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A Novel NEURO-Fuzzy Controller for DFIG Based Wind Energy Conversion System

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ABSTRACT:

In this paper, a vector control scheme is developed to control the rotor side voltage source converter that allows independentcontrol of the generated active and reactive power as well as the rotor speed to track the maximum wind power point. A neuro-fuzzy gain tuner is proposed to control the DFIG. One scheme is realized when a converter cascade is used between the slip-ring terminals and the utility grid to control the rotor power. This configuration is called the doubly-fed induction generator (DFIG). The input for each neuro-fuzzy system is the error value of generator speed, active or reactive power. The choice of only one input to the system simplifies the design.

Index Terms:

Doubly-fed induction generator (DFIG), neuro- fuzzy, vector control, wind power generation..

INTRODUCTION:

The use of doubly-fed induction generators (DFIGs) is receiving increasing attention for grid-connected wind power generation where the terminal voltage and frequency are determined by the grid itself. One configuration is realized by using back-to-back converters in the rotor circuit and employing vector control. This allows the wind turbine to operate over a wide range of wind speed and, thus, maximizes annual energy production. The 750-kW and 1.5-MW turbines and the 3.6-MW prototypes for offshore applications from GE Wind Energy Systems employ vector control of the DFIG rotor currents which provides fast dynamic adjustment of electromagnetic torque in the machine.

Fuzzy logic has been successfully applied to control wind driven DFIGs in different aspects. Fuzzy logic was used to control both the active, and reactive power generation. In and, a fuzzy logic gain tuner was used to control the generator speed to maximize the total power generation as well as to control the active and reactive power generation through the control of the rotor side currents as demonstrated in Appendix A. The error signal of the controlled variable was the single variable used as an input to the fuzzy system. In the above-mentioned applications, the design of the fuzzy inference system was completely based on the knowledge and experience of the designer, and on methods for tuning the membership functions (MFs) so as to minimize the output error.

To overcome problems in the design and tuning processes of previous fuzzy controllers, a neuro-fuzzy based vector control technique is first proposed by the authors to effectively tune the MFs of the fuzzy logic controller while allowing independent control of the DFIG speed, active, and reactive power. The proposed neuro-fuzzy vector controller utilizes six neuro-fuzzy gain tuners. Each of the parameters, generator speed, active, and reactive power, has two gain tuners. The input for each neuro-fuzzy gain tuner is chosen to be the error signal of the controlled parameter. The choice of only one input to the system simplifies the design. In this paper, the two-axis (direct and quadrature axes) dynamic machine model is chosen to model the wind-driven DFIG due to the dynamic nature of the application. Since the machine performance significantly depends on the saturation conditions, both main flux and leakage flux saturations have been considered in the induction machine modeling. The machine model is then used to build and simulate a neuro-fuzzy vector controlled wind-driven DFIG system.

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The controllers used in vector control are a set of standard PI controllers with neuro-fuzzy gain schedulers. In these controllers, both proportional and integral gains are scheduled based upon the value of the error signal of the speed, active, or reactive power as discussed above. The neuro-fuzzy systems are designed and trained to provide the best dynamic performance while tracking the wind turbines maximum power point curve.

CONVENTIONAL CONTROLLER:

Conventional vector controllers utilize a PI controller with fixed proportional and integral gains, Kpand Ki, determined by the zero/pole placement. Such controllers give a predetermined system response and cannot be changed easily. As the system becomes highly nonlinear, more advanced control schemes are required. , an adaptive controller is proposed by the authors that can schedule both Kpand Ki depending on the value of the error. Different characteristics such as linear, exponential, piece-wise linear and fourth-order functions, representing the variation in Kp and Ki as a function of the absolute value of the error are used. The coefficients were selected such that, for the proportional gain, a fast system response with less overshoot and small settling time is obtained. While for the integral gain, it is required to reduce the overshoot and to eliminate the steady state error. It has been found that the performance of the system using the exponential characteristic produces the best system response with less overshoot, less settling time, and steady-state error.A fuzzy algorithm for tuning these two gains of the PI controller is proposed to produce good control performance.

