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# COMPARATIVE PERFORMANCE ANALYSIS OF ANFIS & ANN ALGORITHMS BASED MPPT ENERGY HARVESTING IN SOLAR PV SYSTEM

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**Abstract-** This paper presents the development and performance analysis of Adaptive Neuro-Fuzzy Inference System (ANFIS) based MPPT controller for a DC to DC converter. The proposed system consists of 2.0 kW PV array, DC to DC boost converter and load. In this research work presents the development and performance analysis of Adaptive Neuro-Fuzzy Inference System (ANFIS) and 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 four 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. However, considering the dataset training, the correlation between input-output and error, the Levenberg-Marquardt ANFIS algorithm performs better.
**Keywords:** ANFIS, ANN, BR, SCG, MPPT, DC to DC boost converter.

## 1. INTRODUCTION

The Renewable energy sources (RES) have now been relied upon more regularly. It has provided us the other option for clean energy generation compared to conventional sources. Among renewable sources of energy Photovoltaic (PV) source of energy are becoming popular these days due to current scenario of increasing concerns about depletion of fossil fuel reserves, global warming, greenhouse gases and increasing environmental pollution. The advantage of the AI-based model is the fast-Maximum Power Point (MPP) approximation according to the parameters of the PV panel. The Artificial Neural Network (ANN) is the component of AI. The advantage of ANN based algorithm is this is that there is no need to solve the complex mathematical relation between output power, irradiance of solar PV system, temperature of solar PV system.
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 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 module I-V characteristic 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].
In this paper Adaptive Neuro-Fuzzy Inference System (ANFIS) and 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 four different algorithms. ANFIS has more efficiency than ANN based controller in tracking MPP with less settling time, better efficiency, accuracy and fast response making the system more effective.

## 2. PV SYSTEM MODEL

PV module is composed of solar cells. Individual solar cells are connected in series and parallel and mounted on a single panel. Single diode model of PV cell is most widely used model. Output power can be calculated by current voltage relationship. This current voltage relationship is based on electrical characteristics of the model.

A equivalent circuit of a single diode model is shown in the fig. 2.1.

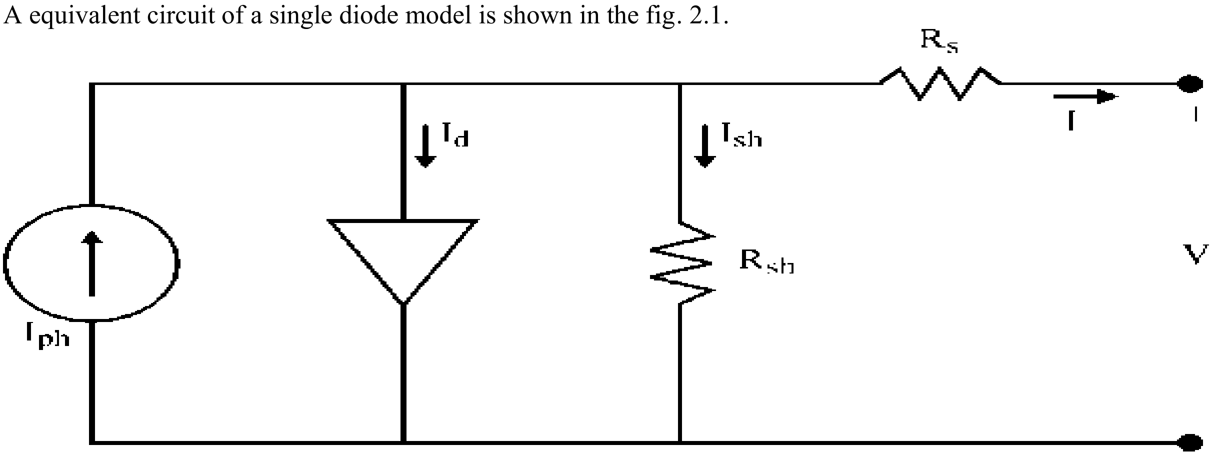


**Fig. 2.1 Equivalent Circuit of Solar PV Cell**

The voltage-current relationship can be written as:

$$I = I_L - I_D = I_L - I_s \left\{ e \frac{q(V + \mathrm{Re})}{AKT} - 1 \right\} - \frac{V + IR_e}{R_{sh}} \tag{2.1}$$

It is possible to enumerate $I_L$:

$$I_L = \frac{\phi}{\phi_{ref}} \left[ I_{L,ref} + \mu_{sc} \left( T_C - T_{c,ref} \right) \right] \tag{2.2}$$

Saturation current $I_s$ can be expressed at the reference condition as:

$$I_s = I_{C,ref} \left( \frac{T_{C,ref} + 273}{T_C + 273} \right)^3 \exp \left[ \frac{e_{gap} N_S}{q_{ref}} \left( 1 - \frac{T_{C,ref} + 273}{T_C + 273} \right) \right] \tag{2.3}$$

$I_{s,rf}$ can be expressed as:

$$I_{s,ref} = I_{L,ref} \exp \left( - \frac{V_{oc,ref}}{\alpha_{ref}} \right) \tag{2.4}$$

