in 3-D figures. ANN is used for the proposed range of irradiance and temperature as model inputs, with the corresponding values of voltages, currents, and power as outputs with its algebraic equations. This neural network unit is 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 curves data. This is done with suitable number of network layers and neurons at minimum error and precise manner.

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