NEURAL NETWORK CONTROLLER FOR A PERMANENT MAGNET GENERATOR APPLIED IN WIND ENERGY CONVERSION SYSTEM

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ABSTRACT

In this paper a neural network controller for achieving maximum power tracking as well as output voltage regulation, for a wind energy conversion system(WECS) employing a permanent magnet synchronous generator, is proposed. The permanent magnet generator (PMG) supplies a dc load via a bridge rectifier and two buck-boost converters. Adjusting the switching frequency of the first buck-boost converter achieves maximum power tracking. Adjusting the switching frequency of the second buck-boost converter allows output voltage regulation. The on-times of the switching devices of the two converters are supplied by thedeveloped neural network(NN). The effect of sudden changes in wind speed ,and/or in reference voltage on the performance of the NN controller are explored. Simulation results showed the possibility of achieving maximum power tracking and output voltage regulation simultaneously with the developed neural network controller. The results proved also the fast response and robustness of the proposed control system.

1.INTRODUCTION

Clean renewable energy sources such as solar and wind, have been developed over recent years. Wind is now on the verge of being truly competitive with conventional sources. The cost, weight, and maintenance needs of mechanical gearing between the wind turbine and the electrical generator pose a serious limitation to the further increase in WECS power ratings. Direct coupled low speed permanent magnet generators (PMG) are under development in response to this need. For DC power generation, the lack of excitation control is not a limitation for terminal voltage and power control , since a diode rectifier and a dc-dc converter system , with various control strategies, permit load voltage and/ or load power control. To achieve load voltage and power control using conventional controllers, such as PID, accurate mathematical models describing the dynamics of the system under control is needed. This can be a limiting factor for systems with unknown varying dynamicsNow-a days, considerable attention has been focused on use of artificial neural network (ANN) on system modeling and control applications [1-3]. The NN has several key features that make it suitable for controlling nonlinear systems. These features include parallel and distibuted processing, and efficient non-linear mapping between inputs and outputs without an exact system model. So far no work has been reported on NN control for output power and regulting output voltage of permanent
magnet generators simultaneously. In this paper, a novel control strategy for maximum power tracking (MPT) and output voltage regulation of a wind energy conversion system (WECS) employing a permanent magnet generator (PMG) is proposed. The PMG output is connected to a diode bridge rectifier followed by two buck-boost converters. A four neuron-input, 8-neuron hidden layer, and two-neuron output layer neural network controller (NNC) is developed to achieve two goals. First, to utilize the maximum power available at each wind speed, i.e. maximum power tracking, by adjusting the on-time of the

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The feasibility of the proposed NNC, is tested by allowing sharp changes in the wind speed as well as step up and down changes in the output reference voltage and deducing

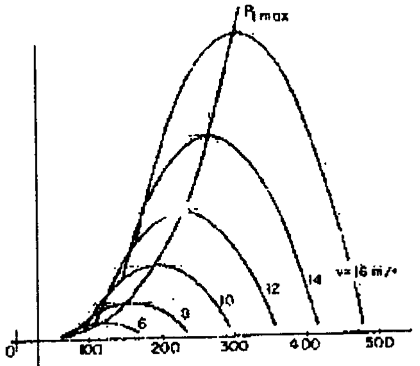
developed NNC enables MPT and output voltage regulation, within the whole wind speed range considered, with great accuracy. Results demonstrated the fast response, and robustness of the developed NNC in conjunction with the proposed WECS.

2.SYSTEM DESCRIPTION

The proposed system consists of a two-bladed, horizontal axis wind turbine coupled to a permanent magnet synchronous generator. An ac-dc power electronic interface with diode bridge rectifier and two dc-dc buck- boost converters are used for variable-speed operation of the wind generator supplying a 110 dc voltage load. The system is designed to achieve maximum power tracking (MPT) and output voltage regulation within wide range of wind speed variation by means of a neural network controller (NNC). The NNC is designed with two outputs,namely; the on-time
$_1$ -boost
converter (BB1), and the on- $_2$
device of the second buck-boost converter (BB2). The NNC is trained to adjust to d_1 to achieve MPT within a wide wind speeds range (6m/sec. to 16 m/sec.), and to adjust d_2 to achieve output voltage regulation within the same wind speed range. The subsystems modeling are described as follows:

2.1Wind Turbine (WT)

To make an optimal use of the available wind power, it is necessary to change the turbine speed ω_m in proportion to the wind speed V_w, to hold λ at the value for maximum C_p as the wind speed varies. The power P_t versus rotational turbine speed at different wind speeds for the two-bladed up wind rotor, blade-pitch regulated, 1.6Kw at 16 m./sec. wind turbine adopted in this work, is shown in Fig.(1) .On the same figure, the maximum power line P_{max} at different speeds is plotted. The maximum power transfer from the wind is achieved by ensuring the operation along the curve given by P_{max} in Fig.(1). To choose the PMG whose parameters match with the wind turbine an equation relating the maximum turbine power with the rotational turbine speed is deduced from the curve shown in Fig.(1) by interpolation. The interpolation resulted in the following equation for maximum wind power as function of ω_m:



