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A Generalized WECS System with Single Phase Multilevel Inverter having MPPT control with Neural Network

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ABSTRACT

This paper describes the efficient MPPT tracking for variable wind speed using an artificial neural network. The neural network has been trained using the backpropagation algorithm and Levenberg-Marquardt (LM) based optimization technique to achieve maximum power point. A multilevel inverter having 10 switches has been used to reduce voltage stress, THD and switching losses resulting in improvement in performance and reduction in the driver circuit for the switches. The proposed system has been validated and simulated in SIMULINK/MATLAB

Keywords: WECS; ANN; MPPT; Boost converter; Bidirectional converter; Duty cycle; Multi-level inverter.

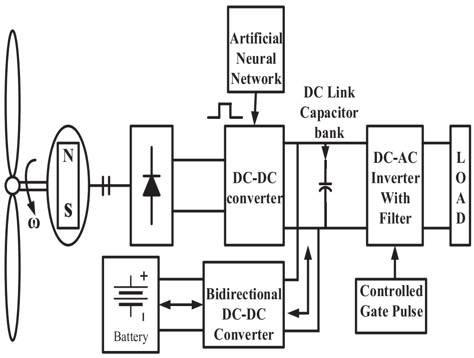
INTRODUCTION

Pollution, global warming, continuous use of conventional limited resources like fossil fuels, natural gas makes a threat to the environment. To counter these threats, the dependency on renewable energy has become a great advantage as renewable energy is abundant in nature.

Wind energy is easily available, clean, and environment friendly. The wind energy system is utilized to extract the energy associated with the wind into a desirable form of electrical energy (Shoaib et al., 2019, Abdullah et al., 2012, & Poompavai et al, 2019). To convert the wind energy into a desirable form, the wind turbine is coupled to wind generators along-with power electronic devices (Verma et al., 2019, El-Hay et al., 2018 & Agarwal et al., 2019). Power electronic devices are used as an interface for the conversion of extracted wind power to suitable electrical power at desired output voltage and frequency along with MPPT. Due to the fluctuating nature of wind speed, the generated voltage is not constant. So, we need some interfacing devices such as boost converter to make the voltage constant and extract maximum power at all speeds. So, MPPT be-comes necessary and challenging for the study of variable speed drive for WECS (wind energy conversion system) (Abdullah et al., 2012 & & Ram et al., 2017). Nowadays, multilevel inverters (MLIS) have been broadly explored and used in areas such as mills, mechanical drives, applications identified with a sustainable power source, grid-connected applications, and so forth and it is also possible to increase the power rating with a high number of voltage levels and variable frequency using inverter (Abdullah et al., 2012, Siddique et al., 2020, Krishna et al., 2016, Shehu et al., 2016 & Ding et al., 2019). Using a multilevel inverter, it is possible to generate a nearly smooth sinusoidal wave-form from the DC-link capacitor voltage of WECS as its input. But one clear dis-advantage of the multilevel inverter is it requires a higher no. of switches and hence causes a large amount of switching loss. So, in order to minimize these losses, the number of switches should be as minimum as possible. So, in this paper an MLI topology having less no. of switches has been used and simulated.

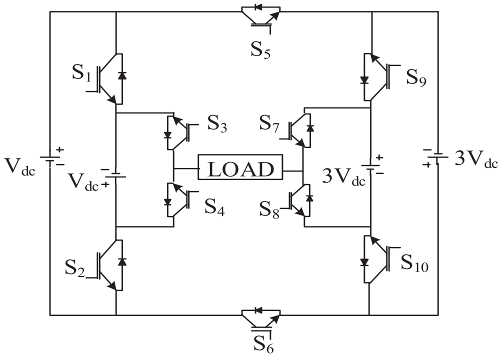
STANDALONE WIND ENERGY CONVERSION SYSTEM

A WECS consists of several components such as wind turbine, PMSG, DC-DC converter, MPPT control unit, battery storage and inverter which has been shown in Figure 1(a) and Figure 1(b). DC-DC converter essentially performs the function as interface module in between the rectified output of the PMSG generator and load to achieve MPPT using an ANN. Battery storage provides the flexibility of storing the extra power available from the wind energy system and supplying the load when less power available due to the intermittent nature of wind speed. However, the 17-level inverter circuit having 10 switches is used to feed the AC load.



(a)

Figure 1. (a) Block diagram of WECS System having multilevel inverter.



