International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-6, April 2020

Accuracy of Detection and Classification of DC Faults using Levenberg Marquardt Based Back Propagation Algorithm

Sujit Kumar, Neel Kamal, Pankaj Kumar, Aditya Gaur, Vikash Tiwari

Abstract: ***Vitality is seen as a prime administrator in the time of wealth and a vital figure budgetary headway. Obliged fossil resources and natural issues associated with them have underscored the necessity for new reasonable vitality supply choices that uses sustainable power sources. Among open developments for essentialness age from solar dependent sources, the photovoltaic system might give a gigantic pledge to develop a progressively feasible imperativeness structure. This paper presents accuracy of detecting DC faults in a photovoltaic (PV) framework based on Levenberg - Marquardt (LM) neural network. The result showed that this model based on LM neural network is effectual to grip doubts and nonlinearities of DC side faults in PV module without using mathematical model. All probable faults in DC side of PV system are obtained over 100 kW plant. It is discovered that the proposed framework has demonstrated its integrity for the pragmatic applications.***

Keywords: Levenberg - Marquardt (LM) Neural Network, 100 Kw PV Array, 11 Kv Grid, DC Side Faults, Grid Connected PV System.

I. INTRODUCTION

As of late, there is an unforeseen power concern appeared throughout the world. Regardless, experts found that using the sustainable power sources gives a key of answers for this issue. PV systems speak to a basic territory in the feasible power source. They supported in light of their clean and eco-accommodating for the earth. They have been adequately used for certain applications [1]. This advancement has been coordinated with investigation into increasingly proficient solar frameworks.

Revised Manuscript Received on April 30, 2020.
* Correspondence Author
Dr. Sujit Kumar*, Department of EEE, NIET, Greater Noida, India. Email: sujitvj.kumar@gmail.com
Dr. Neel Kamal, Department of EEE, NIET, Greater Noida, India. Email: drsaini25aug@gmail.com
Dr. Pankaj Kumar Power, System Consulting Engineer, Mumbai, India. E-mail: pankajkumar666@gmail.com
Mr. Aditya Gaur, Department of EEE, NIET, Greater Noida, India. Email: adityagaur131417@gmail.com
Mr. Vikash Tiwari, Department of Electrical & Electronics Engineering, Noida Institute of Engineering &Technology, Greater Noida, India. E-mail: vikashwish@gmail.com

Productivity is determined as the proportion of occurrence solar vitality towards the greatest achievable yield power, with the ongoing evidence being a proficiency of forty four % [2]. The suitability of sun panels normally goes all through the framework, since any misfortunes will intrude on the last skill of the entire framework. Fig. 1 displays a distinctive configuration of a grid-connected PV System (GCPV).

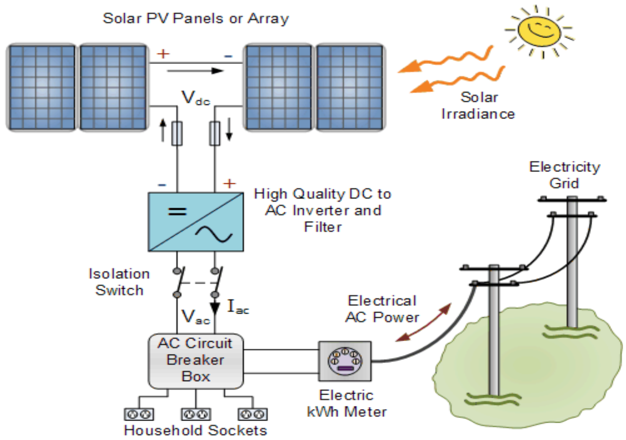

Fig. 1.Schematics of a generalized PV framework

Solar irradiance level and the temperature are the two output characteristics which decide the output of the panel and also force to employ a charger unit that pedals the PV output (V_{PV}, I_{PV}) and delivers the power to the load. Ensuring the high-quality routine action of the PV cells is extremely imperative job. But, due to faults the capability of the PV systems gets affected. PV cell faults in the panel causes two trouble: (1) results in reverse bias operation which may result in hot spots and cause more faulty PV cells, (2) reduction in the current [3]. Some of the fault detection techniques in PV systems have been developed which are shown in below Table 1. (GCPV). In this paper, detection and classification of every single conceivable fault in DC side GCPV system are introduced, where 100 kW array linked with an 11 kV network.

