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Simulation and Experimental validation of Distributed MPPT algorithms for partially shaded Photovoltaic systems

***Abstract**. This paper analyzes the performance of two different maximum power point tracking (MPPT) algorithms for photovoltaic (PV) system: artificial neural network (ANN) and adaptive neuro fuzzy inference (ANFIS) as used by an interleaved soft switching boost converter (ISSBC) system with different conditions, such as partially shaded, condition, changing solar insolation and PV cell temperature. However, under partially shaded conditions, when the PV module characteristics get more complex with multiple peaks of* output power. *Both algorithms are methodically investigated by means of Matlab simulation and hardware experimental validation, compare in terms of parameters tracking speed, power extraction, and harmonic analysis. In this topology, each cascaded H-bridge inverter (CHBMLI) unit is connected to an individual PV module through an interleaved soft switching boost converter (ISSBC). The simulation and hardware results show that ANFIS algorithm is outperforming than the ANN algorithm.*

***Streszczenie. Streszczenie.** W artykule analizowane są dwa algorytmy śledzenia maksymalnej mocy (MPPT) stosowane w systemach fotowoltaicznych: jeden (ANN) wykorzystuje sieci neuronowe a drugi wykorzystuje ANFIS. Układ pozwla na załączanie przekształtnika w zależności od warunków, np. zacienienia czy temperatury.* ***Symulacja i eksperymentalna weryfikacja algorytmów śledzenia mocy w systemach fotowoltaicznych**.*

Keywords: Photovoltaic (PV) system, Maximum power point tracking (MPPT), Microcontroller, Interleaved soft switching boost inverter (ISSBC), Cascade H-bridge inverter (CHBMLI).

.**Słowa kluczowe:** systemy fotowoltaiczne, śledzenie mocy MPPT, ANFIS, scieci neuronowe.

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1. Introduction

Photovoltaic energy has increased interest in electrical power applications, since it is considered as a basically limitless and generally on hand energy resource In general, there is a unique point on the P-V or I-V curve, called the maximum power point (MPP), at which the entire PV system operates with maximum efficiency and produces its maximum output power. The performance of a photovoltaic module is highly affected by the partial shaded condition [1]. Many MPPT techniques have been reported in the literature such as particle swarm optimization [2] perturb and observation [3], incremental conductance [4], fuzzy logic based controller,[5] genetic algorithm, and artificial neural net work etc [6]-[8]. This paper presents a unique combination of an interleaved soft switched boost converter (ISSBC) run by a set of two photovoltaic panels (PV) with a distributed MPPT, suitable to guarantee MPPT even under partial shadowed conditions, managed by an adaptive neuro fuzzy inference (ANFIS) unit. The ISSBC is followed by a, single phase cascaded H bridge five-level inverter (CHBMLI) driven by the individual DC outputs of the ISSBC, with selective harmonic elimination scheme to eliminate typically the high order harmonics[9]. A comparison of ANN maximum power point tracking (MPPT) algorithms for photovoltaic (PV) system under partial shadow conditions is carried out [10]. The experimental system is constituted by three main elements are shown in Fig.1: PV panel, dc-dc interleaved soft switching boost converter, and cascade multileveled H-bridge inverter.

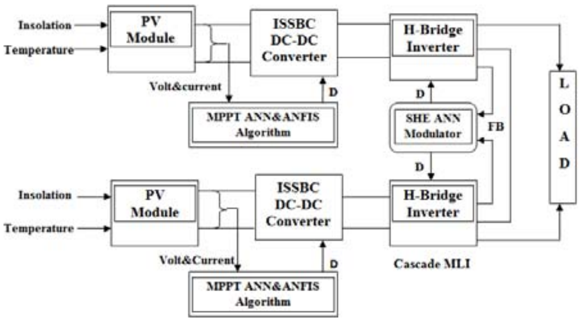

Fig.1. General Diagram of load connected photovoltaic system

Table 1. PV module parameters

Parameter	
Maximum Power (Pmax)	150W
Voltage at Pmax (Vmp)	34.5V
Current at Pmax (Imp)	4.35A
Open-circuit voltage (Voc)	43.5V
Short-circuit current (Isc)	4.75A

2. PV array modeling and simulation

A 150 *W* rated PV panel consisting of 72 multi-crystalline silicon solar cells in series parallel-connected combination used for the application. In this model, a PV cell is representing by a current basis in parallel with a diode and a series resistance. The basic current equation is given in Eq. (1).

$$I = I_{pv} - I_0 \left[exp \frac{qv}{akT} - 1 \right] \tag{1}$$

where I_{PV} = current generated by the incident light, T = Temperature of the PN junction, a = Diode ideality constant I_0, = leakage current of the diode, q = electron charge 1.6021×10-19 C, k = Boltzmann constant (1.38×10-23 J/K. To develop embedded simulink model based on current equation and manufacturer's data sheet parameter as shown in Table 1 of *BP SX 150S* PV module.