(b)

Figure 1. (b) Circuit diagram of 17 levels multi-level inverter topology (Siddique et al., 2020)

TURBINE MODELING

Extracted output power by wind turbines is the change of kinetic energy of wind is given by the following equation (1) (El-Hay et al., 2018 & Youness et al., 2019).

$$P'_t = \frac{1}{2} C'_P \rho'_w A' V'^3_w \qquad (1)$$

Where ϱ_w is the air density, C'_P is the power coefficient, A' is swept area by the blade, and V'w is the wind speed. Here C_P depends on the β' (blade pitch angle) and λ' tip speed ratio and can be computed by equation (2) (Youness et al., 2019).

$$C'_P(\lambda', \beta') = C'_1 \cdot \left(\frac{C'_2}{\lambda'_i} - C'_3 . \beta' - C'_4 \right) . e^{-\frac{C'_5}{\lambda_i}} + C'_6 . \lambda \qquad (2)$$

$$\lambda' = \frac{V'_t R'}{V'_w} \qquad (3)$$

Where C'1=0.5176, C'2=116, C'3 =0.4, C'4=5, C'5=21 and C'6=0.0068. For low-speed β' can be assumed to be zero.

BOOST CONVERTER AND BIDIRECTIONAL CONVERTER

To make DC link capacitor voltage constant, one interface between the rectified output of PMSG and DC link capacitor is required. Boost converter consists of one inductor, diode and one switch is one of the most suitable interfaces for dc-link capacitor and MPPT tracking. To extract maximum power one control mechanism is required to provide the gate signal for the boost converter. Battery has been used through bidirectional converter so that the extra power generated from WECS is used to charge the battery which supplies extra power demanded by the load (Abdullah et al., 2012 & Ullah et al., 2029). Buck-Boost bidirectional converter maintains the constant dc voltage and constant power flow and this can be achieved by charging and discharging the battery (Berigai et al., 2020).

ARTIFICIAL NEURAL NETWORK

To achieve MPPT effectively artificial neural network controller has been implemented for the duty ratio of the boost converter. Feedforward neural network is one of the popular systems which is used widely. In this paper, back propagation algorithm has been used to train the neural network with Levenberg-Marquardt (LM) based optimization technique (Saffaran et al., Yedjour et al., 2020, & Berrezzek et al., 2020).

The output of the neural network based on input training data samples (collected using classical perturbation and observation technique), bias and weights of the neural network. Data samples matrix for the input and output are taken as 10000 by 9 and 10000 by 1 respectively. Data samples are processed through the input layer which calculates the rate of change of gradient k. Now, this k is processed to determine the minimum and maximum value of x and y and the O (output of the input layer) is calculated using equation (4).

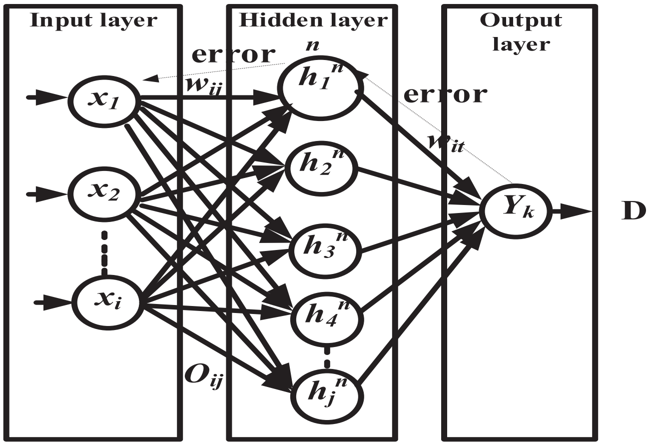


Figure 2. Neural network having back Propagation algorithm for MPPT

Now weight and bias are updated using the backpropagation training algorithm and LM based optimization technique. As shown in Figure 2 weighted sum of the inputs is computed with corresponding weights wij and bias b at hidden node hj, denoted by Ihj (see equation (5)).

$$O_i = (x_i - x_{i\ \min})k + y_{k\min} \tag{4}$$

$$Ih_j = \left(\sum_{i=1}^{i} w_{ij}.O_i + b \right) \tag{5}$$

Output of hidden node is denoted by Oh_j can be calculated using equation (6). At each input node Y_k, weighted sum of output Oh_j of hidden node with corresponding weights U_{jk} are computed and represented by IY_k (see equation (7)). Output value OY_k at kth node is computed by equation (8).