The value of open circuit voltage at reference condition is given by manufacturer.
Value of $\alpha_{ref}$ can be calculated by:

$$\alpha_{ref} = \frac{2V_{mpp,ref} - V_{oc,ref}}{\frac{I_{sc,ref}}{I_{sc,ref} - I_{mpp,ref}} + In \left( 1 - \frac{I_{mpp,ref}}{I_{sc,ref}} \right)} \tag{2.5}$$

$\alpha$ is a function of temperature. The value of $\alpha$ can be calculated by following equation:

$$\alpha = \frac{T_c + 273}{T_{c,ref} + 273} \alpha_{ref} \tag{2.6}$$

The value of series resistance is provided by some manufacturers. To estimate the value of $R_S$ following equation can be used:

$$R_s = \frac{\alpha_{ref} In \left( \frac{I_{mpp,ref}}{I_{sc,ref} - I_{mpp,ref}} \right) + V_{oc,ref} - V_{mpp,ref}}{I_{mpp,ref}} \tag{2.7}$$

After the study of the PV module, it can be said that the temperature plays an important role in the performance of PV module. It is necessary to design a thermal module for the PV system as temperature is major aspect to be considered. Temperature of PV module varies when there is a change in irradiance, its output current and voltage, and the equation can be expressed as:

$$C_{pv} \frac{dT_c}{dt} = k_{a,PV} \phi - \frac{VI}{A} - k_{loss} (T_c - T_a) \tag{2.8}$$

**Table-3.1 Parameters of Solar PV System Used in Simulation**

| | |
|---|---|
| Total capacity of the PV system | 2558W |
| Maximum Power of PV cell(W) | 213.15W |

| | |
|---|---|
| Maximum power point voltage(Vmpp) | 29V |
| Maximum power point current(A) | 7.35A |
| PV system open circuit voltage(Voc) | 36.3V |
| PV system short circuit current(A) | 7.84A |

## 3. FLOWCHART FOR ANFIS BASED MPPT CONTROLLER

Since the output characteristics of PV system are highly nonlinear, the AI techniques are widely used to improve the efficiency of the MPPT controller. The role of the ANFIS controller proposed in our work is to locate the maximum operating voltage which corresponds to the maximum power of the PV array. It uses the ambient parameters of irradiation and temperature as an input together with the PV array parameters. To design MPPT controller using ANFIS, first task is to gather the input–output dataset for training purpose. The training data is generated using the efficient PV model. A step-by-step process of data generation is illustrated in the flowchart shown in Fig. 3. As a first step, values of the five unknown parameters for the considered PV panel are estimated and then these values will be transformed for PV array using the parameters.