Table- I: Fault detection techniques in PV systems

S.No.	Methods Developed	Findings
1.	Earth capacitance measurement (ECM) [4]	Disconnection of PV module in a string is located by an electrical method.
2.	Time-domain reflectometry (TDR) [5]	Not only detection however measures the impedance varies owing to deprivation.
3.	Statistical method based on the ANOVA (Analysis of Variance) test and nonparametric Kruskale-Wallis test [6]	High level of accuracy and fast in fault diagnosis. [6]
4.	Remote monitoring and fault detection method [7]	Uses climate data from satellites observation [8].
5.	Learning techniques [10]	Observes system process and support of the PV framework, regardless of the possibility that it needs various inference sensors, which distinguish shading and inverter failure.
6.	Estimation sensors [11]	Can classify four types of faults: 1) supported zero efficacy faults, 2) brief zero efficacy faults, 3) shading, and 4) non-zero efficacy non-shading issues.
7.	Modest investigative method [12]	With a small number of sensors it can categorize the various faults.
8.	Blocking diode method [13]	Double line fault occurred beneath short light circumstances which were detected by the presence of blocking diode.
9.	Expanded relationship function and element module method [14]	Identifies the malfunction accurately and quickly.
10.	(- dI/dV) - V characteristic method [15]	Partial shadow phenomenon is distinguished in this method.
11.	Decision trees (DT) method [16]	Fault location and classification strategy has been shown with poor accuracy.
12.	Wavelet transform technique [17]	Identifies the fault occurring on the power conditioning system of the PV plant.
13.	Programmed based fault detection technique [18]	Four types of faults has been classified: 1) defective arrays in a cord, 2) broken cord, 3) forged alert and 4) deficient shadow, maturing, and MPPT fault.

II. CATEGORIZATION OF GCPV FAULT

It can be categorized as: DC side and AC side shown in Fig. 2 [19].

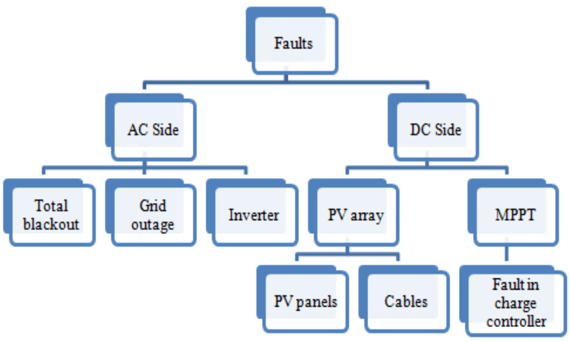

Fig. 2.Fault Classification associated with PV array

Here, in this we report only DC side faults.

A. DC side Faults

The faults arise in DC side of the GCPV system is categorized into two main types: PV array Fault and MPPT Fault [19].

1. PV Array Faults

PV array faults include two core groups [19] shown in Fig. 3.

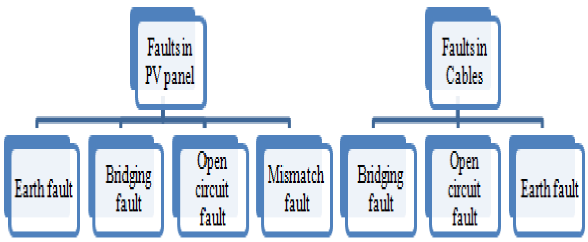

Fig. 3.Fault Classification associated with PV array

2. Maximum Power Point Tracking (MPPT) Faults

The presentation of this fault reduces when the breakdown happens in charge modules. When fault occur in MPPT the output voltage and the output power reduces.

III. MODELING OF PROPOSED SYSTEM

The performance of nervous system in the brains of human is largely replicated by artificial neural network (ANN) [20]. ANNs have been functionalized productively in numerous areas presented in [21].

Usually, these methods have three fundamental processes; information compilation, information preparation (or knowledge) development and output justification.

These methods have various preparation algorithms like back propagation (BP), Levenberg Marquardt (LM), radial basis function (RBF), etc. LM algorithm is higher to other algorithms because of it's a lesser amount of end time and precision [22]. Fig. 4 [22] shows the architecture of proposed model.