3. MPPT control algorithms

The MPPT algorithm is using for extracting the maximum power from the PV module and convey to the load. The ISSB DC-DC converter serves transferring maximum power from the solar PV module to the load by changing the duty cycle. Energy conversion efficiency of MPPT algorithm calculated as Eq. (2)

$$\eta_{MPPT} = \frac{\int_0^t P_{pv-\max(t)dt}}{\int_0^t P_{pv-MPPT(t)dt}} \tag{2}$$

where $P_{pv-MPPT}$ represents the output power of PV with MPPT, P_{pv-max} is the output power true maximum power point.

3.1 ANN MPPT algorithm

Artificial neural networks (ANN) are electronic models based on the neural structure of the brain. This function permits ANNs to be used in the design of adaptive and intelligent systems since they are able to solve problems from previous examples. ANN models involve the creation of massively paralleled networks composed mostly of nonlinear elements known as neurons. The ANN is used to estimate the optimal duty cycle in real time, which corresponds to maximum power at any given input voltage and current.

The MATLAB / SIMULINK based neural network fitting tool is used to select data, create and train a network and evaluate its performance using mean square error and regression analysis. The ANN is using to estimate the optimal voltage (V_{ref}) in real time, which corresponds to the maximum power at any given input insulation (G) and Temperature (T). The operation of this technique is explained in the block diagram in Fig.2. The developed ANN configuration is a multilayer-perceptron structure including an input layer, a hidden layer and output layer, whose function is activated sigmoid.

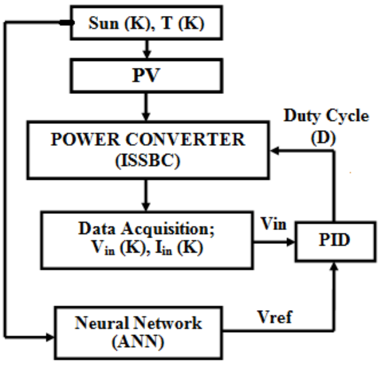

Fig.2. ANN MPPT control system

In this work, database engaged consists of 1250 patterns of PV insulation, temperature and reference voltage variables, which have divided into two sub-databases, 70%, of the samples are used to train the ANN, and the rest 30% are second-hand to test and validate the network. The performance is measured by calculating the mean- square error as shown in Eq. (3).

$$e = \frac{1}{p}\sum_{i=1}^{p}\left\| y^{(i)} - v^{(i)} \right\|^2 \tag{3}$$

Where, p= number of training data entries; y = ANN output vector; v = desired output

For a set of input insolation and temperature, a well-trained ANN would give as an output the reference voltage that is very close to the desired value, giving an error nearly zero. Each neuron a_j computes a weighted sum of its n inputs V_k, k = 1, 2. . . n, and generates an output as shown in Eq. (4).

$$a_j = \tan sig\left(\sum_{k=1}^{n} w_k v_k + bias\right) \tag{4}$$

The tan sigmoid function of the resultant weighted sum that usually has a bias associated with it that can be considered as an additional input gives the output. In (3), w_k represents the synapse weight associated with each one of the n inputs. These training sets chosen to cover all the typical input space in order to get good performance where temperature ranges from 15 °C to 55°C and solar irradiation ranged from 50 W/m^2 to 1050 W/m^2.

3.2 ANFIS MPPT algorithm

The ANFIS system is used to formulate the neural network architecture in the inference engine of a fuzzy controller. The functional block diagram and structure of ANFIS is shown in Fig.3. The structure comprises of three distinct layers namely input layer, hidden layer and output layer.

The input signals error *(e)* and change in error signal *(ce)* whose membership functions are selected as Gaussian membership function; the output is modulation index *(d)*.