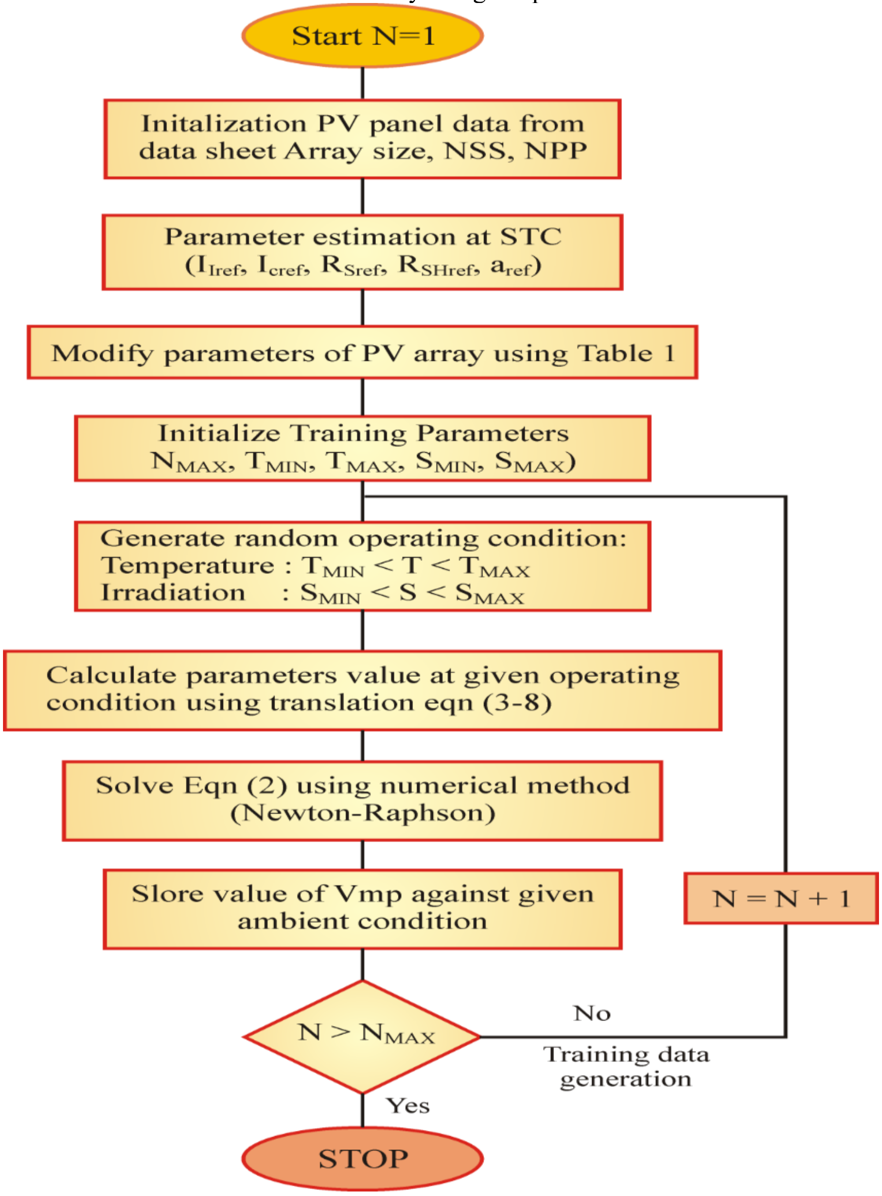


**Fig. 3.1 Proposed Method to Generate Input-output Dataset for ANFIS**

The ANFIS-based MPPT is designed using the hybrid learning algorithm described above. In the learning algorithm, parameters of the membership functions are adapted such that they track the input–output data accurately. Once this voltage is located, the PI regulator forces the PV array to work at that voltage by comparing the actual voltage of the PV array and the reference voltage obtained from the ANFIS controller by controlling the duty ratio of the DC–DC converter. The duty cycle of the DC–DC converter is controlled to force the PV array to generate the maximum power. The duty cycle is generated by the PI regulator based on the error between the

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reference voltage $V_{ref}$ from the ANFIS and the measured PV voltage, $V_{PV}$

## 4. ANFIS LEARNING PROCESS

In the learning algorithm, ANFIS optimizes and adapts its parameters using the training datasets to predict the output data with high accuracy. The Takagi–Sugeno-type model has two types of parameters.

- Nonlinear parameters or membership function parameters (premise parameters).
- Linear parameters or rule parameters (consequent parameters).

The learning method used in this study is based on the hybrid learning algorithm that employs the combination of back-propagation (BP) and least square estimation (LSE) to optimize the premise and consequent parameters. In this method, two-pass learning algorithms (forward pass and backward pass) are used:

- In forward pass, consequent (linear) parameters are calculated using a LSE algorithm, while premise (nonlinear) parameters are kept unmodified.
- In backward pass, premise (nonlinear) parameters are calculated using a back-propagation algorithm, while consequent (linear) parameters are kept unmodified.

LSE learning algorithm calculates the square error between training data output and predicted output that is obtained from the Sugeno-type model. This error is utilized to adapt the consequence parameters. The back-propagation gradient descent method uses the error between output training data and predicted output in backward pass to calculate the error in different nodes.

## 5. SIMULATION RESULT FOR COMPARATIVE SIMULATION RESULTS OF ANN AND ANFIS MPPT ALGORITHM-BASED PV SOLAR ENERGY CONVERSION SYSTEM

The simulation and results are performed in the MATLAB/Simulink software. Simulink blocks and their required interfacing circuitry used for more reliable power generation from solar energy conversion system as shows in fig.5.1.

This system consists of renewable energy source which generates continuous power according to input applies to the system. This system consists of PV solar energy conversion system with resistive load. The boost converter is used to regulate PV output power according to duty cycle generated by MPPT block to achieve maximum power. The intelligent MPPT algorithms are used to achieve maximum power. These intelligent MPPT algorithms includes, Levenberg-Marquardt neural network, Bayesian Regularization network, Scaled conjugate gradient network and ANFIS network. These algorithms continuously monitor input irradiance & temperature and generates reference voltage according to it. The generated reference voltage compares with PV voltage and applied to the PI controller to generate duty cycle and PWM pulses for the boost converter switches. A resistive load is connected at the output of boost converter. An addition load is also applied to the system for a given time period to check system stability in load changing condition.

