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Neural Network Modeling and Simulation of A 265W Photovoltaic Array

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ABSTRACT

This paper presents the Neural Network modeling and simulation of a 265 Watts photovoltaic array installed at the Faculty of Engineering and Engineering Technology of Abubakar Tafawa Balewa University, Bauchi, Nigeria. Hitherto, Mathematical modeling is the favoured method for characterizing photovoltaic (PV) arrays. This approach would require detailed information on the physical parameters relating to the solar cell material, which may not be readily available. Even in situations where the required information is provided on the manufacturer's datasheet, it tends not to be very accurate as it is not representative of the actual field performance of the array. Thus results obtained from mathematical modeling of photovoltaic arrays are only accurate to the extent of the accuracy of the model parameters. A better PV array characterization approach is to use Neural Network modeling because it does not require any physical definitions of the array and hence has the potential to provide a superior method of characterization than the already established conventional techniques. In this paper, two Radial Basis Function Neural Network (RBFNN) trained models are employed to simulate the performance of a 265 Watts photovoltaic array. The first model predicts the array I-V and P-V curves while the second predicts its maximum power for all operating weather conditions. Results of array performance plots show close correlation with those obtained through conventional mathematical modeling. RBFNN returned absolute errors of 1.794 %, 1.594 % and 1.262 % with respect to PV maximum power predictions for harmattan, cloudy and clear sunny seasons respectively.

Key Words: *Solar Cell, Pv Array, Neural Network, Radial Basis Function, Simulation, Absolute Error*

1. INTRODUCTION

Photovoltaic power systems have increasing roles in modern electric power energy mix due to the continuing decline in the world's conventional sources of energy. The major advantages associated with photovoltaic systems are that [1]:

- They have no moving parts.
- They don't produce any noise.
- They require little or no maintenance.
- They work satisfactorily with beam or diffuse radiation, thereby posing no health or environmental hazards.

These systems have many applications including water pumping, refrigeration and vaccine storage, air conditioning, light sources, electric vehicles, PV power plants, and hybrid systems in military and space applications.
Photovoltaic arrays are the electric generators of photovoltaic systems. They have nonlinear current/voltage characteristics under varying solar irradiance and temperature conditions. Furthermore, they suffer from the following disadvantages:

- High fabrication cost.
- Low energy conversion efficiency (typically 12 – 20%) [2].

The efficiency can drop further due to a number of factors such as array temperature and load conditions. Thus in order to use photovoltaic arrays more efficiently, their response to various operating conditions must be understood. It is always desirable to maximize the power derived from the array and thus improve its efficiency by operating it at its optimal power point. Unfortunately however, due to its nonlinear nature, the current and power of the PV array depend on its terminal operating voltage. The conventional photovoltaic array mathematical model requires detailed knowledge of some physical parameters relating to the solar cell material, solar trajectory and wind speed, humidity and illumination factor. At times due to lack of or unreliable information, the derived mathematical model may be inaccurate [3].

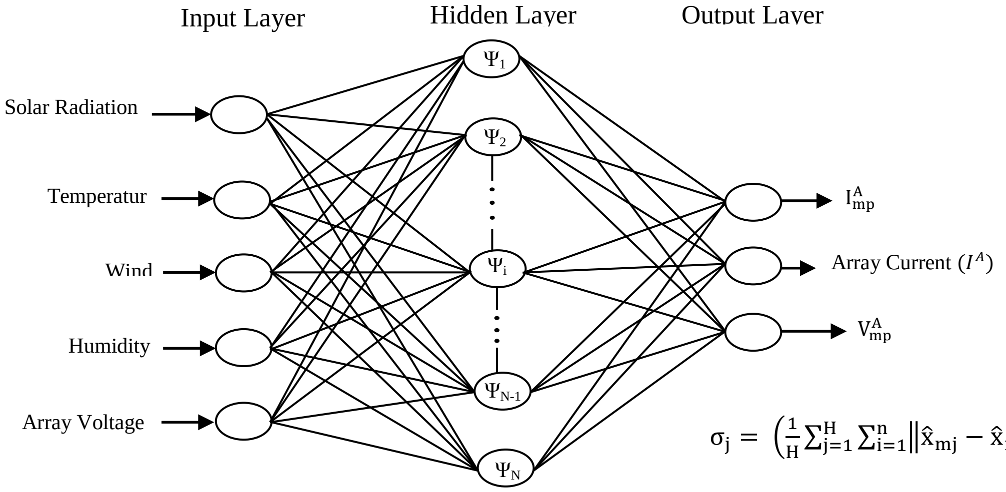
Artificial Neural Network modeling technique has attracted wide spread interest in photovoltaic array modeling because it does not require any physical definitions for the array and has self adopting capabilities which make it suitable for handling nonlinearities, uncertainties and parameter variations which may occur even in a controlled PV array generator. Two artificial Neural Network architectures have been proposed to completely simulate the PV array and both are of the Radial Basis Function (RBF) Neural Network type because of its obvious advantages. The first RBF Neural Network architecture will be trained to predict the array's maximum power point power for Harmattan, Cloudy, and Clear Sunny weather conditions. Solar irradiance (G) and Temperature (Temp.) are the inputs to this network while maximum power current (I_{mp}) and maximum power voltage (V_{mp}) will be its outputs. The second RBF Neural Network architecture is trained to predict the array I-V and P-V characteristic curves for the three weather conditions. Solar irradiance (G), Temperature (Temp.) and Array voltage (V^A) are the Network's three inputs while the Array load current (I^A) is its output. Appropriate test data is used to validate the trained Neural Networks and simulation results are presented and discussed.

2. RADIAL BASIS FUNCTION NEURAL NETWORK MODELING APPROACH

The alternative PV array modeling approach involving radial basis function type neural network as against mathematical modeling is proposed in this paper. In order to achieve the desired objective, suitable RBF Neural Network architectures have been proposed and discussed herein.

