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A Comparative Analysis of ANN Algorithms Performance for Maximum Power Point Tracking in Solar Photovoltaic System

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Abstract: This paper presents the comparative analysis of Artificial Neural Network (ANN) based algorithms in maximum power point tracking (MPPT) for solar photovoltaic system. The algorithms deployed in this paper are Bayesian Regularization (BR), Levenberg- Marquardt (LM) and Scaled Conjugate Gradient algorithm (SCG).The MPPT model for solar photovoltaic system was designed in MATLAB/Simulink environment and ANN toolbox was used to for analysis. For training 70% data was used and rest 30% was used for validation and testing purpose, which was 15% each. The proposed model was trained seven times for each algorithm and best result was taken. The performance of BR algorithm was better in terms of mean square error which was less than LM algorithm. But with LM algorithm the learning rate, thus time required for training is less so it can be preferred over Time constrained system. SCG algorithm trained the system perfectly with low performance hence it is not suitable for MPPT module. Solar module of 200W with 2 modules in series and 1 module in parallel were taken. The output generated from the trained MPPT solar energy system was 400 W.

Index Terms: Photovoltaic Cell, Maximum Power Point (MPPT), Artificial Neural Network (ANN), Bayesian Regularization (BR) , Levenberg- Marquardt (LM) and Scaled Conjugate Gradient algorithm(SCG).

I. INTRODUCTION

The block diagram consistof PV cell, DC-DC boost converter, PWM generator and with ANN controller is shown in Fig.1 [6]. It consist of Artificial Neural Network (ANN) having input *G (radiance)*,*T*(temperature), V_{pv} (voltage across PV module), I_{pv} (current from PV module), PWM generator which will generate duty cycle *D*. It is also an input for DC-DC boost converter. The converter output is connected to load. The voltage across load can be changed by changing the duty cycle. While the duty cycle is decided from ANN.

For the implementation of ANN three techniques has been used namely Bayesian Regularization, Levenberg- Marquardt and Scaled Conjugate Gradient algorithm. A comparative analysis about performance of these algorithms has also been doneunder different constraints.

The PV module has following components PV array, Artificial Neural Network based MPPT, PI controller, PWM Generator, DC-DC boost Convertor shown in Fig 1.

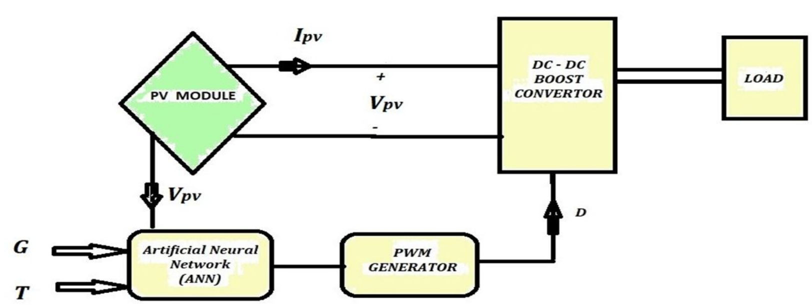
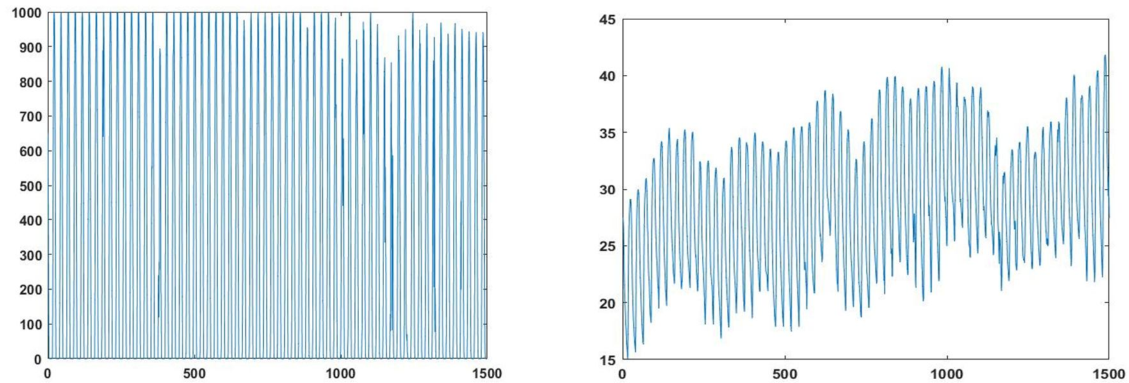


