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S. Senthamizh Selvan

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S. Senthamizh Selvan

Electrical and Electronics Engineering Department,
National Institute of Technology Puducherry,
Karaikal, India
Email: senthamizhselvan@live.com

Abstract: In the mechanised world, carbon-less emission of energy production is vitalised. Despite varied renewable energy sources available, solar PV seems to be an optimum choice due to its ease of installation and maintenance. Though conventional algorithm exists for extracting maximum power, non-conventional algorithm by soft computing is foreseen for high stability during a sudden change in irradiation and load transients. In this article, artificial neural network-based maximum power point tracking is focused. A comparative analysis is carried out between single layer neural network and multi-layer neural network for varied parameters. The multi-layer neural network is found to be advantageous in the case of neuron's requirement, implementation complexity and testing MSE. Hence, the trained neural model is implemented in PV-grid fed DTC-IM drive system with various operating conditions. Simulation results are found to satisfactory. Added energy management condition is also validated for various irradiations.

Keywords: artificial neural network; ANN; single layer feed forward; multi-layer feed forward neural network; maximum power point tracking.

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Biographical notes: S. Senthamizh Selvan is a researcher in the National Institute of Technology Puducherry, India. His researches include solar fed drives and neural network-based MPPT controller.

1 Introduction

In recent times, direct torque controlled (DTC) induction motor drive is popularly used in the industries for high performance variable speed control applications. In the contemporary era of modernisation, carbon emissions have been on rising trends due to the power production stations such as thermal plants and other smaller units. Added carbon emission is also infused due to the vehicular operation. Hence, to annihilate the carbon emission alternative mode of energy productions is being contemplated. Despite many renewable resources available, taping of solar power resources will be of optimum choice as it has inherent advantages like quick installation, hassle free maintenance on comparison with the remaining's. The potential of solar energy is exploited, and input to the drive is from grid and also from solar PV panel. Extracting maximum power from the solar PV will be the utmost task done by conventional algorithms like perturb and observe (P&O) and incremental conductance (InC). The performance and stability of the controller characteristics depend upon the system through which the power is fed (Singh et al., 2015). The maximum power point tracking (MPPT) comparison of P&O and InC for a grid connected system is carried out and various parameters such as switching stress and losses are studied. It is concluded that InC finds suitable for the grid connected system (Sweidan et al., 2019). The PV-grid connected system is tested under faulty conditions of grid and performances were studied. It is concluded that the controller can able to track the maximum power from the PV (Adhikar et al., 2015; Sharma et al., 2016). Discuss the standalone PV feeding the load such as solar rechargeable lanterns, linear and nonlinear loads. The above system elucidates the performance of the conventional controllers such as P&O and InC. It is evident that there are notable behavioural changes in the controller for varied load's such as linear, nonlinear and high transient ones.

Though conventional algorithm exists, there are few disadvantages like high settling time and controller instability due to sudden change in irradiation and load dependence. Thereby soft computing methodology of MPPT is opted out wherein which artificial neural network (ANN) is attempted. Based on ANN, there has been various kind of work carried out in literature.

In Anuradha and Kumar (2015) and Allahabadi et al. (2019), the MPPT is based on sensing the V_{OC} (PV open circuit voltage) which is input to ANN. The trained ANN will predict the V_{MPP} (voltage at maximum power point – MPP) by sensing the V_{OC}. The PI controller will get V_{MPP} as the reference and tracks towards the maximum power. The system will get to vicinity of MPP and after that a hill climbing algorithm is called in (Yaichi et al., 2014; Deniz, 2017). Solar fed drive system-based MPPT is proposed. The drive system is operated by FOC control with the reference speed and load torque values generated from the predicted power by ANN corresponding to the irradiation (G) and temperature (T) (Anuradha and Kumar, 2015; Abdourraziq and Ouassaid, 2016). The MPP is achieved by implementing a fuzzy logic controller. The system alters the step size of duty cycle based on the parameters of irradiation level and I_{PV} (Choudhury and Rout, 2019; Pachauri and Chauhan, 2018). The maximum power is extracted by the power and the change in the power which is being fed into the fuzzy system (Elobaid et al., 2012). A novel methodology of detecting the V_{MPP} by sensing V_{PV} and I_{PV} thereby by predicting the G and T. This predicted G and T are used to predict the V_{MPP}. Due to cascaded NN, the number of training set can be reduced considerably (Sarita et al., 2020). The MPPT is implemented by G and T as the input and V_{MPP} as the output. Thereby by tracking of maximum power is achieved. This is implemented on to the energy management system of PV, wind and V2G vice versa (Zhang et al., 2019). A modified algorithm of perturb and absorb on conjunction with the ANN is implemented. The input and output for ANN is V_{PV}, I_{PV}, G and V_{MPP}, respectively. This holds good for partially shaded conditions also (El-Helw et al., 2017; Chen and Wang, 2019). V_{MPP} is predicted from the G, thereby the duty cycle is calculated from the ratio of V_{PV} to output voltage of converter. MPPT is achieved by a single sensor (Bouakkaz et al., 2020). Parameters such as G and T are taken as input and V_{MPP} as the output of ANN (Mokhlis et al., 2020). The ANN-based integral sliding mode control which has fast tracking time, robustness and quick response to sudden change in irradiations when compared to conventional PI controller (Verma et al., 2020; Berrezzek et al., 2020). The ANN is trained for the variables to give the direct % duty cycle. The system is trained while running the P&O algorithm. The results are being compared with the particle swarm optimisation (PSO) algorithm. PI controller is eliminated (Heelan and Al-Qrimli, 2020). A conjunction of both neural network and the fuzzy logics control is made for MPPT. The system tracks the V_{MPP} voltage by fuzzy logic rather than that of the PI controller, which will ensure the faster tracking of the system under sudden irradiation deflections (Awadallah, 2016). PSO, genetic algorithm (GA) and simulated annealing (SA) types of optimisation is being indulged for the MPPT, thereby both partial shading and uniform shading conditions also met (Roy et al., 2020). The ANN-based system by taking into the consideration of T along with V_{PV} and I_{PV} and V_{MPP} is generated which is further tracked by PI controller (Babaie et al., 2020). A single ANN controller is used to control three individual boost converter of individual panel. The input is being the G, T and three pairs of V_{PV} and I_{PV}. The output is being the three % duty cycle (Bouselham et al., 2017; Rizzo and Scelba, 2015). The ANN generates % duty cycle as output for the input parameters such as V_{PV}, I_{PV}, P_{PV} (PV power) and change in P_{PV}. Thereby, generating the V_{MPP} and power at MPP (P_{MPP}) tracking the corresponding value (Behera and Saikia, 2020). The V_{MPP} is predicted by extreme learning machine variable steepest gradient ascent (ELMVSGA). The inputs are V_{PV}, I_{PV}, G and T. The output V_{MPP} is tracked by the optimisation-based PI-FOI controller. This suits well for both uniform and partial shading (Çelik and Teke, 2017). A novel fine tuning loop along with the P&O algorithm is implemented. Thereby, a V_{MPP} generated by ANN is being set reference to P&O loop. A fluctuation-less output is obtained with faster response by this modified method (Messalti et al., 2017). A novel methodology of generating an unit step increment or decrement in the %duty cycle by ANN is done with the input of VPV and IPV. By this, the system can operate hassle free, quick response and accurate one towards the MPP (Chandra et al., 2020). The ANN input is taken as I_{PV}, G and T. The output of ANN is being % duty cycle. The system is fed to the solar water pump. Hence by this modification, partial shading of solar PV fed drive is being discussed. The system settles faster by giving a quick response time.

