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A Comparative Performance Analysis of ANN Algorithms for MPPT Energy Harvesting in Solar PV System

RAJIB BARAN ROY[1], MD. ROKONUZZAMAN[2,3], (Member, IEEE), NOWSHAD AMIN[2,3], (Senior Member, IEEE), MAHMUDA KHATUN MISHU[2,3], (Member, IEEE), SANATH ALAHAKOON[1], SAIFUR RAHMAN[4], (Life Fellow, IEEE), NADARAJAH MITHULANANTHAN[5], (Senior Member, IEEE), KAZI SAJEDUR RAHMAN[6], MOHAMMAD SHAKERI[2], (Member, IEEE), AND JAGADEESH PASUPULETI[2], (Senior Member, IEEE)

[1]School of Engineering and Technology, Central Queensland University, Gladstone, QLD 4680, Australia
[2]Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional (The National Energy University), Kajang, Selangor 43000, Malaysia
[3]College of Engineering (COE), Universiti Tenaga Nasional (The National Energy University), Kajang, Selangor 43000, Malaysia
[4]Advanced Research Institute, Virginia Polytechnic Institute and State University, Arlington, VA 22203, USA
[5]School of Information Technology and Electrical Engineering (ITEE), The University of Queensland, St. Lucia, QLD 4072, Australia
[6]Solar Energy Research Institute, Universiti Kebangsaan Malaysia (The National University of Malaysia), Bangi, Selangor 43600, Malaysia

Corresponding authors: Md. Rokonuzzaman (rokonuzzaman@uniten.edu.my) and Nowshad Amin (nowshad@uniten.edu.my)

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ABSTRACT In this paper, artificial neural network (ANN) based Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG) algorithms are deployed in maximum power point tracking (MPPT) energy harvesting in solar photovoltaic (PV) system to forge a comparative performance analysis of the three different algorithms. A comparative analysis among the algorithms in terms of the performance of handling the trained dataset is presented. The MATLAB/Simulink environment is used to design the maximum power point tracking energy harvesting system and the artificial neural network toolbox is utilized to analyze the developed model. The proposed model is trained with 1000 dataset of solar irradiance, temperature, and voltages. Seventy percent data is used for training, while 15% data is employed for validation, and 15% data is utilized for testing. The trained datasets error histogram represents zero error in the training, validation, and test phase of data matching. The best validation performance is attained at 1000 epochs with nearly zero mean squared error where the trained data set is converged to the best training results. According to the results, the regression and gradient are 1, 1, 0.99 and 0.000078, 0.0000015739 and 0.26139 for Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms, respectively. The momentum parameters are 0.0000001 and 50000 for Levenberg-Marquardt and Bayesian Regularization algorithms, respectively, while the Scaled Conjugate Gradient algorithm does not have any momentum parameter. The Scaled Conjugate Gradient algorithm exhibit better performance compared to Levenberg-Marquardt and Bayesian Regularization algorithms. However, considering the dataset training, the correlation between input-output and error, the Levenberg-Marquardt algorithm performs better.

INDEX TERMS Solar photovoltaic (PV), energy harvesting (EH), maximum power point tracking (MPPT), artificial neural network (ANN), Levenberg-Marquardt (LM), Bayesian regularization (BR), scaled conjugate gradient (SCG).

I. INTRODUCTION

Solar PV energy is an integral part of our energy use and a vital component of renewable energy networks. With the rapid advancement of technology, PV module prices are declining and PV panels become more efficient. National economies are making ambitious investments in off-grid PV systems and grid-connected PV networks [1], [2]. PV electricity is volatile, relies on solar irradiation and other meteorological influences, such as temperature, humidity,

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precipitation, wind direction, and cloud coverage, unlike conventional energy production systems [3]. The introduction of large-scale grid-connected solar PV plants has posed significant problems for power grids, such as lack of device flexibility, efficiency, and energy balance [4]. It is crucial to forecast solar energy production to ensure a reliable energy supply across PV grids.

Accurate predictive models minimize the influence of solar PV performance, increase the reliability of the devices, and reduce the expense of additional equipment maintenance [5]. A PV modules I-V characteristics are a feature of irradiation and temperature. MPPT controllers for maximum usage performance follow solar cell arrays. Karami *et al.* compiled a detailed list of 40 distinct MPPT techniques and their classification [6]. Several works are available in the literature detailing different MPPT algorithms and designs to boost PV device performance [7]. The Perturb and Observe (P&O) [8], Incremental conductance (INC) [9], Fuzzy Logic Controller (FLC) [10], P&O approach based on Particle Swarm Optimization (PSO) [11], and ANN [12] are most effective and standard algorithms. These strategies differ in oscillation across the absolute maximum power point (MPP), convergence speed, difficulty, stability, cost, and electronic equipment requirements [13].

During a rapid irradiance shift contributing to a distortion of the PV systems operational parameters, the P&O algorithm utilizing the controller temporarily struggles to exceed the MPP [14]. Still, the controller decreases the algorithm's error, which tracks the MPP again with some time delay. Furthermore, terminal voltage oscillates across the MPP, resulting in power loss. The minimal disruption phase size can be used for compensating these oscillations. Again, the minor phase speeds down the algorithms beginning transient and adjusts the systems weather responsiveness. The INC Algorithm using the Proportional Integral (PI) controller fits well in the abrupt modifications in irradiance and decreases the rip oscillation across the MPP. Therefore, the reaction and swing pace would still be balanced because the INC algorithm often separates itself from the MPP during abrupt irradiance shifts. According to Esram and Chapman [15], these algorithms cannot track the full power rapidly and reliably due to oscillations at the highest point.

The biological neural networks seen in human brains inspire the ANN system. It is used to train and evaluate the I-V and P-V nonlinearity relationship of a PV system. ANN retrieves inputs such as input current, input voltage, irradiance, temperature, and metrological data and constantly learns to adapt the behaviour of the solar power system for maximum power [16]. FLC design may be modelled using ANN for more accuracy and more straightforward converter implementation [17]. The dataset is obtained from the simulation or hardware setup by entering solar irradiances, temperatures, solar power system voltage or current to ANN to discover the relevant maximum power (Pmax) or maximum voltage (Vmax) output. These data are transformed into training data and fed into the intended ANN to train it how to function. Following training, test datasets are utilized to assess the performance of the constructed ANN, and mistakes are sent back to the ANN for further correction [18]. It may help to anticipate MPP with state estimation using Sequential Monte Carlo (SMC) filtering. A state-space model for sequential maximum power point (MPP) estimate may fit alongside the incremental conductance (IC) MPPT methodology framework. The ANN model monitors voltage and current or irradiance data in forecasting global MPP (GMPP) to improve SMC estimate [19]. The benefits of ANN include extraordinary accuracy in modelling nonlinearity and solving problems without previous information or models [20]. ANN may be used to increase tracking speed and accuracy by modelling and forecasting a solar power system [21]. It has been shown to have a faster reaction time and reduced oscillation around MPP [22]. Under real-world operating conditions, ANN-based MPPT can monitor MPP with minimal transient time and low ripple [23]. The square error approach is used as the feedback correction for the error computation [24]. An accurate, standardized, and appropriate training set of data, on the other hand, is a significant restriction for the ANN to work effectively without significant training error [25]. However, the differences in training and operating settings of a solar system, developing an ANN model training approach is difficult. Thus, the authors in [26] proposed a MATLAB/Simulink model of Particle Swarm Optimisation (PSO) technique to determine the optimal topology and compute the ANN models optimal starting weights to increase the ANN model accuracy. As a result, the conflict between processing time and the best-fitting regression of the ANN model is resolved, and the mean squared error is minimized. The findings demonstrate that utilizing actual data, the optimized feedforward ANN methodology based on the PSO algorithm effectively forecasts the highest power point, with hourly average efficiencies of more than 99.67% and 99.30% on sunny and cloudy days, respectively. In comparison to perturb & observe (P&O) and incremental conductance (IC), an ANN-based MPPT controller exhibits lower steady-state error and a faster reaction to rapid changes in solar temperature and irradiance [27].

On the other hand, an enhanced P&O algorithm with variable step size is intended to decrease steady-state fluctuation or oscillation and increase tracking speed during abrupt irradiance changes or partial shading condition (PSC). ANN and FLC are well-suited for integration with more traditional MPPT techniques such as P&O and IC. The ANN technique calculates the MPP in the absence of shade or panel temperature, but the hill-climbing (HC) technique further enhances the outcome. Other hybrid MPPTs include P&O-ANN and IC-ANN, which are connected with the stacked autoencoder (SAE) controller using deep learning (DL) training and building blocks. It is trained using a greedy layer-wise pattern to obtain the highest energy possible from the solar energy system. Following that, it employs backpropagation and supervised learning to fine-tune the deep neural network using traditional MPPT-IC and P&O to get the maximum power [28]. Another hybrid MPPT is the adaptive neuro-fuzzy inference system (ANFIS), which combines ANN and FLC. ANFIS and fuzzy logic are optimum, versatile, and adaptive to any new configuration for smart power management and solar power systems [29]. Neuro-adaptive learning is used to simulate the fuzzy approach needed to learn all the information about a dataset. ANFIS creates a fuzzy inference system (FIS) employing input-output datasets. The model calculates the membership function parameters that provide the greatest fit for tracking the input-output data [30]. The parameters of the fuzzy membership function are changed using a hybrid learning technique that incorporates backpropagation and least squares algorithms [31]. MPPT based on ANFIS has been shown to increase the conversion efficiency of solar energy systems [32].

