

Maximum power point tracking in wind energy conversion system using radial basis function based neural network control strategy

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ABSTRACT

In this paper, a neural network tuned controller for maximum power point tracking (MPPT) in wind energy conversion system (WECS) is proposed. This technique utilizes radial basis function based neural networks (RBF-NN) and tracks the MPP using duty cycle control. The WECS is based on permanent magnet synchronous generator (PMSG). The rectifier output voltage and power are measured and fed into an RBF-NN controller. The MPPT algorithm controls the duty cycle of a DC-DC boost converter to extract the maximum power. The output of the boost converter is tied to the grid using a voltage source inverter (VSI). Unlike conventional methods, MPPT using proposed method does not require knowledge of wind turbine power characteristics, thus minimizes the need for various measuring instruments. The method implemented is also compared with other commonly used MPPT techniques like fuzzy logic control (FLC), perturb & observe (P&O), and back-propagation (BP) based NN. The proposed system provides better results as compared with other relevant results available in the literature. The proposed method is implemented using MATLAB/Simulink and then validated in real-time using digital simulation hardware, OPAL-RT 4510.

Introduction

Due to increasing global warming, pollution and fossil fuel exhaustion renewable energy sources are being used increasingly nowadays. Wind power is reliable and quick developing among various renewable energy sources. Wind energy has gained importance as a renewable and green energy resource in the last few years [1]. In a WECS, kinetic energy of the wind is converted to mechanical energy of the rotor, which is then converted to electrical energy through the permanent magnet synchronous generator (PMSG) [2]. The PMSG based WECS is used in this work, as it has multiple advantages like, lower excitation losses, better efficiency, higher power density, better grid support capacity and much lower maintenance cost as compared to other types. PMSG also has the advantage of no field losses and high frequency regulation in addition to smaller blade diameter [3–6].

As the wind speed varies, the power output varies thus it is mandatory to track the maximum power output from a WECS. Wind turbines are mainly of fixed and variable speed type. Variable speed wind turbines have better quality and more control over output power [7–9]. These turbines can be used to track MPP for various wind speeds by varying the rotor speed to keep the power coefficient (C_p) maximum

at all times. Pitch angle control can further be implemented in these wind turbines to achieve maximum power at speeds above rated wind speed. These wind turbines have higher starting torque, more stable and flatter torque curves. They are also more resilient to turbulent wind speeds and give low mechanical stress [10].

Ample research is being carried out to tap the maximum power from wind energy [11]. Some of the more common methods used to implement MPPT are tip-speed ratio (TSR) control, P&O, optimal torque (OT) control and power signal feedback (PSF) methods [12]. In case of TSR control, the rotor speed is adjusted to get the optimum TSR for each wind speed to obtain maximum power. In this control, the wind and the rotor speeds need to be measured, which increases the cost as the anemometers and tachometers required to measure those speeds, are expensive. In P&O method, maximum power is obtained in much iteration, which makes this method ineffective for rapidly varying wind speeds. However, it has an advantage of not requiring the turbine power characteristics or the wind speed knowledge. In PSF method, the knowledge about wind turbine maximum power curves is essential [13–18].

The conventional strategy like P&O, TSR, and OT etc. perform poorly during varying wind speeds and require precise mathematical

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Nomenclature

A	Area swept by the blades
BP	Back-propagation
C_p	Power coefficient
D	Duty cycle
FLC	Fuzzy logic control
MPPT	Maximum power point tracking
NN	Neural network
OT	Optimal torque
PMSG	Permanent magnet synchronous generator
P&O	Perturb& observe

PSF	Power signal feedback
R	Radius
RBF	Radial basis function
T	Torque
TSR	Tip-speed ratio
v	Velocity
v_d	Direct axis voltage
v_q	Quadrature axis voltage
WECS	Wind energy conversion system
β	Pitch angle
ω_m	Rotor speed

models. These conventional controllers have problems of inefficient tuning of their gains therefore intelligent controllers are used to overcome this problem and for better system performance.

The usage of artificial intelligence (AI) based control methods minimizes some of these issues and play a significant role in extracting MPP [19,20]. The AI approaches such as neural network and fuzzy system do not require mathematical models and are capable of approximating nonlinear systems. As a result, many researchers have used these to depict complex plants and build sophisticated controllers. The FLC based MPPT was applied to control the boost converter to achieve maximum efficiency for small scale WECS due to its fast convergence [21,22]. Li et al. [23] presented the BP-NN based MPPT to extract maximum power with higher efficiency, reliability and without using mechanical sensor.

Based on the power slope versus the wind turbine rotation speed, this study proposes a novel MPPT algorithm employing AI based techniques to avoid the effect of oscillation and uncertain parameters in wind turbine generators. The output voltage and current characteristics of the wind turbine generator are determined by the amount of wind speed. The ambient air density and the electrical load characteristics are required to implement MPPT algorithms to ensure that wind turbine generators achieve optimum efficiency under different operating conditions.

Being powerful for mapping a function, NN are used in many fields,

such as prediction of wind and power. To enhance MPPT's efficiency, a novel controller using the RBF-NN based adaptive strategy is proposed here for WECS. The proposed RBF-NN approach optimizes the duty cycle to extract MPP. The RBF-NN is a feedforward NN with a much simpler structure than BP-NN. It provides a robust and adaptive control system. In addition, the boost converter duty cycle is controlled using voltage and power as inputs to the NN, the need of knowing the wind turbine characteristics is eliminated. Thus, it does not need sensors to measure the wind speed (anemometer) or to measure the turbine speed (tachometer) which makes this MPPT control technique much more cost-efficient. This control strategy provides efficient MPPT, reduces ripples, minimizes load variations& discontinuities and yields fast response. This method is also compared with P&O, FLC and BP-NN to check its performance.

A double stage grid interfaced WECS topology is designed, modeled and implemented in this paper. In first stage, the WECS is implemented as a standalone system in which a load is connected at the output of the boost converter. In the second stage, the WECS is tied to a grid. The major contributions of this work are as follows:

- The WECS is designed and implemented in MATLAB/Simulink.
- The maximum power point is tracked using various techniques namely, RBF-NN, P&O, FLC and BP-NN techniques and best (RBF-NN) is selected.