From the literature survey, different types of ANN-based MPPT and its varied topologies can be observed. In general, parameters such as V_{PV}, I_{PV}, G and T and its different combinations are taken as input to ANN. V_{MPP} is taken as the output for most cases. % duty cycle and P_{MPP} is opted secondary to V_{MPP}. Different topologies have pros and cons like opting V_{MPP} needs a PI controller to track the ANN output whereas in case of % duty cycle as output, the PI controller can be eliminated and also the system becomes compact. Almost all the literature, authors' has implemented MPPT via single layer neural network (SLNN). Exceptionally Messalti et al. (2017) and Berrezzek et al. (2020) have implemented multi-layer NN for MPPT. Berrezzek et al. (2020) utilises G and T parameters which were found to be expensive on the basis of sensor cost.

In this paper, maximum power is tracking using ANN is attempted. The ANN is trained for the set of values with the inputs such as solar PV voltage (V_{PV}) and solar PV current (I_{PV}). The target is fixed to be % duty cycle with the error tolerance limit of 10^{-06}. The ANN is trained, tested and the suitable network is generated via Simulink. The obtained ANN *cum* MPPT is implemented in PV-grid tied DTC-induction machine (IM) drive system.

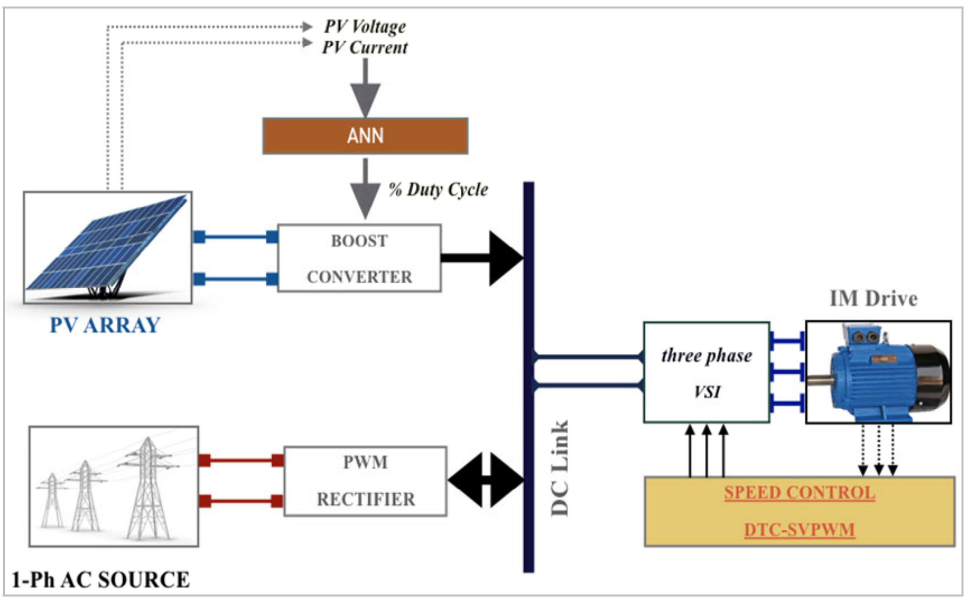
Novel contribution in this article:

- Multi-layer neural network (MLNN) is opted for MPPT. It reduces the number of neurons compared to SLNN and provides the required accuracy.
- Electrical parameters like V_{PV} and I_{PV} are taken as an input to ANN which in-turns predict the % duty cycle. Rather, G as one of the inputs is avoided. Irradiation sensor is avoided by which system cost is reduced.

2 Proposed solar-grid tied DTC-IM drive system

Solar PV with grid tied system feeding DTC-IM drive has been taken for the study. Figure 1 gives the overall architecture of proposed system which is designed on the imitation of real time scenario.

Figure 1 Proposed solar PV-grid tied DTC-IM drive (see online version for colours)



The DTC-IM drive is energised with two sources namely solar PV and grid. Two sources are connected to a common DC link that supplies the required power to IM drive. Power is extracted from the PV via a conventional boost converter using an MPPT algorithm. On the other hand, the grid supply is managed using a pulse width modulation (PWM) rectifier which possesses many advantages such as bidirectional power flow, maintaining the power factor to near unity and reduction in % total harmonic distortion (THD) level of grid supply. Grid supply also takes care of maintaining of DC link voltage around 600 V.

Since the power generated from the PV depends upon the G and T, there are occasions where the generated power may exceed or insufficient against the drive demand. Therefore, a reliable system is developed by which the excess of power in PV is pumped into grid and also power is obtained from the grid in case of PV power is insufficient to meet out the drive demand. During all the operations, the DC link voltage is maintained constant. The maximum power from the solar panel is extracted using ANN controller.

3 ANN-based MPPT controller

ANN evolves on the basis of biological neurons structure. As in the case of biological neurons that has dendrites and synapsis, the ANN has activation functions, weights and bias. Adjustment of the weights and bias with proper activation function makes the neurons to train better and meet out the required outputs.

Activation function which is being utilised is *tan-sigmoidal* function [equation (1)], with the training algorithm of *Levenberg Marquett*. Output function is *pureln* (*pure linear function*).

$$y(k) = \frac{2}{1 - e^{2n}} - 1 \tag{1}$$

Variables such as V_{PV} and I_{PV} are taken as the input and % duty cycle as the target for training the ANN. A set of 810 data is considered for the training. This 810 set of data's is mined from the irradiation level of 1,000 to 200 in steps of 100. For the testing purposes 300 set of data from the irradiation level of 950 to 350 in steps of 100 is obtained. Since ANN work better over the data range of –1 to +1, the raw data is normalised and fed into the system. Equation (2) gives the mathematical relation to normalise the raw datasets.

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}} + \left(X_{max\,new} - X_{min\,new}\right) + X_{min\,new} \tag{2}$$

where

X is the absolute value

X_{min} is the minimum value of unnormalised dataset

X_{max} is the maximum value of unnormalised dataset

X_{minnew} is the minimum value of normalised dataset

X_{maxnew} is the maximum value of normalised dataset.

SLNN is the simplest form of neural architecture shown in Figure 2. In SLNN, the neurons are added one by one in single hidden layer. SLNN is implemented as the initial architecture for the error tolerance of 10^{-06}. The aforementioned error tolerance is met by adding 150 neuron in the hidden layers. Figure 3 gives the training performance of SLNN where the error reached is $9.9992e^{-07}$ at 8,753 epochs.

Figure 4(a) gives the target value and the SLNN predicted value. Figure 4(b) shows error difference between the SLNN and the actual target value. The mean squared error (MSE) of testing data using SLNN is found to be 213.922.

Figure 2 Architecture of single layer feed forward network

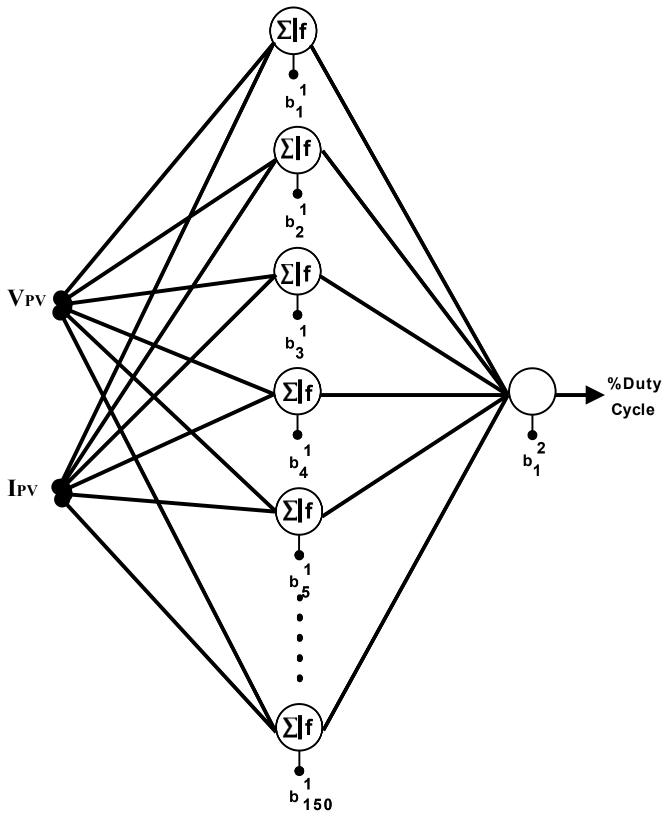


Figure 3 Training performance of SLNN (see online version for colours)