Additionally, the fuzzy neural network can correct bit errors when predicting and forecasting meteorological data for solar energy systems [33]. ANN may be deployed using a combination of PSO and Gravitational Search Algorithm (GSA) and FLC. PSO-GSA, for example, produces a random starting population first and then sends it to an ANN for data training [34]. Another hybrid MPPT technology is a more sophisticated open-circuit voltage model and a smart power scanning mechanism. Smart power scanning monitors voltage to determine a partial shading condition (PSC) [35]. Apart from ANN, FLC is adaptable enough to be used with P&O algorithms which combines the benefits of both techniques [36]. The FLC-based P&O employs a variable step size to assure low oscillation and rapid reaction; a large step size provides a quick response but results in excessive fluctuation. A small step size results in a sluggish response but less oscillation [37]. The IC approach may also be used with the PSO algorithm to overcome the incapacity of traditional MPPT to track GMPP under PSC conditions while increasing convergence speed and tracking accuracy [38].

Literature review shows different Artificial Intelligence (AI)-based algorithms for energy harvesting with the PV system; therefore, very few works have been done with LM, BR and SCG algorithms [39]. The AI algorithms show a sustainable track to foresee optimum power with minimal error in different atmospheric conditions. The neural network usage makes the processing of high quantities of data insignificant, quick and fast [40]. According to the literature and published work, a few research works is found on comparative analysis of different MPPT topologies for the solar PV system. However, a significant research gap is observed in comparative performance analysis of various ANN algorithms based MPPT for solar energy harvesting. In recent ANN-based MPPT research, the authors have only designed and analyzed the system using a single algorithm. Therefore, in this paper, a comparative performance analysis of three ANN-based algorithms namely LM, BR, and SCG, is proposed for MPPT solar energy harvesting. The developed model depicts a clear representation of the applicability and feasibility of those algorithms. Three performance parameters like regression, gradient and momentum parameter are analyzed for relative comparison for identifying the best performing algorithm among the three algorithms. A holistic approach is used for analyzing the performance parameters of three ANN algorithms with training, validation, and testing of the real dataset of solar irradiance, temperature, and generated voltage. A simulated model is deployed using MATLAB/Simulink for comparative performance analysis, which gives a clear scenario on the implementation of ANN algorithms for MPPT in solar PV system. The ANN-based MPPT algorithm is trained with real field data, which justifies the applicability of this technology in practical application. The remainder of the article is structured as follows. Section II presents the state of the art of ANN. Section III describes the proposed model of the ANN-based MPPT energy harvesting in Solar PV system with three distinct algorithms in (A) LM, (B) BR and (C) SCG, followed by Section IV results and discussions. The paper concludes in Section V.

II. STATE OF THE ART OF ANN AND MPPT

ANN reflects the replication of the biological neural network that essentially connects multiple parameters to specific data points. ANN models do not need any mathematical equation or complex mathematical basis to combine various parameters [41]. Thus, ANN needs less theoretical work than traditional approaches to relate many parameters with vast quantities of unknown data points [42]. ANN is trained with imported data called supervised learning or training. ANN consists of a variety of neurons, like in the human brain [43]. These neurons are connected by a fractional number called weight [44]. The consequences are changed during the training phase to predict the exact outcomes and weight amounts become constant until the error exceeds the permissible value [45]. The basic form of the two-layer ANN model is shown in Fig. 1. According to the neural network's right side, the inputs could be integrated into the network at different time points. Entire input-output parameter data sets are split into two classes, one group with a higher percentage of data points named the training data set through which the neural network is equipped. In contrast, the second group with the remaining data points is used to verify the trained neural network, called the validation data set [46]. Input-output parameters in the neural network with their training data points are imported. This network is conditioned until it receives a permissible mistake. Once a proper error has been obtained, the qualified network is validated by importing the validation data set input parameters and predicting the corresponding output parameter values.

These projected values of the validation data set output parameter are correlated with the corresponding actual values of the validation data set output parameter. If the error between the real and predicted results is below the allowable maximum, the qualified neural network may be recommended as the optimal prediction neural network. The neural network forecasts the corresponding input values

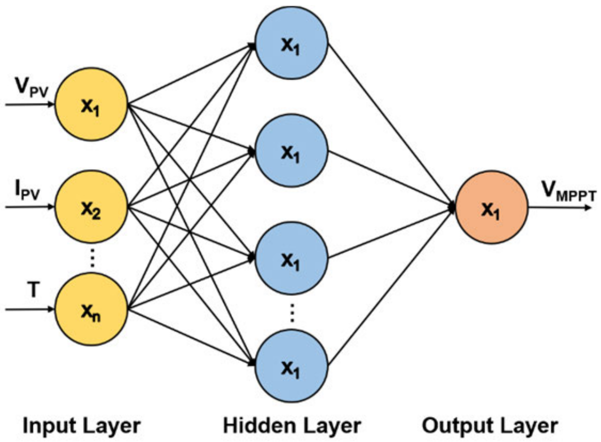

FIGURE 1. The basic structure of two-layer ANN.

output parameters for the required training algorithm and training times. If the error magnitude is less than the acceptable value, the qualified neural network with the training algorithm combination will be chosen as the optimized neural network with the optimal training algorithm. The neural network is equipped with the same training algorithm for greater error value but with different epochs or different training algorithms before an allowable error is obtained [47]. Findings projected using validation data points from the optimal neural network validate trained neural network generalization [48].

Another study examined different MPPT algorithms for PV systems [49]. The methods were categorized depending on the number of control variables, forms of control tactics, etc. In the sense of PV voltage ripple dynamic reaction utilizing MATLAB/Simulink and dSPACE Frameworks, the authors provided hands-up assessments for most used MPPT algorithms [50]. The preliminary findings for traditional MPPT algorithms have been introduced and enhanced with a PI controller. The authors in [50] have mentioned the benefits and demerits of P&O and INC algorithms in simulation results in MATLAB by modifying environmental conditions such as fluctuating irradiance and rising temperatures. The authors propose a new solution to strengthening P&O algorithms limitations in the face of unexpected irradiance changes [51]. The suggested scheme has two algorithms. The original disturbance algorithm allows the panel to work in the MPP. The adaptive control algorithm may define the current operating point in abrupt shifts. Then experimental findings contrasted the proposed algorithm with the traditional algorithm. The authors in [52] also suggested an updated P&O algorithm with a thorough description of the drift phenomenon's root. They changed the algorithm using adaptive measures and contrasted the effects of studies and simulations with standard P&O algorithms.

The INC MPPT algorithm was tested in [52]. The authors provided an experimental assessment of the INC algorithm utilizing an isolated PV pumping method, which perturbed reference voltage and disrupted service speeds. Here, the impact on disturbance size and phase size for previous disturbance has been clarified, Which often indicates the uncertainty of the algorithm due to abrupt shifts in irradiance. Finally, the achievement is related to the suggested algorithm. For the P&O algorithm and the INC algorithm, a comparative analysis is conducted to track the PV features of MPP.

In comparison, INC has a quicker transient solution with reference voltage disturbance and job ratio disturbance. It has shown that the INC MPPT strategy is less confused with noise and device dynamics. This phenomenon has demonstrated greater stability at quickly changing irradiance in the device proposed. In [26], the authors have published experimental experiments at elevated INC algorithm perturbation rates. It is noticed that INC provides faster transitional response at higher disruption speeds. The algorithm is disturbed due to noise or radiance shifts, and it also provides a quicker recovery of the MPP. Many MPPT algorithms with PI controller have been used to date.

However, ANN as the MPPT controllers was the most unsettling and unique concept for PV system implementation. Elobaid *et al.* described the ANN MPPT with several off-line preparation features, nonlinear mapping, higher speed answer, and lower calculation effort [53]. The authors in [30] suggested a new neural network (NN) MPPT controller for PV systems. Data were collected from the P&O system using MATLAB/Simulink to train and test the NN model. The simulation findings indicated improved monitoring precision, reaction time, and overflow with the proposed NN controllers quickly shifting insulation. The study is interesting by integrating configuration parameters with reliability measures to achieve the electronic power grids optimum design with Artificial Intelligence [54]. This article details the essential determination of device stability, efficiency, and expense by swapping frequency and voltage series. It also offers an in-depth analysis of artificial neural network data extraction and training. Another ANN MPPT [55] shows better results than the climbing algorithms. The authors have developed a feedback network with a backpropagation algorithm of Levenberg-Marquardt to map the world peak by MATLAB NN-Tool. The simulation findings have revealed that the suggested model performs well with better root mean square error than the climbing algorithm. Using the changed techniques, the essence and function of various MPPTs are realized. It is suggested that a methodology should use traditional MPPT algorithms using a NN controller rather than a PI controller. Thus, the PI dependent algorithms can offer better dynamic, stable status with sudden environmental changes.