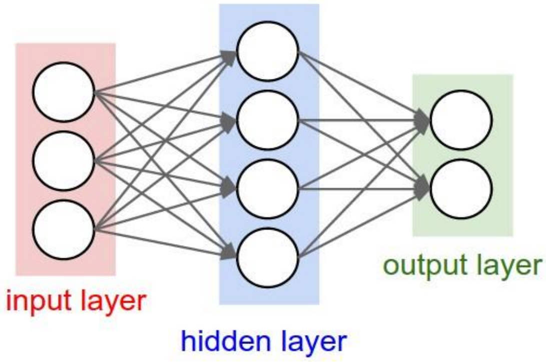

Fig. 4.Architecture of ANN

Here, PV current, voltage, module temperature, solar irradiance and power in normal bright days have been measured shown in Table 2.

There are five inputs fed to the ANN; PV voltages (Vpv), currents (Ipv) and power (P), irradiance (G) and module temperature (T). 5-types of the faults were trained in the projected model. There were five output numbers (1 – 5) which represents the DC faults in PV system, O1: signifies the deprivation condition, O2: signifies the SC condition, O3: signifies the OC condition, O4: signifies the fractional darkness. O5: signifies the charge controller collapse condition.

From table 2 we have taken two data; module temperature and irradiance value as 39^0, 45^0 and 270, 750 Watt/m^2 respectively for simulation results.

IV. RESULTS AND DISCUSSION

Every probable fault of GCPV (DC) is simulated with 100 kW array connected to an 11 kV grid, and the measured data has been fed to ANN by MATLAB model.. The greatest selection consists of 5 – 40 – 6 illustrated in Fig. 5.

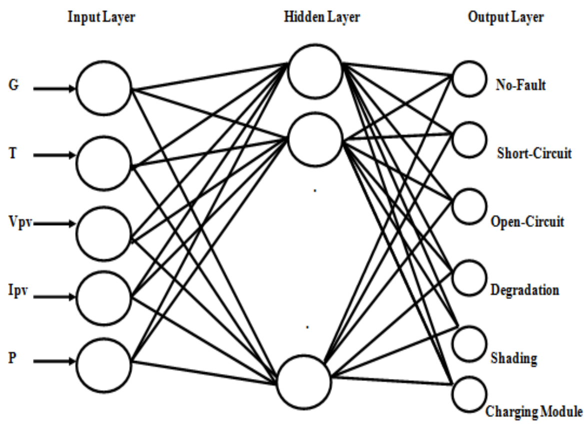

Fig. 5.Proposed ANN Network

Table- II: Measured data from solar panel

Occasion (a.m/p.m)	Voltage (V)	Currents (A)	Power (Watts)	Solar irradiance (Watt/m^2)	Module temperature
9:30 a.m	10.97	2.80	30.72	276	39.40^0
10:30 a.m	11.01	2.95	38.72	340	40.40^0
11.30 a.m	13.85	6.6	91.47	465	43.10^0
12:30 p.m	18.71	7.6	142.2	764	48.68^0
1:00 p.m	22.83	8.1	185	997	57.50^0
1:30 p.m	20.83	7.1	180	985	54.50^0
9:30 a.m	10.87	2.89	34.72	283	40.40^0
10:30 a.m	11.21	2.99	39.72	348	41.40^0
11:30 a.m	12.6	4.5	56.72	276	44.20
12:30 p.m	1971	7.9	162.2	802	50.68^0
1:00 p.m	22.93	8.5	196	992	55.50^0
1:30 p.m	20.43	6.9	175	979	52.50^0

For preparation mean squared error (MSE) is used as presentation purpose and is given by [23] revealed in equation (1):

$$E = \frac{1}{n}\left(\gamma \sum_{i=n}^{n} e^2 + (1-\gamma)\sum_{j=1}^{n} w_j^2\right) \tag{1}$$

For updating the weights and biases of the network we use equation (1) for Levenberg Marquardt (LM) programming [23], broadly utilized in an extroverted area.