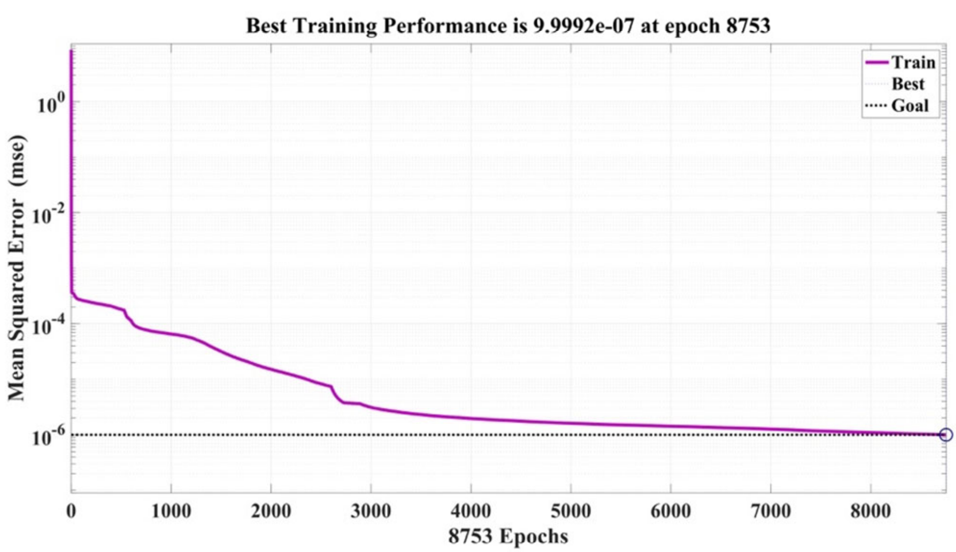
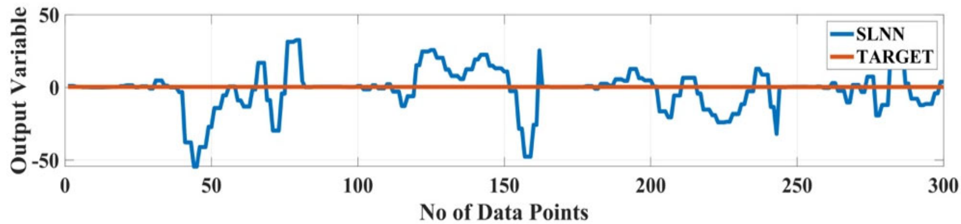
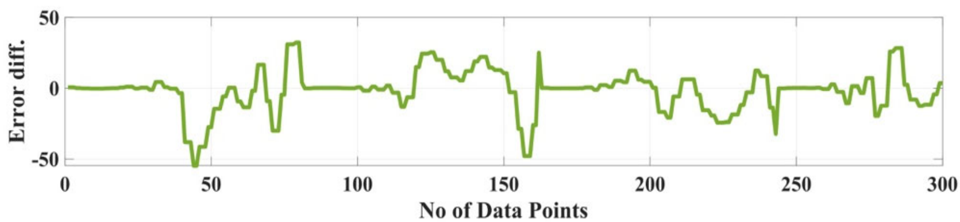


Figure 4 Testing plot of SLNN (see online version for colours)

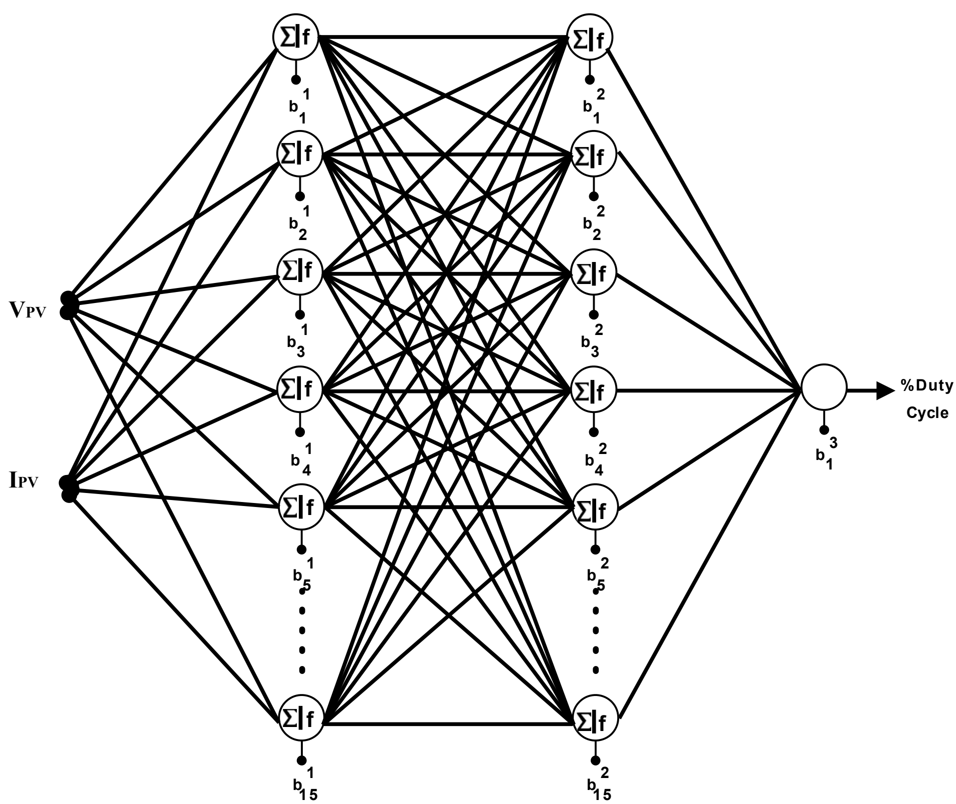


(a)



(b)

Figure 5 Architecture of multi-layer feed forward network



Multi-layer neural network (MLNN) is an advanced architectural scheme compared to SLNN (Venkadesan et al., 2016, 2012). The MLNN is also trained for the same target accuracy of 10^{-06}. Two hidden layers are considered for study. The equal number of neurons is kept in both the hidden layers. The nonlinear mapping capability is better in multi-layer architecture than single layer architecture thereby better results can be obtained as shown in Figure 5. From Figure 6, it is concluded that the two layers of 15 neurons each could able to meet the require error tolerance. Best training performance of $9.1061e^{-07}$ is obtained at 494th epoch.