III. MODELLING OF ANN-BASED MPPT FOR SOLAR PV SYSTEM

A. SOLAR PV CELL

Solar PV cells are semiconductor device that turns sunlight into electrical energy. The efficiency of a solar cell depends on the strength of the sunlight, the temperature, and the cell materials basic properties. It must then be an actual load to be transformed into an equivalent circuit to approximate the measurement.

The equivalent electrical circuit of a PV cell is shown in Fig. 2. Therefore, it needs to build a PV cell simulation model to permit the solar panels maximum power point to perform their photoelectric conversion efficiency by influencing the solar panels production capacity by their light intensity and the outside temperature. It can better consider the effect on its production capacity of the external climate.

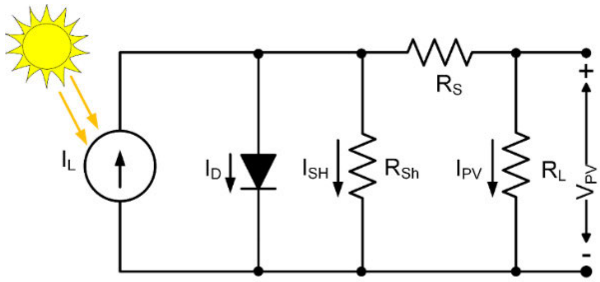

FIGURE 2. The equivalent electrical circuit model of a solar cell [14].

Fig. 3a displays the current-voltage (I-V) characteristics at different irradiance of 200 W/m^2, 400 W/m^2, 600 W/m^2, 800 W/m^2, and 1000 W/m^2 in 25 °C. The fluctuations of solar irradiance cause changes in solar voltage and current. Fig. 3b shows that the light strength determines the solar cells production capacity. Although keeping the same solar cell temperature, the only optimum energy point is the same light intensity.

Let, I_{sc} is the short circuit current, I_o is the saturation current, a is the diode ideality constant, N_s is the series-connected cell, T is the temperature of the cell, $K = 1.38 \times 10^{-23} J/K$ is the Boltzman constant, $q = 1.6 \times 10^{-19} C$ is the charge of an electron, and R_S, and R_{sh} are the series and shunt resistance of the array, respectively. Then the solar cell current can be expressed in (1) and (2).

$$I = I_{sc} - I_o \left[exp\left(\frac{V + R_S I}{\frac{N_s KT}{q} a} \right) - 1 \right] - \left(\frac{V + R_S I}{R_{sh}} \right) \quad (1)$$

$$I = I_{sc} - I_o \left[exp\left(\frac{V + R_S I}{V_t a} \right) - 1 \right] - \left(\frac{V + R_S I}{R_{sh}} \right) \quad (2)$$

Equation (1) can be rewritten by (2) if the thermal voltage of the array can be replaced as, $V_t = \frac{N_s KT}{q}$.

B. ANN-BASED MPPT FOR SOLAR PV SYSTEM

The proposed simulated model of the ANN-based solar PV system is designed by MATLAB/Simulink as shown in Fig. 4. In this model, 1Soltech ISTH-215-P solar panel is used. Table 1 presents the electrical specification of the solar PV panel. The simulated model comprises two main subsystems which are ANN_MPPT and Switching block. The ANN_MPPT subsystem has a comparator that compares the output voltage, V_1 of ANN, with the PV array voltage. The generated voltage of the PV array acts as the reference

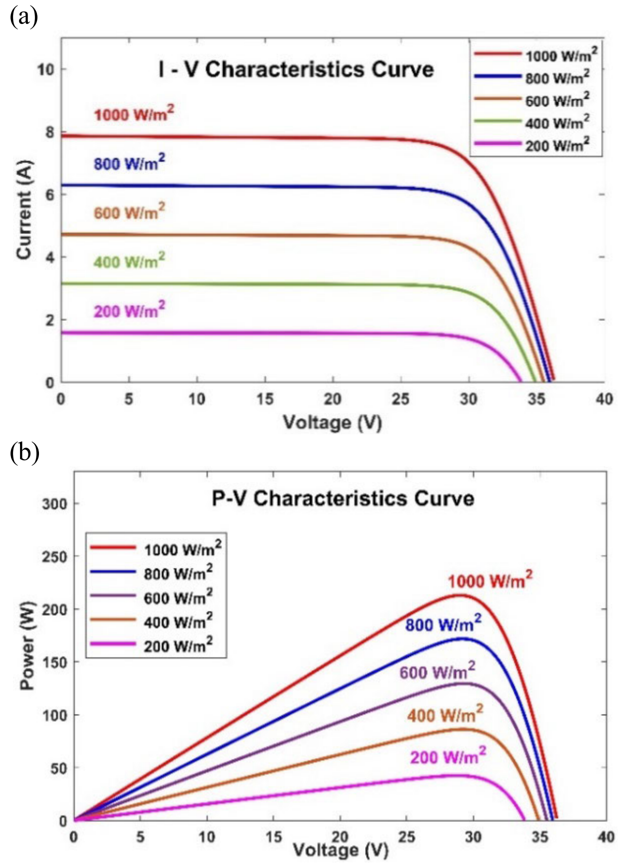

FIGURE 3. Solar PV module 1Soltech ISTH-215-P characteristic curve a. I-V curve, and b. P-V curve.

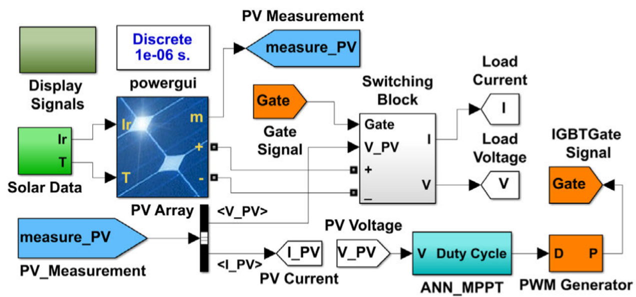

FIGURE 4. Proposed ANN-based MPPT energy harvesting model with 1Soltech ISTH-215-P solar PV panel.

voltage for the comparator. The Proportional Integral Derivative (PID) controller generates a duty cycle signal according to the difference between V and V_1. The switching block contains a boost converter where the insulated-gate bipolar transistor (IGBT) is activated by the gate signal generated by the pulse width modulated (PWM) generator. The respective voltage difference of the comparator controls the duty cycle of PWM.

The ideal correlation between the target and trained value of ANN algorithm ensures a constant duty cycle for PWM which smoothens the switching operation of IGBT. The solar data subsystem delivers input data (irradiance and array temperature) to the PV array sequentially; thus, the simulation time matches with the input data transfer time.

TABLE 1. Specification of 1Soltech ISTH-215-P module.

Parameter	Value
Maximum Voltage, V_{MPS}	29.0 V
Maximum Current, I_{MPS}	7.35 A
Maximum Power	213.15 W
Open Circuit Voltage, V_{OC}	36.3 V
Short Circuit Current, I_{SC}	7.84 A
No. of Cell in Series, N_S	60
No. of Cell in Parallel, N_P	1
Series Resistance, R_S	0.3938 Ω
Shunt Resistance, R_{SH}	313.4 Ω
Ideality Factor	0.9812
Nominal Cell Temperature, °C	47.4
Current temperature coefficient, α	0.102%/°C
Voltage temperature coefficient, β	- 0.36099%/°C

Electricity generation from solar panels depends on solar irradiance and solar panel temperature; therefore, the input data set of irradiance and temperature for ANN are calculated by (3) and (4), respectively.

Irradiance, G (W/m^2):

$$G = [(G_{max} - G_{min}) \times rand] + G_{min} \tag{3}$$

Temperature, T (°C):

$$T = [(T_{max} - T_{min}) \times rand] + T_{min} \tag{4}$$

Maximum Voltage, V_{MP}(V):

$$T = [(T_{max} - T_{min}) \times rand] + T_{min} \tag{5}$$

Maximum Current, I_{MP} (A):

$$T = [(T_{max} - T_{min}) \times rand] + T_{min} \tag{6}$$

Maximum Power, P_{MP}(W):

$$P_{MP} = V_{MP} \times I_{MP} \tag{7}$$

The MPPT technology for ANN is created using corresponding solar irradiance, temperature, and maximum generated voltage as shown in Table 2 (appendix). The solar data subsystem sends selected data of solar irradiance and temperature to the solar PV array. Equations (5)-(7) are used for calculating maximum generated voltage (V_{MP}), maximum current (I_{MP}), and maximum generated power (P_{MP}), respectively of the solar panel for various irradiance and temperature. The generated voltage of the solar panel is considered as output data for the neural network. The input and output dataset used for designing the MPPT technology is based on the rated voltage, rated current, and temperature coefficient of the 1Soltech ISTH-215-P solar panel. The standard irradiance, *Gs*, and standard temperature, *Ts*, are considered 1000 W/m^2 and 250 °C, respectively. The maximum irradiance, G_{MAX}, and minimum irradiance, G_{MIN} are taken 1000 W/m^2 and 0 W/m^2 respectively. Similarly, the maximum temperature, T_{MAX}, and minimum temperature, T_{MIN} is considered 35 °C and 15 °C, respectively.