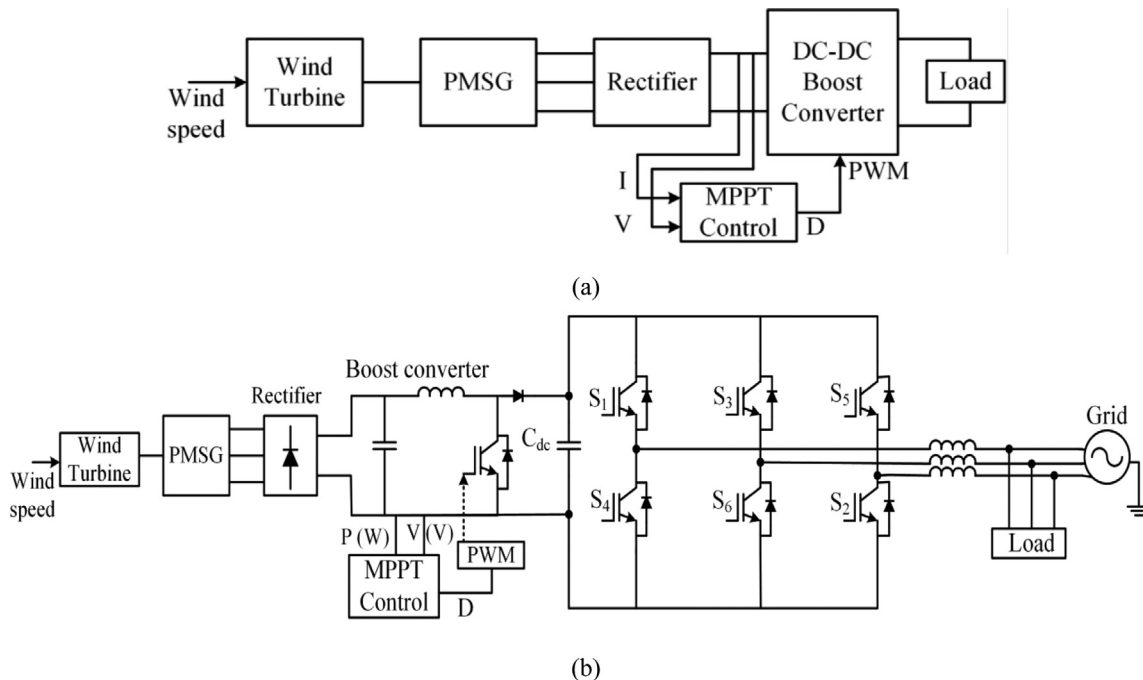


Fig. 1. (a) Standalone WECS (b) Grid-tied WECS.

- iii. The proposed RBF-NN is also compared with MPPT algorithms used in other similar works.
- iv. The simulation results are validated in real-time digital simulator hardware, OPAL-RT 4510.

The proposed circuit diagram is given in Fig. 1 and can be explained as follows: The wind turbine with blades is coupled with PMSG and the AC output of PMSG is converted to DC using a rectifier. This DC output is then passed through a DC-DC boost converter whose duty cycle is being controlled using the RBF-NN based MPPT strategy. The output of the boost converter is then connected to a load in case of a standalone system in Fig. 1a. or converted to AC using VSI and then supplied to the grid in case of grid-tied system in Fig. 1b.

The paper is organized as follows. In Section “Wind turbine rotor model”, wind turbine rotor model is described. In Section “PMSG and rectifier characteristics and working of MPPT method”, an overview of PMSG and rectifier characteristics is given and also rationale behind the selected MPPT method is described. Section “Radial basis function-neural network” is devoted to the proposed RBF-NN algorithm of MPPT. Grid tied WECS is introduced in Section “Grid tied wind energy system”. Section “Results and discussion” demonstrates the simulation results of the proposed and conventional methods and real-time results validated in OPAL-RT. Finally, the conclusion is presented in Section “Conclusion”.

Wind turbine rotor model

To get the maximum power, it is required that the wind turbine must operate at maximum power coefficient (C_p). This can be understood by the Eq. (1) of power captured by the wind turbine as follows [24].

$$P = \frac{1}{2} \rho A v^3 C_p(\lambda, \beta) \quad (1)$$

where, P is the power generated, ρ is the air density, A is the area swept by the blades, v is the velocity of wind and C_p is the power coefficient. β is the pitch angle and λ is the TSR.

In general, $C_p(\lambda, \beta)$ is the efficiency of power i.e. ratio of power generated to available in the wind. Its dependence on λ and β can be formulated by Eq. (2) as [18,25]:

$$C_p(\lambda, \beta) = 0.5176 \left(116 \times \frac{1}{\lambda_i} - 0.4\beta - 5 \right) e^{\frac{-21}{\lambda_i}} + 0.068\lambda \quad (2)$$

$$\text{where, } \frac{1}{\lambda_i} = \frac{1}{(\lambda + 0.08\beta) - \left(\frac{0.035}{1 + \beta^3} \right)}$$

The turbine power coefficient $C_p(\lambda, \beta)$ describes the power extraction efficiency of the wind turbine and is defined as the ratio between the mechanical power available at the turbine shaft and the power available in wind. A generic equation is used here to model $C_p(\lambda, \beta)$.

The TSR is defined as the rotor speed divided by the wind speed [17] shown in Eq. (3)

$$\lambda = \omega_m \times \frac{R}{v} \quad (3)$$

where, ω_m is the rotor speed and R is radius of the blades.

The torque (T) is given as in Eq. (4)

$$T = \frac{P}{\omega_m} \quad (4)$$

It can be seen clearly from Eq. (2) with constant β that for each wind speed, there is an optimum rotor speed corresponding to which maximum power is obtained. The same thing can be inferred from the wind turbine rotor characteristics in Fig. 2.

PMSG and rectifier characteristics and working of MPPT method

The generator is connected to the load using a three phase rectifier and a boost converter. The boost converter regulates the amount of voltage as referred to the generator side. Usage of diode bridge rectifier ensures that the effective load referred to generator side is purely resistive so that one obtains a constant DC voltage. Fig. 3 shows a per phase equivalent circuit as seen on the generator side with V_s as the rectifier diode's referred voltage. In this figure, the arrow inside V_s signifies that the power is flowing in only one direction. (See Fig. 4).

In the presented steady state analysis, the battery is thought to be a voltage source that gives pure sinusoidal voltage and same is with the rectifier, therefore, UPF current flows in the load. The stator resistance (R_s) is neglected here for the ease of calculations [26].

Therefore, in this circuit

$$E = V_s \quad (5)$$

And using the law of conservation of energy, one can write

$$V_{dc} I_{dc} = 3 V_s I_s \quad (6)$$

where, V_{dc} is the rectifier output voltage, I_{dc} is the rectifier output current. V_s is the per phase voltage as referred to the AC side and I_s is the stator current.

Further, the relationship between the DC bus voltage and generator line voltage can be written as

$$V_{dc} = V_{line} \times \frac{3\sqrt{2}}{\pi} \quad (7)$$

$$\text{So, } V_{dc} = V_s \times \frac{3\sqrt{6}}{\pi} \quad (8)$$

which gives,

$$I_s = \frac{\sqrt{6}}{\pi} I_{dc} \quad (9)$$

The relation between the voltage E of the PMSG and the rotor speed ω_m is as below.

$$E = k \phi \omega_m \quad (10)$$

where, ϕ is the air gap flux and k is a constant. The speed of a synchronous generator is shown in Eq. (11)

$$\omega_m = \frac{120f}{p} \quad (11)$$

where, f = frequency of the induced voltage in the generator. p = No.

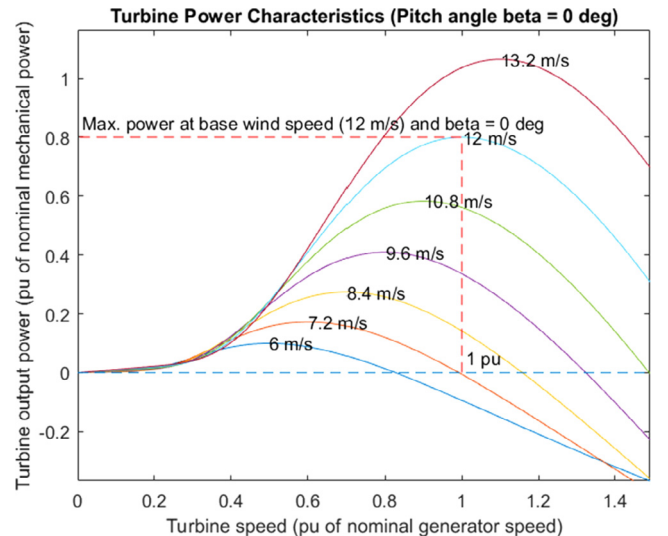


Fig. 2. Wind turbine power characteristics.