Figure 6 Training performance of MLNN (see online version for colours)

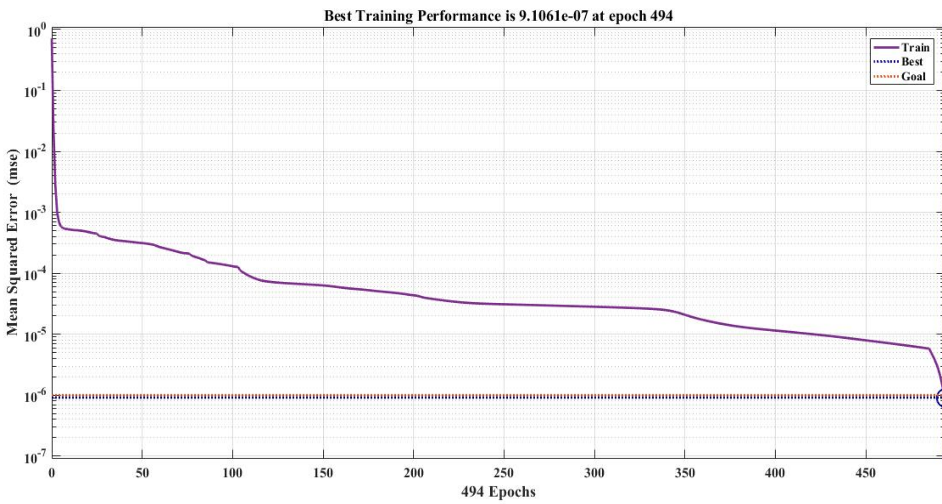
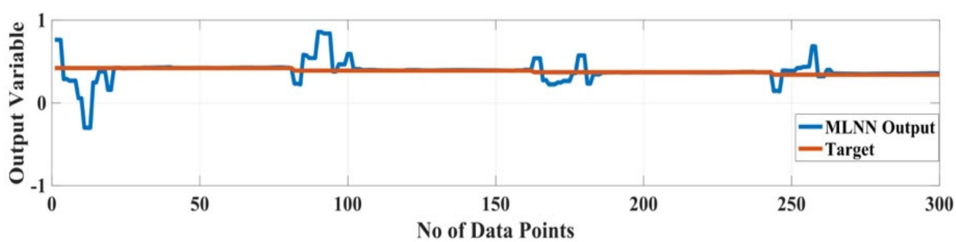
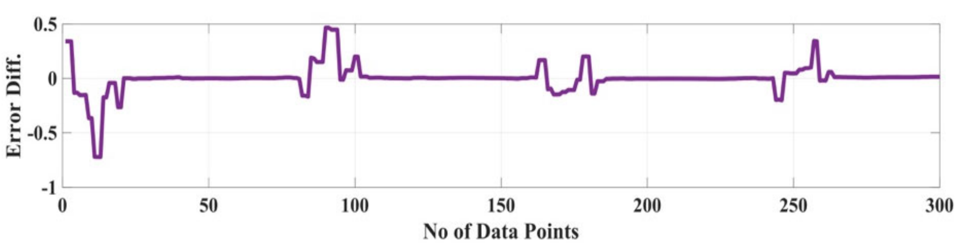


Figure 7 Testing plot of MLNN (see online version for colours)



(a)



(b)

The MLNN network is subjected for testing with the same testing and target data's used in SLNN. Figure 7(a) gives the predicted output as well as the actual target values. Figure 7(b) gives the error difference value between MLNN and the actual target value. The MSE of testing data using MLNN is found to be 0.01549.

The mean square error of MLNN is found to be 0.01549 which is much lesser when compared to SLNN which is 213.922. Table 1 shows the comparative analysis between SLNN and MLNN for various parameters. It is observed that the MLNN with 30 neurons can able to achieve the required target error tolerance but SLNN takes 150 neurons to meet the required error tolerance. It is also seen that number of additions, products and activation functions is more in the SLNN. Hence, MLNN-based MPPT controller is compact and found to provide the required accuracy and suitable to track MPPT. As it results in compact controller, it provides faster computation in real time digital implementation.

Table 1 Comparative analysis of SLNN and MLNN-based MPPT controller

Arch.	*Target*	*Testing MSE*	*Hidden layer*	*No. of neurons*	*No. of addition's*	*No. of product's*	*No. of tansig*
SLNN	Met	213.922	1	150	450	450	150
MLNN	Met	0.01549	2	30	270	270	30

4 Simulation results and discussion

The MLNN is identified to be the suitable architecture for MPPT tracking. The performance of MLNN-based MPPT controller is studied under various irradiance conditions and energy management in the drive is also studied.

4.1 Performance of ANN-based MPPT controller under various irradiance conditions

The ANN-based MPPT is implemented in the proposed system shown in Figure 1. MLNN is implemented in the proposed system and results are tabulated and observed for forthcoming operating conditions.

The ANN-based system in implemented in MATLAB/Simulink environment. Since temperature does not have much impact on the PV characteristics, it is always considered to be constant at 25°C. The system is made to ply on operating conditions show in Table 2.

Table 2 Operating conditions of the proposed system

Operating condition	*Irradiation change type*	*Values*
I	Step	900 to 500 W/m^2
II	Practical	200 to 1,000 W/m^2

Note: In all the operating condition, the drive is kept at its rated conditions of speed at 148 rad/sec and load torque at 7.5 Nm.

4.1.1 Operating condition 1: irradiation changes: step 900 to 500 W/m^2

Figure 8 plots the level of irradiation fed into the system. Irradiation of 900 W/m^2 is subjected for 0 to 1 sec and a step change made from 900 W/m^2 to 500 W/m^2 for 1 to 2 sec. This step change in irradiation is similar to that of the sudden change in irradiation in real time scenario. Figure 9 shows the plot of power characteristics for the irradiation change from 900 to 500 W/m^2. The ANN-based MPPT can able to track the maximum power of 1,654 Watts and 942 Watts respectively for the corresponding irradiation of 900 and 500 W/m^2. The difference of 0 Watts and 1.9 Watts deviation from the theoretical value is observed.

Figure 8 Irradiation plot for step change 900 to 500 W/m^2 (see online version for colours)

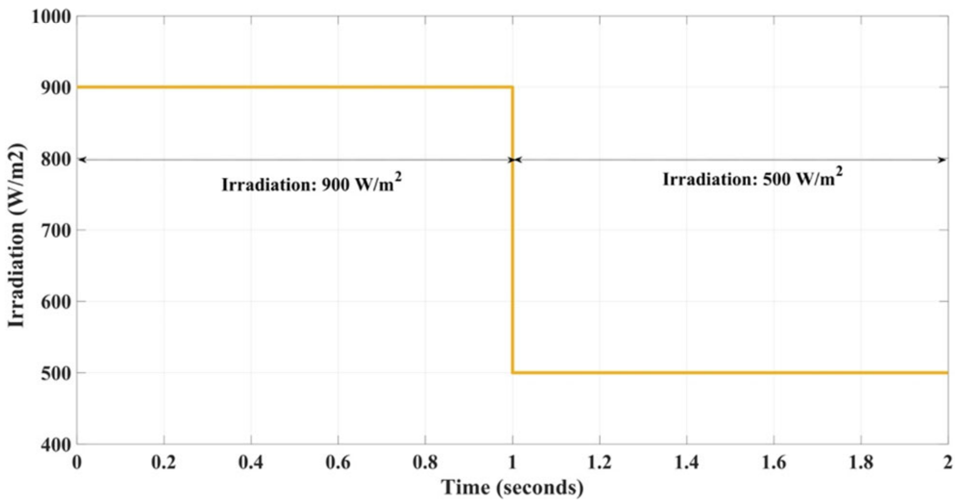


Figure 9 Power plot for Irradiation change 900 to 500 W/m^2 (see online version for colours)