Parameters trained for ANN programming:

Teaching pattern = 5295

Knowledge tempo = 0.001

Point error set = 0.01

Valid rate = 1000

Thrust = 0.95

Three miscellaneous accurate markers were utilized toward justification of the system. These are shown in equations 2, 3 and 4:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_{predicted} - Y_{true}| \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_{predicted} - Y_{true})^2 \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{predicted} - Y_{true}}{Y_{true}}\right|^2 \quad (4)$$

where $Y_{predicted}$ and Y_{true} are probable and actual fault values over panels respectively. From the three markers MAPE and MSE are used whose output have less fluctuation when deals with sample to sample variation [22].

MSE achieved is 9.99×10^{-3} which is fine under the point error in 1000 valid rates as revealed in Fig. 6. Accurateness of training was proved by validation means the data which were not included in the training were also validated properly and the MSE obtained from validation found 8.3857×10^{-3}. Table 3 represents the simulated results obtained from the proposed artificial neural network system.

Table- III: Simulated results obtained from an ANN

Fault Type	Surrounding Circumstances		Replication Results	
	Warm °C	Radiation Level (W/m²)	ANN System	
			Accuracy	Time (sec.)
No-Fault	39	270	99.3	5.6
	45	750	99.01	5.3
Short-Circuit	39	270	99.1	6.1
	45	750	98.9	6.2
Open-Circuit	39	270	99.5	5.8
	45	750	99.1	5.9
Degradation	39	270	99.6	5.5
	45	750	99.3	5.3
Shading	39	270	99.7	6.4
	45	750	99.2	5.9
Charging Module	39	270	98	6.7
	45	750	98.7	5.9