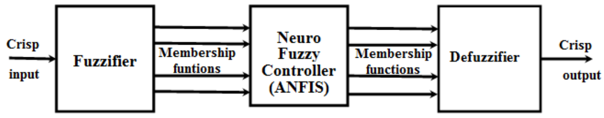

Fig. 3 (a) Adaptive neuro fuzzy control system

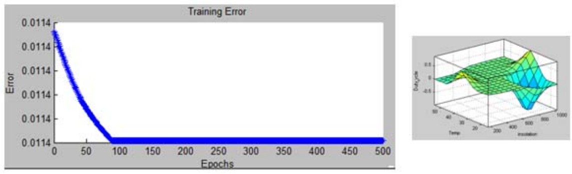

Fig. 4. ANFIS Training error and Surface view

The input membership functions are mapped to the output membership function by 49 rules through grid partitioning method using the FIS generator in Matlab Simulink. The 2500 data sets to train ANFIS are obtaining from workspace from the previous ANN MPPT algorithm, such as insolation, temperature and reference voltage. The learning data trained through back propagation technique for 500 epochs for minimum error tolerance. The network training is performing repeatedly until the performance indexes $E_p = \left(V_{ref} - V_{pv}\right)^2$ reduce below a specified value ideally to zero. In other words when $E_p \to 0$ leads to $\left(V_{ref} - V_{pv}\right)^2 \to 0$, then the trained ANFIS connecting weights are adjusted in such a way that the estimated array voltage is identically equal to the MPP voltage. The trained surface rule phase view shown in Fig.4, the trained data set exports the simulation and observes the performance different partial shading condition.

4. Soft switching boost inverter

The interleaved boost inverter consists of two single-phase boost converters that are connected in parallel and converters operating 180 degrees out of phase with 30 kHz switching frequency. It is pointed out that in interleaved converter mode 60 kHz effect is achieved by phase shifting of the two 30 kHz switching signals. The input-inductor-ripple-current cancellation occurs at 50% duty cycle. Hence, the design value of the duty ratio is 0 to 0.5 in this system. Therefore, the interleaved converter have lower switching losses, therefore the output voltage of the solar cell can be boosted with high efficiency [11].

5. Single phase CHBML inverter

In this paper, selective harmonic elimination pulse with modulation technique is implemented to generate the switching duty cycle for CHBMLI [12], [13]. Equation (5) shows the contents of the output voltage at infinite frequencies, the module voltage V_{pv1}-V_{pv2} are associated to their respective switching angle α_1- α_2.

$$V_{ab}(\alpha) = \sum_{n=1,5,7,11..}^{\infty}\left[\frac{4}{\pi . n}.\left(V_{pv1}\cos(n\alpha_1) + V_{pv2}\cos(n\alpha_2)\right)\right] \tag{5}$$

These trigonometric transcendental equations can be solved by GA fitting tool. To find the switching angle (offline) for a set of predetermined modulation indices to get the required fundamental output voltage in a five level cascaded multi level inverter. The switching angles *(α_1, α_2)* lie in between zero and *$\pi/2$*. The collected the set of data trained in ANN Simulink tool and exported to the system. The ANN is train, to output the set of angles for each input voltage situation.

6. Simulation Results

The simulink software validates the performance of the MPPT techniques under different operating conditions. The PV module parameters are obtained from the 150-Watts multicrystalline PV Module technical data sheet. Such parameters are considered in the Standard Test

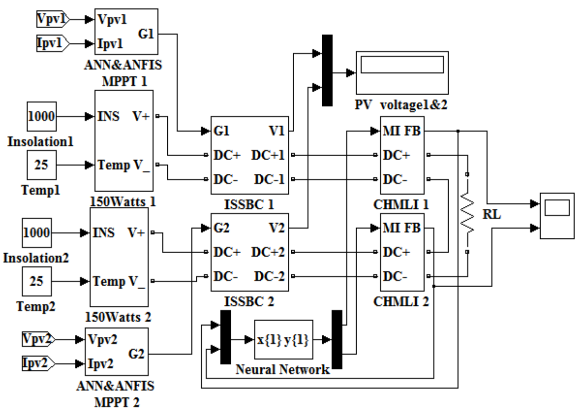

Fig.5. Simulation block diagram of the system

Condition (STC): 1000W/m^2 and cell temperature of 25°C. The simulation block diagram is shown in Fig.5. First, the characteristics of the PV module are validated and connected with converter system then the performance of the MPPT techniques under various conditions is evaluated. The simulation validation of PV module and converter results of the I-V and P-V characteristics of PV module as a function of irradiation and temperature shown in Fig. 6-7. It can be observed quite similar to the PV module as per data sheet. In order to achieve the maximum power point of PV modules, ANN and ANFIS MPPT controller has been developed using Matlab Simulink model. The simulation result is presented for the following configurations.