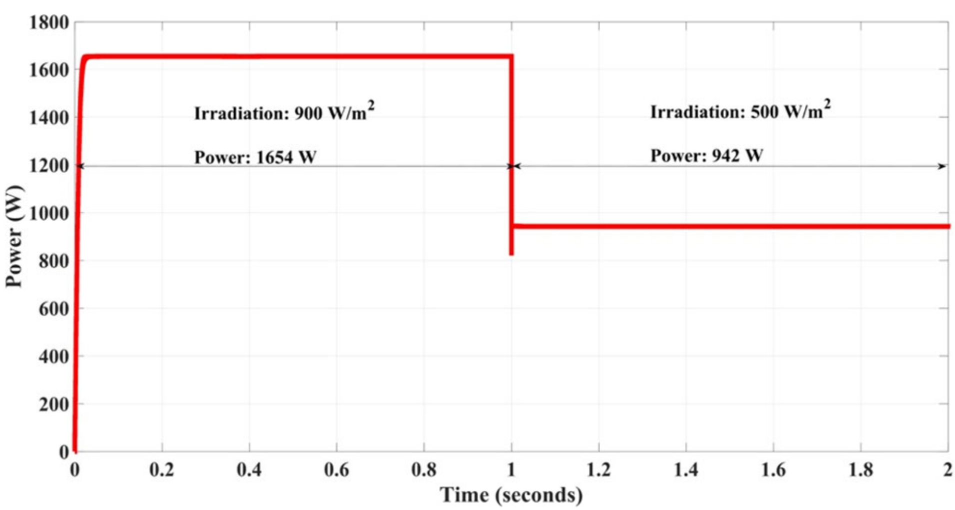


Figure 10 gives the % duty cycle plot, i.e., the MLNN output from 40.7% to 29.08%. It is evident that the ANN can able to respond faster to the sudden change in irradiation level. Figure 11(a) shows the change in V_{PV} for the change in irradiation. As the irradiation changes the V_{MPP} too changes proportionally.

Figure 10 % duty cycle plot for 900 to 500 W/m² (see online version for colours)

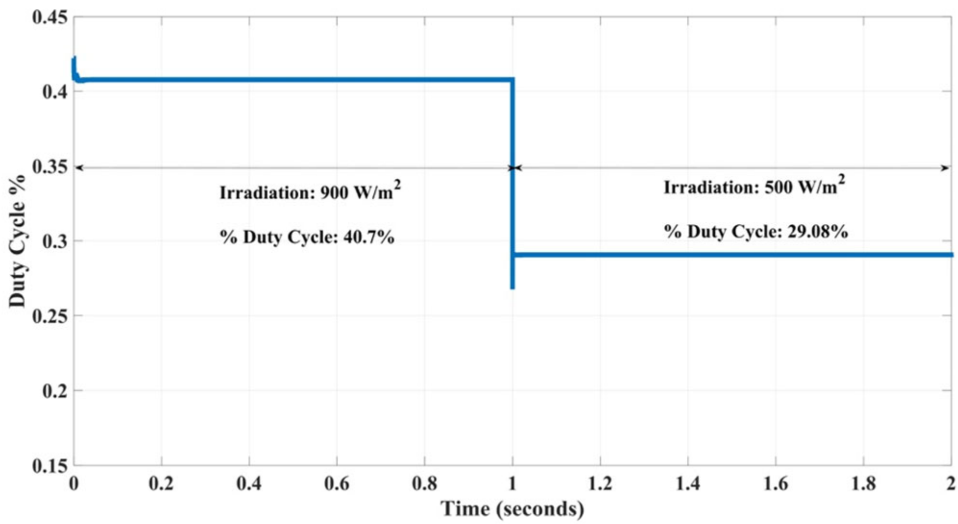
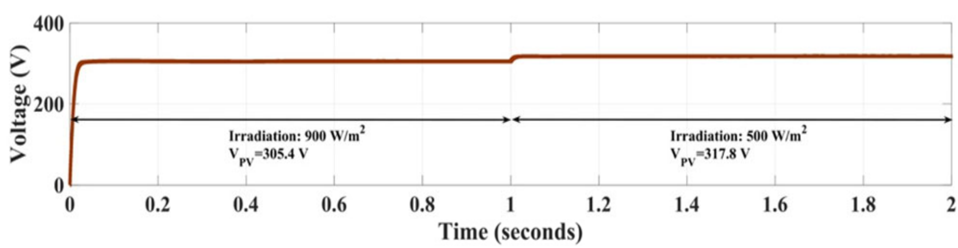
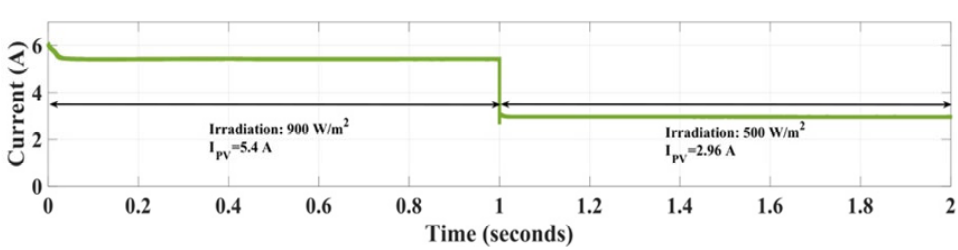


Figure 11 (a) V_{PV} and (b) I_{PV} plot for irradiation change – 900 to 500 W/m² (see online version for colours)



(a)



(b)

Figure 14 gives the plot of grid voltage and grid current. For the irradiation level of 900 W/m², the maximum power generated is 1,654 Watts which is excess against the drive demand of 1,364 Watts. Hence, the remaining power is fed into the grid and it is signified by negative power factor. For 500 W/m², the generated PV power is insufficient to meet-out the drive demand and hence the grid supplies the sufficient power thereby making the power factor positive. Hence by virtue, it can be seen that the grid tied system gives more reliability and stable functionality for drive operation.

Figure 12 Speed characteristics of DTC-IM drive (see online version for colours)

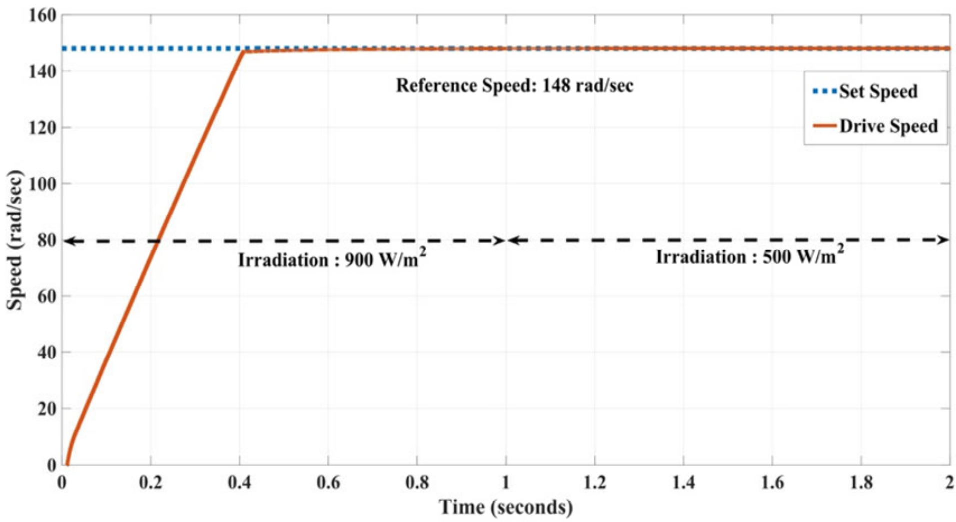
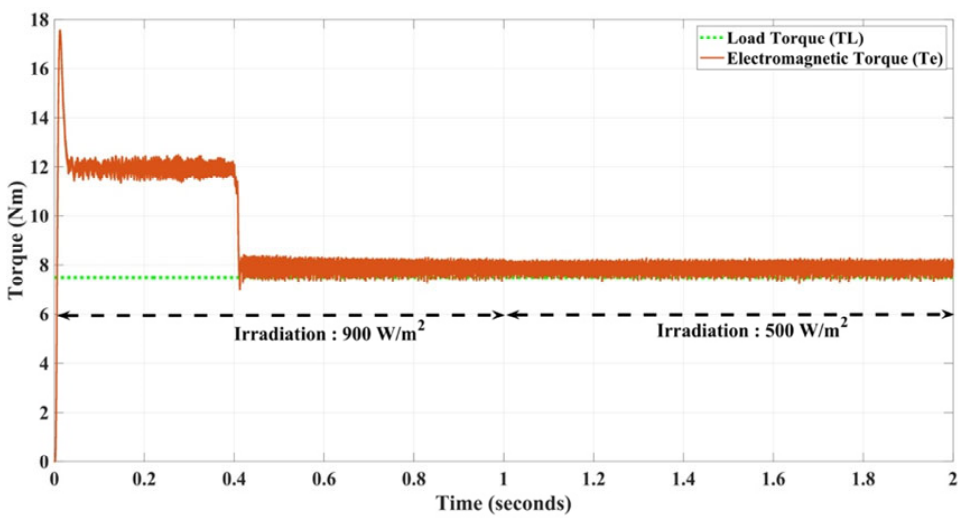