2.1 Proposed Architecture of RBF Neural Network for PV Array Modeling

The generalized architecture of RBF neural network model for the experimental PV array test rig is shown in Fig. 1 comprising multi-inputs mapped into multi-outputs via N dimensioned hidden layer. The hidden layer nodes are defined by parameter vector and scalar quantity called 'center' and 'width', respectively whilst each hidden layer node (also known as RBF unit) uses Gaussian density function as activation function. The admissible input signals for comprehensive solar energy modeling are as shown in Fig. 1 but the most critical signal inputs being solar irradiance G, PV array temperature, T and PV array voltage, V^A. The desired output signals: I_{mp}^A, V_{mp}^A and I^A are also assigned to the nodes of the output layer.



$$\sigma_j = \left(\frac{1}{H}\sum_{j=1}^{H}\sum_{i=1}^{n}\left\|\hat{x}_{mj} - \hat{x}_{mi}\right\|\right)^{1/4} \quad (2)$$

Figure 1: Generalized RBF Neural Network Architecture for Array Performance Modeling

For the sake of generalization, let the assumed input signals (solar radiation, temperature, wind, humidity and array voltage) be denoted as $(x_1, x_2.x_3, x_4\ and\ x_5)$ and output signals $(I_{mp}^A, V_{mp}^A$ and $I^A)$ be denoted as $(y_1, y_2 and\ y_3)$. If the output layer is a set of linear mapping functions of the hidden layer, then the input-output mapping for the RBFNN can now be cast by equation (1) as follows:

$$\hat{y}_k = a_k + \sum_{j=1}^{H} v_{jk}\eta_j \ ; k = 1,2 \dots n' \quad (1)$$

Where $\eta_j = \exp\left(-\sum_{i=1}^{N} {[x_i - \hat{x}_{ij}]^2}/{\sigma_j^2}\right)$; $\hat{y}_k$: is the final output at node k; n' : is the number of output nodes; H: is the number of hidden layer nodes; a_k: is the bias of the k^{th} output node; N is the number of input nodes; $\hat{x}_{ij}$: is center of j^{th} RBF unit for input variable i; σ_j is the width of j^{th} RBF unit and v_{jk} is the weight between k^{th} output and j^{th} node of hidden layer.

The parameters of RBFNN that need to be determined include RBF unit centers, widths and weights. These parameters are usually determined through three steps of training activity [4]. The RBF centers are usually determined via k-means clustering algorithm and once established, the width σ_j of the j^{th} RBF unit in the hidden layer is computed by equation (2) as:

Where $\hat{x}_{mj}$ and $\hat{x}_{mi}$ are the m^{th} element of the center of j^{th} and i^{th} RBF units.

The literature is quite rich in methods for determining RBF centers and widths as well as other pertinent parameters. Moody and Darken, [5] have presented such methods for the computation of RBF parameters and are adopted for implementation in this paper.

It is worthy of mention again that the RBFN has been established to be superior to back- propagation Neural Network from the standpoint of predictive accuracy [6]. Different configurations of Radial Basis Function Networks will therefore be trained to simulate the performance of a stand-alone photovoltaic array of fixed orientation to predict its maximum power outputs for different microclimatic conditions. The training of RFBN must of necessity rely on field measurements with respect to the experimental PV array test rig. In the next section, the modalities for the acquisition of field data on the PV array are described in sufficient detail.

3. EXPERIMENTAL PV ARRAY TEST RIG: DATA COLLECTION AND CREATION OF DATABASE

The principal goal of this research effort concerns the acquisition of long term PV array test rig field measurement data. Towards the realization of this goal, an in-depth experimental PV array test rig and fairly elaborate measurement procedure was setup. The field data acquisition scope encompasses hourly solar irradiance, cell temperature, array current and voltage over a prolonged period. More specifically, a methodology is evolved for the collection and creation of database in order to characterize the PV array current/voltage relationships and maximum power point values as functions of irradiance, G and PV array temperature, T_{cell}.

The flowchart depicted in Fig. 2 constitutes the experimental procedure with which to create the necessary current/voltage database on the experimental PV array test rig. We reiterate again that the prime objective of field measurements is to underpin realistic model development for the polycrystalline silicon type PV array test rig for its performance evaluations under different microclimatic conditions of the site.

For the avoidance of doubt, the depth and scope of the field measurements embarked upon with respect to the experimental PV array test rig entail the executions of the following:

- Hourly PV array open circuit voltage, V_{oc}, short circuit current, I_{sc} as well as hourly irradiance, G and PV cell temperature, T_{cell} measured from daily sunrise to sunset for some selected days within each Bauchi microclimatic period considered i.e. harmattan, cloudy and clear sunny seasons.
- I-V curve trace data generated by discretely varying load across the PV array from minimum to maximum at fixed G and T for some selected days within each Bauchi microclimatic condition.
- At constant solar irradiance G, quickly pre-cool the experimental PV array temperature (via PV surface heat extraction and shading earlier described) below ambient temperature; turn off cooling system, un-shade the PV array and measure its voltage/current relationship per incremental rise in PV array temperature. Repeat experimentation to capture all microclimatic attributes at experimental PV array site.
- Entry of all the PV array measurements into microcomputer computing facility to create necessary database and data classifications in accordance with climatic attribute of the PV array site.
- Extensive pre-processing of PV array data and plotting of benchmark I-V curves as well as extracting their respective maximum power points (I_{mp}, V_{mp}) as functions of G and T with respect to all microclimatic conditions of the site.