Fig. 1 Block Diagram of proposed ANN based MPPT

For inputs of PV array Solar Irradiance is taken in W/m^2 and temperature is taken in degree in degree Celsius. The data is collected from the Lucknow City in India (26.84^{o}N , 80.94^o E) to get hourly average values of solar energy dataset. Depending upon the data set a plot between hourly temperature (T) and irradiance (G) is shown in Fig. 2.



a) Irradiance data b) Temperature data

Fig. 2 Solar cell data taken as sample

The artificial neural network based MPPT was trained from the given solar energy data. The boost DC-DC convertor is used in a circuit which is controlled by duty cycle. Duty cycle is generated from the PWM generator from output of difference between PV module voltage and voltage output from artificial neural Network based MPPT algorithm.

II. POWER CIRCUIT

It consists of PV cell and DC-DC boost converter. For detailed analysis of power circuit small signal model of PV cell is already available in literature [15].

A. PV cell

PV cell's model is shown in Fig. 3 [15]. It consists of one current source, one photo detector diode and two resistances. The cell photocurrent or current source is represented by the I_p. The current through the diode is represented by i_d. The intrinsic shunt and series resistances of the cell are denoted as R_{sh} and R_s, respectively. Since R_{sh} and R_s typically have very large values, respectively, it is possible to ignore them to make the analysis simpler. Practically speaking, PV cells are arranged into bigger units called PV modules, and these modules are linked together in series or parallel to create PV arrays.

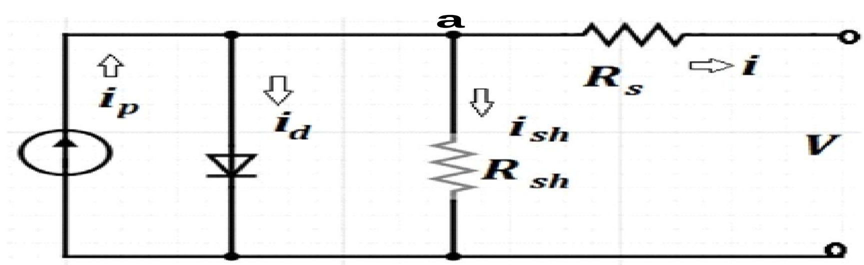


Fig.3 Model of PV cell

By applying KCL at the point *a*, the complete equation of current can be shown in equation (1). After substituting the value of i_{Rsh} and i_d . The net equation can be given as (2).

$$i_p = i_d + i_{Rsh} + i \qquad (1)$$

$$i = i_p - I_o\left(e^{\frac{V+iR_s}{nV_T}} - 1\right) - \frac{V+iR_s}{R_{sh}} \qquad (2)$$

B. DC-DC Boost Convertor

After PV module the output is fed to DC-Dc boost converter. It is required for enhancing the output voltage obtained from PV cell. The schematic diagram of boost converter is shown in Fig. 4 [8]. It consist of one diode, inductor L_s, input Capacitor C_i , output Capacitor C_o and a controlled switch can be MOSFET or IGBT.

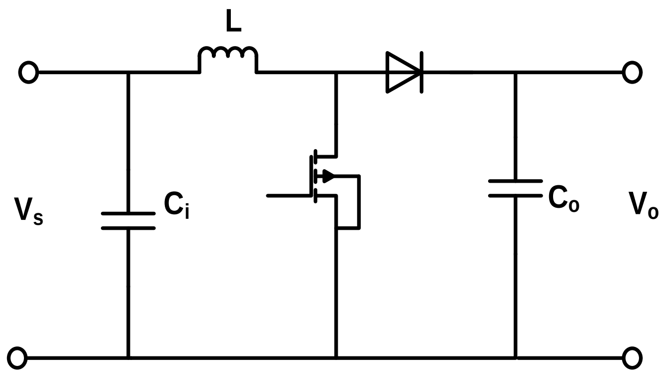


Fig.4 Schematic diagram of boost converter

The input voltage of DC-DC boost Convertor is given by V_s and output voltage is given by V_o. Inductance of the DC-DC boost convertor is calculated using inductor ripple current denoted by ΔI_L and switching frequency if the circuit denoted by f_s.

$$L = \frac{V_s \times (V_o - V_s)}{\Delta I_L \times f_s \times V_o} \qquad (4)$$

The preferred value of inductor should be higher because it leads to maximum output current because of lower ripple current.Due to bigger size and having larger flux related difficulties there is a trade off between the size and efficiency of the circuit. So the optimum size of inductor should be chosen to make circuit performance better. For simulation purpose the chosen value of these components is given in TABLE I.