ω_m (rpm)

Figure 1. Turbine Power-Speed Characterisics

$P_{max} = 0.0005 * \omega_w^3 \; 0.00125 * \omega_w^2 + 0.7 * \omega_w \; 74.6$ watts (3)

2.2The Permanent Magnet Synchronous Generator

A 2 Kw, 24 pole, 500rpm rated speed, permanent magnet generator (PMG), is selected for the direct drive proposed applicationThe generator output voltage varies according to the wind speeds variation. Hence, the 3-phase output of the PMG is rectified with a full wave diode bridge rectifier, filtered to remove significant ripple voltage components, and fed to two consecutive dc-dc buck-boost converters. For an ideal PMG, the line to line voltage is given as:

$$V_L = K_v \; \omega_e \sin \omega_e t \quad [V] \qquad (4)$$

Where K_v is the voltage constant and ω_e is the electrical frequency related to the mechanical speed ω_m by:

$$\omega_e = \omega_m \; *(n_p/2) \quad [rad./sec.] \qquad (5)$$

where n_p is the number of poles of PMG.

Neglecting commutation delays, the dc rectifier voltage V_d is given as:

$$V_d = (3\sqrt{2}/\Pi) * V_{Lrms} (3 \; \omega_e L_s / \Pi) I_d \qquad (6)$$

Where V_{Lrm} is the rms value of the PMG output voltage, I_d is the rectifier output current, and L_s is the stator inductance.

Neglecting the generator and rectifier losses, the PMG output rectified electrical power P_{dc}, is equal to the mechanical power input to it. Hence, for maximum power extraction, P_{dc} is set equal to P_{max} and is calculated as:

$$P_{dc} = P_{max} = V_d I_d \qquad (7)$$

The value of P_{dc} is forced to follow P_{max} by adjusting the on time of the switching device of the first buck-boost converter (BB1).

2.3 Buck-Boost Converters

Fig.(2) shows the basic buck boost converter circuit diagram. The state- space averaging method is used for analyzing the switching circuit performance, giving the following two nonlinear equations:

$$pX_1 = (1-d)/L \,(X_2) + d/L.U \qquad (8)$$

$$p X_2 = -(1-d)/C \,(X_1) - X_2 / R C \qquad (9)$$

BB1 parameters are substituted for by:
$U= U_1= V_d$, $C_1= 10$ mF, $L_1= 10$ mH , and R_1 is the equivalent input resistance of the second buck boost converter BB2 as seen by BB1.
The parameters of BB2 in equations 15 and 16 are :
U_2=output dc voltage of BB1, $C_2= 10$ mF ,L_2=10mH, and R=the load resistance R_L

3. CONTROL STRATEGY

Under steady state operation, (p=d/dt=0), the equations of the generator, the rectifier, the average of the states of the first buck-boost converter (BB1), and the average of the states of the second buck-boost converter (BB2) are manipulated to achieve the two goals of this research:
(i) Maximum power tracking, achieved by varying the on-time (d_1) of the switching device of the first buck-boost converter(BB1).
(ii).Regulation of the output voltage of the conversion system, achieved by varying the on-time (d_2) of the switching device of the second buck-boost converter(BB2).
Manipulating these equations, and setting d^*_1 as the switching time allowing MPT, and d^*_2 as the switching time that enables output voltage regulation, leads to the following expressions for (d^*_1), and (d^*_2):

$$d^*_1 = z/(1+z) \qquad (10)$$

where,

$$z = [\,(R_L/2 P_{max})]^{1/2}.V_{rms} + [(\,R_L.\,V^2_{rms})/(2 P_{max}\,\omega^2_e.L^2_s)]^{1/2} \; [\Pi.R_L / 3\,\omega_e.L_s]^{1/2}$$

and,

$$d^*_2 = y/(1+y) \qquad (11)$$

where,

$$y = (V_{ref} / P_{max})[\,(\sqrt{2}\, V_{Lrms} / \omega_e.L_s) + (V^2_{Lrms}/2\;\omega^2_e.L^2_s)^{1/2} (\Pi\, P_{max} / 3\,\omega_e.L_s)^{1/2}\,]$$

4.NEURAL NETWORK STRUCTURE

The proposed control scheme, imposing maximum power tracking and output voltage regulation, dictates the outputs of the NN controller. The NN controller is designed to give two outputs; these are d^*_1 and d^*_2, as given by equations 17 and 18 .
Off line training for the proposed NNC was applied. Data for off-line training can be obtained either by simulation or experiment. For this present work, the data is obtained by simulating the proposed WECS in open-loop system . The simulation is carried out at random wind speeds, and different values of reference voltage.. Following the control strategy, described in section 3 of this paper, d^*_1 and d^*_2

are calculated, which present the targets of the NN controller.