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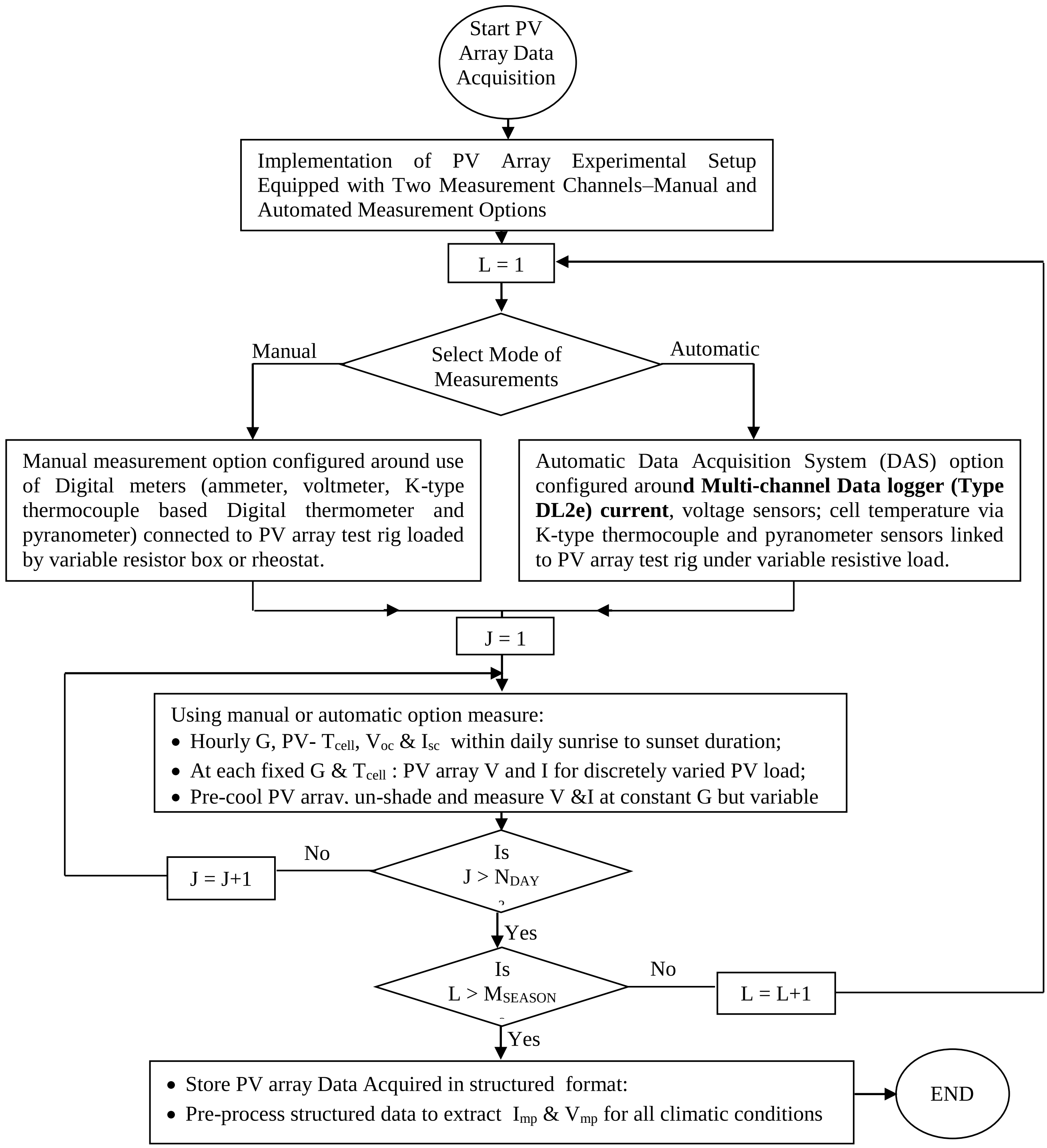

Figure 2: Flowchart of Experimental PV Array Test Rig Data Acquisition Framework

4. ALGORITHMIC FLOWCHARTS FOR SOFTWARE IMPLEMENTATIONS

This section presents computational procedure driven flowcharts to facilitate software implementation of the proposed simplified analytical and RBFNN models for the experimental PV array test rig. The two proposed models are so structured to rely exclusively on long-term field measurements with respect to the experimental PV array test rig. For the purpose of comparative evaluations, we have extended the existing techniques that rely entirely on manufacturer data specifications to the proposed simplified analytical model.

Fig. 3 provides the generalized flowchart for the training requirements of the proposed RBFNN so as to be able to predict the performance of the experimental PV array test rig. As matter of fact, determining the structure of the RBF Neural Network is based on the underlying theory about what influences the dependent variables. This involves choosing input variable(s), number of input neurons, number of hidden neurons, the transfer function type, choosing the output variable(s) and the number of output neurons. The PV array field measurements naturally constitute the training and verification data to be used in determining the optimum configuration and parameters of the RBFNN.

An integrated functional block diagram portraying the inter-relationship among the three models studied and for which results are compared is depicted in Fig. 4. Against this backdrop, the training and ultimate implementation of the proposed RBFNN PV model has been fully explored in MemBrain software platform.