$$Oh_j = \left(\sum_{i=1}^{i} w_{ij}.O_i + b \right) \log sigmoid \tag{6}$$

$$Iy_k = \left(\sum_{i=1}^{i} U_{ik}.Oh_i + U \right) \tag{7}$$

$$Oy_k = \left(\sum_{i=1}^{i} U_{ik}.Oh_i + U \right) \log sigmoid \tag{8}$$

The corresponding duty ratio is obtained in the output layer using equation (9).

$$D = (y_k - y_{k\min})k + x_{i\min} \tag{9}$$

MULTILEVEL INVERTER TOPOLOGY

In this paper multilevel inverter (MLI) consists of several unequal DC voltage sources to create a smoother output waveform (see Figure 1(b)). The obtained output waveform has lower THD due to increment in number of level but the problem is circuit becomes more complex as the number of voltage levels increases and required a complicated switching controller circuit. MLI topology comprises 10 switches (Siddique et al., 2020). The arrangement of four dc voltage sources with the switches has been done in such a way that the switching sequence generates the 17 level output waveform. The switches of the topology are kept in two distinct sets, set 1 comprises of switch sets (S1, S2), (S5, S6), and (S9, S10) creates H-bridge (Siddique et al., 2020). Similarly, set 2 comprises of switch sets (S3, S4), (S5, S6) and (S7, S8) and creates another H-bridge. To avoid short-circuiting all these switches must operate in a complementary manner. The topology can be cascaded to reach a higher number of voltage level to improve the power quality.

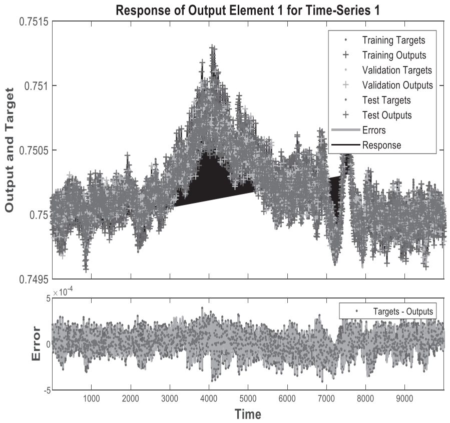
$$\theta_i = M_a \sin^{-1}\left(\frac{2i-1}{N-1} \right) \tag{4}$$

Where Ma is modulation index and i=1, 2… $\frac{N-1}{2}$

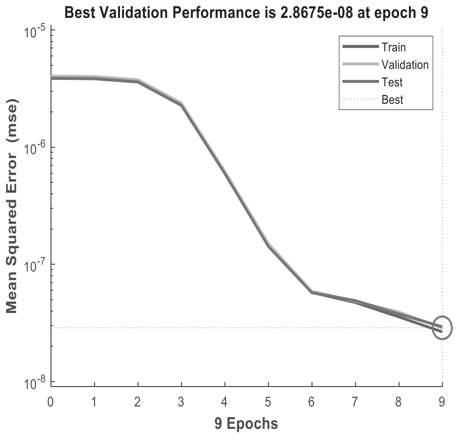
The equation (4) has been used to generate the reference signal to provide the gate signal to the switches. Multilevel inverter topology is also capable of higher voltage level because the stress of the switches is lesser. Though it contains multiple frequencies still it has superior features over convention topologies of multilevel inverters in terms of rating of power switches required for the topology.

RESULT AND DISCUSSION

In this paper WECS has been implemented with an artificial neural network for the MPPT along with the inverter topology and the result has been simulated in MATLAB/SIMULINK for various loads such as resistive (R=4Ω), inductive (R=4Ω, L=100mH).



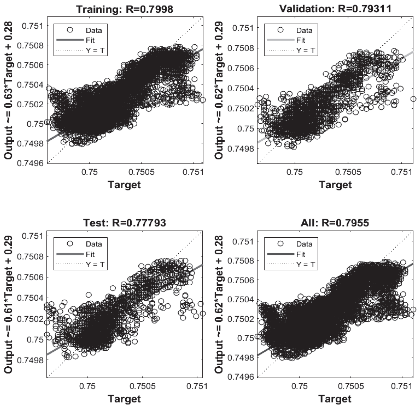
(a)



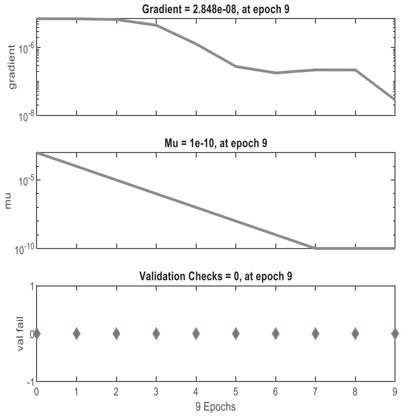
(b)

Figure 3. Output: (a) neural network output

Figure 3. (b) performance of the neural network in terms of Mean Square error.