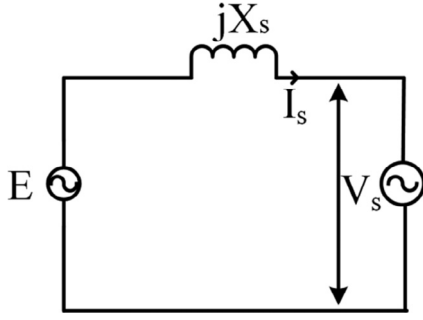


Fig. 3. Per phase equivalent circuit of the system [2].

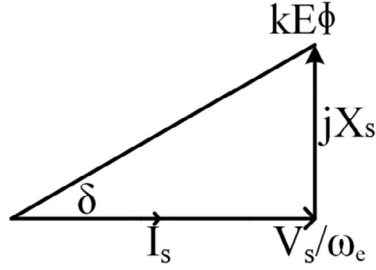


Fig. 4. Phasor diagram for the AC side equations [2].

of poles in the generator.

Thus, it is seen that there is a single solution at any given frequency. So to change the torque produced the only method is to change the frequency.

here $\omega_e = 2\pi f_e$.

In steady state,

$$V_s^2 = E^2 - (\omega_e L_s I_s)^2 \quad (12)$$

Therefore, combining the above equations,

$$P_g = \frac{3\sqrt{6}}{\pi} \omega_m I_{dc} \sqrt{k^2 - \frac{6}{\pi^2} (pL_s)^2 I_{dc}^2} \quad (13)$$

$$T_g = \frac{3\sqrt{6}}{\pi} I_{dc} \sqrt{k^2 - \frac{6}{\pi^2} (pL_s)^2 I_{dc}^2} \quad (14)$$

Also,

$$\omega_m = \frac{T_m - T_g}{B_t} \quad (15)$$

where, B_t is the turbine rotor friction coefficient.

From above analysis it is clear that, the DC current is directly related to the DC bus voltage (V_{dc}) which is controlled using duty cycle. By changing the diode rectifier current, torque can be controlled and by controlling the torque one can in turn control the rotor speed to obtain maximum power. The power produced by WECS depends on the climatic conditions as can be seen in Fig. 5 which gives the wind turbine torque for various wind velocity. The MPPT algorithms are required to harvest the maximum available energy. As seen in Fig. 5, the duty cycle can be modified to follow the path of the target torque to achieve the maximum power as represented by red dotted line in figure. The duty cycle control helps in manipulating the rotor speed efficiently in a feed-forward fashion using a NN. The load can further be removed and the system can be integrated with a power grid or for any other application.

Radial basis function-neural network

To train the MPPT controller, authors have used RBF based NN controller in this work. RBF networks are easy to design, they have strong tolerance to input noise because of the construction of the function and thus are more suitable for use in flexible control systems

like wind energy conversions. Due to the simple architecture of RBF-NN, it is easier and faster to train them. The NN generally has three layers. The first is an input layer, next is the hidden layer with multiple neurons and the last is the output layer.

The hidden layer neurons use RBF for activation. Two inputs i.e. the rectifier output voltage and power are given to NN. The target is the duty cycle of the boost converter. The NN is then trained based on the sample data for the duty cycle corresponding to maximum power for different voltages and powers. Fig. 6 shows the basic model of the RBF-NN.

The hidden neurons are assigned weights corresponding to each input. The linear combination of these weights then gives a relation using the power and voltage to give the output duty cycle. If the inputs are real numbers, then the output can be defined as a scalar function of these input vectors. The weights between the hidden and output layers are modified during training. The output of the hidden layer containing the RBF neurons can be formulated as in Eq. (16).

$$\varphi_i(u_1, u_2) = \exp\left(-\frac{\|u - c_i\|^2}{2\delta^2}\right) \quad (16)$$

where u_1 and u_2 are the two inputs to the NN, c_i is the center for the neuron i , δ is the width of the Gaussian error function.

Finally, the output D can be written as a linear combination of all the neurons with weights w_i assigned to them.

$$D = \sum w_i \varphi_i \quad (17)$$

The weights can be decided by a variety of methods. The most commonly used is gradient descent method. The centre and width may be chosen by methods like k-means clustering. If the numbers of hidden neurons are sufficient, then it is possible to determine the relation between any continuous variable with an arbitrary amount of accuracy.

Grid tied wind energy system

The grid side system consists of a three phase VSI that converts the DC link voltage to AC which is then connected to the grid. There is also a nonlinear load connected to the point of common coupling (PCC). As a part of the grid connected inverter, there are two controlling loops in cascade. The active and reactive powers are controlled using external loop, while the grid current is controlled using the internal loop. The grid current and voltage waveforms are modified by synchronously rotating reference frame with the grid voltage in d-q frames to obtain the decoupled control of the active and reactive powers. Using Park's transformation we get the active and reactive power as:

$$P = v_d i_d + v_q i_q \quad (18)$$

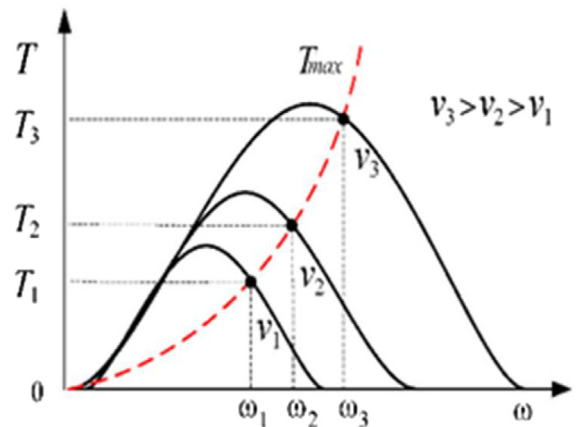


Fig. 5. Wind Turbine Torque Curves. The dotted line in red corresponds to the optimal torque line which must be followed for maximum power.

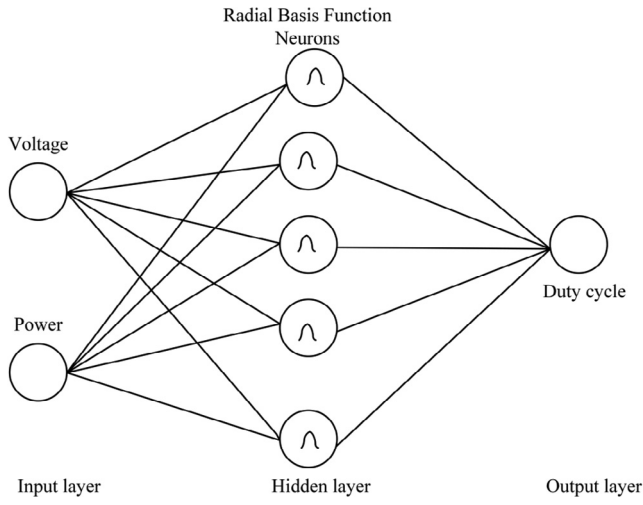


Fig. 6. Radial basis function neural network.

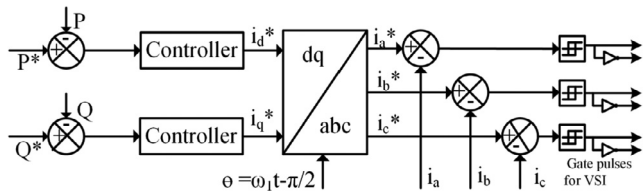


Fig. 7. Grid connected voltage source inverter.