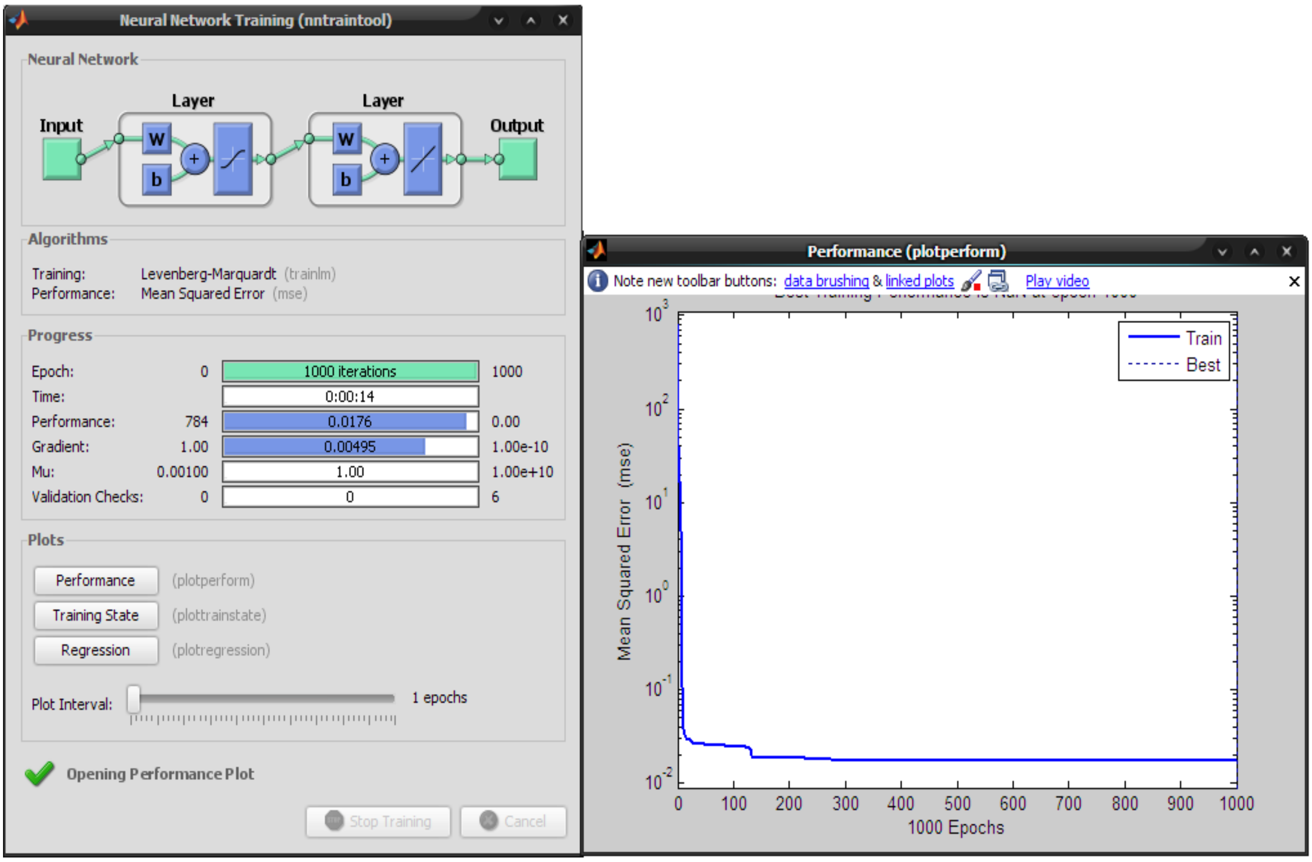

Fig. 6.Training results of ANN in Matlab Simulink and evolution of the performance error

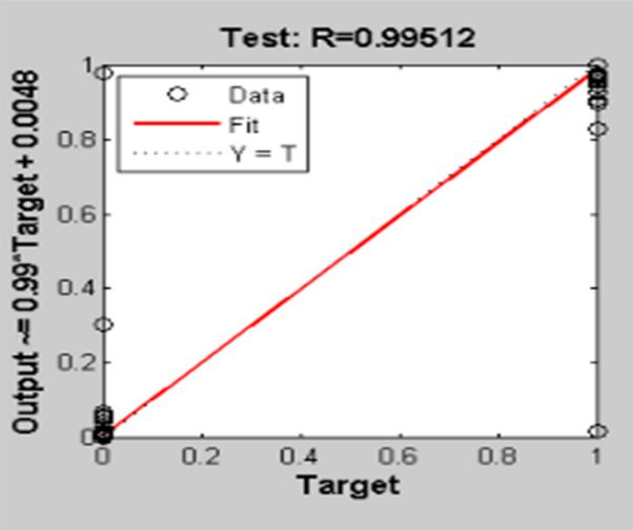

Fig. 7.Test phase performance of ANN model

The overall data set and results were shown in Fig. 7. Network test error obtained as 1.02023e-3 and regression coefficient (R) obtained as 9.8401e-1.

MAPE for the proposed model found to be 0.5% also, Fig. 8 shows the confusion matrix which tells that the faults are accurately classified and tested with the other fault samples which were not trained in the training period. (O1 – O5, explained in section 3)

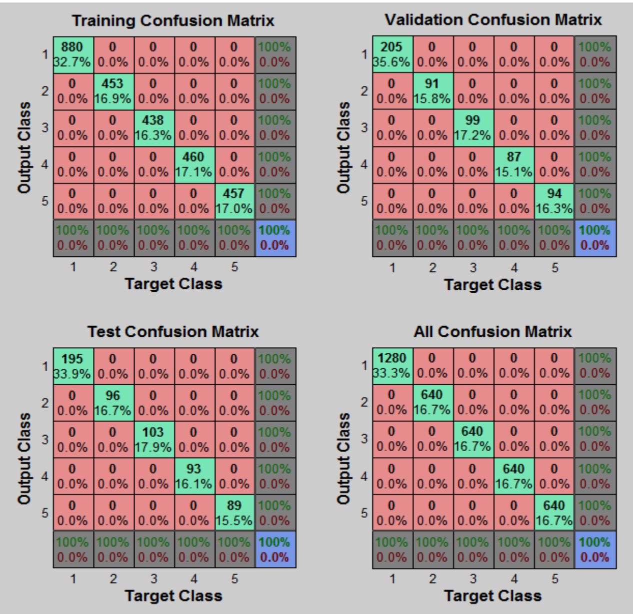

Fig. 8.Confusion Matrix with proper classification of all DC faults

V. CONCLUSION

The detection, classification, simulation and discussion of all possible faults in DC side of a GCPV system have been presented. Different fault conditions with their output power waveforms are plotted. The fault can be effortlessly recognized by relating the output powers with no fault condition. Trouble free ANN model has been developed that detect and classify the fault on solar panel of 250 Wp. The results show that ANN has potential to effectively detect the fault information with a precision of 100%.