Figure 13 Torque characteristics of DTC-IM drive (see online version for colours)



It should be ensured in the system that for various changes in irradiation or load demand the DC link voltage feeding the drive should be closer to 600 V. This DC link voltage is maintained by PWM rectifier as stated above. Figure 15 gives the DC link voltage near to

600 V which is almost maintained constant irrespective of irradiation change with a miniscule level of dip during transients.

Figure 14 Voltage and current characteristics of single phase grid (see online version for colours)

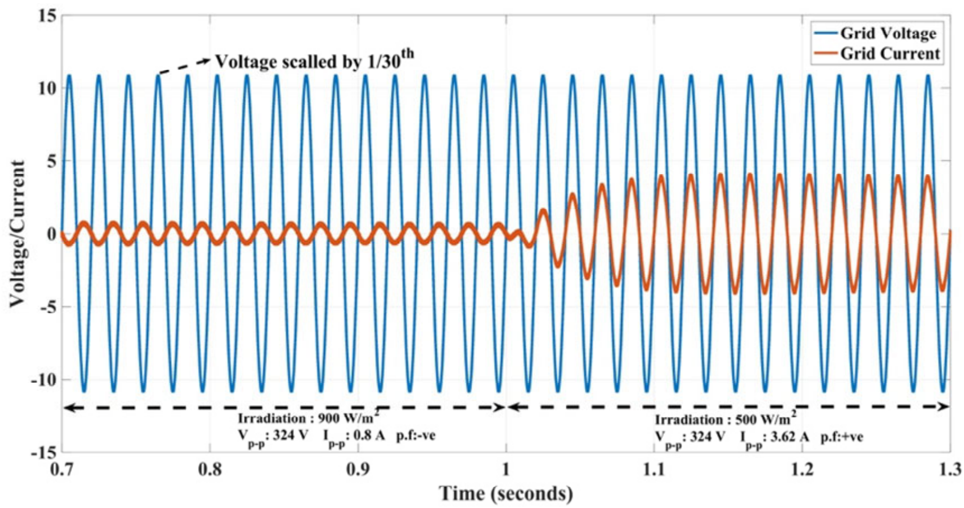
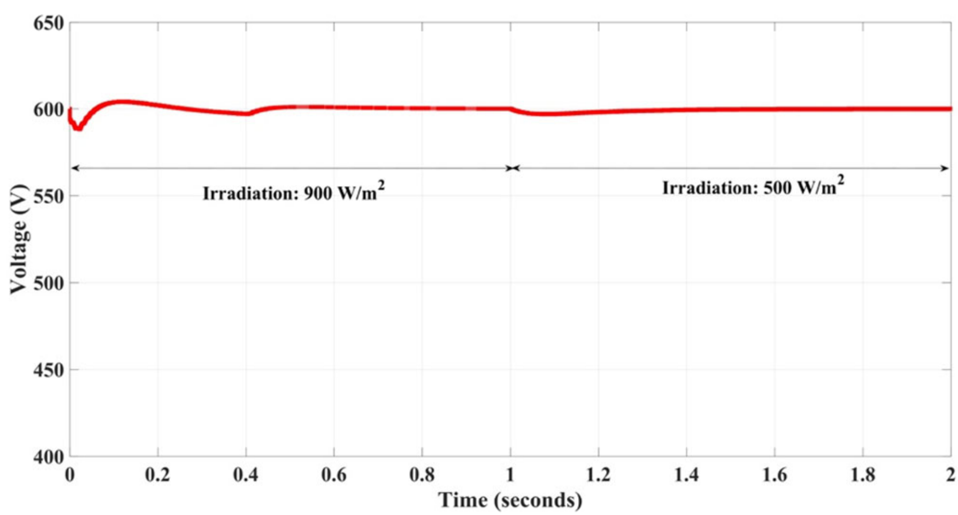


Figure 15 DC link voltage plot for step change in G (see online version for colours)



4.1.2 *Operating condition 2: practical irradiation change 200 to 1,000 W/m^2*

In this operating condition, the system is subjected to continuous variation in irradiation. This can be witnessed in the real-time scenario of PV panel affixed over a dynamic system such as solar vehicle, aircraft and miscellaneous mobile applications. Hence, the system has to track the MPP continuously and also to quickly respond for variation change. The signal is generated under normal distribution using the MATLAB command with mu as 4 and sigma as 1.5. The system is set for the minimum irradiation level of 200 and maximum level of 1,000 W/m^2. Figure 16 gives the irradiation curve for the PV panel. This plot almost dictates the real-time scenario which could able observe the response of the ANN. Figure 17 gives the corresponding power characteristics to the irradiation change and MLNN-based MPPT could able to track the MPP with almost a smooth variation. Figure 18 gives the plot of the ANN output (% duty cycle), i.e., the response of the system when subjected to irradiation changes.

Figure 16 Input irradiation characteristics for solar PV (see online version for colours)

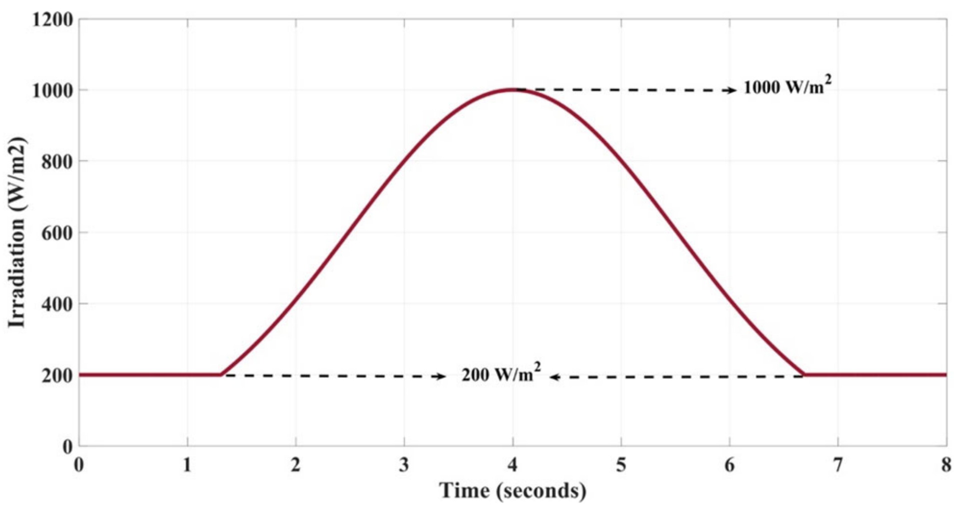
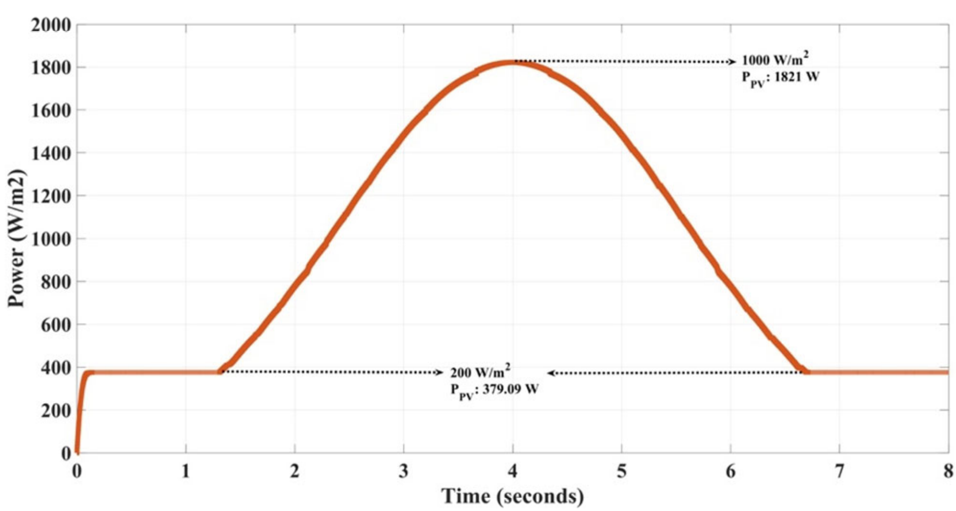