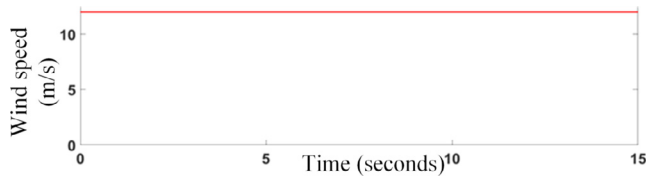


Fig. 8. Constant wind speed.

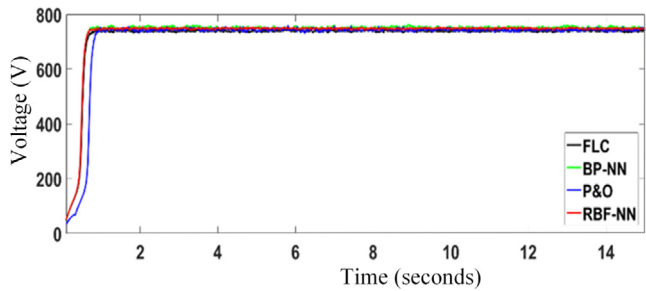


Fig. 9. Output DC-link voltage for constant wind speed of 13 m/s.

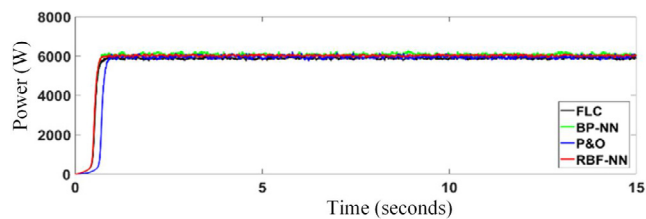


Fig. 10. Output power for constant wind speed of 13 m/s.

and

$$Q = v_d i_q - v_q i_d \quad (19)$$

The system gets v_q as 0 when aligned with the reference frame to the

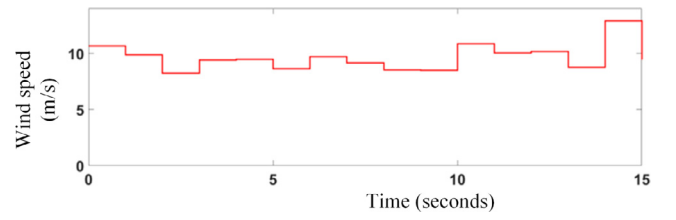


Fig. 11. Step changes in wind speed.

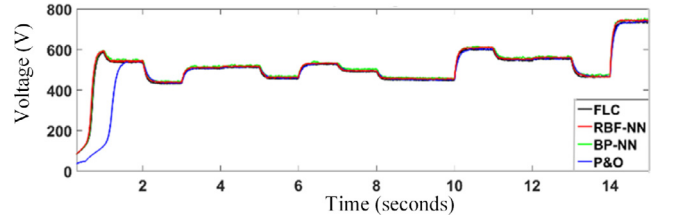


Fig. 12. Output DC-link voltage for step changes in wind speed.

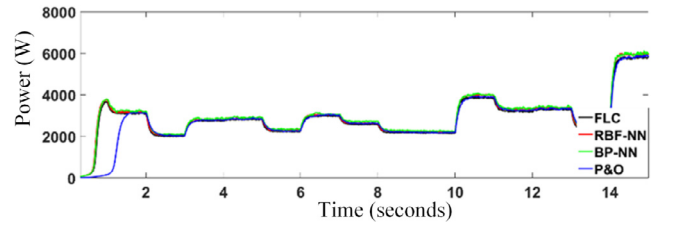


Fig. 13. Output power for step changes in wind speed.

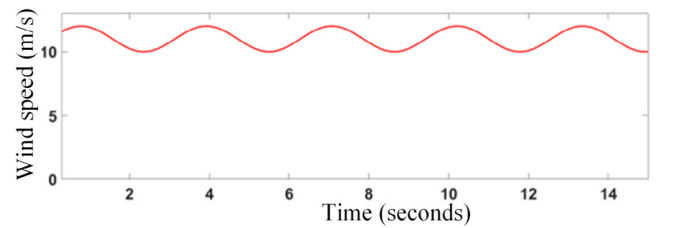


Fig. 14. Continuously changing wind speed.

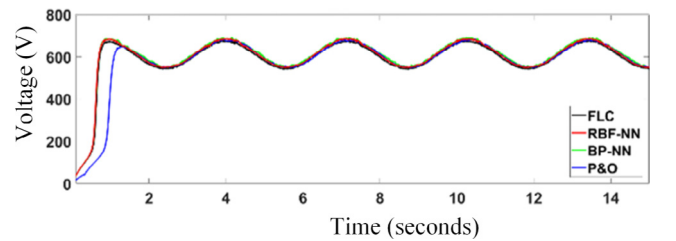


Fig. 15. Output DC-link voltage for continuously changing wind speed.

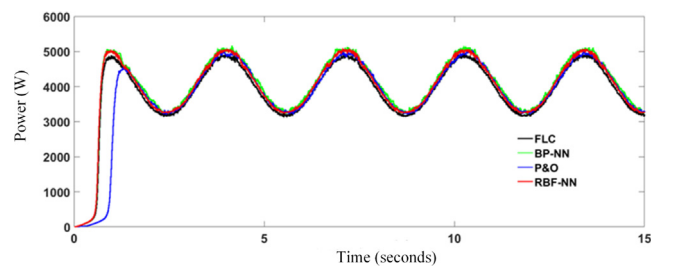


Fig. 16. Output power for continuously changing wind speed.

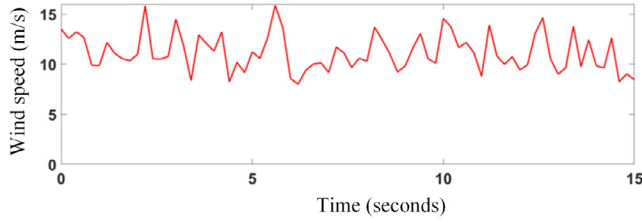


Fig. 17. Randomly varying wind speed.

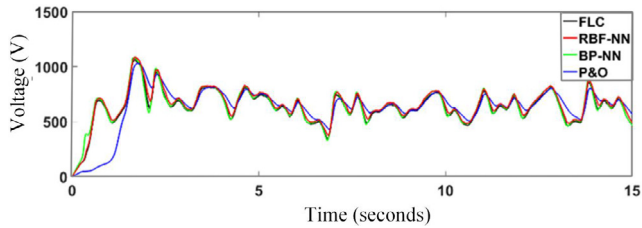


Fig. 18. Output DC-link voltage for randomly varying wind speed.

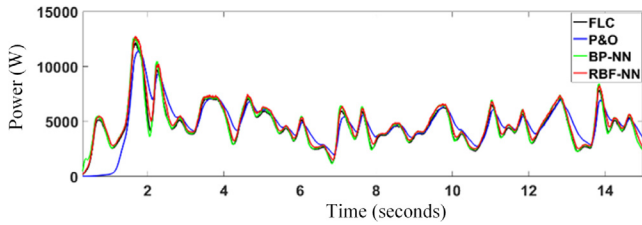


Fig. 19. Output power for randomly varying wind speed.

Table 1
Comparison of proposed techniques.