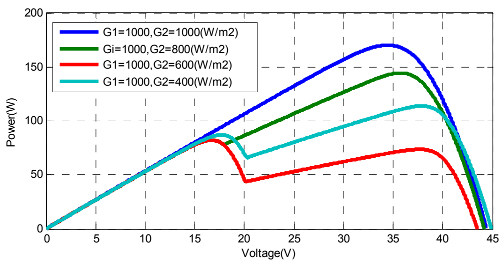

Fig. 6. P-V Curve at 25°C

6.1. Dynamic Changing the Solar Radiation

Simulations are carried out converter alone with two techniques under dynamically changing solar irradiations at temperature of 25°C.The simulation pattern and corresponding result parameter detailed in Table 2 and Table 3 respectively. Fig. 8 shows simulation output voltage, power and efficiency of sudden changes in solar irradiation from 500 to 1000 W/m^2 of PV module 1 (PD1) and PV module 2 (PD2) at 400 W/m^2. In this analysis, the two techniques are able to extract the MPP. Higher power extracted from ANFIS algorithm compared to ANN also gives a fast steady state response with less oscillation.

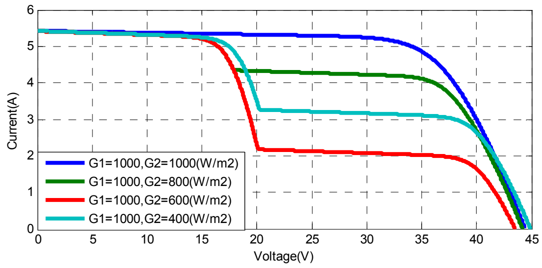

Fig. 7. I-V Curve at 25°C

Table 2. Dynamic response of shaded irradiation pattern

Pattern	Irradiation G1 (W/m2) (from t=0s to t=200s)	Irradiation G2(W/m2) (from t=200s to t=400s)	Cell Temperature T(°C)
PD1	500	1000	25
PD2	400	400	25

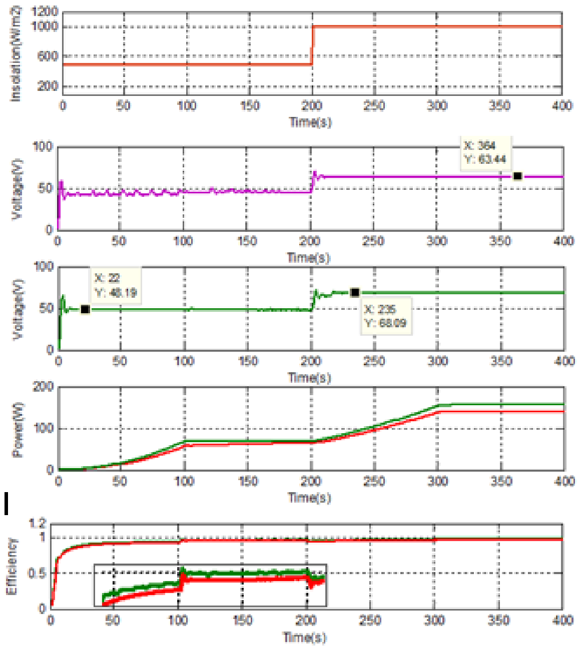

Fig. 8. Dynamic response change in irradiation

6.2 Effect of Partially Shaded Solar Irradiation

In order to verify the performances of the ANN and ANFIS algorithm, the ISSBC-CHBMLI configuration and connected to an RL load (R=100 ohm and L=20mH). The ISSB Converter is controlled by MPPT algorithms and the CHBML inverter controlled by SHE PWM technique (detailed explained in chapter 5). The simulation carried out insolation configuration of partial shaded condition is PV1 equal to 800 W/m^2 constant (non-shaded), the PV2 initially 50% artificially closed condition (shaded) after 300s interval of time fully opened. The simulated detailed output result ISSBC and CHBMLI tabulated in Table.4. The stepped output voltage and corresponding harmonic spectrum of 7.5 kHz both non-shaded and shaded condition of ANN and ANFIS algorithm shown in Fig.9 (a-b) to Fig.12 (a-b). Observe the simulation result more DC power extraction, higher AC output voltage with less harmonics in ANFIS controlled algorithm compare to ANN algorithm both non-shaded and partially shaded condition.