Figure 17 Power characteristics response (see online version for colours)



Figures 19(a) and 19(b) give the characteristics plot of V_{PV} and I_{PV} for the change in irradiation. For the practical test signal also the MLNN-based MPPT controller can able to track the MPP.

Figure 18 % duty cycle characteristics (see online version for colours)

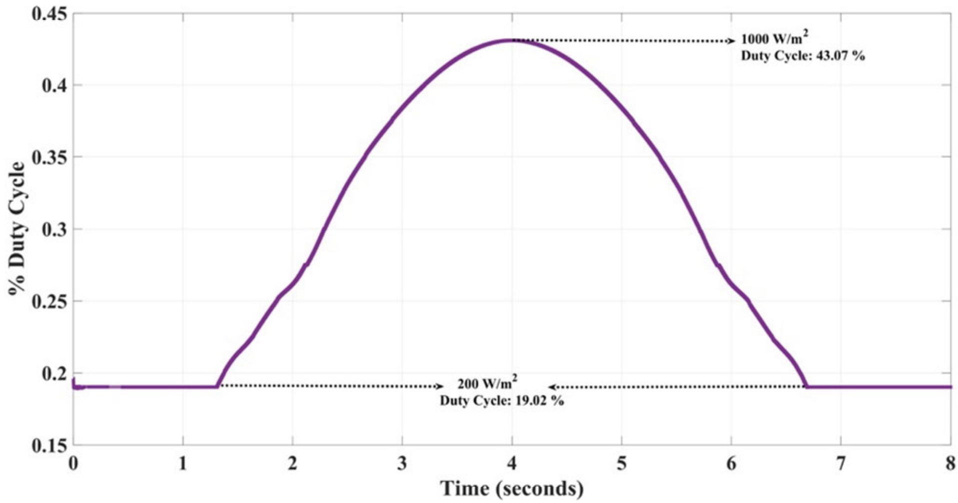
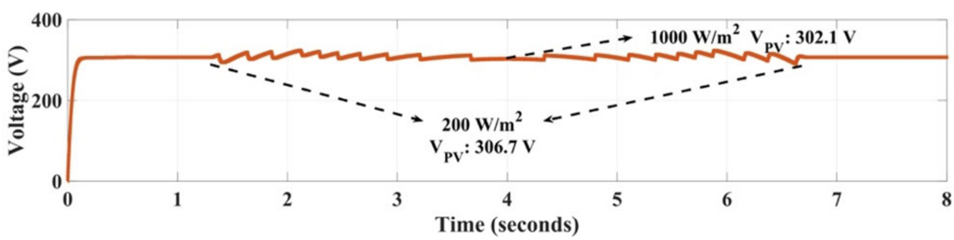
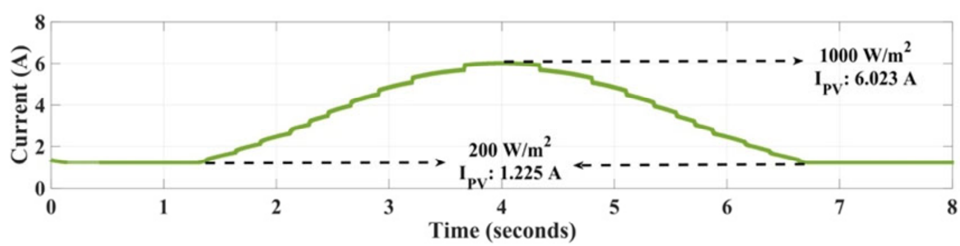


Figure 19 (a) V_{PV} and (b) I_{PV} plot for Irradiation change 200 to 1,000 W/m^2 (see online version for colours)



(a)



(b)

Figure 20 shows the variation of DC link voltage during the practical irradiation condition. It can be inferred that the 600 V is almost maintained constant with little fluctuations.

ANN-based MPPT is implemented in the PV-grid tied system feeding DTC-IM drive. The system is subject to various irradiation level and observation are made over the power generated and power balance among source's and load.

Figure 20 DC link voltage plot for practical change in Irr (see online version for colours)

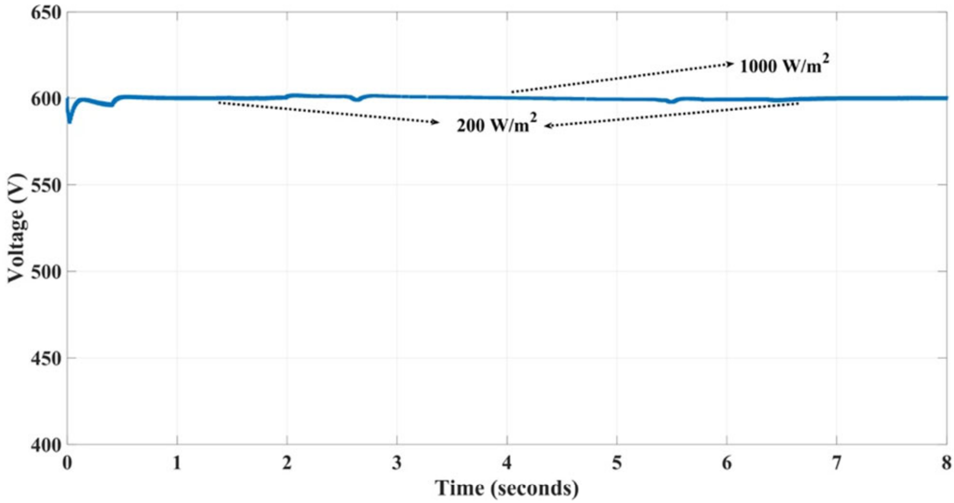


Table 3 deals with the MPPT by ANN controller. The system is subjected to various irradiation level of 1,000 to 400 W/m^2. The results are tabulated and it is observed that maximum % error of 0.35 and the minimum % error is of 0. The average error value is found to be 0.12%.