Algorithm 1 : Proposed ANN Algorithm

//Neural Network Constants//
Define: Ts=Timestep, X=Input over Ts, Y=Output over Ts, Q=Sample/series
1. Star
2. Input: X [Xoffset, Gain, Ymin]
3. Hidden Layer
   Layer 1: b1, W1; Layer 2: b2, W
4. Output: Y [Ymin, Gain, Xoffset]

//Simulation//
5. Input Argument
   if X={X}
   end
6. Dimensions: TS= size (X,2)
   if Q=size (X{1}, 1)
   else Q=0
   end
7. Allocate Outputs: Y= cell (1, TS)
8. Time Loop: For ts=1:Ts
   Input 1; Layer 1; Layer 2; Output
   end
9. Final Delay States:
   Xf=cell (1,0), Af=cell (2,0)
10. Format Output Agreements: if Y=cell2mat (Y)
   end

//Module Functions//
11. Min. and Max. Input Processing Function (PF)
12. Sigmoid Symmetric Transfer Function:
   function a=tansig_apply (n,~)
   a=2. / (1 + exp(−2*n)) −1
   end
13. Min. & Max. Output Reverse PF
14. Stop

Fig. 5 shows the ANN algorithm masked with an ANN block for the proposed system. The proposed ANN algorithm is generated by the neural network toolbox function 'genFunction'. Here, the fitting application of the ANN toolbox of MATLAB/Simulink is used to select data, create and train a network to evaluate its performance.

According to consistent data, a two-layer feedforward network with sigmoid hidden neurons and linear output neurons can fit multi-dimensional mapping problems. For creating the neural network, 1000 datasets are used for irradiance, temperature, and generated voltage of the selected solar panel. The data are randomly divided into 70% data for training, 15% data for validation and 15% data for testing. The number of neurons for the hidden layer is considered 10 for designing the feedforward network. Several algorithms [56], [57], such as LM, BR, SCG, etc., are used to train ANN datasets [58]. The LM algorithm is also known as the damped least-squares method where the mean squared error (MSE) is the average squared difference between outputs and targets. The standard LM approach benefits from operating two approaches

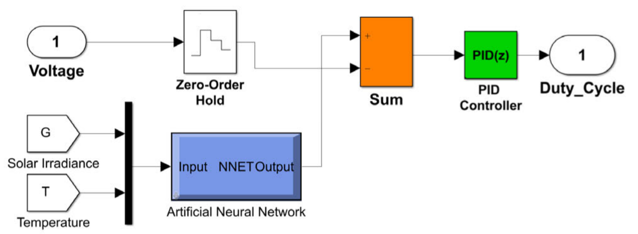

FIGURE 5. **The developed block of ANN algorithm.**

focused on opposite gradient orders: "steepest descent" and "Gauss-Newton" with complementary characteristics. Effectively, the LM approach starts with the steepest decline to take advantage of its low sensitivity to the initial values. Gauss-Newton takes over if the measured values are like the final solution, allowing for a rapid convergence rate. Automatic switching of the steepest descent to Gauss-Newton using the LM approach is guaranteed by the control parameter λ called "damping factor." The parameters θ to be defined are then modified for each iteration according to the following expression [59]:

$$\theta_{k+1} = \theta_k - \left[\frac{J'\varepsilon}{J'J + \lambda_k I}\right]_{\theta=\theta_k} \tag{8}$$

where,
J = Jacobian Matrix; I = Identity matrix; λ = Damping factor; ε = error between the desired and measured performance of the network; k = No. of iteration; $J'J + \lambda_k I = Hessian\ Matrix$.

Due to the algorithm's convergence, the damping factor $\lambda > 0$ must be calculated in any LM isolation. When the LM is at the steepest descent point, the factor λ takes essential values and makes the Hessian matrix powerful in the diagonal in Equation 8. However, when LM is in Gauss-Newton point, λ switches immediately and takes minimal values. This implies that the Hessian $J'J$ exceeds the $\lambda_k I$ matrix. This algorithm generally works with the loss functions, which take a sum of squared errors. This algorithm works with the gradient vector and the Jacobian matrix rather than with the Hessian matrix. The LM algorithm appears to be the fastest method for training moderate-sized feedforward neural networks. It also has an efficient implementation in MATLAB software because the matrix equation's solution is a built-in function. Hence, its attributes become even more pronounced in a MATLAB environment. Generally, the lower values of mean squared error are better, with zero means no error. The regression R measures the correlation between outputs and targets, with value 1 (one) represents perfect correlation, and 0 (zero) represents random correlation.

Bayesian regularized artificial neural networks (BRANNs) are more stable than traditional backpropagation nets. BRANNs may minimize or remove the need for extensive cross-validation [60]. BR is a mathematical method that transforms a nonlinear regression into a statistical problem that is "well-posed," similar to ridge regression. Since a validation set is not required, the iterative procedure to self-consistency only needs to be run once to produce the "most generalizable" model. However, since the technique employs a conjugate gradient descent or equivalent minimizer, it is necessary to arrive at a local minimum rather than a global minimum. Experiments have shown that repeating the same process five times is adequate to prevent any abnormal behaviour. This is compared to the hundreds or thousands of repeat measurements that may be performed for unregularized ANNs. Authors are described the mathematical model and every aspect of BRANN in [36], [37] elaborately.

It is well established that the scaled conjugate gradient (SCG) training approach is successful for broad problems. It employs second-order knowledge without employing the line-search technique. Thus, the volume of memory used can be decreased by growing the amount of gradient knowledge computed. The final SCG algorithm is described in depth in [61], [62].

IV. RESULTS AND DISCUSSIONS

The proposed model for solar energy harvesting is simulated for 1000 second to correlate sequential transfer of 1000 input data of PV array with the simulation time. The discrete simulation is used instead of continuous simulation for optimal analysis. The perfect prediction of ANN depends on the volume of the trained dataset and the training algorithm. Generally, the ANN predicts negligible error for the large volume of the trained dataset. The input data (solar irradiance and array temperature) are fed to the solar panel from the lookup table, synchronized by a clock.

In this paper, a relative comparison of three algorithms is discussed to represent the applicability for solar energy harvesting. The parameters like regression, mean square error, gradient, momentum parameter (Mu) and validation check are commonly used for identifying the performance and accuracy of any algorithm for the trained dataset. The regression represents the predictive quality where output is a function of inputs, whereas error is calculated by subtracting output from the target. Three types of samples are used for the neural network: training, validation, and testing. The training is used for train the dataset, and the network is adjusted according to its error. The validation is used for the generalization of the network, which halts training during error handling. In contrast, testing provides an independent measure of network performance during and after training which causes no effect on the training of the dataset.

An epoch refers to one cycle for the training dataset. The training process of a neural network takes more than a few epochs. The epoch is related to the iteration, which is the number of batches or steps for partitioned packets of the training data needed to complete one epoch. Heuristically, it gives the network a chance to see the previous data to readjust the model parameters. The model is not biased towards the last few data points during training. The gradient is a numeric calculation for adjusting the parameters of the ANN in such a way that its output deviation is minimized.

It is a multivariable derivative of the loss function with respect to all the network parameters arranged in the matrix or vector form. The Mu is included in the weight update expression to avoid the local minimum problem because sometimes the ANN may get stuck to the local minimum, and convergence does not occur. Therefore, its value directly affects the convergence error during training of the dataset, and its value lies between 0 and 1. The validation check is the representation of error minimization of trained data.

The evaluation and validation of an ANN prediction model are based on one or more selected error metrics. The ANN algorithm performs a function approximation task using a continuous error matrix such as mean absolute error (MAE), mean square error (MSE), or root mean square error (RMSE). The errors are summed up over the validation set of inputs - outputs and normalized according to the validation set size. The mean square error measures the average error which is the average squared difference between the estimated value and actual value. It is a loss function squared and averaged over the whole dataset at every data instance to optimize the overall process of the predictive model. The ANN adjusts its predicted output with respect to its actual output by error minimization, also known as backpropagation.