The input capacitance C_i is necessary because it stabilize the input voltage because of the peak current is required in switching power supply.

The output Capacitance C_o should be always above the required minimum capacitance value. Output Capacitance is given by:

$$C_o = \frac{I_o \times D}{f_s \times V_o} \qquad (5)$$

III. CONTROLLING CIRCUIT

For controlling of DC-DC boost converter Maximum Power Point Tracking (MPPT) algorithm has been used. MPPT technique is implemented through ANN. Three algorithms Levenberg Marquardt, Bayesian Regularization and Scaled Conjugate Gradient is used.[6] Comparative analysis has been done for these three methods and discussed in SIMULATION section. To extract the maximum power from PV cell Maximum Power Point Tracking (MPPT) algorithm has been implemented by using these three ANN techniques.

A. Maximum Power Point Tracking (MPPT)

To extract maximum power from the solar panel MPPT is used. In a photovoltaic module maximum power can be drawn from a single operating point at any given time [3]. This operating point is denoted as Maximum Power Point Tracking (MPPT).The core concept of maximum power point tracking is to maintain the operating point of photovoltaic module at maximum power point [8].To get maximum Power Point the line peak power point in P-V curve and load line intersection in I-V curve should be on a same line. Since output power of solar panel is dependent on irradiance and temperature which changes frequently so to extract maximum power output at changing irradiance MPPT algorithms are widely used.

DC-DC convertor is used to supply DC supply to load and it is controlled by duty cycle. Various MPPT algorithms are used for tracking maximum power point. In this research paper we are using neural network based MPPT

B. Artificial Neural Network (ANN)

Artificial Neural Network is a collection of artificial neurons which replicate the human neurons. Input is given to each artificial neuron which produces an output. Each input signal is associated to a weight to give targeted output.[2]

$$y = \sum x_i w_i + b \qquad (6)$$

Where,

x_i- input to each neuron.

W_i – weight associated to each input.

b – bias.

The neural network is generally consists of three layers, Input layer, Hidden layer, Output layer []. Input layer is used to feed data to a neural network, it is followed by hidden layer. Hidden layers are used to process the input data using non linear functions to give output from the given set of data. Hidden layers are integral part of ANN as it enables learning of neural network and play major role in training of neural network. There can be more than one hidden layers in an ANN. The output layer stores the output of the neural network model.

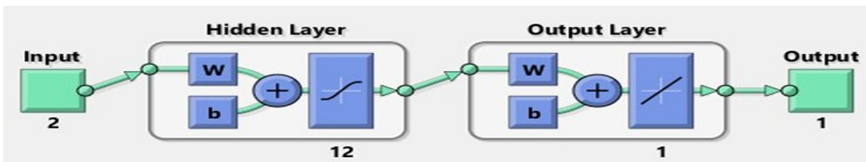


Fig. 5 Basic Structure of ANN

Mean Square Error(MSE) plays crucial role in training of an ANN model. Error E_i can be denoted by the difference between desired and estimated output as shown in equation (7). If it is a targeted output and y is output from the neural network. MSE relation with Ei is shown in equation (8) [].

$$E_i = (t - y) \qquad (7)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} E_i^{\,2} \qquad (8)$$

Where n is total number of input.

ANN models are trained using various algorithms such as Levenberg- Marquardt [LM], Bayesian Regulation [BR], Scaled Conjugate Gradient and various others. LM algorithm gives a solution to the problem of reducing a nonlinear function. This algorithm is widely known as damped least-mean square method in which MSE is difference between expected and actual output. Levenberg–Marquardt algorithm gives another approximation to Hessian matrix [10] to make sure it is invertible.

$$H = J^T J + \mu I \qquad (9)$$

where ,μ is combination coefficient and I is the identity matrix.