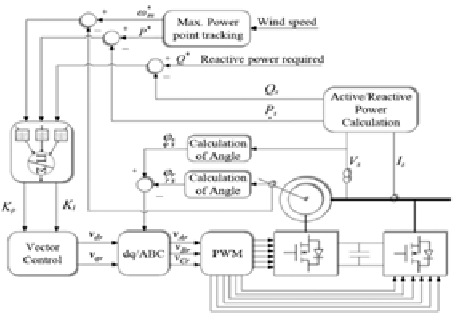

Fig 1: Neuro-fuzzy gain scheduler for vector control of wind-driven DFIG.

When parameter variations take place and/or when disturbances are present. This approach uses fuzzy rules to generate proportional and integral gains.

The design of these rules is based on a qualitative knowledge, deduced from extensive simulation tests of a conventional PI controller of the system for different values of Kp and Ki, for operating conditions.

PROPOSED NEURO-FUZZY (NF) CONTROLLER:

In the neuro-fuzzy system, a learning method similar to that of neural network is used to train and adjust the parameters of the membership functions. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. Then, the parameters of membership functions that best allow the associated fuzzy inference system to track the given input/output data are computed.

The vector control technique is implemented in Fig.1. As shown in this figure, the wind speed is measured in order to determine the set values for both the maximum DFIG output power and the corresponding generator speed in order to track the maximum power curve. These set values are then used to calculate the error signal which is the set value minus its corresponding measured actual value.

The absolute value of the error signal is used to calculate the scheduled proportional and integral gains using the neuro-fuzzy controller for each of the speed, active and reactive power controllers. To apply the vector control to the DFIG system, six neuro-fuzzy gain tuners are trained offline. Two for each of active power, reactive power, and speed controllers. One unit is responsible for tuning the proportional gain and the other for tuning the integral gain.

The developed neuro-fuzzy system is a first-order Sugeno type which has a single input with ten Gaussian distribution membership functions. It has ten if–then rules. A simple structure of the developed neuro-fuzzy system is shown in Fig.2 where the input is the error signal of the controlled variable of speed, active, or reactive power. The training is performed using the hybrid back-propagation algorithm. The training data used are collected from extensive simulations of the vector controller system with various PI gains so that the trained tuner can tune the PI gains online based on the knowledge of the different PI controllers under different operating conditions.

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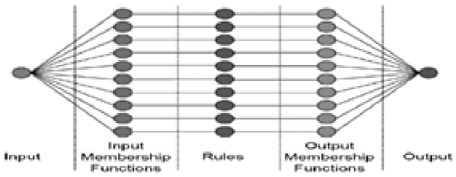

Fig 2: Simple structure of a single unit of the neuro-fuzzy gain scheduler.

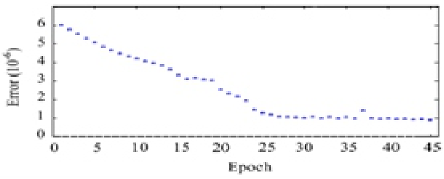

Fig 3: Training error for the speed neuro-fuzzy gain tuner.

The number of training epochs is set to 45 with an error tolerance of 10-6. The number of epochs is chosen to be the highest number after which there is no significant reduction in the training error. Fig. 3 shows the error while training at each epoch for the neuro-fuzzy gain tuner of the speed controller. After the training process, the input membership functions for the neuro-fuzzy proportional gain tuner of both active power and speed are shown in Fig.7. The output membership functions are chosen to be linear; the parameters of the ten linear output membership functions for the speed controller and active and reactive power controllers are listed in Tables I and II, respectively.