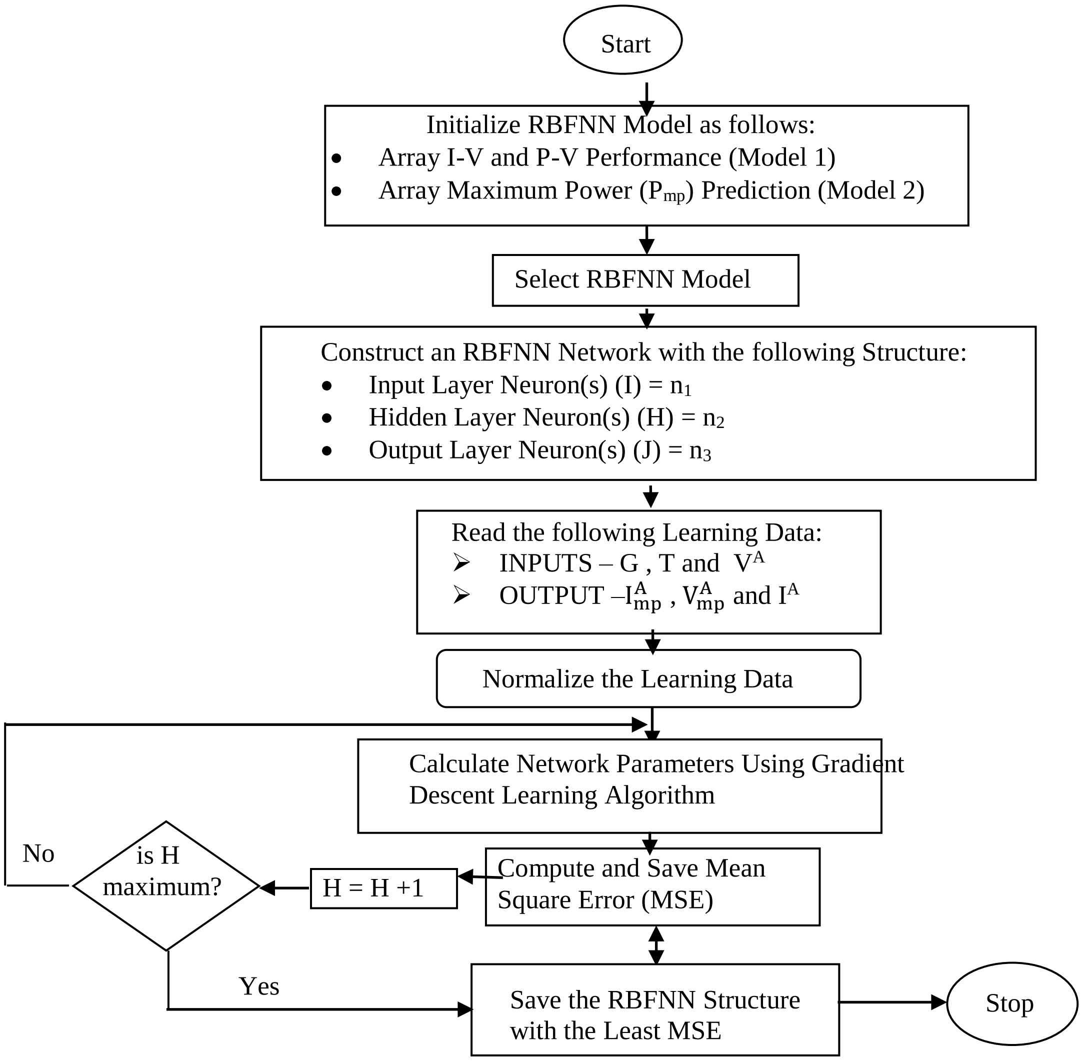

Figure 3: Generalized Flowchart for the Training of the RBFNN Models

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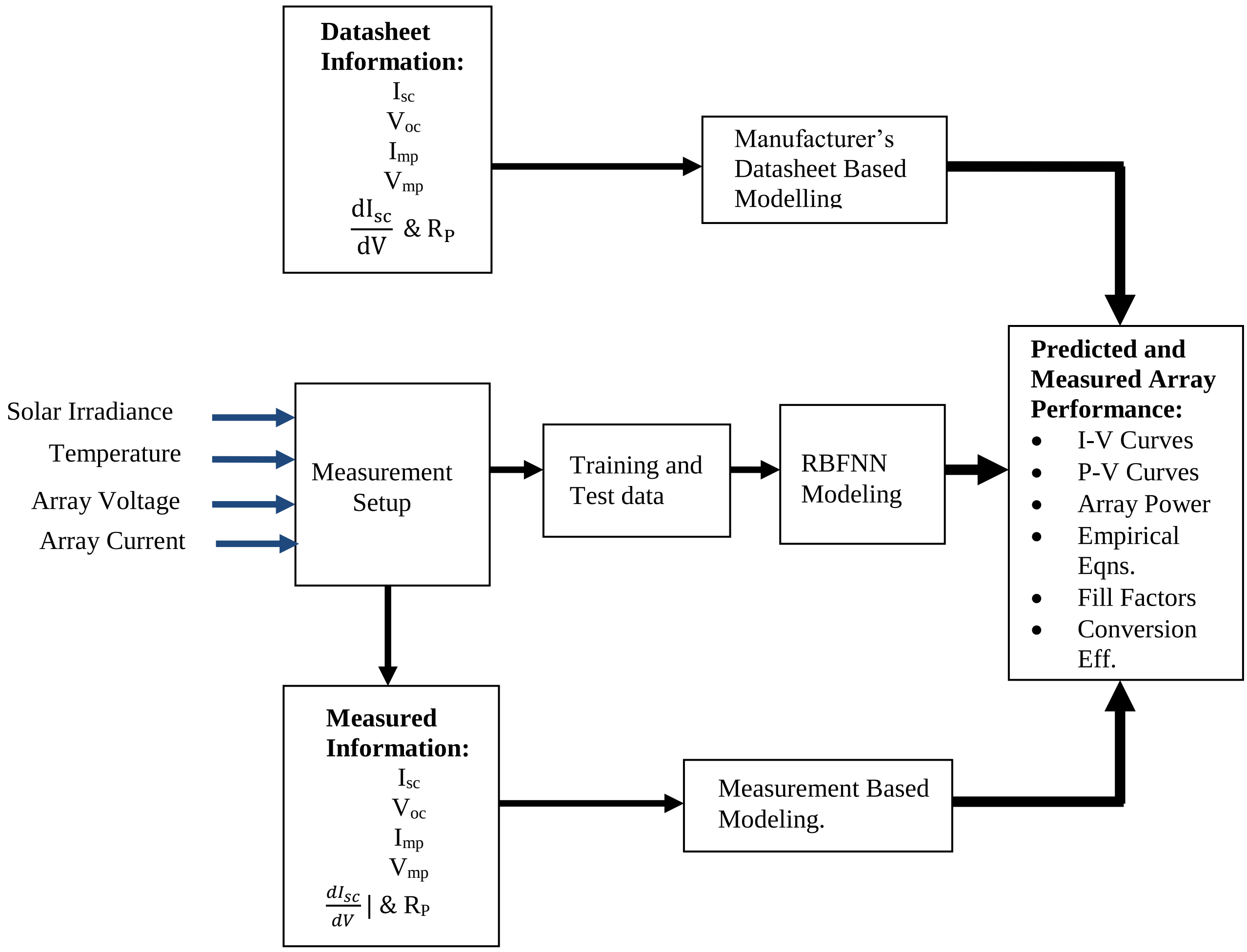

Figure 4: Integrated Functional Block Diagram of PV Array Models Studied and Compared

5. DEVELOPED RBF NEURAL NETWORK ARCHITECTURES

The exact structures of the proposed Neural Networks for modeling the photovoltaic array and maximum power point prediction are indicated in Figs. 5 and 6 respectively. The input to the array current/voltage performance modeling Network (Fig. 5) is a linear layer consisting of three neurons whose inputs are solar irradiance, temperature and array voltage. The hidden layer consists of 5 neurons with radial basis function. The output layer consists of one neuron which gives the values of array load current. Similarly, the input to the maximum power prediction network (Fig. 6) is also a linear layer consisting of two neurons whose inputs are solar irradiance and temperature.