Parameters	BP-NN	FLC	P&O	Proposed Algorithm RBF-NN
Ripple factor	4%	3%	3%	2%
Time of response (second)	0.42	0.47	1.28	0.46

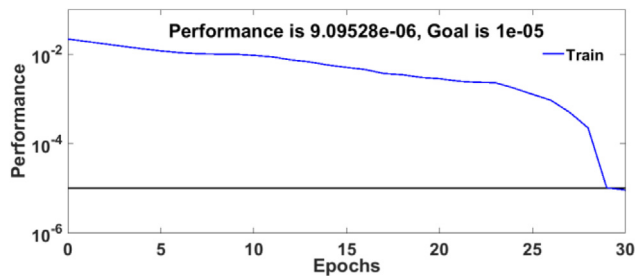


Fig. 20. Mean square error performance of RBF-NN.

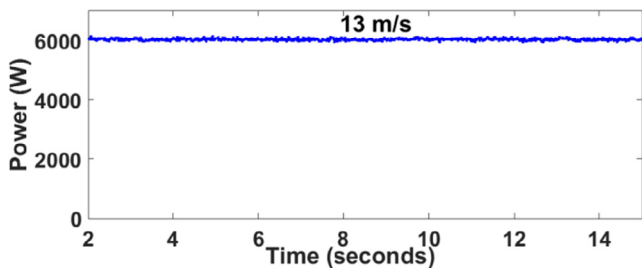


Fig. 21. Output power with a ripple factor of only about 2%

Table 2

Comparison of proposed technique with other control techniques.

Parameters	RBF-NN	Other works			
		Ref. [1]	Ref. [5]	Ref. [6]	Ref. [8]
MSE	9.09×10^{-6}	NA	NA	NA	9.9854×10^{-5} [7]
Ripple Factor (%)	2	NA	NA	10	NA
Overshoot	Little	Large	Little	Medium	Large
Time for learning/starting to track MPP	0.46 s	NA	50 s	55 s	NA

NA: not available.

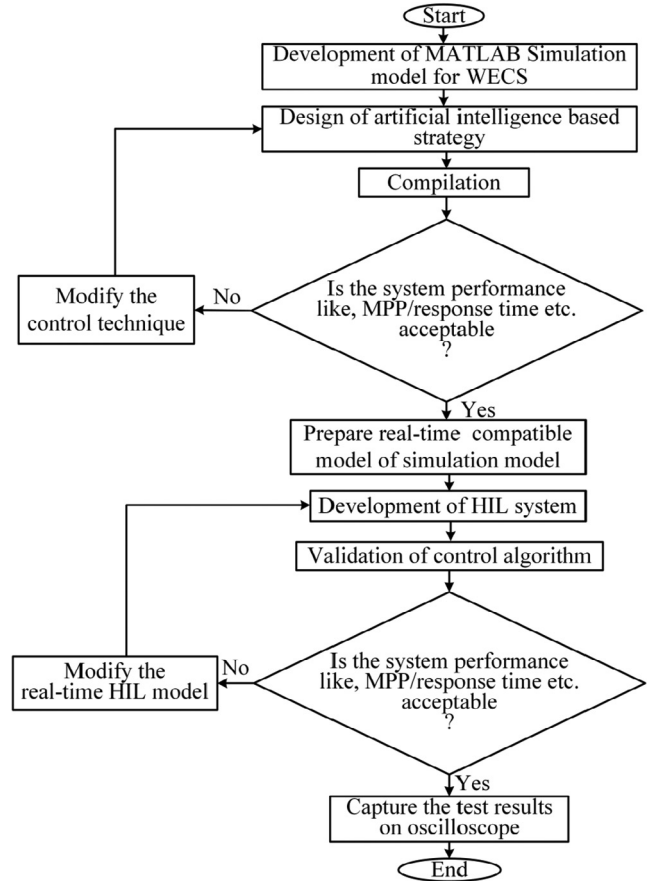


Fig. 22. Flowchart of the WECS testing process using real-time.

d-axis. And, assuming that the grid voltage is constant i.e. v_d is constant. Thus, Eqs. (18) and (19) are given by

$$P = v_d i_d \quad (20)$$

and

$$Q = v_d i_q \quad (21)$$

The inverter switches are then controlled using the pulses generated by the current control loop which is done after the reference currents are generated. Three phase currents are generated when an inverse Park's transformation is applied on the reference currents in d-q frame. It is tried here that the difference between reference and output currents is minimal. Hysteresis controller scheme is used to control the current loop. Switches are triggered by comparing the measured and reference currents into the hysteresis block. Fig. 7 shows the schematic of this grid connected inverter.

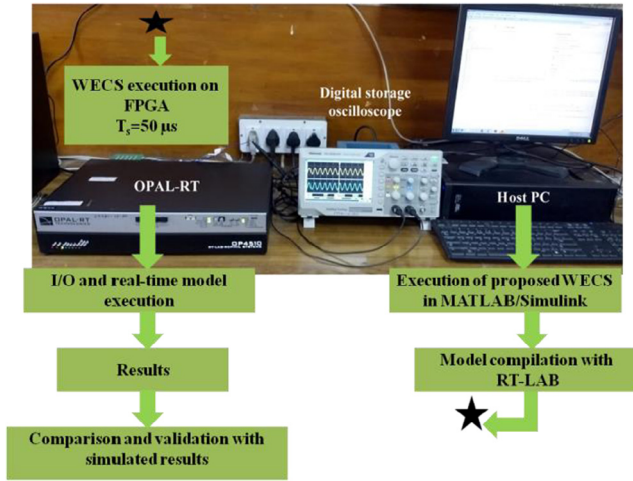


Fig. 23. OPAL-RT laboratory set up.

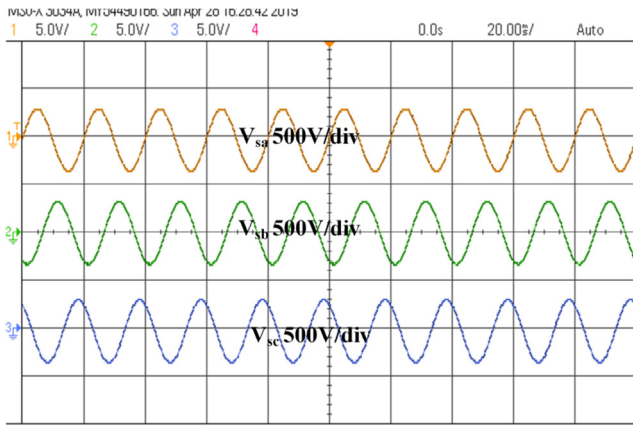


Fig. 24. Grid voltage.

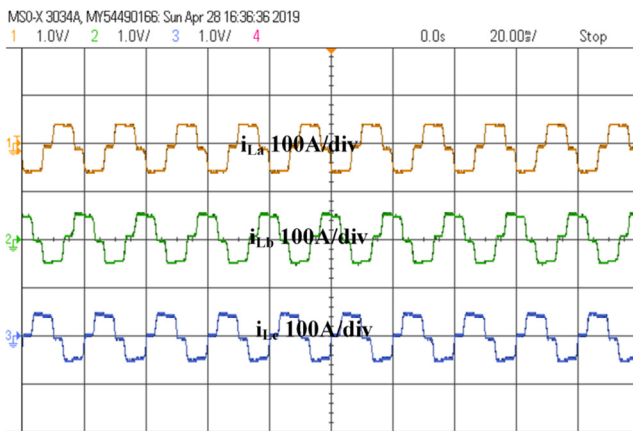


Fig. 25. Nonlinear load current.