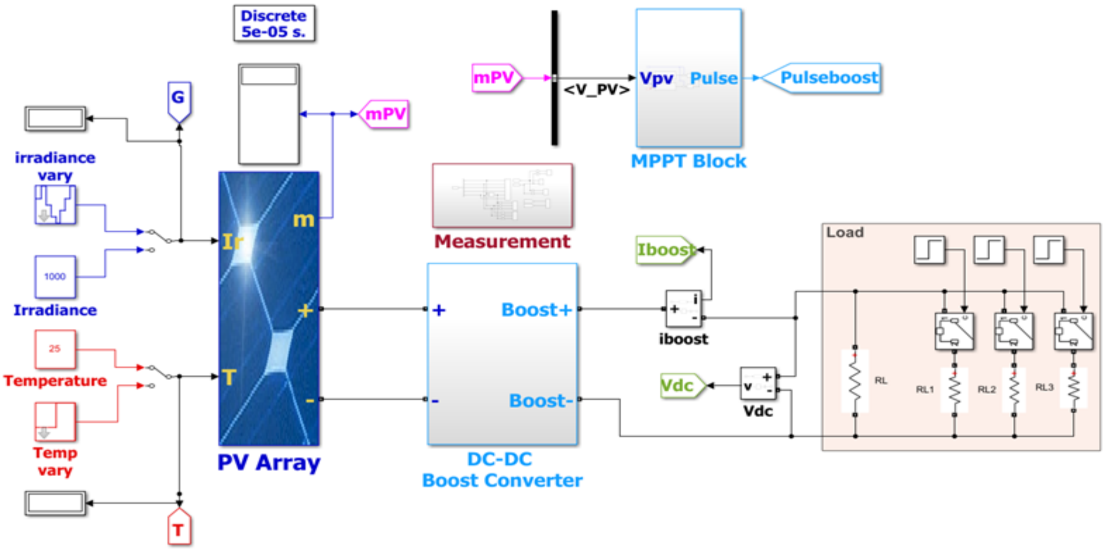



**Fig. 5.1 Simulink Model of ANFIS & ANN MPPT Algorithm-based PV Solar Energy Conversion System**

### 5.1 Simulation Results at Constant Irradiance & Temperature of 1000w/m$^2$ & 25°C

In this case, irradiance and temperature is kept constant at base irradiance of 1000 w/m$^2$ and 25°C, respectively. load also kept constant. The simulation results are shown in the following figures.

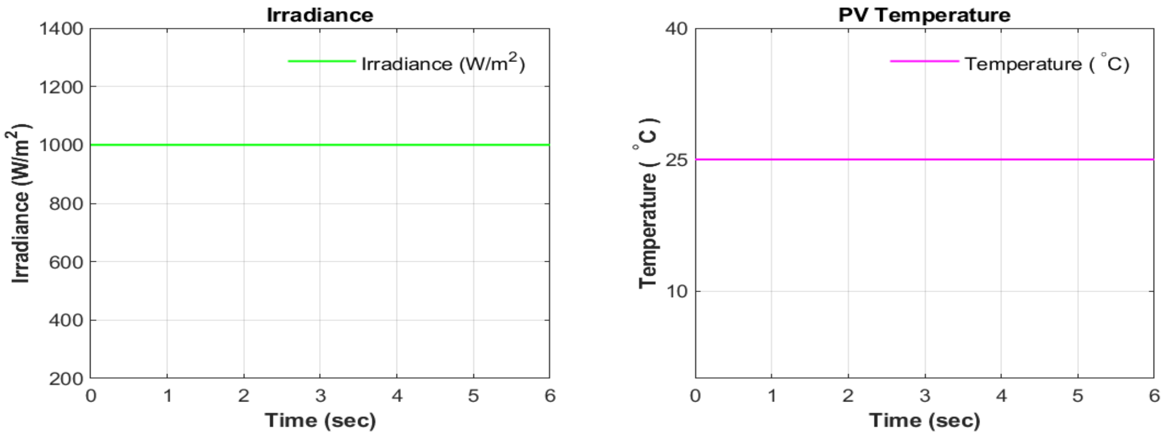



**Fig. 5.2 Simulation Results at Constant Irradiance and Temperature of 1000w/m² & 25°C, respectively, Waveform of Irradiance and Temperature**

Waveforms of irradiance and temperature applied at the input of PV array are showing in the fig. 5.2.

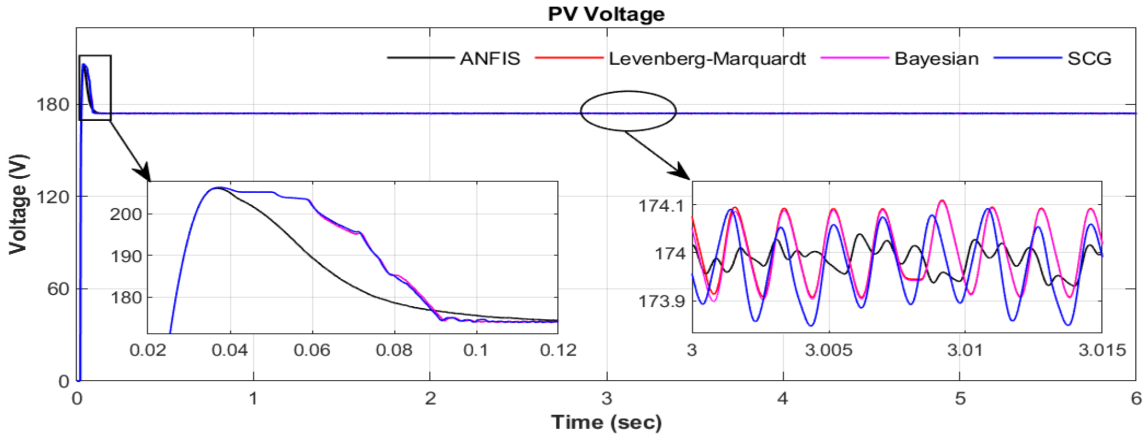



**Fig. 5.3 Simulation Results at Constant Irradiance and Temperature of 1000w/m² & 25°C, respectively, Waveform of PV Voltage**

Fig. 5.3 shows, waveform of voltage generated by PV array. As seen by the figure the PV voltage is around 174v for whole simulation time. There are two zoomed subplot windows taken to show the difference among Levenberg-Marquardt neural network, Bayesian Regularization network, Scaled conjugate gradient network and ANFIS network for MPPT algorithms. First window shows the early response of the algorithm between time duration of t=0.02sec to 0.12 sec where the ANFIS algorithm has good response in compare with other neural network algorithms. Second window is taken between time duration of t=3sec to 3.015 sec. where the PV voltage by other neural networks is fluctuating in nature as compare to ANFIS algorithm.