Since elements on the main diagonal in above equation of the approximated Hessian matrix will be greater than zero which will make sure Hessian matrix is always invertible.[9]

Now LM algorithm can be presented as

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \qquad (10)$$

Where w_k is the function of weight.

If the combination coefficient μ in above equation is very large value then it can be interprets learning coefficient in the steepest descent method

$$\alpha = \frac{1}{\mu}$$

where α is learning coefficient.

Bayesian Regularization [BR] minimise a linear combination of square errors and weights of the neural network model. Linear combination is also modifieds for better quality of training. BR algorithm does not require cross-validation.[6]

Overtrain the BR algorithm is difficult since evidence procedures enable a Bayesian objective criterion for terminating training. Because the BRANN calculates and trains on a number of effective network characteristics or weights, essentially turning off those that are not significant, they are also challenging to overfit. Typically, this effective value is much lower than the weights in a typical fully connected back-propagation neural network.

Scaled Conjugate Gradient algorithm is based on conjugate directions, but no line search is performed at every iteration. So SCG was designed to reduce computational cost. Thus it reduces memory requirement. SCG algorithm is explained in depth in [16].

IV. SIMULATION RESULTS

A prototype has been developed in MATLAB for implementation of the ANN based algorithm. For training of data using ANN algorithm neural network toolbox is used. Fig. shows the proposed schematic diagram in MATLAB. Boost converter is used as DC-DC converter. Table I shows the details of components used for the simulation results. Kyocera Solar KC200GT model is used in this research paper. Two modules in series and 1 in parallel configuration is taken. The parameters of solar module are given in Table II.

Table I .Boost Convertor Parameters

Components	Value/Type
Inductor	3.3 mH
Diode	Power Diode
Input Capacitance	1000 µF
MOSFET	Mosfet
Output Capacitance	300 µF
Load	12 ohm

Table II. Solar Module Data

PARAMETERS	VALUE
Maximum Power (W)	200 W
Open Circuit Voltage (V_{oc})	32.9 V
Max Power Point Voltage	26.3 V
Short Circuit Current	8.21 A
Max Power Point Current	7.61 A

The input data are irradiance and temperature were fed to the ANN. 1500 samples of irradiance and temperature were collected from location 26.8^o N 80.9^o E located in India. Output from the trained neural network is Voltage data. Comparative analysis for Bayesian Regularization, Levenberg- Marquardt and Scaled Conjugate Gradient algorithms has been done using NN toolbox. The result from each algorithm is compared to show their application in solar energy. For measuring performance and accuracy of these algorithms parameters such as Mean Square Error (MSE), Gradient, Momentum parameter, regression data, validation check are used.

Gradient is defined a calculation for tuning parameter of ANN model in a manner such that output deviation can be minimised. Epoch is defined as single cycle for training data; it is each trail to train from datasets. Momentum (Mu) is used to avoid local minima problem leading to no convergence. Larger Mu may lead to fast convergence. Validation check is used to reduce model overfitting. Regression is ANN is learning relationship between input and output of the model.

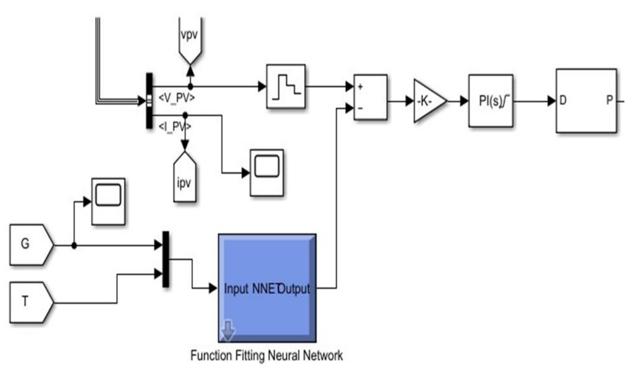
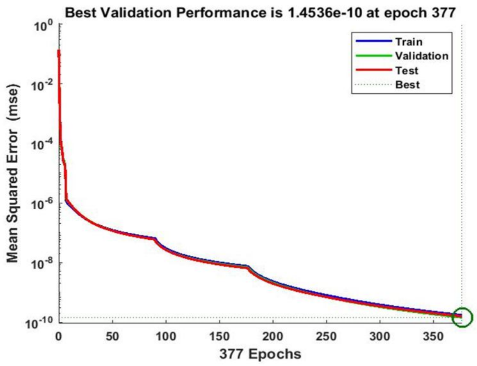