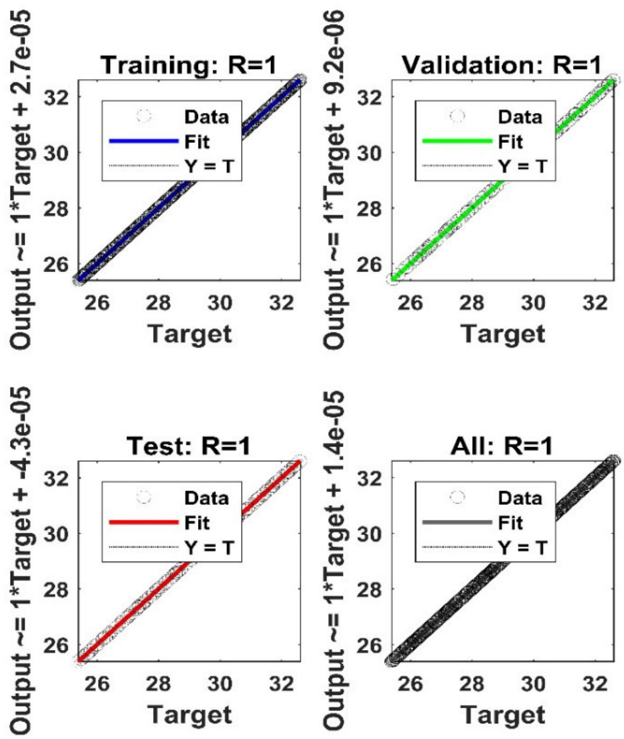

FIGURE 6. Regression plot of the proposed ANN model.

A. LEVENBERG MARQUARDT (LM)

The regression plot for the ANN of Fig. 6, regression, R = 1, represents the perfect prediction of output according to input and correlation between output generated voltage and target generated voltage of the selected solar panel. Generally, an error is calculated by subtracting output from the target. The regression plot of Fig. 6 shows that the data is perfectly trained using the Levenberg-Marquardt algorithm with negligible error where the output follows the target value.

Fig. 7 also validates this algorithm for ANN, representing zero error in training, validation, and test phase of data matching. The bins represent the number of vertical bars in the error histogram of Fig. 7, where the total error of ANN ranges from −0.00015 (leftmost bin) to 0.000164 (rightmost bin).

The error range is divided into 20 smaller bins with a bin width of 0.0000157. Each vertical bar represents the number of samples from the selected dataset which lies in a particular bin. In the middle of the error histogram, the bin has an error of −0.0000027 for 150 samples of the validation dataset. The error histogram converges at 20 bins with zero error which represents the applicability of ANN for MPPT.

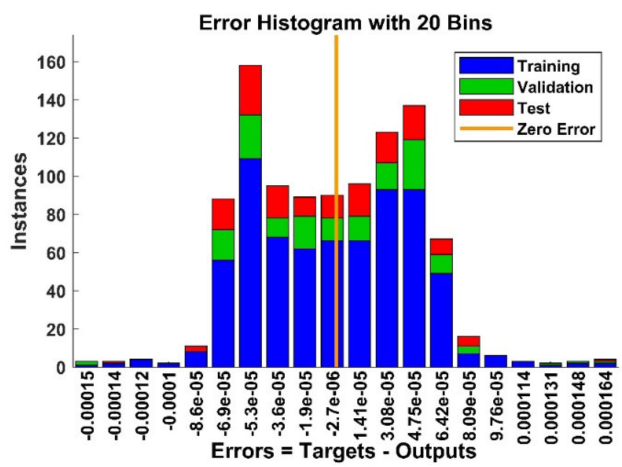

FIGURE 7. Error histogram plot of the proposed ANN energy harvesting model.

Fig. 8 and Fig. 9 show the training state and performance phase of ANN for handling the selected dataset. In Fig. 8, gradient, momentum parameter (Mu) and validation check of the trained dataset are represented at 1000 epochs. According to the simulation, the gradient is 0.000078 at 1000 epoch, representing the negligible deviation of trained data with a minimal loss function. According to the simulation result, the summed error is the mean per input vector and a zero-output decision. The very small value near zero of Mu, gradient and validation checks of the trained dataset justifies the applicability of the Levenberg Marquardt algorithm for MPPT.

In Fig. 9, the mean squared error is represented for different epochs where the samples of the trained data set are converged with the best training result at 1000 epochs. Therefore, the best validation performance of the trained dataset is attained at 1000 epochs. According to the simulation result, the best validation performance is 0.0000000027133, which is attained at 1000 epoch. The near to zero validation performance represents negligible error for MPPT prediction by the Levenberg Marquardt algorithm.

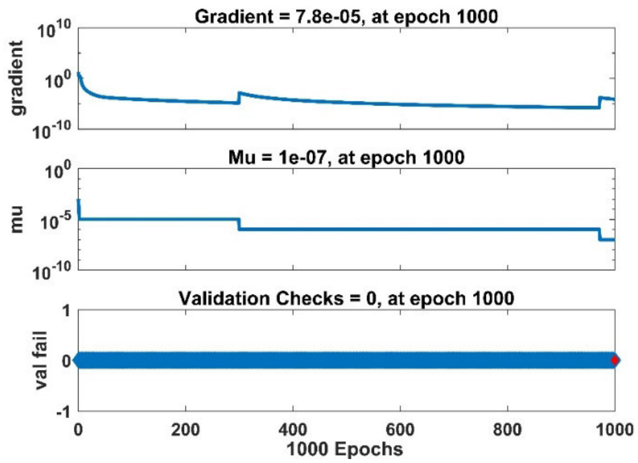

FIGURE 8. Training state plot of the proposed ANN MPPT.

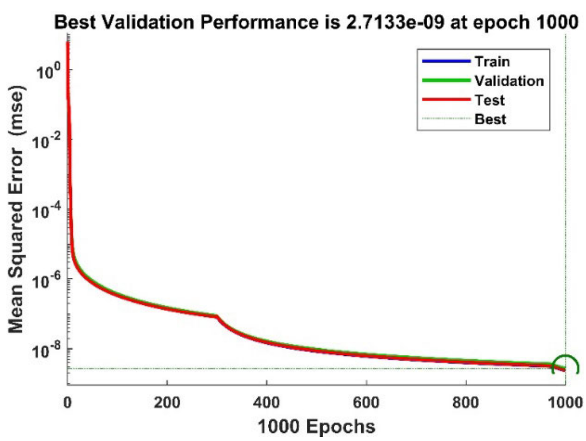

FIGURE 9. Performance test of the proposed ANN algorithm.

B. BAYESIAN REGULARIZATION (BR)

The BR algorithm for the neural network is based on probabilistic interpretations of network parameters. Therefore, the validation phase of the trained dataset is not required as shown in the regression plot of Fig. 10. $R = 1$ represents the ideal correlation between output and target generated voltage with properly trained data for the solar PV system in the regression plot.

Fig. 11 presents zero error in the training and test phase of the trained dataset with total error ranges from -0.00102 (leftmost bin) to 0.001125 (rightmost bin). The error range is divided into 20 smaller bins with a bin width of 0.00010725. According to the error histogram, the middle bin has a near zero error of -0.0000056 for 150 samples, greater in value than that of the LM algorithm. In the training state phase of Fig. 12, the gradient and Mu are 0.0000015739 and 50000 respectively at 1000 epoch.

The effective number of parameters and the sum squared parameters are 9.6438 and 44.349, respectively, at 1000 epoch. The large value of Mu and an effective number of parameters with zero validation checks represent the slower backpropagation capability of the trained dataset

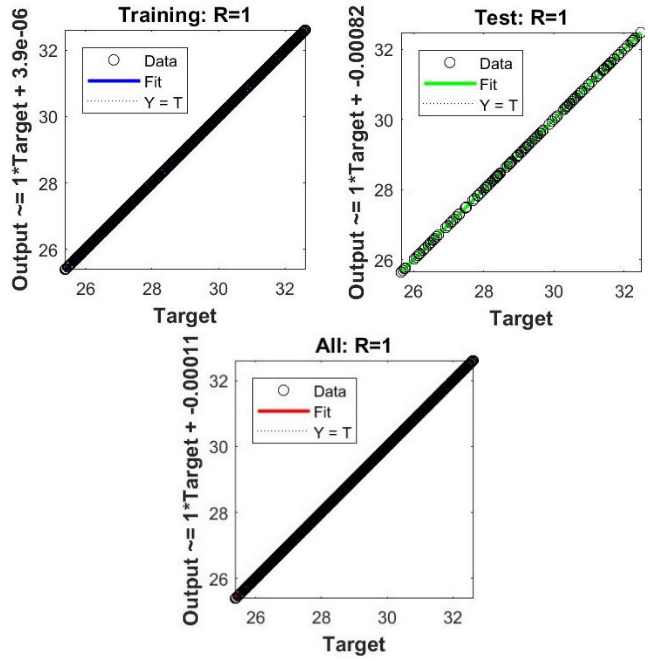

FIGURE 10. Regression plot of the BR algorithm.