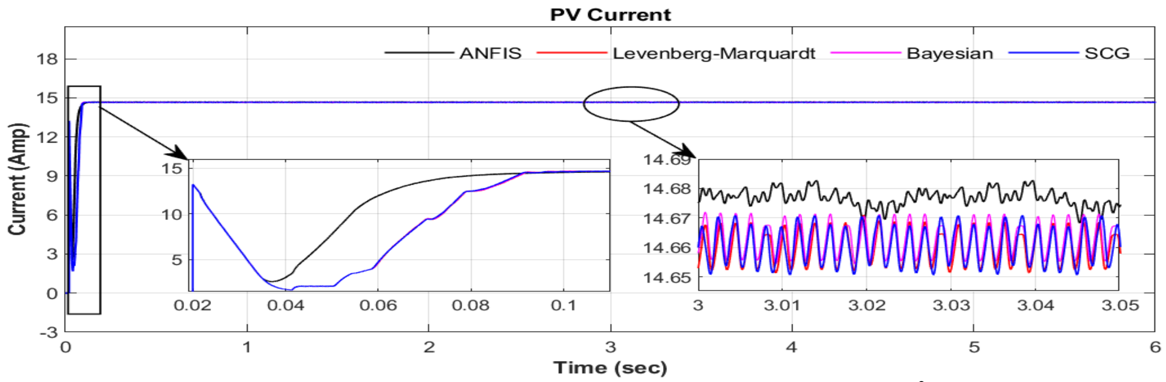



**Fig. 5.4 Simulation Results at Constant Irradiance and Temperature of 1000w/m² & 25°C, respectively, Waveform of PV Current**

Fig. 5.4 shows, waveform of PV array current. There are two zoomed subplot windows taken to show the difference among Levenberg-Marquardt neural network, Bayesian Regularization network, Scaled conjugate gradient network and ANFIS network for MPPT algorithms. First window shows the early response of the algorithms between time duration of t=0.02sec to 0.12 sec where the ANFIS algorithm has good response in compare with other neural network algorithms. Second window is taken between time duration of t=3sec to 3.05 sec. where the PV current due to neural network is between 14.65amp and 14.67amp whereas PV current due to

ANFIS algorithm is around 14.68amp which is stable in compare with other.

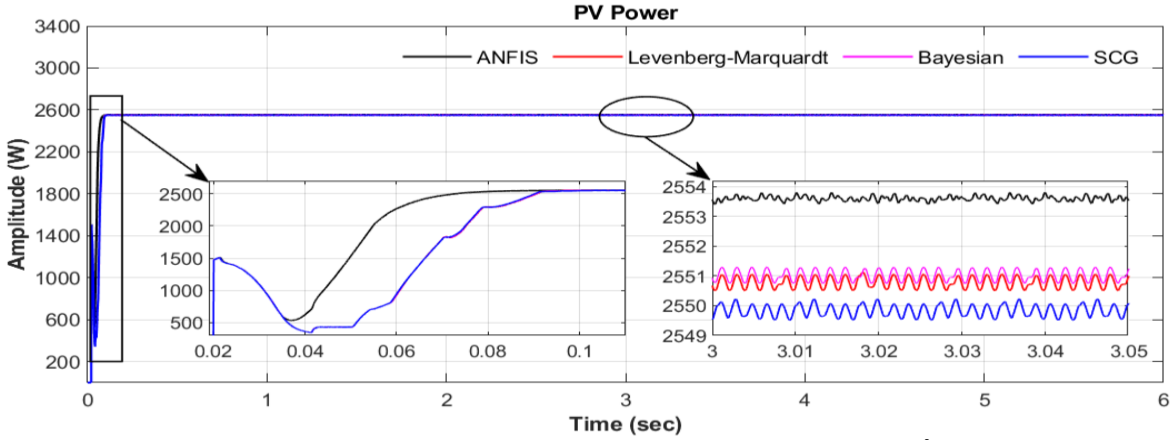
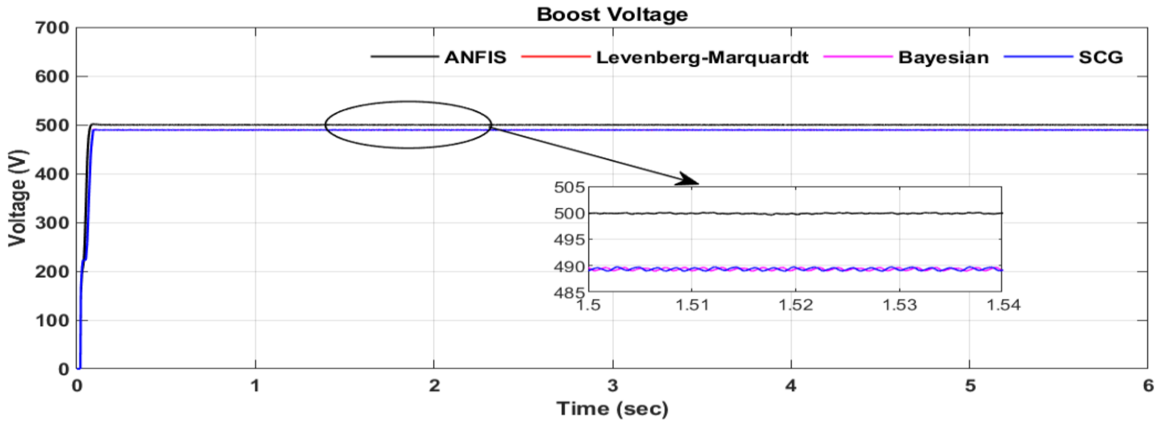