(a)

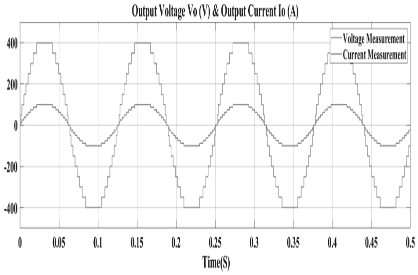


(b)

Figure 4. Output: (c) Represents fitting of output and target

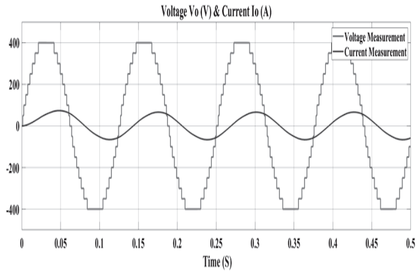
Figure 4. (b) represents training states at epoch 9.

To achieve efficient MPPT for wind energy systems having variable wind speed, the P & O algorithm has been used for the collection of ten thousand data samples further this data has been used to train the neural network using the backpropagation algorithm and Levenberg and Marquardt optimization technique.



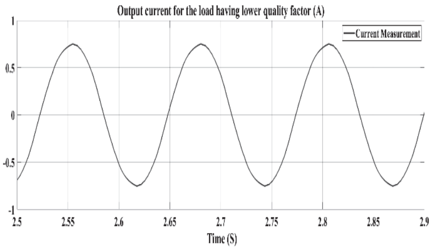
(a)

Figure 5. (a) Output voltage and current waveform for the resistive load



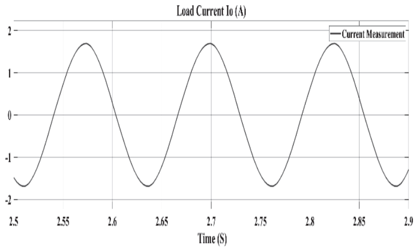
(b)

Figure 5. (b) Output voltage and current waveform for inductive load



(c)

Figure 5. (c) Output current waveform for the inductive load having low quality factor



(d)

Figure 5. (d) Output current waveform for the inductive load having a high-quality factor.

The output of the neural network is a duty ratio as shown in Figure 3(a). Figure 3(a) and 3(b) shows the neural network output, training, testing validation whereas Figure 4(a) and 4(b) shows the regression analysis and training states respectively. The MLI contains four dc voltage sources out of which two are 50V and two are 150V. Figure 5(a) shows the simulation results for 17-level output voltage and current waveform for the purely resistive load (R=4Ω). Both voltage and the current waveform are stepped in nature for purely resistive circuit.

Whereas for the inductive load (R=4Ω, L=100mH) the nature of voltage and current has been shown in Figure 5(b). Figure 5 (c-d) shows the multilevel inverter output current for an inductive load having low (R=100Ω, L=100mH) and high (R=4Ω, L=100mH) quality factor at the same frequency respectively. The single module produces an output voltage waveform having 17-level with 10 switches (less no. of switches) causes less stress for the switches.

So the no. of driver circuit required is less and various features like reduced harmonic distortion (THD), higher no. of voltage level, higher power quality, lower switching losses, lower cost can be achieved successfully.

CONCLUSION

In this paper, WECS has been implemented to harness the maximum power utilizing the artificial intelligence for MPPT and storing available extra wind energy in the battery. Battery fed the extra load when the load demand is higher than available wind power. The MLI comprises 10 switches and utilizes four dc voltage sources for the inverter to generate an output waveform of 17-level. The feature and performance of MLI topology are better than the other topologies proposed in the literature. Particularly the stress to the switches being reduced and the driver circuit required for the switches become less as the no. of switches required is less in comparison to other topologies. These viewpoints have been checked through simulation.

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