The hidden layer consists of sixty neurons with radial basis function. The output layer consists of two neurons which give the values of maximum power current (I_{mp}) and maximum power voltage (V_{mp}). Every neuron in both network structures is appropriately biased.

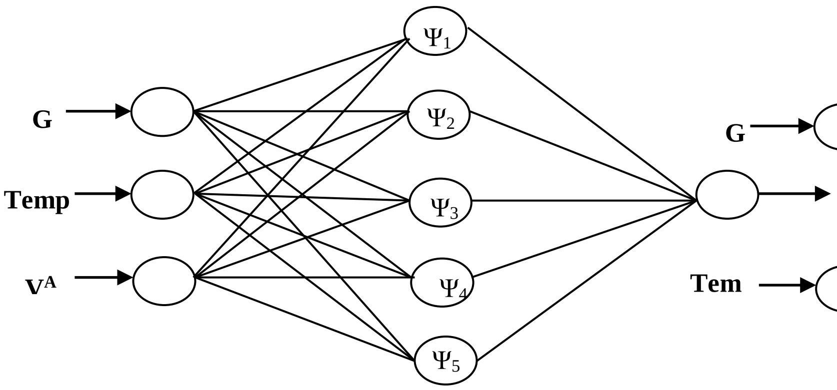

Figure 5: RBF Neural Network Architecture for I-V and P-V Performance Modeling

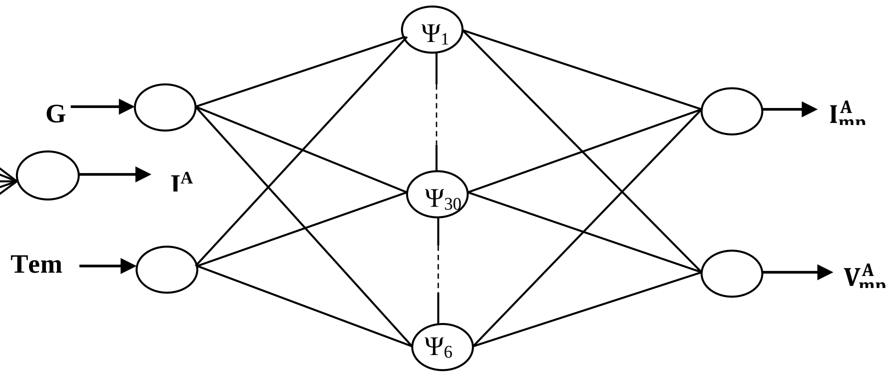

Figure 6: RBF Neural Network Architecture for Maximum Power

5.1 Training of the Radial Basis Function Neural Network

There is no 'rule of thumb' on the optimum number of neurons in a given Network structure. However, the number of neurons in the input layer equals the number of input variables while the number of neurons in the output layer equals the number of output variables. For our proposed structure (Fig. 5), the number of input layer neurons equals 3, since there are three input variables while only 1 neuron is used in the output layer. The number of neurons in the hidden layer was determined by trial and error via suitably modified MemBrain neural network that faithfully implemented the RBFNN. This was then achieved by training different structures with arbitrarily chosen number of hidden neurons and selecting the structure with the lowest Mean Square Error (MSE). Table 1 provides the summary of MSEs as obtained from some selected trained Networks. From Table 1, the lowest mean square error of 407.1 x10^{-6} is obtained from the structure with five neurons in its hidden layer. This structure is therefore adopted and appropriately re-trained. The required database that is created was first divided into training and testing (validation) sets. In this case, there were a total of 983 data patterns, out of which 25 % was set aside as the testing set (246 data patterns). The remaining 737 data patterns constitute the training set and were used to train the network.

The trained RBF neural network was then validated by using the testing set of 246 patterns. Both training and testing sessions were preceded by appropriate normalization of the data.

5.2 Training of the Maximum Power Prediction Network

The proposed structure for the maximum power point prediction has two input variables and two output variables (see Fig. 6). Thus the number of neurons in the input and output layers are 2 each. To determine the number of neurons in the hidden layer, a number of training sessions for different arbitrarily chosen number of hidden neurons was carried- out with the results summarized in Table 2.
From Table 2, the lowest mean square error of 299.40 x10^{-6} is obtained from the Network structure having 60 neurons in its hidden layer. This structure is therefore adopted and re-trained for maximum power point prediction. The database created was also divided into training and testing sets. There were a total of 60 data patterns, out of which 25 %, i.e. 25 data patterns were set aside for testing and validation. The remaining 45 data patterns constitute the training set and used to train the Network. Herein, both the training and testing data sets were appropriately normalized.

Table 1: Mean Square Error for Different Numbers of Hidden Layer Neurons as Obtained from the Array Modeling Network

S/N	Hidden Layer Neurons	Mean Square Error (MSE) x 10^{-6}
1	3	368.0
2	4	762.6
3	5	407.1
4	6	672.4
5	12	1029.6
6	20	1171.0
7	30	1312.0
8	50	1190.6
9	150	2777.0
10	200	1130.0

5.3 Simulation Results of RBFNN Based PV Array Performance Evaluation

The simulation results based on RBF neural network, for I-V and P-V performance modeling of the experimental PV test rig, are shown in Figs. 7 to 9 that principally reveal the effects of harmattan, cloudy and clear sunny season, respectively at the experimental site. These figures essentially combined the results of I-V and P-V plots of RFBN and field measurement approach for the three principal seasons considered.