**Fig. 5.5 Simulation Results at Constant Irradiance and Temperature of 1000w/m$^2$ & 25°C, respectively, Waveform of PV Output Power**

Fig. 5.5 shows the waveform of PV output power. The first window shows the response of MPPT algorithms between time duration of t=0.02sec to 0.12 sec. The output power generated by PV array by ANFIS algorithm is 2554w at 1kw/m$^2$ irradiance, 2551w by Levenberg-Marquardt & Bayesian Regularization neural network algorithm and 2550w by Scaled conjugate gradient network algorithm, as showing in the second window.




**(a)**

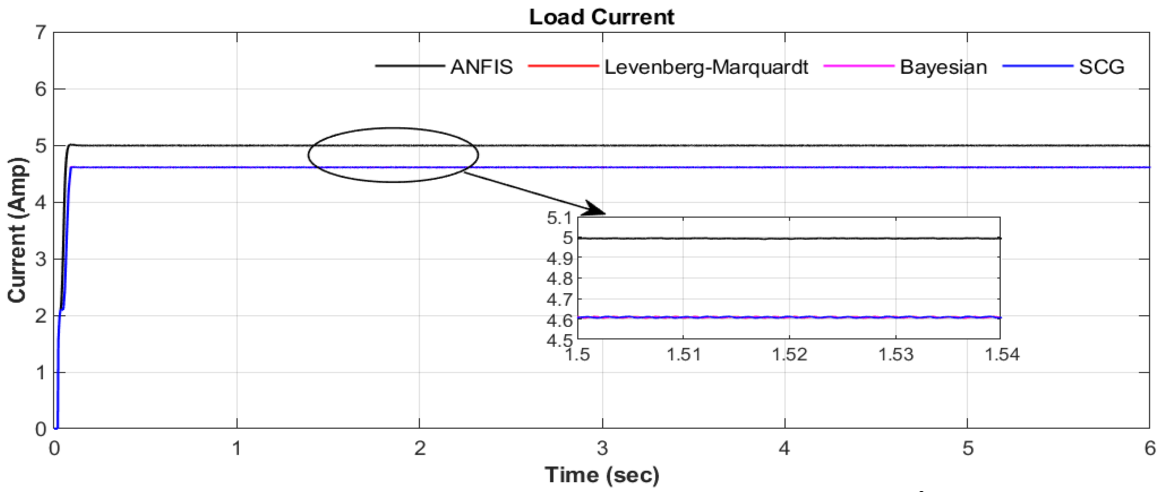



**Fig. 5.6 Simulation Results at Constant Irradiance and Temperature of 1000w/m$^2$ & 25°C, respectively, Waveform of (a) Boost Converter Output Voltage and, (b) Load Current**

Fig. 5.6 (a) and (b), shows boost converter output voltage and load current respectively. A zoomed window is taken between time duration of t=1.5sec to 1.54 sec. In fig. 5.6 (a), boost converter output voltage is remains constant at 500v by ANFIS algorithm and around 490v by other neural network algorithms. In fig. 5.6 (b), load current also remains constant at 5amp by ANFIS algorithm and around 4.6amp by other neural network algorithms for whole simulation time.