Table 3. Dynamic response of simulation

MPPT	Pattern	Simulation time configuration									
		From t =0s to t=200s					From t =200s to t = 400s				
		Vdc	Pdc	MI	Response Time (ms)	Efficiency (%)	Vdc	Pdc	MI	Response Time(ms)	Efficiency (%)
ANN	PD1	25.73	37.98	0.22	15	96.82	44.22	128.91	0.22	13	97.20
	PD2	20.34	24.04	0.21	15	98.52	20.34	26.86	0.21	13	96.69
ANFIS	PD1	27.13	42.71	0.23	12	98.60	47.13	114.32	0.23	10	98.70
	PD2	21.53	26.86	0.22	12	98.70	21.53	24.04	0.23	11	98.71

Table 4. Simulation result of partially shaded and non-shaded connected with inverter

MPPT	Insolation (G1/G2) W/m2 at T= 25°C	ISSBC		CHI		
		PV1 (V)	PV2 (V)	Stepped Voltage (V)	Vrms	THD (%)
ANN	800/800	39.67	39.67	74.47	39.25	23.87
	800/400	39.67	20.42	55.65	44.68	43.06
ANFIS	800/800	42.03	42.30	74.70	51.50	20.15
	800/400	42.30	21.52	56.39	39.78	40.04

7. Experimental validation

The experimental set up of the proposed system is shown as in Fig.13. The both ISSB converter and CHBML inverter, consists of IRF840 MOSFETs four for converter and eight for inverter through proper optical isolation using MCT2E opto coupler ICs, program is then downloaded, into the memory of ARM processor LPC 2148, using the Phillips flash tool, 16F877A microcontroller, serial port MA232, digital oscilloscope, rheostat is used as DC resistive load for dynamic response and RL load (R=100 ohm and L=20mH) AC load for partially shaded experimental validation.

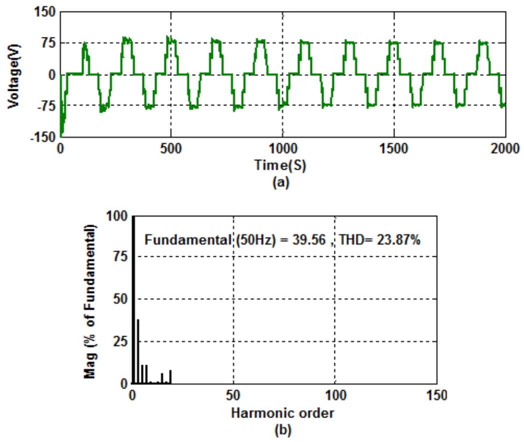

Fig.9.Simulation results for ANN MPPT under balanced condition (a) output voltage (b) voltage harmonic spectrum

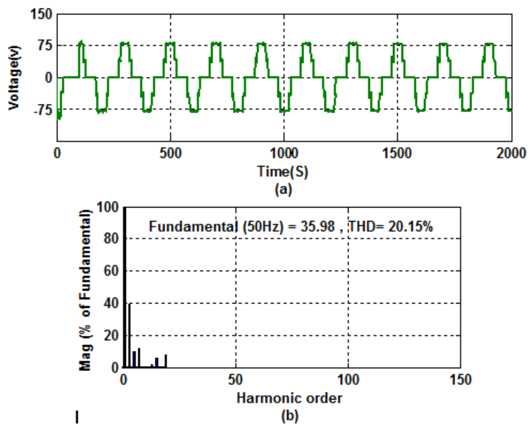

Fig.10 Simulation results for ANFIS MPPT under balanced condition (a) output voltage (b) voltage harmonic spectrum

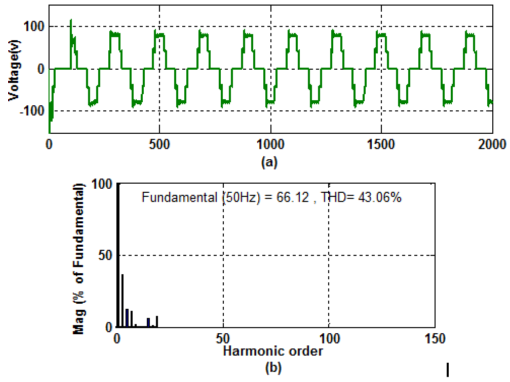

Fig.11.Simulation results for ANN MPPT under unbalanced condition (a) output voltage (b) voltage harmonic spectrum