Results and discussion

This paper presents the behaviour of MPPT for a standalone and grid tied system. The MPPT was tested for different types of loads like, purely resistive load, RL load and non-linear loads. Similar results were obtained for all the cases concluding that the proposed MPPT is compatible to different types of loads.

The modelling and simulation of the entire system is carried out in MATLAB/Simulink environment. MATLAB/Simulink was used for the application pertaining to the ease of use and the flexibility to model the

individual blocks in the WECS. The proposed system is later verified by hardware based real time data simulation using OPAL-RT.

The different MPPT techniques applied are compared based on few parameters namely, ripple factor, mean square error (MSE) in the training of NN, response time to changes in wind speed and overshoot.

Ripple factor can be defined as the ratio (in %) of the root mean square (RMS) value of the ripple voltage to the DC component value which is fairly constant for a constant wind speed.

$$\text{Ripple factor (R)} = \frac{\text{RMS value of ripple voltage}}{\text{Mean value of DC component}}$$

MSE metric used to compare NN, is the square of the means of individual errors. This gives a measure of deviation from trained value of given NN. The lower the value of MSE, the more accurate will be the prediction by NN over a range of values. A goal is set for NN to reach during the training of the NN.

$$\text{Mean squared error (MSE)} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

where $Y_i - \hat{Y}_i$ is a single error.

And the response time is defined as the time taken by a MPPT technique to follow the MPP accurately after sudden change in wind speed. It is the time taken in reaching 10% to 90% of the maximum power value.

Overshoot is an unwanted effect that causes the system to draw more current than nominal and these results in a momentary increase in power which is undesired. The % overshoot value is calculated as the ratio of power increase above the constant DC value to the stable power value (DC component).

$$\% \text{ overshoot} = \frac{\text{overshoot value (kW)}}{\text{stable DC power value (kW)}} \times 100$$

Standalone wind energy system

For a standalone WECS, the results are tested for different types of wind waveforms like step changes, continuously varying, constant wind speed and random wind speed.

For all the cases, the RBF-NN based MPPT is compared with other MPPT methods used in literature namely, P&O, FLC and BP-NN.

Case Study 1: Constant wind speed

Firstly, the wind speed is set at 13 m/s as shown in Fig. 8 and the outputs are taken as the load voltage and power. The outputs are then compared to P&O method, FLC method and BP-NN method. The corresponding results for output DC-link voltage and power are shown in Figs. 9 and 10 respectively. The proposed MPPT algorithm takes about 1 s to start following the maximum power curve. The proposed RBF-NN performs better than the other methods.

Case Study 2: Step changes in wind speed

Instantaneous step changes (small turbulences) in wind speed is implemented by a random number generator within given ranges of wind speeds of 8 m/s–13 m/s as presented in Fig. 11. Again, the output voltage and power for RBF-NN control was compared to other techniques of MPPT. The notable thing here is that no peak overshoot is observed using this method. This is desirable in such systems as sudden surge of power may result in breakdown of some of the system components. The RBF-NN exhibits better performance as compared to other methods in this case as well. The output voltage and power are displayed in Figs. 12 and 13 respectively.

Case Study 3: Continuously changing wind speed

For implementing continuously changing wind speed (turbulences), authors have taken the sample as a sinusoid with a frequency of 2 rad/s and amplitude of 1 m/s with an offset of 11 m/s as shown in Fig. 14. The corresponding results are shown in Figs. 15 and 16. It is seen that the MPP is followed in the case of continuously changing wind speed as

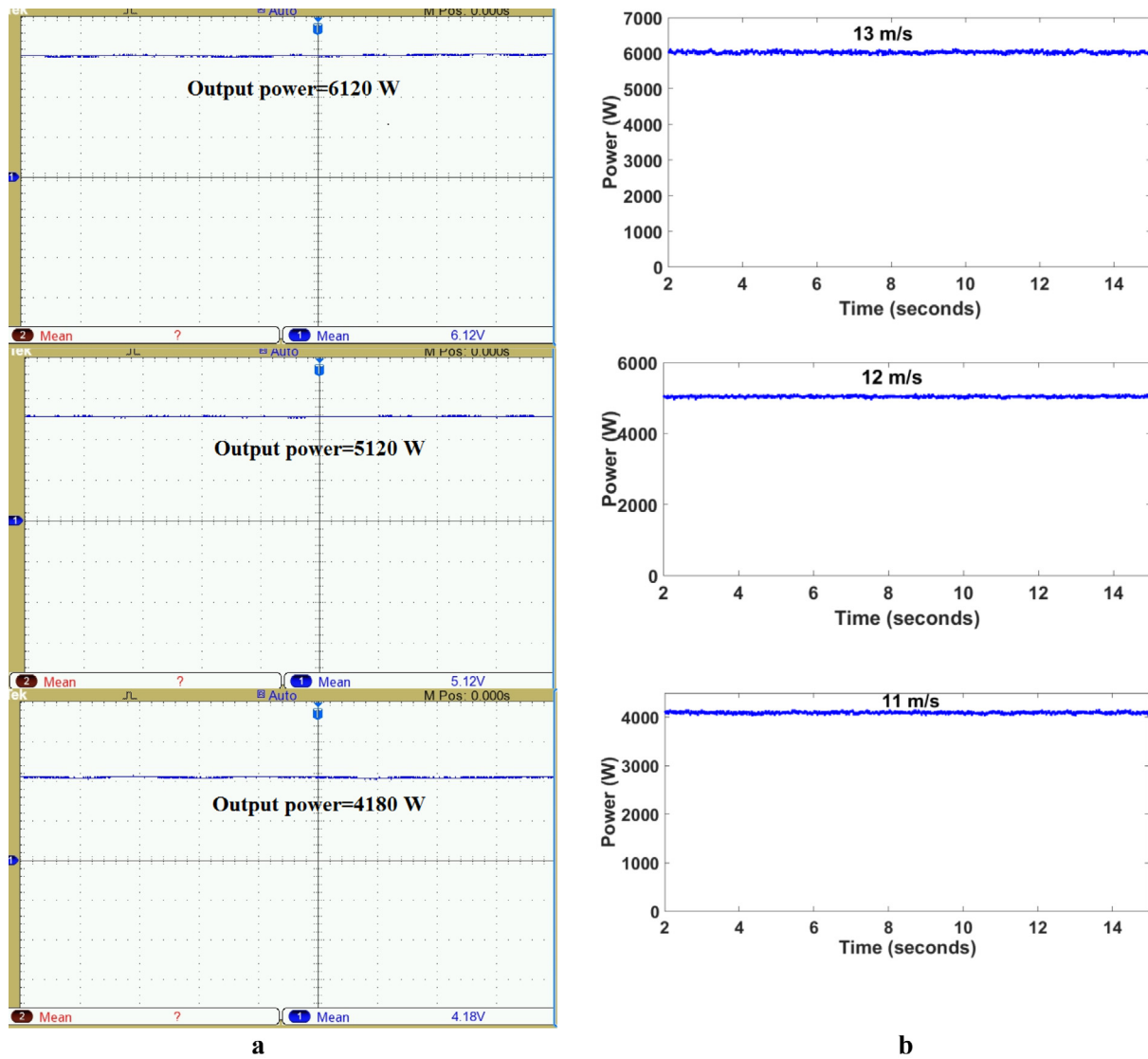


Fig. 26. a. Output power using OPAL-RT at wind speeds of 11 m/s, 12 m/s and 13 m/s b. Output power using MATLAB at wind speeds of 11 m/s, 12 m/s and 13 m/s.

well.