After many trials, the developed NNC, shown in Fig.(4), eventually employed a 4-neurons input layer, an 8-neurons hidden layer, and a 2-neurons output layer. The input network parametrs are; the generator speed ω_e , the rectifier output voltage V_d , the inductance current of the first converter I_{L1} , and the difference between the actual output voltage and the reference output voltage V_{ref}.

For the present work, such NNC structure gave satisfactory results with small number of neurons , hence better in terms of memory and time required to implement the NN in control. The transfer function used in the input and hidden

is used for the output layer. The training process has been carried out during 1000 epochs, using 6000 input-output patterns. It was designed for achievement of maximum power tracking and voltage regulation of the proposed WECS.

5.SIMULATION RESULTS

Evaluating the performance of the NN controlled WECS is done by exciting the proposed wind generation system with sudden sharp changes in wind speed and step up and down changes in reference voltage , and deducing the NNC outputs responses following these variations. Simultaneous abrupt changes in the wind speed and step change in the reference voltageare also applied and NNC response plotted.

Fig.(3) shows the two outputs of the proposed NNC following a step rise of 50 rpm in shaft speed coresponding to change in wind speed, at constant reference voltage. On the same figure, the values of d^*_1 and d^*_2 required to achieve the two goals of the proposed system, i.e. the targets, are also shown. The trivial differences between the NNC actual outputs and the targets prove that the proposed controller accurately tracks the targets without overshooting.

Fig.(4) shows the response of the proposed NNC before and after a step rise in the reference voltage from 110 to 150 volts for a time interval of 3 units, at constant wind speed. Accurate tracking of NNC to reference voltage with maximum power capturing is obvious.

The NNC outputs following simultaneous step rise in wind speed (50 rpm) and step rise in V_{ref}(40 V.)are shown in Fig.(5). Comparing these outputs with the values of d^*_1 and d^*_2 required to achieve the two control system goals, proves the validity of the developed NNC under such complicated variation . Such accurate tracking is also shown in Fig.(6), where a step rise of speed (50 rpm) is allowed with a step drop in V_{ref}(40 V step).

In Fig. (7), the feasibility of the NNC is further tested by comparing its output after high rise in shaft speed (100 rpm) simultaneous with a step drop in V_{ref}(40 V step), with values of d^*_1 and d^*_2 required to achieve the two goals. The figure demonstrates the accurate tracking of the controller to the system targets.

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6.CONCLUSION

In this paper the feasibility of a neural network controller developed for achieving maximum power tracking as well as output voltage regulation, for a wind energy conversion system(WECS) employing a permanent magnet synchronous generator, is tested. The PMG output is connected to a diode bridge rectifier followed by two buck-boost converters. The proposed control strategy aims at achieving two goals : first, to utilize the maximum power available from the wind, i.e. allow maximum power tracking, the on-time d^*_1 of the switching device of the first

ed to follow variation in wind speeds. Second goal is to regulate the load voltage by adjusting the on-time d^*_2 of the switching device of the the

-input, 8-neurons hidden layer, and two-neurons output layer neural network controller (NNC) is developed to achieve the two goalsimplied by the control strategy. The feasibility of the proposed NNC, is tested by simulating sharp changes in the wind speed as well as step up and down changes in the output reference voltage and deducing the NNC outputs response . The validity of the developed NNC is also proved by applying simultaneous variation in the shaft speed and in the reference voltage , and deducing the NNC outputs response. Results proved the accuracy of the developed NNC, its fast response and robustness.The relatively small number of neurons offers a simple way of implementing the controller.

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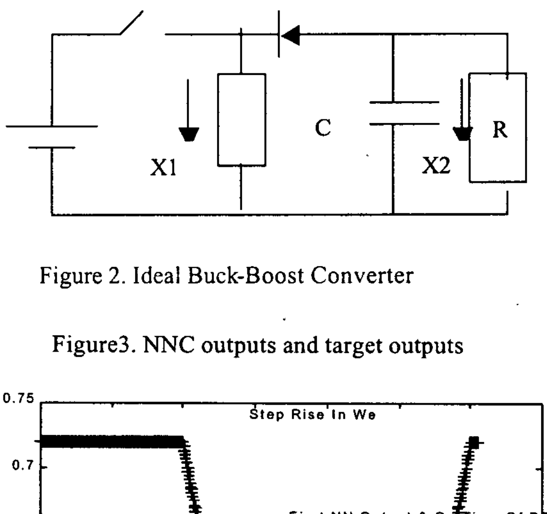