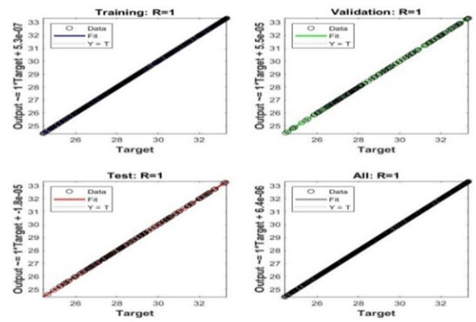
Fig.6 Circuit diagram of ANN in MPPT

A. Levenberg –Marquardt (LM)

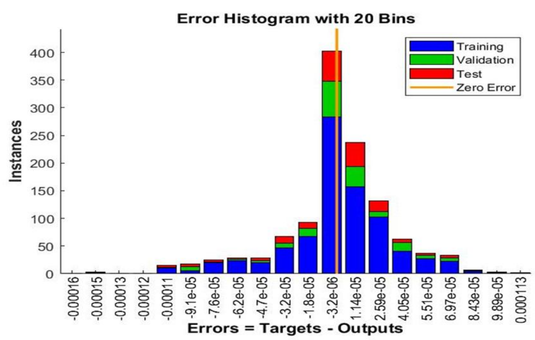
Training of ANN based MPPT using LM algorithm was successful as regression is equal 1 as shown in Fig .It means that there was perfect prediction of output voltage based on input data and its corelation with output. The best validation performance of LM based ANN is ---- at 377 epoch, means the performance of LM is good for training MPPT based ANN. In Fig. the zero error in histogram lies at -3.2 e^{-06}. Gradient of LM is 9.9914e^{-08} which prove the convergence of result is satisfactory.Value of Mu for LM is 1e^{-08} as shown in Fig. 7.



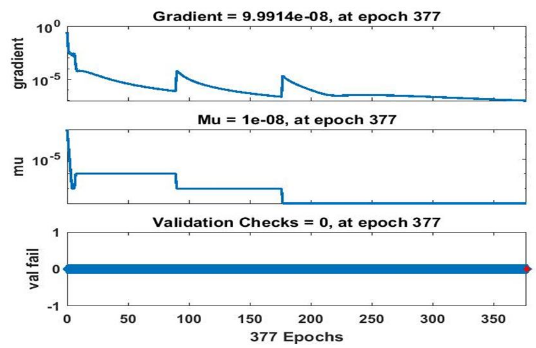
a) Performance result of LM algorithm



b) Regression Plot for LM algorithm



c) Error Histogram of LM

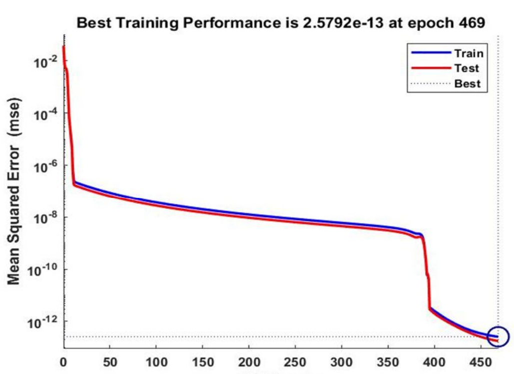


d) Fig Performance Parameter of LM

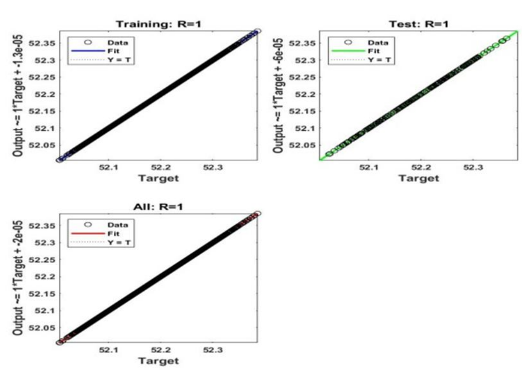
Fig. 7 Simulation results of LM algorithm