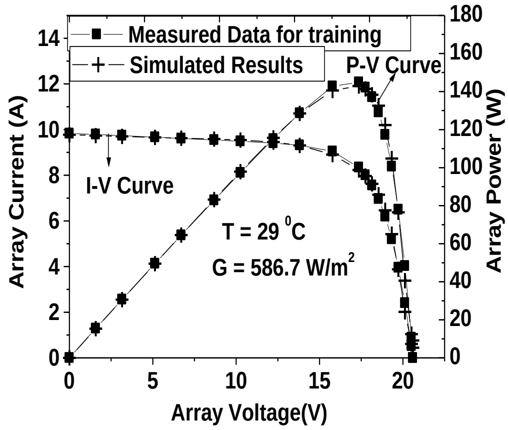

Figure 7: I-V and P-V Plots of Measured and RBFNN Simulated Results for Harmattan Season

Table 2:Mean Square Error for Different Numbers of Hidden Layer Neurons as Obtained from the Maximum power Prediction Neural Network

S/N	Hidden Layer Neurons	Mean Square Error (MSE) x10^{-6}
1	5	855.1
2	12	443.54
3	14	447.302
4	44	428.63
5	45	329.56
6	46	494.819
7	59	432.608
8	60	299.40
9	61	367.2
10	65	792.640
11	70	857.32
12	80	875.91
13	100	946.18

Furthermore, simulations based on RBF neural network of Fig. 6 were done to characterize PV maximum power, P_{mp} as function of PV temperature or solar irradiance. With each season fixed at its average seasonal irradiance, Figs. 10 to 15 depict, in pair of, field measurement and RBFN prediction of the variations of P_{mp} versus temperature for harmattan, cloudy and clear sunny seasons.

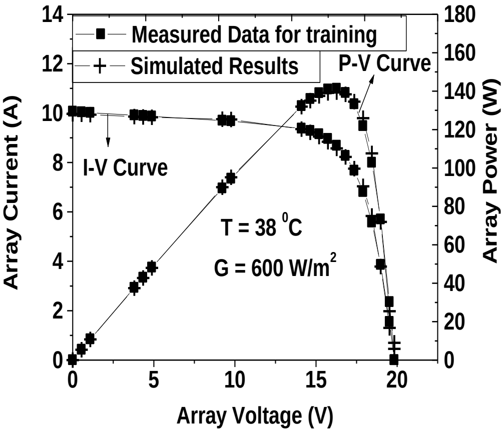

Figure 8: I-V and P-V Plots of Measured and

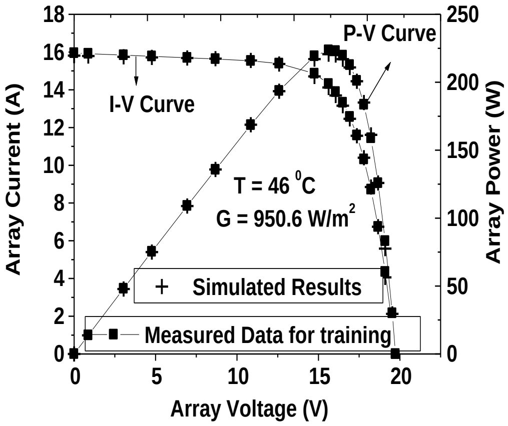

Figure 9: I-V and P-V Plots of Measured and RBFNN Simulated Results for Clear Sunny

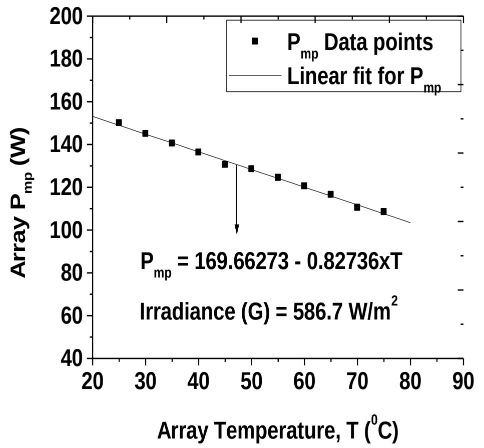

Figure 10: Plot of Measured Array P_{mp} versus Temperature for Harmattan Season

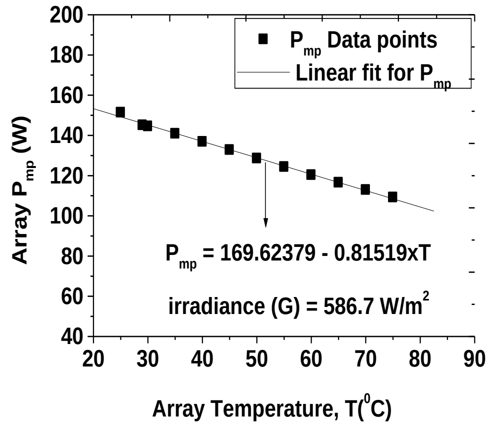

Figure 11: Plot of RBFNN Predicted Array P_{mp} versus Temperature for Harmattan Season

The same simulations were repeated to characterize the variations of P_{mp} with the solar irradiance and compared with its counterpart field measurements for the three seasons at their respective average seasonal temperature. The field measurements paired with their counterpart simulation results for this scenario are shown in Figs. 16 to 21. In summary, these figures are essentially plots of measured and RBFN predicted P_{mp} of the experimental PV array as function of solar irradiance for all seasons also parameterized by their respective specified average seasonal temperatures.