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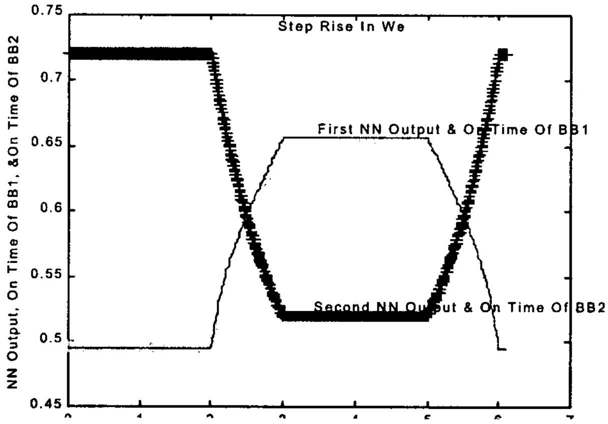
Figure 2. Ideal Buck-Boost Converter

Figure3. NNC outputs and target outputs



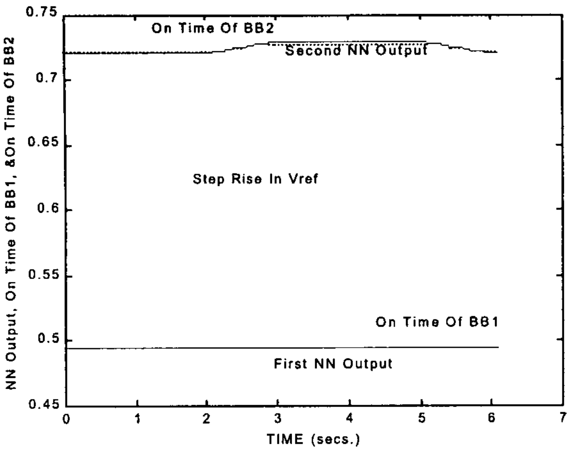


Figure 4. NNC outputs and target outputs following step rise in reference voltage

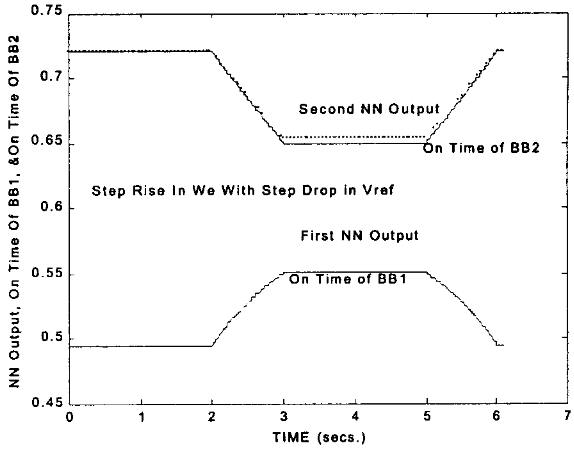


Figure 6.Response to step rise in We and step drop in Vref

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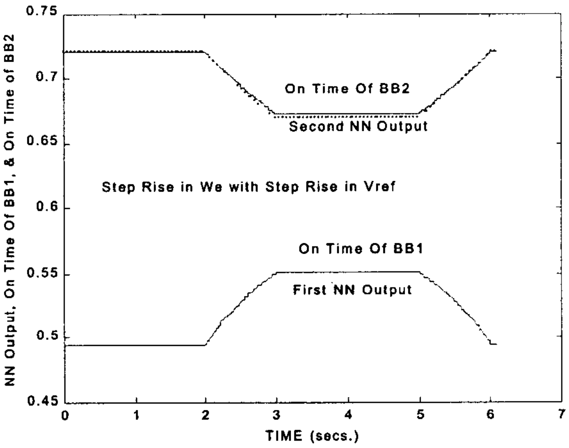

Figure 5. Responses to step rise in We with step rise in reference voltage

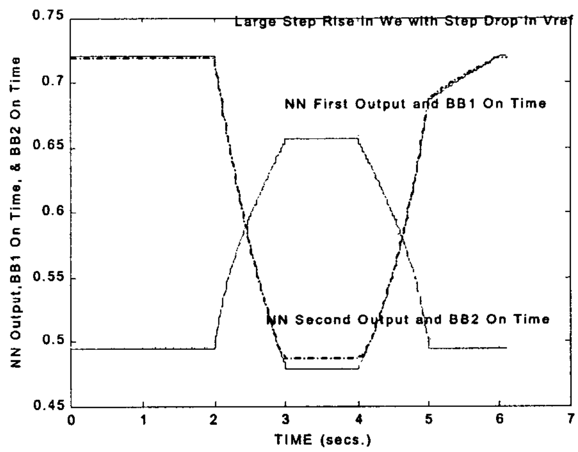

Fig ffFigure 7. Responses to large step rise in We with step drop in in