B. Bayesian Regularization (BR)

The best training performance using BR algorithm is 2.57e^{-13} with epoch at 469 proves that BR algorithm provides better training than LM with trade of with time taken during training which is higher in BR. Fig.-- . The gradient amd momentum parameter in BR is 9.78e^{-8} and 500000 respectively shows that learning rate is slower in BR when comparing it with LM.Error histogram shows that the zero error is at -4.6e^{-}08l. Validation error is zero in BR trained network as shown in Fig---. Output from ANN and the target matches perfectly as value of R is 1 as shown in Fig.8



a) Performance result of BR algorithm



b) Regression Plot of BR algorithm

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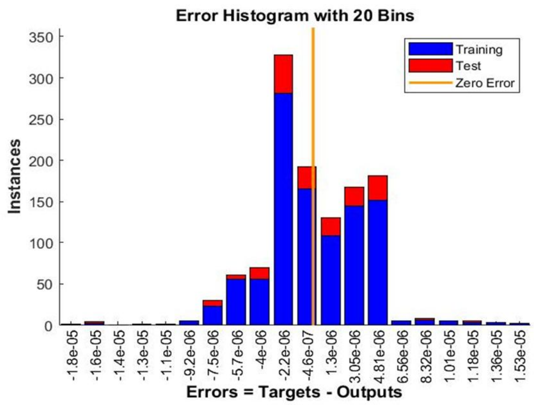
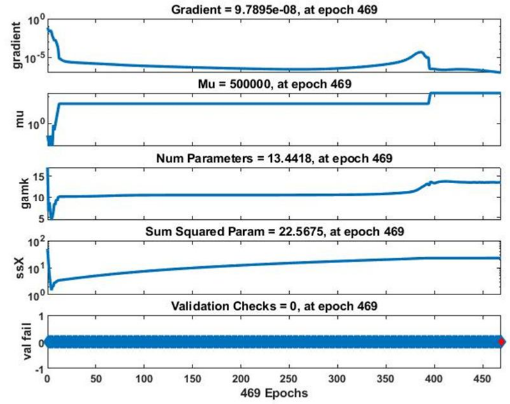


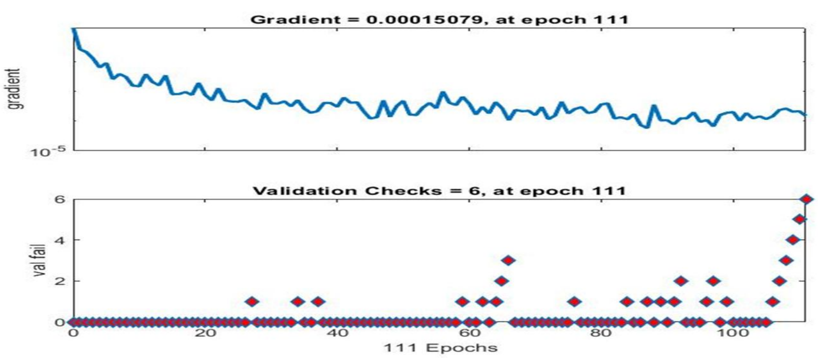


c) Error Histogram for BR d) Performance Parameter of BR

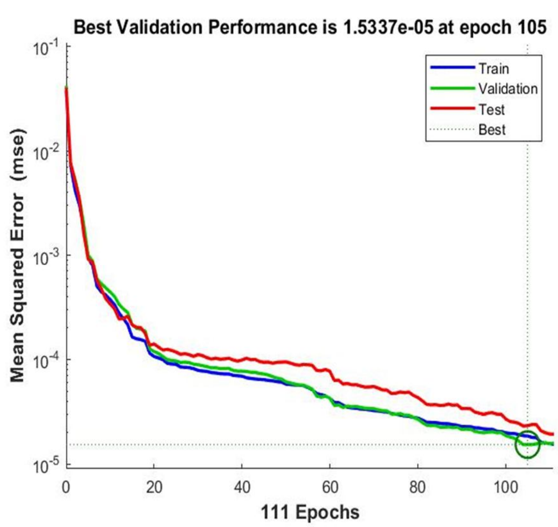
Fig. 8 Simulation results of BR algorithm