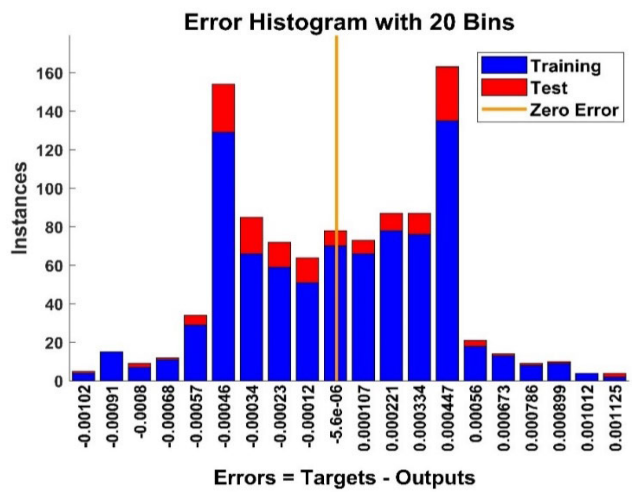

FIGURE 11. Error histogram of BR algorithm.

concerning the LM algorithm. The LM algorithm provides faster convergence in predicting trained data with near-zero error, whereas the BR algorithm initiates an objective function for the prediction that includes the residual sum of squares and the sum of squared weights for minimizing prediction error. Therefore, the BR algorithm takes more time in the overall processing of trained datasets than the LM algorithm. The mean squared error at different epoch is represented in Fig. 13, which depicts the convergence of trained data with the best training result at 1000 epochs. The best training performance is 0.0000001709 at 1000 epoch without any validation phase, representing the BR algorithm's robustness.

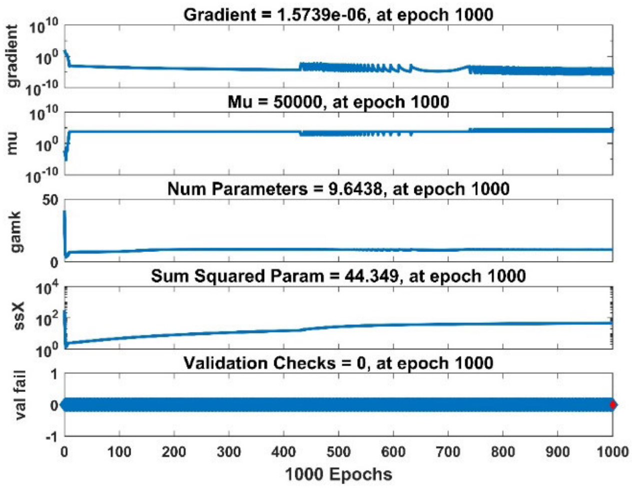

FIGURE 12. Training performance of the BR algorithm.

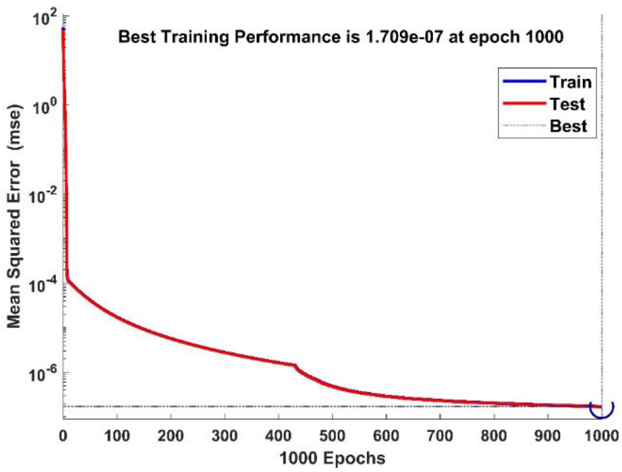

FIGURE 13. Validation performance of the BR algorithm.

C. SCALED CONJUGATE GRADIENT (SCG)

The SCG algorithm is based on conjugate directions, unlike other conjugate algorithms which require line search at each iteration of the data training process. Generally, the step size is a function of quadratic approximation of the error function, making the SCG algorithm more robust and independent of user parameters. According to the regression plot of Fig. 14, the R is slightly less than 1 compared to that of LM and BR algorithms.

Fig. 15 shows that the total error ranges from −0.8062 (leftmost bin) to 0.6491 (rightmost bin) with zero error in the training, validation, and test phase of the trained dataset. In the error histogram, the middle bin has an error of 0.001985 for 150 samples greater in value than LM and BR algorithms. The gradient and validation checks are 0.26139 and 6, respectively, at 30 epochs in Fig. 16. Data training is stopped at 30 epochs which minimizes the SCG's performance for attaining the desired goal.

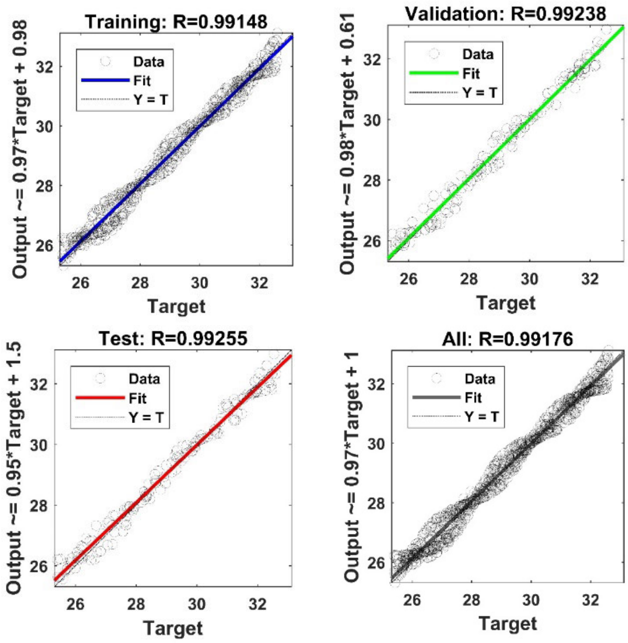

FIGURE 14. Regression plot of the SCG algorithm.

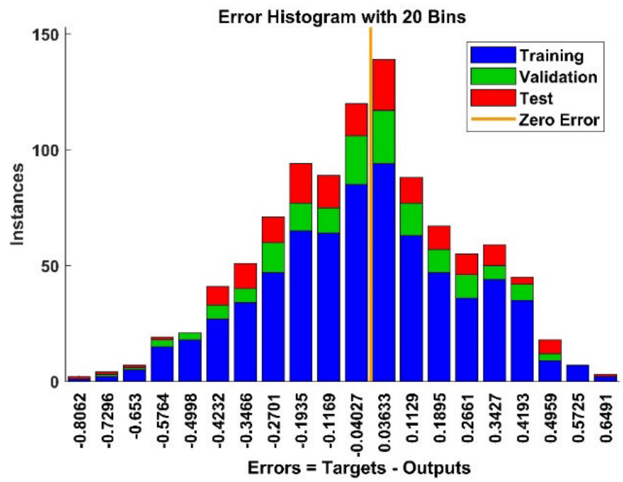

FIGURE 15. Error histogram of the SCG algorithm.

The performance gradient falls below the minimum gradient, and the validation performance is increased more than the max-fail time. The mean squared error at different epoch is represented in Fig. 17, which depicts the convergence of trained data with the best validation performance is 0.065951 at 24 epochs. Though the higher validation performance is attained compared to those of LM and BR algorithms, overall training performance is lower than those of the other two algorithms, making the SCG algorithm inappropriate for the trained data set of the solar PV system.

A relative comparison of three algorithms in terms of performance parameters obtained in this study is mentioned in Table 3. According to the simulation result, the

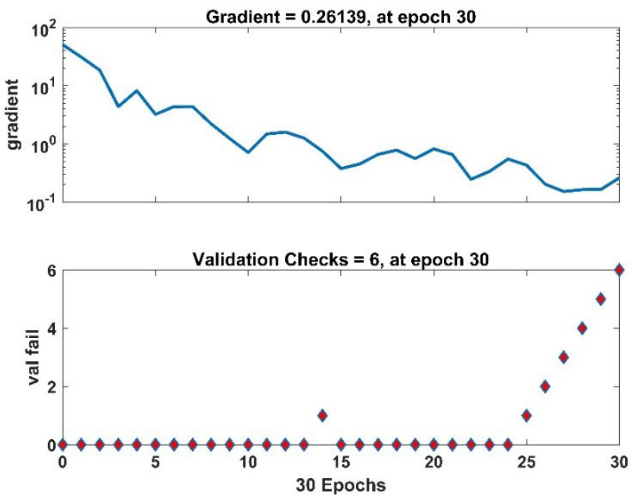

FIGURE 16. Training performance of SCG algorithm.

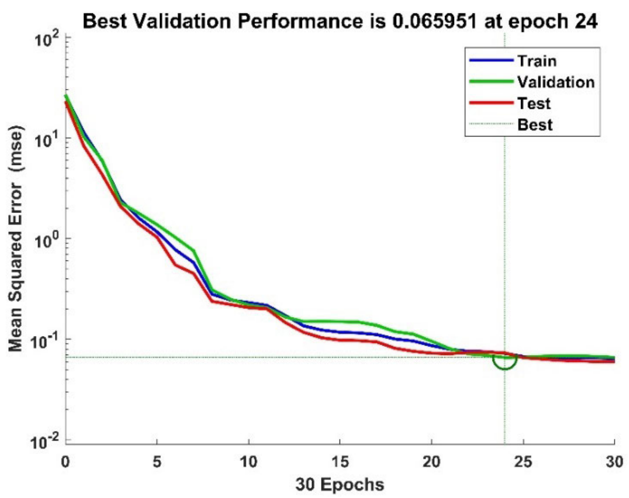

FIGURE 17. Validation performance of SCG algorithm.