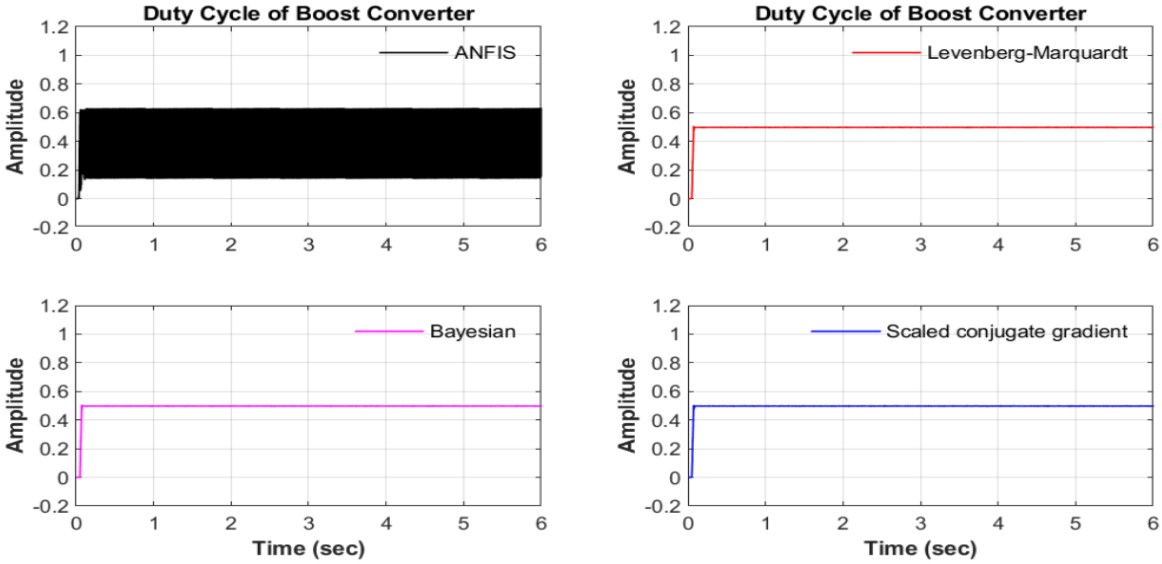



**Fig. 5.7 Simulation Results at Constant Irradiance and Temperature of 1000w/m$^2$ & 25°C, respectively, Waveform of Boost Converter Duty Cycle**

Fig. 5.7 shows, the waveform of comparison of MPPT algorithms for generating boost converter duty cycle.

## CONCLUSION

In this paper a DC-DC converter for standalone solar energy conversion system with maximum power point tracking (MPPT) technique is developed to achieve the maximum power using ANFIS (Adaptive-Network-Based Fuzzy Inference System) based MPPT Controller. 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 ANFIS algorithm shows better performance in overall data processing with near-zero error at the middle epoch. 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.

## REFERENCES

[1] S. Kouro, J. I. Leon, D. Vinnikov, and L. G. Franquelo, ‘‘Grid-connected photovoltaic systems: An overview of recent research and emerging PV converter technology,’’ IEEE Ind. Electron. Mag., vol. 9, no. 1, pp. 47–61, Mar. 2015, doi: 10.1109/MIE.2014.2376976.

[2] B. Tarroja, B. Shaffer, and S. Samuelsen, ‘‘The importance of grid integration for achievable greenhouse gas emissions reductions from alternative vehicle technologies,’’ Energy, vol. 87, pp. 504–519, Jul. 2015, doi: 10.1016/j.energy.2015.05.012.

[3] M. Rokonuzzaman, M. K. Mishu, N. Amin, M. Nadarajah, R. B. Roy, K. S. Rahman, A. M. Buhari, S. Binzaid, M. Shakeri, and J. Pasupuleti, ‘‘Self-sustained autonomous wireless sensor network with integrated solar photovoltaic system for internet of smart home-building (IoSHB) applications,’’ Micromachines, vol. 12, no. 6, p. 653, Jun. 2021, doi: 10.3390/mi12060653.

[4] S. Koohi-Kamali, N. A. Rahim, H. Mokhlis, and V. V. Tyagi, ‘‘Photovoltaic electricity generator dynamic modeling methods for smart grid applications: A review,’’ Renew. Sustain. Energy Rev., vol. 57, pp. 131–172, May 2016, doi: 10.1016/j.rser.2015.12.137.

[5] M. G. De Giorgi, P. M. Congedo, and M. Malvoni, ‘‘Photovoltaic power forecasting using statistical methods: Impact of weather data,’’ IET Sci. Meas. Technol., vol. 8, no. 3, pp. 90–97, May 2014, doi: 10.1049/ iet-smt.2013.0135.

[6] N. Karami, N. Moubayed, and R. Outbib, ‘‘General review and classification of different MPPT techniques,’’ Renew. Sustain. Energy Rev., vol. 68, pp. 1–18, Feb. 2017, doi: 10.1016/j.rser.2016.09.132.

[7] M. K. Mishu, M. Rokonuzzaman, J. Pasupuleti, M. Shakeri, K. S. Rahman, F. A. Hamid, S. K. Tiong, and N. Amin, ‘‘Prospective efficient ambient energy harvesting sources for IoT-equipped sensor applications,’’ Electronics, vol. 9, no. 9, p. 1345, Aug. 2020, doi: 10.3390/electronics9091345.

[8] M. Rokonuzzaman, M. Shakeri, F. A. Hamid, M. K. Mishu, J. Pasupuleti, K. S. Rahman, S. K. Tiong, and N. Amin, ‘‘IoT-enabled high efficiency smart solar charge controller with maximum power point tracking—

Design, hardware implementation and performance testing,'' Electronics, vol. 9, no. 8, p. 1267, Aug. 2020, doi: 10.3390/electronics9081267.

[9] P. Sivakumar, A. A. Kader, Y. Kaliavaradhan, and M. Arutchelvi, ''Analysis and enhancement of PV efficiency with incremental conductance MPPT technique under non-linear loading conditions,'' Renew. Energy, vol. 81, pp. 543–550, Sep. 2015.

[10] R. B. Roy, E. Basher, R. Yasmin, and M. Rokonuzzaman, ''Fuzzy logic based MPPT approach in a grid connected photovoltaic system,'' in Proc. 8th Int. Conf. Softw., Knowl., Inf. Manage. Appl. (SKIMA), Dec. 2014, vol. 1, no. 1, pp. 1–6, doi: 10.1109/SKIMA.2014. 7083525.