REFERENCES

1. Chao, K. H., Li, C. J., and Ho, S. H. Modeling and fault simulation of photovoltaic generation systems using circuit-based model, *Proceedings of IEEE International Conference on Sustainable Energy Technologies*, 2008, pp. 195-202.
2. World record solar cell with 44.7% efficiency. http://phys.org/news/2013-09-world-solar-cell-efficiency.html.
3. Davarifar, M., Rabhi, A., El-Hajjaji, A., Bosche, J. andPierre, X. Improved Real Time Amorphous PV Model for Fault Diagnostic Usage, *Sustainability in Energy and Buildings, Springer Berlin Heidelberg*, 2013, pp. 179-188.
4. Takashima, T, Yamaguchi, J, Otani, K, Oozeki, T, Kato, K and Ishida, M. Experimental studies of fault location in PV module strings, *Solar Energy Material Solar Cells, vol. 93, 2009, pp. 1079-82.*
5. Schirone, L, Schirone, L, Califano, FP and Pastena, M. Fault detection in a photovoltaic plant by time domain reflectometry, *Progress in Photovoltaics: Research and Applications. vol. 2, 1994, pp. 35-44.*
6. Vergura, S, Acciani, G, Amoruso, V and Patrono, G. Inferential statistics for monitoring and fault forecasting of PV plants, *Proceedings of the IEEE international symposium, industrial electronics, Cambridge, UK. 2008, pp. 2414-19.*
7. Drews, A, de Keizer, AC, Beyer, HG, Lorenz, E, Betcke, J and van Sark, WGJHM. Monitoring and remote failure detection of grid-connected PV systems based on satellite observations, *Solar Energy, vol. 81, 2007, pp. 548-64.*
8. Muselli, M, Notton, G, Canaletti, JL and Louche, A. Utilization of Meteosat satellite derived radiation data for integration of autonomous photovoltaic solar energy systems in remote areas, *Energy Conversion and Management, vol. 39,1998, pp. 1-19.*
9. Drif M, Mellit, A, Aguilera, J and Perez, PJ. A comprehensive method for estimating energy losses due to shading of GC-BIPV systems using monitoring data, *Solar Energy, vol. 86, 2012, pp. 2397-404.*
10. Syafaruddin, S, Karatepe, E and Hiyama, T. Controlling of artificial neural network for fault diagnosis of photovoltaic array, *Proceedings of the 16th international conference on intelligent system application to power systems (ISAP), Greece, 2011, pp. 1-6.*
11. Ducange, P, Fazzolari,M, Lazzerini, B and Marcelloni, F. An intelligent system for detecting faults in photovoltaic fields, *Proceedings of the IEEE 11th international conference on intelligent systems design and applications, Cordoba, Spain, 2011, pp. 1341-46.*
12. Yagi, Y, Kishi, H, Hagihara, R, Tanaka, T, Kozuma, S and Ishida, T. Diagnostic technology and an expert system for photovoltaic systems using the learning method, *Solar Energy Material Solar Cells, vol. 75, 2003, pp. 655-63.*
13. Firth, SK, Lomas, KJ and Rees, SJ. A simple model of PV system performance and its use in fault detection, Solar Energy, vol. 84, 2010, pp. 624-35.
14. Gokmen, N, Karatepe, E, Celik, B and Silvestre, S. Simple diagnostic approach for determining of faulted PV modules in string based PV arrays, *Solar Energy, vol. 86, 2012, pp. 3364-77.*
15. Miwa, M, Yamanaka, S, Kawamura, H, Ohno, H and Kawamura, H, Diagnosis of a power output lowering of PV array with a (-dI/dV)-V characteristic, *Proceeding of IEEE 4th world conference on photovoltaic energy conversion, 2006, pp. 2442-45.*
16. Zhao, Y, Yang, L, Lehman, B, DePalma, JF, Mosesian, J and Lyons, R. Decision-based fault detection and classification in solar photovoltaic arrays, *Proceedings of the Twenty seventh annual IEEE applied power electronics conference and exposition,2012, pp. 93-99.*
17. Il-Song, K. Fault detection algorithm of the photovoltaic system using wavelet transform, *Proceedings of the IEEE India international conference on power electronics, New Delhi, 2010, pp.1-6.*
18. Chouder, A, and Silvestre, S. Automatic supervision and fault detection of PV systems based on power losses analysis, *Energy Conversion Management, vol. 51,2010, pp. 1929-37.*
19. Sabbaghpur Arani, M. and Hejazi, M. A. The Comprehensive Study of Electrical Faults in PV Arrays, *Journal of Electrical and Computer Engineering, vol. 16, 2016, pp. 1-11.*
20. Roshchupkin, Oleksiy, Smid, Radislav, Kochan, Volodymyr and Sachenko, Anatoly. Multi-sensors Signal Processing Using Microcontroller and Neural Networks Identification, Sensors & Transducers Journal, vol. 24, no. 8, 2013, pp. 1-6.