Table 3 MPPT using ANN

Irradiation W/m^2	*Power (Watts)*		*Error (%)*
	Actual power	*Power (ANN)*	
1,000	1,821	1,821	0.00
950	1,738	1,735	0.17
900	1,654	1,654	0.00
850	1,566	1,566	0.00
800	1,482	1,480	0.13
750	1,394	1,394	0.00
700	1307	1,306	0.08
650	1,217	1,217	0.00
600	1,127	1,123	0.35
550	1,036	1,035	0.10
500	944	942.1	0.20
450	844	839.8	0.50
400	758	758	0.00

4.2 Energy management

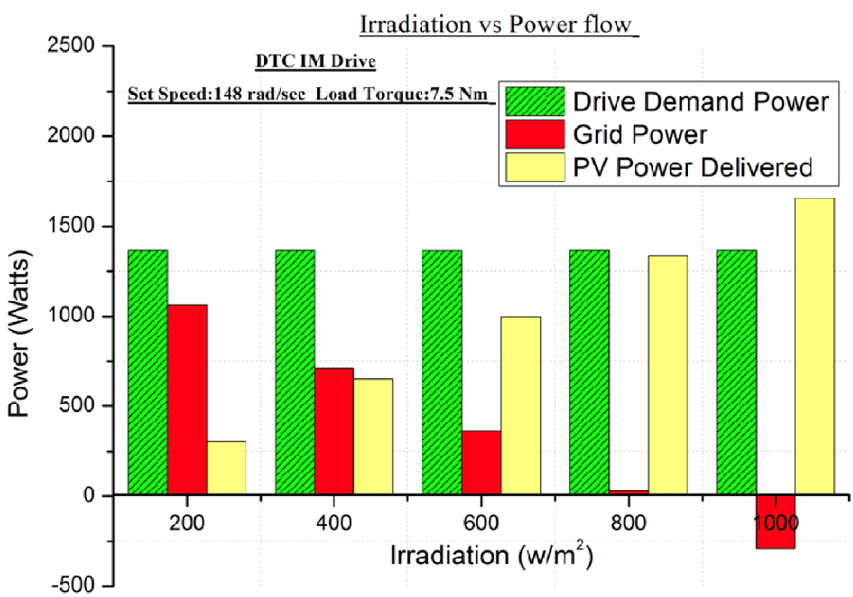
Table 4 details the power sharing between the PV and grid on balancing the drive demand. Whenever the generated PV power is high against the load demand, the excess is sent back to the grid. For irradiation 1,000 and 900 W/m^2, the PV power is more than sufficient to meet out the drive demand and hence the excess of power is pumped into the grid which is empirically denoted by –ve sign on grid power. On the other hand, for the irradiation level less than 900 W/m^2, the power generated is insufficient to meet out the drive load demand. This remaining power is shared by the grid which is denoted by +ve.

Table 4 Overall energy flow for various irradiation

Irradiation W/m²	*PV power (Watts)*	*Grid power (Watts)*	*Drive demand (Watts)*
1,000	1,654	–280	1,364
900	1,499	–134	1,364
800	1,311	+52	1,364
700	1,141	+223	1,364
600	961	+402	1,364
500	819	+546	1,364
400	634	+727	1,364

Figure 21 bar chart gives the overall flow of power consumption between the DTC-IM drive, grid and solar PV.

Figure 21 Power changes for various irradiation changes (see online version for colours)



For evaluation in all case, the load demand is always maintained constant irrespective of irradiation change. The power flow balance is given by equation (4)

$$PV_{Power} + Grid_{Power} = IM\_Drive_{Demand\ power}. \tag{4}$$

4.3 *Performance comparison of proposed ANN-based MPPT technique with other ANN-based MPPT techniques*

Table 5 shows the performance and architectural comparisons of various ANN's implemented for MPPT in solar PV system. The proposed system shows the superiority in rapid tracking of MPP with a settling time of 5 microseconds which can be implemented in the system of high dynamics. On comparing the system compactness, Behera and Saikia (2020) have made the ANN system with less number of neuron (five neurons) which is found to be compact than the proposed system of 30 neurons. But the drawback of Behera and Saikia (2020) is the error tolerance is of 0.113 whereas in case of proposed system which is found to be 10^{-06}. Added the settling time of Behera and Saikia (2020) is 13 milliseconds whereas in the proposed system it is found to be 5 microseconds which is far advantageous and rapid tracking. Hence, the proposed is found to compact and efficient in MPPT for all type of dynamics and transient conditions.

Table 5 Comparison of proposed ANN-based MPPT with other ANN-based MPPT

Author	*Architecture*	*Structure*	*No. of hidden neurons*	*Eff. (%)*	*MSE*	*Settling time (ms)*
Deniz (2017)	Feed-forward	Input: G and T (2-19-25-13-1)	57	-	-	100
El-Helw et al. (2017)	Feed-forward	Input: G (1-180-2)	180	-	-	2.5
Behera and Saikia (2020)	Feed-forward	Input: V_{PV}, I_{PV}, G, T (4-5-1)	5	98.83%	0.113	13
Chandra et al. (2020)	Radial basis function	Input: I_{PV}, G, T (3-811-1)	811	95.35%	-	61.2
Proposed	*Feed-forward*	*Input I_{PV}, V_{PV} (2-15-15-1)*	*30*	*99.2%*	*0.01549*	*0.005*

5 Conclusions

Solar fed DTC-IM drive with grid tied is considered for the study. The efficacy of ANN for MPPT is exploited in this paper. It is found that the MLNN shows lesser test MSE with a lesser number of neurons and reduced addition and multiplication computations. The MLNN also produces low testing MSE of 0.01549 when compared to SLNN which has 213.922. The MLNN is identified to provide compact architecture and also provide the required accuracy for MPPT. It is identified to be promising alternative for MPPT. The overall system is subjected to various operating condition such as step and nonlinear changes in irradiations. In all the case, the tracked power is tabulated and compared with the theoretical values. The ANN-based MPPT shows a maximum error % of 0.35 and minimum error % of 0. The average error % amounts to be 0.12. It is evident that the outputs are satisfactory and can be implemented for system with high dynamics in irradiation such as solar vehicles and more electric aircrafts. The energy management is also studied in the proposed system and found that the energy is well balanced in the system.

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Nomenclature

ANN	Artificial neural network
SLNN	Single layer neural network
MLNN	Multi-layer neural network
V_{MPP}	Voltage at maximum power point, V
I_{MPP}	Current at maximum power point, A
P_{MPP}	Power at maximum power point, W
V_{PV}	Solar PV voltage, V
I_{PV}	Solar PV current, A
V_{OC}	Solar PV open circuit voltage, V
I_{SC}	Solar PV short circuit current, A
G	Irradiation, W/m^2
T	Temperature, °C
P&O	Perturb and observe
InC	Incremental conductance
MSE	Mean squared error
PSO	Particle swarm optimisation
GA	Genetic algorithm
SA	Simulated annealing
DTC	Direct torque controlled
IM	Induction machine
THD	Total harmonic distortion
PWM	Pulse width modulation

Appendix

Solar panel

Parameter	*Values*
Maximum power	31.41 W
V_{OC} (V)	13.6 V
V_{MPP} (V)	10.47 V
I_{SC} (A)	3.35 A
I_{MPP} (A)	3 A
No. strings in cell module	36
No. of strings in parallel	2
No. of strings in series	29

DC-DC boost converter

Parameter	*Values*
Inductance (L)	1.76 mH
Capacitance (C)	470 μF
PV capacitor	200 μF
Switching freq.	10 KHz
Maximum input voltage (V)	380 V
Maximum input current (A)	6.8 A

Three phase IM machine parameter

Parameter	*Values*
Stator resistance (Rs)	6.03 ohms
Rotor resistance (Rr)	6.085 ohms
Stator inductance (Ls)	0.5192 H
Rotor inductance (Lr)	0.5192 H
Mutual inductance (M)	0.4893 H
Total inertia (J)	0.011787 kg/m_2
Friction coefficient (B)	0.0027 kgm^2/s
No. of poles	4
Rated power	1.1 KW
Rated voltage	415 V
Rated current	2.77 A
Rated speed	1,415 rpm
Rated torque	7.74 Nm