[11] A. R. Bhatti, Z. Salam, B. Sultana, N. Rasheed, A. B. Awan, U. Sultana, and M. Younas, ''Optimized sizing of photovoltaic grid-connected electric vehicle charging system using particle swarm optimization,'' Int. J. Energy Res., vol. 43, no. 1, pp. 500–522, Jan. 2019, doi: 10.1002/er.4287.

[12] T. V. Dixit, A. Yadav, and S. Gupta, ''Experimental assessment of maximum power extraction from solar panel with different converter topologies,'' Int. Trans. Electr. Energy Syst., vol. 29, no. 2, pp. 1–33, Feb. 2019, doi: 10.1002/etep.2712.

[13] M. Rokonuzzaman and M. Hossam-E-Haider, ''Design and implementation of maximum power point tracking solar charge controller,'' in Proc. 3rd Int. Conf. Electr. Eng. Inf. Commun. Technol. (ICEEICT), Sep. 2016, pp. 1–3, doi: 10.1109/CEEICT.2016.7873139.

[14] Rajib Baran Roy et al., "A Comparative Performance Analysis of ANN Algorithms for MPPT Energy Harvesting in Solar PV System," Elsevier Renewable and Sustainable Reviews,Vol. 13, October 2009, pp.2096-2103.

[15] Nema, P; Nema, R.K and Rangnekar, S. "A Current and Future state of art development of Hybrid Energy system using Wind and PV Solar," IEEE Access,Vol. 9, 2021, pp.102137-102152.

[16] Sassi, A., Zaidi, N., Nasri, O and Slama, J.B.H. 2017. Energy management of PV/wind/battery hybrid energy system based on batteries utilization optimization, IEEE International Conference on Green Energy Conversion Systems held at Tunisia during Mar. 23-25, 2017, pp. 1-7.

[17] Rehman, S; Alam, MD.M; Meyer, J.P and Al-Hadhrami, L.M. " Feasibility study of a wind-pv-diesel hybrid power system for a village," Elsevier Renewable Energy, vol. 38, Febuary 2012, pp.258- 268.

[18] Khan, B.H "Non-Conventional Energy Resources," Tata McGraw-Hill Pub.Co., 2009.

[19] Dali, M., Belhadj, J., Roboam, X.: 'Hybrid solar-wind system with battery storage operating in grid–connected and standalone mode: Control and energy management-experimental investigation', Energy, 2010, 35, pp. 2587–2595.

[20] Nguyen, X. H. and Nguyen, M. P. 2015. Mathematical modeling of photovoltaic cell/module/arrays with tags in Matlab/Simulink, Environmental Systems Research.4(1):1-13.

[21] Kamal, T., Karabacak, M., Hassan, S. Z., Li, H., Arsalan, A., & Rajkumar, R. K. 2017. Integration and control of an off-grid hybrid wind/PV generation system for rural applications. International Conference on Innovations in Electrical Engineering and Computational Technologies held at Karachi, during 5-7 April 2017, pp. 1-6.

[22] Priyadarshi, N., Padmanaban, S., Ionel, D. M., Popa, L. M. and Azam, F., "Hybrid PV-Wind, micro-grid development using quasi-z-source inverter modeling and control-experimental investigation," Energies, vol. 11, pp.1-15, 2018.

[23] Zeng, J., Ning, J., Du, X., Kim, T., Yang, Z. and Winstead, V., "A four-port DC-DC converter for a standalone wind and solar energy system," IEEE Transactions on Industry Applications, vol. 56, pp. 446-454, 2020.

[24] Khateb, A. H. E., Rahim, N. A., Selvaraj, J. and Williams, B. W., "DC-to-DC converter with low input current ripple for maximum photovoltaic power extraction," IEEE Transactions on Industrial Electronics, vol. 62, pp. 2246-2256, 2015.

[25] Ahmadi, M. and Shenai, K., "New, efficient, low-stress buck/boost bidirectional DC-DC converter," In: Proceedings of IEEE Energy tech conference held at Cleveland during May 29-31, 2012, pp. 1-6.

[26] Wandhare, R.G. and Agarwal, V., "Novel integration of PV-Wind energy system with enhanced efficiency," IEEE Transactions on Power Electronics, vol. 30, pp. 3638-3649, 2015.

[27] Sharma, A. and Jamuna, K., "Coordination of energy storage devices in hybrid power systems," In: Proceedings of Springer International conference on Emerging Trends in Electrical, Communications and Information Technologiesheld at India during November 15-16, 2016, pp. 327-336.

[28] Manandhar, U., Tummuru, N. R. and Kollimalla, S. K., "Validation of faster joint control strategy for battery- and super capacitor-based energy storage system," IEEE Transactions on Industrial Electronics, vol. 65, pp. 3286-3295, 2018.

[29] Lei, M., Yang, Z., Wang, Y., and Honghua, X., "Design of energy storage control strategy to improve the PV system power quality," In: Proceedings of IEEE 42nd Annual Conference of the Industrial Electronics Society (IECON) held at Italy during October 23-26, 2016, pp. 2022-2027.

Faria, J., Pombo, J., Calado, M. and Mariano, S., "Power management control strategy based on artificial neural networks for standalone PV applications with a hybrid energy storage system," Energies, vol. 12, no.2, pp. 1-24, 2019.