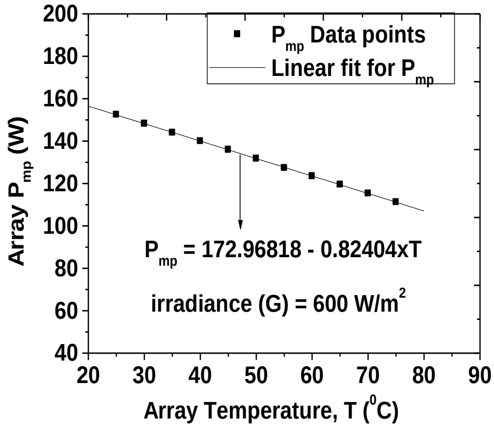

Figure 12: Plot of Measured Array P_{mp} Versus Temperature for Cloudy Season

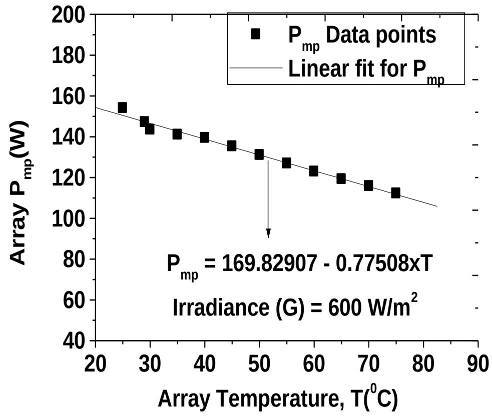

Figure 13: Plot of RBFNN Predicted Array P_{mp} versus Temperature for Cloudy Season

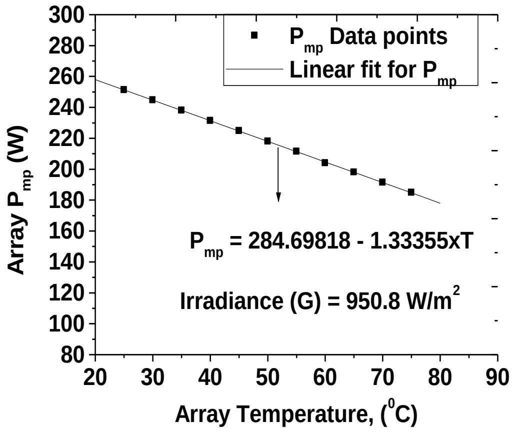

Figure 14: Plot of Measured Array P_{mp} versus Temperature for Clear Sunny Season

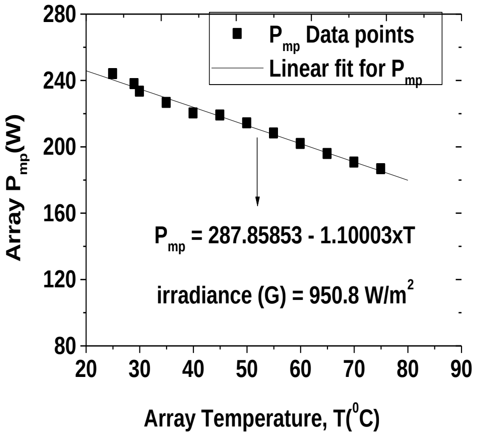

Figure 15: Plot of RBFNN Predicted Array P_{mp} versus Temperature for Clear Sunny Season

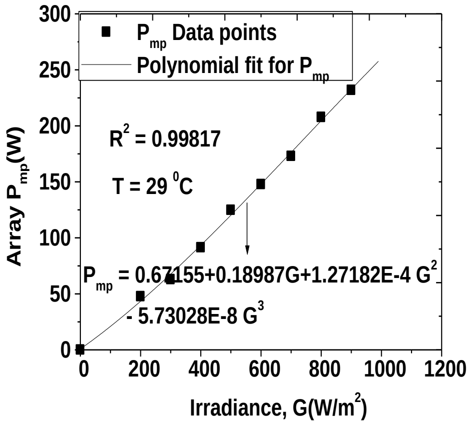

Figure 16: Plot of Measured Array P_{mp} Versus Irradiance for Harmattan Season

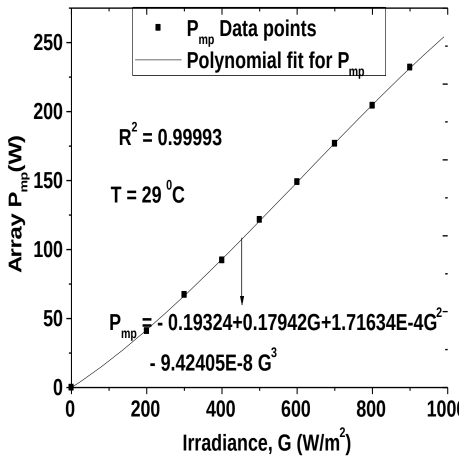

Figure 17: Plot of RBFNN Predicted Array P_{mp} versus Irradiance for Harmattan Season

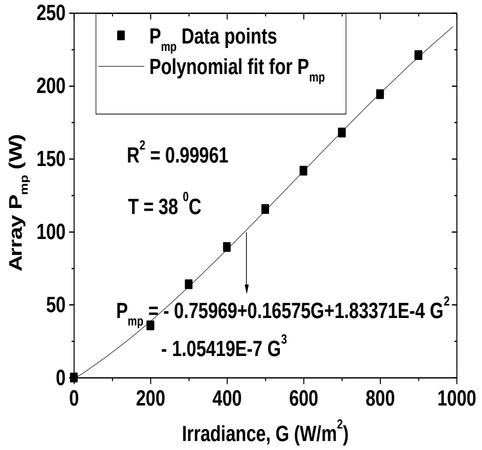

Figure 18: Plot of Measured

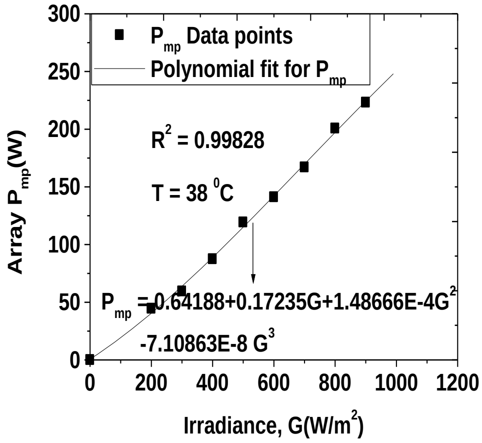

Figure 19: Plot of RBFNN Predicted Array P_{mp} versus Irradiance for Cloudy Season