Case Study 4: Randomly generated wind speed

Practically, the wind speed is continuously varying randomly (strong turbulences) and thus it is important to test the MPPT controller in such a condition. The random waveform as given in Fig. 17 is generated by using a Gaussian noise function and specifying the frequency of the noise. This corresponds to what wind speed over time would look like practically. Figs. 18 and 19 correspond to the output voltage and power under these conditions of rapidly varying wind speed.

The results obtained using P&O method is shown in blue color. As compared to the RBF-NN controller, P&O is much slower to respond and its efficiency is also less as it extracts lesser power. In addition, the output is more stable in case of RBF-NN.

FLC is an efficient algorithm for wind energy MPPT but RBF-NN controller is even faster and the efficiency is also better as more power and voltage are obtained for the same system parameters. The FLC method is given in black color in the results.

Compared to BP network the stability of the outputs in the proposed method is more. Since both are NNs the difference is not so significant other than the fact that the mean square error (MSE) performance obtained is much better in case of RBF-NN than in BP networks. In addition, the training time is shorter in RBF-NN. The output power and voltages for BP networks are shown in green color.

A comparison of results obtained at wind speed of 13 m/s using various methods is given below in Table 1. Based on these, RBF-NN is chosen and then validated in real-time.

Case Study 5: Comparison with other works

In comparison with several other works already done in this field, the proposed method is better in several ways. The RBF-NN based controller provides a MSE of 9.09×10^{-6} . This performance of the artificial NN was at least ten times better when compared to the performance obtained by [7] in their paper on MPPT using BP method. The proposed output is very stable and has low fluctuations at steady state. The training time taken in proposed method corresponds to only 30 epochs as compared to 5812 epochs in [8]. Figs. 20 and 21 shows the MSE and output ripple factor.

As compared to 10% ripple factor in FLC implemented by [5], it is found to be 2% in the proposed method as given in Fig. 21. The stable output is desirable largely thus, the RBF-NN method yields much better results. It can be seen that the output is much stable with a ripple factor of about 2%. Table 2 shows the comparison of the proposed method with other relevant work cited in literature. (See Table 3).

As compared to the work by Ref. [1] whose results have a considerable overshoot, the proposed methods has very little overshoot. This is desirable as a sudden surge in power can damage some component of the WECS. Further, the MPP is tracked within a second after

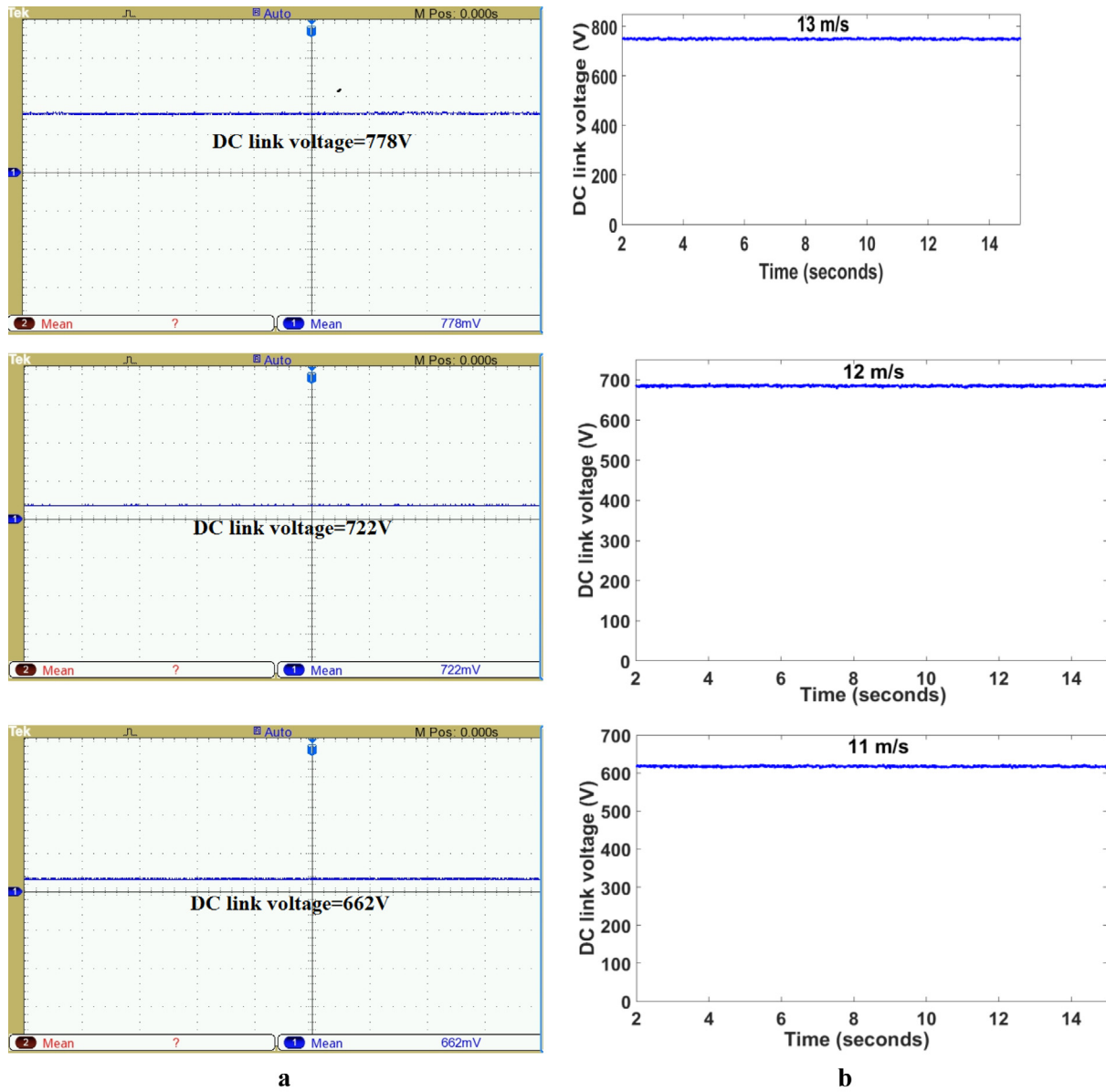


Fig. 27. a. Output DC- link voltage using OPAL-RT at wind speeds of 11 m/s, 12 m/s and 13 m/s b. Output DC- link voltage using MATLAB at wind speeds of 11 m/s, 12 m/s and 13 m/s.

Table 3
Parameters of wind turbine model and PMSG [27].

Parameter	Value	Parameter	Value
Nominal output power	6 kW	Capacitance	1600 μ F
Base wind speed	12 m/s	Load	$R = 10 \Omega$, $L = 1$ mH
Grid voltage	400 V	Inductance	1.11 mH
Inductance	1.11 mH	Switching frequency	10 kHz

starting as compared to the methods by Refs. [1] and [4] which take a pretty long time of 50 s. The proposed method can be implemented as soon as the data is trained which takes less than a second and makes the algorithm considerably faster.