Levenberg Marquardt algorithm performs better in the proper dataset training and perfect correlation between input and output with negligible error than those of Bayesian Regularization and Scaled Conjugate Gradient algorithms for this research. Though the SCG takes less time for the overall processing of data within 24 epochs, the high value of gradient and error makes this algorithm inappropriate for this research. Similarly, the high momentum parameter and high processing time for prediction make the BR less appropriate than the LM algorithm.

Fig. 18a-d depict the PV array's generated power and load power according to the solar irradiance and solar PV array temperature. Both powers follow the solar irradiance and PV array temperate according to the MPPT topology of ANN. The generated power of PV array, load power, irradiance and temperature are shown based on the simulation time. The maximum power (400 W) is attained at maximum solar irradiance (1000 W/m^2) and array temperature (35 °C), whereas the minimum power (100 W) is attained at minimum solar irradiance (200 W/m^2) and array temperature (15 °C) which fulfils the requirement of MPPT. In this model, no filter section is used for the elimination of ripples in output power.

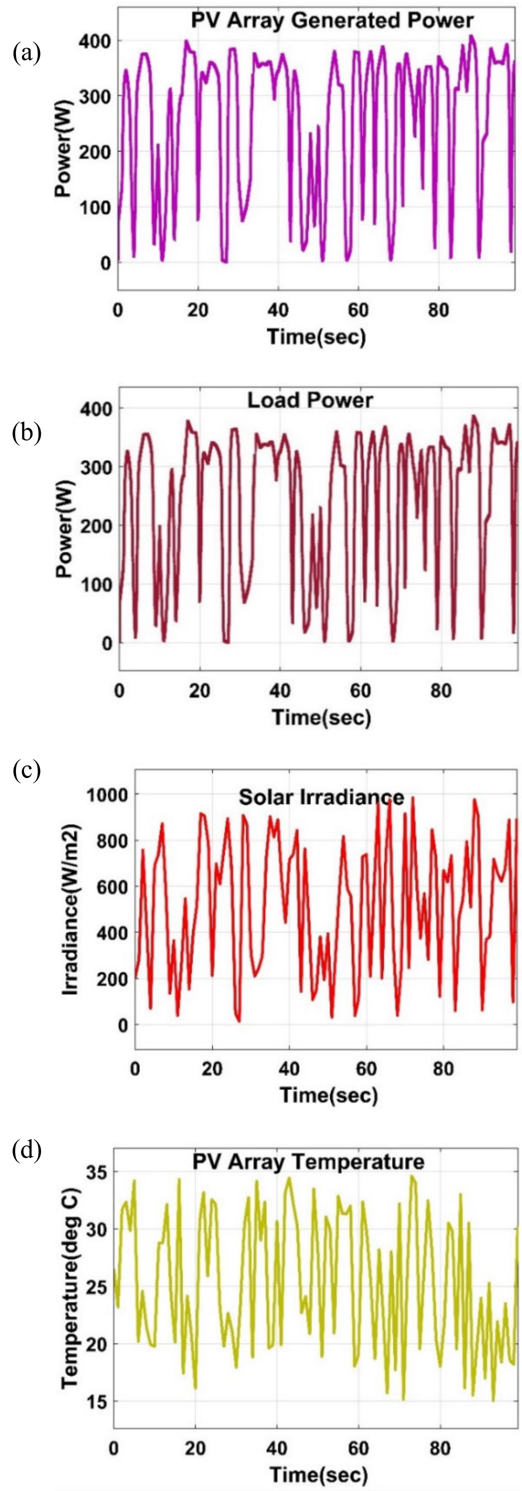

FIGURE 18. (a) Power versus time generated from the PV array, (b) Power versus time from the load, (c) Irradiance versus time of the solar panel, (d) Temperature versus time of the solar panel.

TABLE 2. ANN datasets of corresponding solar irradiance, G (W/m^2), temperature, *T* (°C), maximum voltage, V_{MAX} (V).

Sl. No.	Solar Irradiance G (W/m^2)	Temperature T (^{0}C)	Maximum Voltage V_{MAX} (V)
1	200.36	26.48	1.90
2	284.31	23.19	20.71
3	757.35	31.68	32.14
4	416.93	32.32	28.00
5	69.94	29.85	5.60
6	687.19	34.17	31.48
7	735.63	20.20	33.40
8	871.37	24.57	33.46
9	561.02	21.45	31.92
10	134.49	19.92	9.94
11	363.67	19.75	25.32
12	39.02	28.76	3.47
13	260.82	28.77	18.63
14	546.11	32.13	30.60
15	152.67	24.21	11.22
16	391.65	20.12	27.06
17	519.42	34.29	30.05
18	914.89	17.42	34.47
19	904.68	24.13	33.62
20	782.19	20.84	33.55
21	213.04	16.12	15.20
22	696.81	30.53	31.97
23	608.88	33.16	31.08
24	753.12	25.89	32.81
25	893.77	32.55	32.56
26	683.24	32.12	31.70
27	47.86	23.15	4.06
28	13.96	19.77	1.73
29	907.12	22.63	33.81
30	867.33	21.07	33.87
31	309.91	17.94	21.73
32	210.18	23.36	15.11
33	242.55	30.35	17.42
34	297.54	32.72	21.19
35	724.12	18.81	33.51
36	901.47	34.14	32.40
37	813.47	29.01	32.70
38	888.21	32.33	32.57
39	626.48	19.61	32.77
40	442.68	19.88	29.56
41	715.83	30.66	32.06
42	737.83	19.89	33.45
43	842.23	33.16	32.31
44	142.86	34.43	10.65
45	762.05	32.14	32.11
46	901.01	19.85	34.13
47	62.79	23.97	5.08
48	368.50	16.99	25.58
49	380.07	25.27	26.40
50	717.58	15.03	33.92
51	459.42	30.21	29.39
52	107.43	22.68	8.12
53	147.25	24.11	10.84
54	380.42	20.87	26.39
55	193.47	33.49	14.11
56	394.23	28.10	27.16
57	31.74	18.87	2.94
58	313.33	31.04	22.22
59	590.63	29.94	31.29
60	815.50	20.93	33.69
61	589.58	32.85	30.95
62	555.13	31.30	30.79

TABLE 2. *(Continued.)* ANN datasets of corresponding solar irradiance, G (W/m^2), temperature, *T* (°C), maximum voltage, V_{MAX} (V).

63	38.35	31.29	3.43
64	114.49	31.97	8.67
65	728.03	18.02	33.62
66	738.01	19.04	33.56
67	209.04	32.34	15.16
68	613.30	29.58	31.52
69	959.34	25.26	33.65
70	200.74	18.69	14.41
71	739.11	28.18	32.47
72	976.08	22.49	34.04
73	328.25	15.70	22.91
74	39.35	28.02	3.49
75	238.74	17.71	16.95
76	914.48	32.19	32.68
77	246.18	15.15	17.41
78	984.51	27.19	33.49
79	619.19	34.59	30.99
80	373.76	33.97	26.01
81	568.18	19.55	32.21
82	281.10	26.20	19.96
83	845.64	32.44	32.41
84	723.67	27.96	32.42
85	121.99	20.33	9.09
86	667.91	18.02	33.26
87	617.69	21.73	32.45
88	732.94	30.51	32.16
89	59.90	29.73	4.91
90	466.28	19.54	30.36
91	544.24	32.98	30.49
92	794.49	16.14	34.17
93	509.02	30.50	30.29
94	975.53	15.52	34.89
95	459.42	30.21	29.39
96	621.15	18.39	32.86
97	677.08	23.49	32.68
98	887.46	18.58	34.24
99	97.85	18.20	7.44
100	894.08	30.23	32.85

TABLE 3. Comparative performance analysis of the ANN algorithms.

Parameters	Algorithm Name		
	LM	BR	SCG
Regression	1	1	0.99
Gradient	0.000078	0.0000015739	0.26139
Error at middle bin	-0.0000027	-0.0000056	0.001985
Performance	0.0000000027133	0.0000001709	0.065951
Momentum Parameter	0.0000001	50000	-
Epochs	1000	1000	24

Therefore, the waveshapes of generated and load powers have significant ripples.

V. CONCLUSION

This paper proposes a novel approach for a comparative performance analysis of three ANN algorithms namely Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms for MPPT energy harvesting in a solar PV system. Two-layer feedforward neural network in the ANN toolbox is trained with real-time input datasets of solar irradiance, panel temperature and output dataset of generated voltage. The ANN algorithms are trained with 1000 datasets to identify the appropriate algorithm. The Levenberg-Marquardt algorithm shows better performance in overall data processing with near-zero error at the middle epoch. The near to zero value of momentum parameter, gradient and validation checks at 1000 epochs justify the improved performance of the Levenberg-Marquardt algorithm for the proposed MPPT energy harvesting. The highest validation efficiency is achieved at 1000 epochs. The generated power and load power follow the MPPT, which justifies the perfect correlation between input and output data. The proposed MPPT can be applied for a large dataset with a multilayer neural network that may enhance its applicability for large-scale applications. The proposed ANN-based MPPT energy harvesting model can be utilized in a standalone and grid-interactive solar PV system. The proposed system may also be implemented for various solar PV systems and high-end technological applications such as space satellites, telecommunications, and military equipment. Furthermore, the model can be integrated to solar radiation and temperature forecasting, energy consumption prediction, energy management system, smart home, and smart cities.