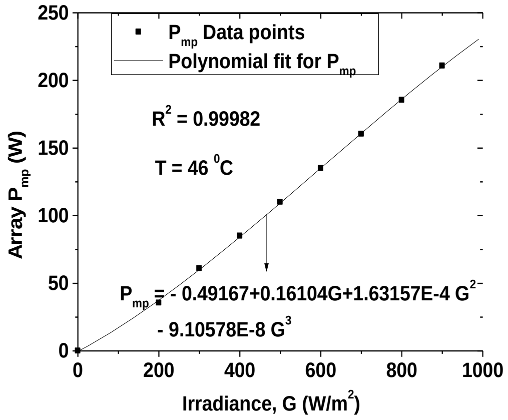

Figure 20: Plot of Measured Array P_{mp} versus Irradiance for Clear Sunny Season

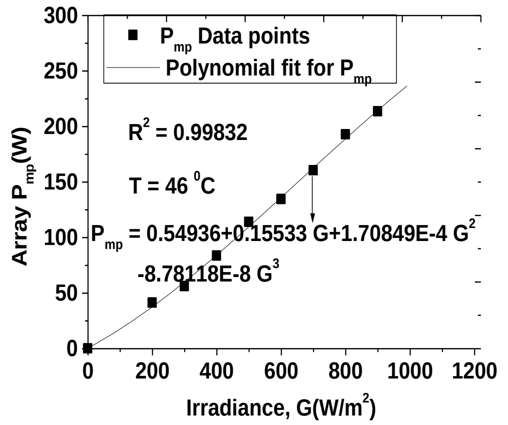

Figure 21: Plot of RBFNN Predicted Array P_{mp} versus Irradiance for Clear Sunny Season

6. RESULTS OF PV ARRAY MAXIMUM POWER OUTPUTS FOR EACH CLIMATIC CONDITION USING RBFNN AND OTHER METHODS

The major goal of this paper is to test Radial Basis Function Neural Network and Simplified Analytical Models that we developed by way of predicting the operational performance of a PV array under different climatic conditions and benchmarking them against similar results via field measurements. From this standpoint, the operational performance of the PV array is principally characterized in terms of its maximum power delivery capability during solar irradiance period and throughout the year. As a corollary, the maximum power delivered by the experimental PV array test rig was done via the following methods:

- PV array based field measurements during harmattan, cloudy and clear sunny climatic conditions;
- Field Measurement Based PV Simplified Analytical Model (FMB-PV-SAM) maximum power computations for harmattan, cloudy and clear sunny climatic conditions;
- Manufacturer Datasheet Based PV Simplified Analytical Model (MDB-PV-SAM) maximum power computations for harmattan, cloudy and clear sunny climatic conditions;
- RBFNN based maximum power computations for harmattan, cloudy and clear sunny climatic conditions;

A comprehensive summary of the results obtained are presented in Table 3.

7. COMPARATIVE EVALUATION OF ANALYTICAL MODELS AND RBFNN SIMULATION RESULTS

Mathematical and Neural Network modeling have been carried-out on a 265 W photovoltaic array. Power outputs from the array for harmattan, cloudy, and clear sunny seasons have been determined and the main results are summarized in Table 3. This table is essentially a compendium of the overall results achieved. With the field measurement results admitted as the benchmarks, error analyses revealed that FMB-PV-SAM returned absolute errors of 0.110 %, 0.106 % and 0.063 % with respect to PV maximum power predictions for harmattan, cloudy and clear sunny seasons whilst, for the same scenario, RBFNN returned absolute errors of 1.794 %, 1.594 % and 1.262 %. Finally, the predictive errors returned by MDB-PV-SAM are 4.900 %, 5.148 % and 1.311 %. Comparison of these errors reveals the superior accuracy levels of the PV array analytic models as well as the meta-heuristic technique based model over existing model based on manufacturers' datasheets. Also noteworthy, is the appreciable reduction of power output of the PV array, most especially during the harmattan and cloudy or rainy seasons.
Expectedly, the clear sunny climatic condition yielded the highest harvest of solar energy by the experimental PV test rig sited at Bauchi locality with 84.34 % of the manufacturer specified baseline rating attained. Conversely, harmattan bearing climatic condition at PV site
yielded one of the least PV array power output predictions with only 55 % of the manufacturer specified rating attained according to PV model predictions supported by field measurement verifications.

8. CONCLUSION

The results of PV array field measurements, two analytical models and radial basis function neural network based model have been presented and discussed extensively. More specifically, the I-V and P-V characteristic curves of the array as determined via field measurements and trained RBF Neural Network have been characterized extensively. Furthermore, comparative plots of measured array maximum power and RBFNN predicted array maximum power have also been presented. The far reaching results generated from the field measurements and PV models were discussed from the standpoints of their capabilities to accurately predict the performance parameters of an experimental PV array test rig subjected to different climatic conditions. The field measurement based analytical model and RFBNN architecture for PV performance evaluation yielded superior results when compared with that of the manufacturer datasheet based mathematical model. Various algorithmic procedures have also been evolved which are aimed at guiding the development of suitable software programs on MATLAB and other platforms

Table 3: Comparisons of PV Array Power for each Climatic Condition via Different Methods

Method	Harmattan+ P_{mp}(W)	Climatic Seasons Cloudy* P_{mp}(W)	Clear Sunny** P_{mp}(W)	Remarks
Field Measurement	145.51	141.80	223.49	Taken as benchmark results
Manufacturer Datasheet Based PV Simplified Analytical Model (MDB-PV-SAM)	152.64	149.10	226.42	Very Popular among researchers in the literature
Field Measurement Based PV Simplified Analytical Model (FMB-PV-SAM)	145.67	141.65	223.35	Technique based on field measurement
RBFNN Based Model	142.90	139.54	220.67	Neural network based on field measurement
PV Based++ Datasheet Estimate	265	265	265	Based on standard test conditions

+:Average season Solar Irradiance = 586.7 W/m^2 & Average Seasonal Temperature = 29 ^{o}C
*:Average season Solar Irradiance = 600.0 W/m^2 & Average Seasonal Temperature = 38 ^{o}C
**: Average season Solar Irradiance = 950.8 W/m^2 & Average Seasonal Temperature = 46 ^{o}C
++: Standard test condition (STC): T = 25 ^{o}C & G = 1 000 W/m2 irrespective of prevailing weather condition

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