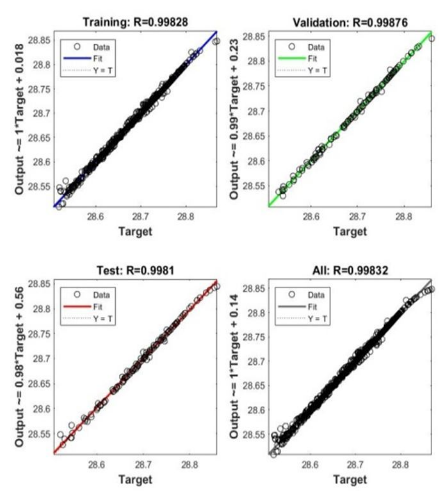
C. Scaled Conjugate Gradient (SCG)

In SCG trained neural network since Regression is 0.99 with high validation error. The model is trained for just 105 epoch thus it gives poor training performance which shows that SCG algorithm cannot be used for training MPPT based neural network as shown in Fig 9.



a) Performance Parameter of SCG





b) Performance result of SCG algorithm c) Regression Plot of SCG algorithm

Fig. 9 Simulation results of SCG algorithm

The MPPT based neural network is generating maximum power with change in irradiance values that shows that the MPPT was successfully implemented using artificial neural network as shown in Fig 10 and Fig 11.

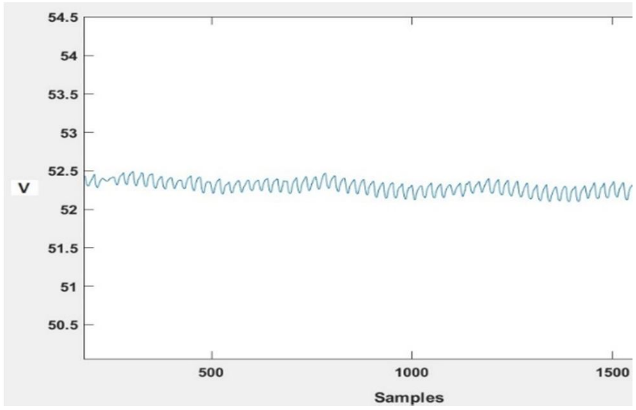


Fig 10. Voltage output from trained ANN

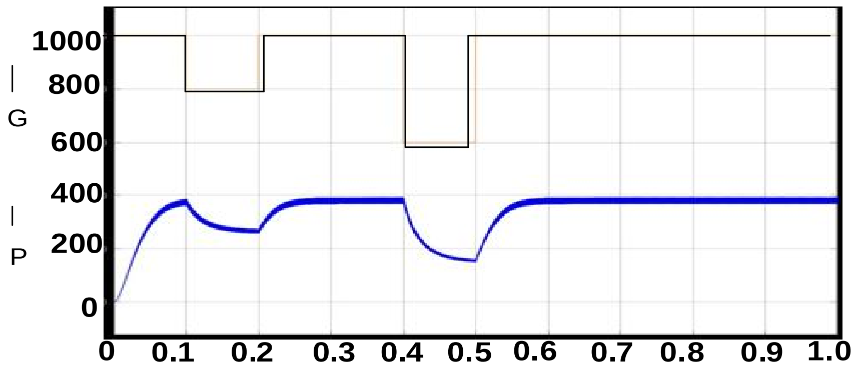


Fig. 11 Output Power generated based on different Irradiance at 25^0 C

V. CONCLUSION

The Performance of Levenberg Marquardt, Bayesian Regularization and SCG algorithms were analysed for MPPT based solar power system. The neural network based MPPT trained with BR algorithm gives better performance with least mean square error but it is at the cost of higher training time whereas LM algorithm provides faster learning rate leading to lower training time.So there is trade-off between performance and time cost for training. If there is time constraint in project then LM algorithm should be preferred over BR. SCG algorithm is not suitable for training of neural network for MPPT. The output power generated at 1000 Irradiance at 25^0 C temperature is 400 W. MPPT based solar panel generated maximum power with every variation in irradiance value thus extracting maximum power from solar power system under varying weather conditions.

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