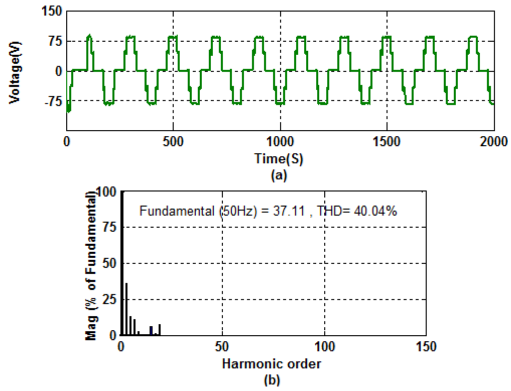

Fig.12.Simulation results for ANFIS MPPT under unbalanced condition (a) output voltage (b) voltage harmonic spectrum

Table 5. Non-shaded and shaded pattern for experimental condition

Pattern	Insulation G1 (W/m2)	Insulation G2 (W/m2)	Cell Temperature (°C)
D1	804	804	37
D2	804	400	37

Table 6. Comparative analysis of experimental condition

MPPT	Pattern	Converter				Inverter (DSO output)	
		PV1 (V)	PV2 (V)	Total (W)	Efficiency (%)	Stepped voltage (V)	Vrms (V)
ANN	D1	41.48	37.95	175.1	0.97	72.70	49.50
	D2	39.97	18.32	95.98	0.969	54.39	36.78
ANFIS	D1	41.03	38.39	177.7	0.98	73.10	49.87
	D2	39.56	18.99	98.64	0.98	55.78	37.29

The validation partially shaded experimental condition both ANN and ANFIS algorithm. The experimental pattern as shown in Table 5, which insolation pattern D1 both PV module G1 = 804W/m^2(non-shaded), pattern D2 shaded test condition G2 = 804 W/m^2 changed after 300s from fully illuminated to 45%-50% suddenly closed condition. During experimental, the PV module in partially shaded response detailed result as shown in the Table 6. Obtained experimental measurements take through DSO (MAKE UNI-T) parameters of the non-shaded and shaded voltage and corresponding harmonic spectrums shown in Fig.14.

Fig.13. Experimental arrangements

Hence, in both non-shaded and partially shaded operation modes, ANFIS algorithm improves the voltage quality, power extraction, harmonics elimination as compared to the ANN algorithm.

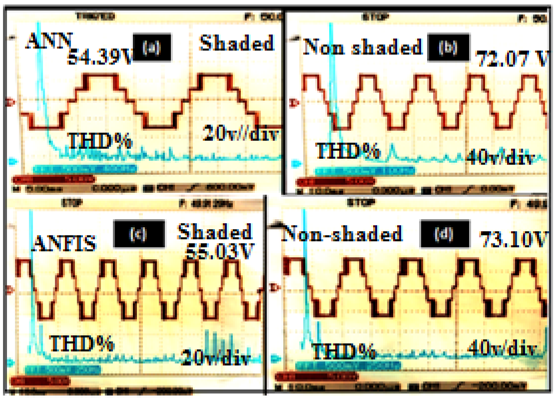

Fig.14.Experimental result for (a) shaded ANN output voltage and harmonic spectrum (b) Non-shaded ANN voltage harmonic spectrum (c) shaded ANFIS out voltage and harmonic spectrum (d) non-shaded ANN out voltage and harmonic spectrum

8. Conclusion

This paper analyzes the performance of ANN and ANFIS MPPT algorithms by stand-alone PV system. The configuration for the proposed system is designed and simulated using MATLAB/Simulink and implemented in 16F877A microcontroller platform. The proposed system shows a good dynamic performance, algorithm to track the MPP of the PV units even under the rapid change in irradiation cell temperature and partial shaded condition. ANFIS can provide the overall efficiency higher than ANN algorithms. The CHBMLI integrate with SHE ANN modulation technique improved output voltage quality and reduction in THD percentage even in partially shaded of PV modules with the ANFIS based MPPT algorithm.

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