Real-time results and discussion

The results obtained using MATLAB simulations are verified by hardware based real time simulation on OPAL-RT 4510. OPAL-RT has a very good compatibility with the MATLAB/Simulink environment. It is

very flexible and can validate any type of control model in it. The OPAL-RT consists of two main parts, first is the simulation environment in RT-Lab and the second is hardware in the loop package (HIL). It allows inculcation of FPGA boards for HDL or Xilinx functions. The results are then shown on the OPAL-RT or on the digital storage oscilloscope (DSO) [22]. Fig. 22 shows a flowchart for testing procedure of WECS in real-time environment. The OPAL-RT set up used to carry out the validation of this present work is given in Fig. 23. The real time validation of simulated results is done for three different wind speeds i.e. 11 m/s, 12 m/s and 13 m/s. Figs. 24 and 25 depict the grid voltage

and nonlinear load current waveforms respectively. The results for power and DC link voltage are shown in Figs. 26 and 27 respectively for three different wind speeds i.e. 11 m/s, 12 m/s and 13 m/s. It is seen that the real-time results for output power and DC link voltage are same as what we have obtained from the simulation. Thus, this also verifies proposed MPPT algorithm. To accommodate the outputs, the scale is decreased by a factor 1000 in voltage and power measurement.

Conclusion

In this paper, a RBF-NN based novel control strategy for MPPT in WECS is proposed. This method uses duty cycle control to achieve the maximum power point. This method does not require actual

measurement of the turbine/wind speed and knowledge about the turbine power characteristics that reduces the cost of implementing this algorithm. The proposed approach is first simulated in MATLAB/Simulink environment and then validated in real-time through real-time digital simulation hardware OPAL-RT 4510. The real-time results obtained using proposed algorithm are compared with MPPT techniques, namely P&O, FLC and back-propagation networks applied in different other papers and found to be superior. This method provides the almost constant DC link voltage with minimal ripples in the response. This method is fast, efficient and reliable in tracking the MPP. Thus, the simulation as well as the real-time results obtained using proposed RBF-NN strategy prove its superiority over other methods.

Appendix A

Parameters of Grid tied WECS system

Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.seta.2019.100533>.

References

- [1] Li S, Wang H, Aitouche A, Li S, Wang H, Aitouche A. A RBF neural network based MPPT method for variable wind speed turbine. IFAC Symp 2015;244–50.
- [2] Simões MG, Farret FA, Blaabjerg F, Godoy M, Farret FA, Blaabjerg F, et al. Small wind energy systems. Electr Power Components Syst 2016;43:1388–405. <https://doi.org/10.1080/15325008.2015.1029057>.
- [3] Liserre M, Cárdenas R, Molinas M, Rodríguez J. Overview of multi-MW wind turbines and wind parks. IEEE Trans Ind Appl 2011;58:1081–95.
- [4] Wei C, Zhang Z, Qiao W, Qu L. An adaptive network-based reinforcement learning method for MPPT control of PMSG wind energy conversion systems. IEEE Trans Power Electron 2016;31:7837–48.
- [5] Farh HM, Eltamaly AM. Fuzzy logic control of wind energy conversion system. J Renew Sustain Energy 2013;5:023125 <https://doi.org/10.1063/1.4798739>.
- [6] Gupta RA, Bhim Singh BBJ. Wind energy conversion system using PMSG. IEEE Conf 2015:199–203.
- [7] Dahbi A, Nait-said N, Nait-said M. A novel combined MPPT-pitch angle control for wide range variable speed wind turbine based on neural network. Int J Hydrogen Energy 2016;41:9427–42.
- [8] Bin Wu, Lang Y, Zargari N, Kouro S. Power conversion and control of wind energy systems. IEEE Press 2011.
- [9] Lin W, Hong C, Ou T, Chiu T. Hybrid intelligent control of PMSG wind generation system using pitch angle control with RBFN. Energy Convers Manage 2011;52:1244–51. <https://doi.org/10.1016/j.enconman.2010.09.020>.
- [10] Zhang J, Cheng M, Chen Z, Fu X. Pitch angle control for variable speed wind turbines. IEEE Conf 2008:2691–6.
- [11] Karakaya A. Implementation of neural network-based maximum power tracking control for wind turbine generators. Turkish J Electr Eng Comput Sci 2014;22:1410–22. <https://doi.org/10.3906/elk-1201-70>.
- [12] Chen J, Yau H, Hung W. Design and study on sliding mode extremum seeking control of the chaos embedded particle swarm optimization for maximum power point tracking in wind power systems. Energies 2014;7:1706–20. <https://doi.org/10.3390/en7031706>.
- [13] Kumar R, Chaturvedi P, Bansal HO, Ajmera PK. Adaptive artificial neural network based control strategy for shunt active power filter. Int Conf Electr Power Energy Syst 2016:194–9.
- [14] Sefidgar H. Fuzzy logic control of wind turbine system connection to pm synchronous generator for maximum power point tracking. IJ Intell Syst Appl 2014;07:29–35. <https://doi.org/10.5815/ijisa.2014.07.04>.
- [15] Elnaggar M, Fattah HAA, Elshafei AL. Maximum power tracking in WECS (Wind energy conversion systems) via numerical and stochastic approaches. Energy 2014;74:651–61.
- [16] Tsai F, Tseng C, Hung H. A novel MPPT control design for wind-turbine generation systems using neural network compensator. IEEE Conf 2012:3521–6.
- [17] Kalaitzakis EK. Design of a maximum power tracking system for wind-energy-conversion applications. IEEE Trans Ind Electron 2006;53:486–94.
- [18] Worku MY, Abido MA, Irvani R. PMSG based wind system for real-time maximum power generation and low voltage ride through. J Renew Sustain Energy 2017;9:013304 <https://doi.org/10.1063/1.4976141>.
- [19] Abdullah MA, Yatim AHM, Tan CW, Saidur R. A review of maximum power point tracking algorithms for wind energy systems. Renew Sustain Energy Rev 2012;16:3220–7. <https://doi.org/10.1016/j.rser.2012.02.016>.
- [20] Kesraoui M, Korichi N, Belkadi A. Maximum power point tracker of wind energy conversion system. Renew Energy 2011;36:2655–62. <https://doi.org/10.1016/j.renene.2010.04.028>.
- [21] Narayana M, Putrus GA, Jovanovic M, Leung PS, McDonald S. Generic maximum power point tracking controller for small-scale wind turbines. Renew Energy 2012;44:72–9. <https://doi.org/10.1016/j.renene.2011.12.015>.
- [22] Eltamaly AM, Farh HM. Maximum power extraction from wind energy system based on fuzzy logic control. Electr Power Syst Res 2013;97:144–50.
- [23] Li H, Shi KL, McLaren PG. Neural-network-based sensorless maximum wind energy capture with compensated power coefficient. IEEE Trans Ind Appl 2005;41:1548–56.
- [24] Keivanpour S, Ramudhin A, Kadi DA. The sustainable worldwide offshore wind energy potential: a systematic review. J Renew Sustain Energy 2017;9:065902.
- [25] Yin M, Li G, Zhou M, Zhao C. Modeling of the wind turbine with a permanent magnet synchronous generator for integration. IEEE Power Eng Soc Gen Meet PES 2007;2007:1–6. <https://doi.org/10.1109/PES.2007.385982>.
- [26] Muljadi E, Drouilhet S, Holz R, Division WT, Renewable N, Gevorgian V. Analysis of wind power for battery charging. Wind Technol Div n.d. National Renewable Energy Laboratory.
- [27] Kumar R, Bansal HO. Design and Control of Wind integrated Shunt Active Power Filter to Improve Power Quality. In: IEEE 8th Power India International Conference (PIICON-2018), at NIT Kurukshetra, India, December; 2018;10–12: p. 1–5. DOI: [10.1109/POWERI.2018.8704377](https://doi.org/10.1109/POWERI.2018.8704377).