APPENDIX

See Table 2.

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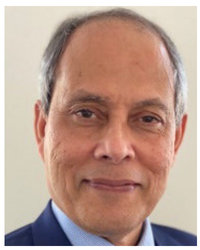
RAJIB BARAN ROY received the B.Sc. degree in electrical and electronic engineering from the Chittagong University of Engineering and Technology (CUET), Chittagong, Bangladesh, and the M.Sc. degree in sustainable energy system and management from the University of Flensburg, Germany. He is currently pursuing the Ph.D. degree with the School of Engineering and Technology, Central Queensland University, Gladstone, Australia. He has a couple of years of teaching experience as a Faculty Member with the Electrical and Electronic Engineering Department in different private universities of Bangladesh. So far, he has 30 publications in international journals. His research interests include electrical power system analysis, reactive power compensation, hybrid power systems, renewable energy-based distributed power systems, and industrial electronics in power systems. He was awarded the German Government Exchange Program (DAAD) Scholarship.

MD. ROKONUZZAMAN (Member, IEEE) received the B.Sc. degree in electrical and electronic engineering (EEE) from the University of Information Technology and Sciences (UITS), Dhaka, Bangladesh, and the M.Sc. degree in electrical, electronic and communication engineering (EECE) from the Military Institute of Science and Technology (MIST), Dhaka. He has served as an Assistant Professor and the Head of the Department of Electronics and Communication Engineering (ECE), ISTT, National University, Dhaka. For two years, he worked as a Lecturer with the Department of EECE, MIST, for one year, as a Sessional Academic with the Department of Information and Communication Technology (ICT), Bangladesh University of Professionals (BUP), Dhaka. He is currently a Ph.D. Research Fellow with Universiti Tenaga Nasional (UNITEN, The National Energy University), Kajang, Malaysia. His research interests include artificial intelligence, the IoT, smart grid, energy management system, solar PV applications, and renewable energy. He is an Active Member of IEEE PES, IAENG, and BES. He is the Founder Branch Counselor of IEEE ISTT Student Branch, Dhaka. In 2014, he achieved the Best Paper Award at the 8th International Conference on Software, Knowledge, Information Management, and Applications (SKIMA) from IEEE Bangladesh Section. For the period 2018–2021, he has been awarded the 'UNITEN BOLD Postgraduate Strategic Hire' Fellowship.

NOWSHAD AMIN (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from the Toyohashi University of Technology, in 1996, and the master's and Ph.D. degrees in electrical engineering from the Tokyo Institute of Technology, Japan, in 1998 and 2001, respectively. He is currently working as a Professor with the Institute of Sustainable Energy, Universiti Tenaga Nasional (UNITEN, The National Energy University), Kajang, Malaysia, and an Adjunct Professor with the Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM, The National University of Malaysia). After the higher secondary education from his native country, Bangladesh, he received the Japanese Ministry of Education (MONBUSHO) Scholarship to study electrical engineering in 1990. His areas of interests include solar photovoltaic energy applications and solar cell development. He is actively involved in promoting solar energy to the developing countries in South and South East Asia.

MAHMUDA KHATUN MISHU (Member, IEEE) received the B.Sc. degree in electrical and electronic engineering from the University of Information Technology and Sciences (UITS), Dhaka, Bangladesh. She is currently pursuing the M.Sc. degree (research-based) in electrical engineering with Universiti Tenaga Nasional (UNITEN, The National Energy University), Kajang, Malaysia. Her current research interests include the low power energy harvesting systems, the IoT, wireless sensor networks (WSNs), power electronic devices, and renewable energy. She is an Active Member of IAENG. In 2019, she achieved the Best Presenter Award at the 5th International Conference on Energy and Environment (ICEE), Malaysia. For the period 2018–2020, she has been awarded the 'UNITEN BOLD Postgraduate Strategic Hire' Fellowship.

SANATH ALAHAKOON received the B.Sc. degree in electrical and electronics engineering (EEE) from the University of Peradeniya, Sri Lanka, in 1994, and the Ph.D. degree in digital motion control from the Electrical Machines and Power Electronic Department, Royal Institute of Technology (KTH), Sweden, in 2000. From 2000 to mid of 2009, he worked as a Senior Lecturer and the Head of the Department of EEE, University of Peradeniya. He is currently a Senior Lecturer and the Discipline Leader in electrical engineering with the School of Engineering and Technology (SET), CQUniversity, Gladstone Campus. His research interests include electrical machines and drives, digital control, nonlinear control, instrumentation, automation, renewable energy, microgrids, and hybrid electric systems.



SAIFUR RAHMAN (Life Fellow, IEEE) is currently the Director of the Advanced Research Institute, Virginia Polytechnic Institute and State University, USA, where he is the Joseph Loring Professor of electrical and computer engineering and also directs the Center for Energy and the Global Environment. He has published over 150 journal articles in the areas of smart grid, conventional and renewable energy systems, load forecasting, uncertainty evaluation, the IoT, and sensor integration. He was a member of the IEEE Board of Governors. He is a Member-at-Large of the IEEE-USA Energy Policy Committee. He was the Program Director of the Engineering Directorate, National Science Foundation. He was the President of the IEEE Power and Energy Society, in 2018 and 2019. He served as the Chair for the NSF Committee on International Science and Engineering. He has served as the Chair for the IEEE Publications Board. He was the Founding Editor-in-Chief of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY and *IEEE Electrification Magazine*. He is a Distinguished Lecturer of the IEEE Power and Energy Society.

NADARAJAH MITHULANANTHAN (Senior Member, IEEE) received the Ph.D. degree in electrical and computer engineering from the University of Waterloo, Waterloo, ON, Canada, in 2002. He worked as an Electrical Engineer with the Generation Planning Branch of Ceylon Electricity Board, Sri Lanka, and a Research Leader with Chulalongkorn University, Bangkok, Thailand. He has served as the coordinator for energy field of study and the Director of the Regional Energy Resource Information Center (RERIC), Asian Institute of Technology, Bangkok. He is currently an Associate Professor with The University of Queensland, Brisbane, Australia. He is the Director of the Higher Degree Research Training, School of Information Technology and Electrical Engineering, The University of Queensland. His main research interests include voltage stability and oscillation studies on practical power systems, application of FACTS controller, EV, and renewable energy integration into power systems.

KAZI SAJEDUR RAHMAN received the B.Sc. degree in electrical and electronic engineering from the Chittagong University of Engineering and Technology (CUET), Bangladesh, in 2011, and the M.Sc. and Ph.D. degrees from Universiti Kebangsaan Malaysia (UKM; The National University of Malaysia), in 2014 and 2018, respectively. For almost two years, he worked as a Postdoctoral Researcher with the Institute of Sustainable Energy, Universiti Tenaga Nasional (UNITEN; The Energy University), Malaysia. Since 2012, he has been working on thin-film solar cell science and technology. He is currently working as a Senior Lecturer with the Solar Energy Research Institute (SERI), UKM. His primary research focus is on exploring low-cost and high-efficiency CdTe thin-film solar cells. He has authored several peer-reviewed articles and a few book chapters related to thin-film solar cells. His research interests include thin-film solar cells (CdTe, CZTS, CIGS), semiconductor physics and devices, and solar photovoltaic applications.

MOHAMMAD SHAKERI (Member, IEEE) was born in Mashhad, Iran, in 1984. He received the B.E. degree in electrical engineering from the University of Bojnord, Iran, in 2006, and the master's and Ph.D. degrees in electrical engineering from the National University of Malaysia (UKM), Kuala Lumpur, Malaysia, in 2013 and 2018, respectively. In 2019, he joined the Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional (UNITEN, The National Energy University), Malaysia, as a Postdoctoral Researcher. He has more than seven years of experience in electrical engineering, renewable energy, energy management, and embedded systems. He has high quality published journals and conferences in the area of electrical engineering, smart grid, and renewable energies.

JAGADEESH PASUPULETI (Senior Member, IEEE) is currently the Head of hybrid renewable energy systems with the Institute of Sustainable Energy, Universiti Tenaga Nasional, Malaysia. He is also research and postgraduate coordinator of electrical power engineering. He has 32 years of teaching, research, and administrative experience. He has taught many subjects in electrical and electronics engineering both at undergraduate and postgraduate level. He has supervised 30 postgraduate students. He was involved in 40 research and consultancy funded projects in renewable energy and power system area. He has presented and published 100 papers in international conferences and international journals. He was an international program committee member, the session chair, a reviewer of international conferences and Elsevier journals on power and energy systems area. He was a keynote speaker in national and international conferences. He is a member of IET (U.K.), EI (U.K.), BEM (Malaysia), and ISTE (India). He is a Chartered Engineer (U.K.) and a Professional Review Interviewer for C.Eng. (U.K.).