21. Turchenko I, Kochan, V. and Sachenko, A. Accurate Recognition of Multi-Sensor Output Signal Using Modular Neural Networks, *International Journal of Information Technology and Intelligent Computing, vol. 2, no. 1,2007, pp. 27- 47.*
22. Sujit Kumar, Vikramaditya Dave. ANN Based Controller to Mitigate Soiling Loss on Solar Panels, *IEEE Conference on the Twenty first 21 Century Energy Needs – Materials, Systems And Applications, 2016, pp. 1 – 6.*
23. DJC MacKay. A practical Bayesian framework for back propagation networks. *Neural Computation, vol. 4, 1992, pp. 448 – 72.*

AUTHORS PROFILE

Dr. Sujit Kumar received his Ph.D. degree in Electrical Engineering from Maharana Pratap University of Agriculture and Technology (MPUAT), College of Technology and Engineering, Udaipur with the collaboration of IIT Roorkee, his Master of Technology from Sharda University, Greater Noida and his Bachelor of Technology from B K BIET Pilani (BITS Cmpus), Pilani. Right now he is posted as an Assistant Professor in EEE, Department of NIET, Greater Noida, India. His area covers Nanotechnology, Conventional Energy, and Artificial Intelligence..

Dr. Neel Kamal awarded his Ph.D. degree in Electrical Engineering from Mewar University, his M.Tech from M. D. University, Rohtak, Haryana and his B.Tech from G. B. Pant University of Agriculture and Technology, Uttrakhand. At the moment he is posted as an Associate Professor in EEE, Department of NIET, Greater Noida, India. His area covers Renewable Energy, Power Electronics.

Dr Pankaj Kumar, FIE, C. Eng(I), was awarded PhD (Electrical Engineering) in 2018 from BIT, Sindri, Dhanbad, India (Vinoba Bhave University); M.Sc. Engineering (Electrical) with specialization in Power System from NIT Jamshedpur in 2008, B.Sc. Engineering (Electrical) from BIT Sindri, Dhanbad, India (Ranchi University) in 1991. Currently, he is a Power System Consulting Engineer and has served Alstom Power, Tata Power, Technip France AD, L&T Power, Hindalco, JSW Energy, Lahmeyer, Dodsal, Electricity and Water Authority Bahrain, Dodsal Dubai for Plant Conceptualization, Front End Engineering Design, Detailed Design & Engineering, Project Engineering Management, Planning, Erection and Commissioning, Operation & Maintenance & Technical Services in Clean Technologies, Power Station (Coal, CCPP, Hydro, Wind, Solar), Carbon Capture, Offshore & Onshore Oil & gas Facilities, Desalination Plant, Stainless steel Plant, etc. His research area includes Energy sector, Power System Studies, Pollution control, High Voltage & Control System.

Mr. Aditya Gaur received his M.Tech. Degree VLSI Technology from Sharda University, his B.Tech. in Electrical & Electronics Engineering from Sharda University. Presently he is working as an Assistant Professor in Electrical and Electronics Engineering department of Noida Institute of Engineering and Technology, Greater Noida, India. His area of interest includes Wireless sensor network and fabrication of MEMS based sensor.

Mr. Vikash Tiwari received his M.Tech. Degree in Power Electronics, Electrical Machines & Drives from Lingayas University, Faridabad, Haryana, his B.Tech. in Electrical & Electronics Engineering from V.I.E.T., G. B. Nagar under Uttar Pradesh Technical University. Presently he is working as an Assistant Professor in Electrical and Electronics Engineering department of Noida Institute of Engineering and Technology, Greater Noida, India. His area of interest includes Electrical machines and drives control, nonlinear control system.