Table I:Parameters Of The Linear Output Membership Functions Of The Speed Controller

	Proportional Gain		Integral Gain	
	p_i	r_i	p_i	r_i
MF 1	-387.0	-339.1	175.9	179.9
MF 2	-203.3	-117.4	52.38	46.06
MF 3	-171.7	-53.78	38.23	32.38
MF 4	-26.53	18.04	-1.405	19.37
MF 5	-197.6	3.579	26.85	23.29
MF 6	-63.12	26.77	-63.06	27.92
MF 7	-0.272	21.15	-7.523	19.54
MF 8	95.26	-14.91	-72.93	50.47
MF 9	146.9	-65.40	-79.23	70.89
MF 10	373.0	-323.0	-190.5	196.1

Table II:Parameters Of The Linear O/P Membership Functions Of The Active And Reactive Power Controllers

	Proportional Gain		Integral Gain	
	p_i	r_i	p_i	r_i
MF 1	-95.32	-56.11	140.6	142.8
MF 2	-15.95	13.24	16.96	26.35
MF 3	-4.948	22.90	5.534	17.16
MF 4	-2.390	11.85	6.732	29.42
MF 5	-2.023	11.63	3.208	28.50
MF 6	2.023	11.63	-3.208	28.50
MF 7	2.390	11.85	-6.732	29.42
MF 8	4.948	22.90	-5.534	17.16
MF 9	15.95	13.24	-16.96	26.35
MF 10	95.32	-56.11	-140.6	142.8

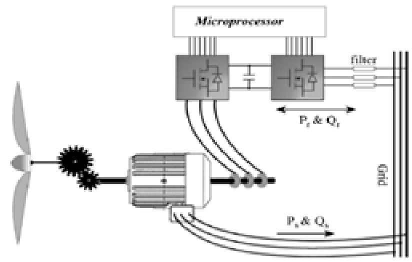

Fig 4: Wind-driven DFIG system configuration.

The proportional and integral gains are inputs to the standard PI controller part of the vector controller to generate the control signals vdrand vqr. Then vdrand vqr along with the stator and rotor angles are used to generate signals for the back-to-back converter. The angle and are calculated. These angles along with vdr and vqr help evaluate a three-phase stator voltage signal that is sent to a PWM controller to generate switching pulses for the back-to-back converters.

SIMULATION RESULTS FOR SUBSYNCHRONOUS AND SUPER-SYNCHRONOUS OPERATIONS OF THE DFIG:

The system considered in this project is a grid connected wind driven DFIG with the rotor circuit connected to the grid through back-to-back PWM voltage source converters in a configuration shown in Fig.4.While the rotor-side converter controls the rotor speed and the active and reactive power output through d-and q-axis components of the rotor voltage, vdrand vqr, by using the neuro JABR fuzzy-based vector control strategy outlined previously, the grid side converter is controlled to maintain a constant voltage level across the coupling capacitor as demonstrated.

Table III: Parameters Of The Dfig Used

Rated power	2.0 kW	Magnetizing inductance	0.066 H
Rated stator voltage	120/208 V	Stator winding resistance	0.564 Ω
Rated rotor voltage	120/208 V	Rotor winding resistance	0.450 Ω
Rated frequency	60 Hz	Stator leakage inductance	0.0033 H
Rated Speed	1,720 rpm	Rotor leakage inductance	0.0032 H

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A transformer is usually used in the rotor circuit due to the different voltage levels between the stator and the rotor. Also, a filter is utilized to minimize the harmonics injected into the grid due to the switching of the power electronic devices.

A. DFIG Used in the Investigations:

The parameters of this machine are presented in Table III. The DFIG parameters have been determined by conducting dc, no-load, and locked-rotor tests on the machine. These tests are explained in the IEEE standard of Test Procedure for Poly-Phase Induction Motors and Generators and produce unsaturated machine parameters. In order to obtain a more realistic representation of the machine, saturation in the magnetic circuit along the main and leakage flux paths should be included in the machine model. To determine the saturation characteristics of the magnetizing, stator and rotor leakage inductances, two unconventional tests are carried out. These test procedures are explained in detail in. The no-load generator test at synchronous speed is carried out to determine the main flux saturation characteristics in Fig.5 (a). The terminal voltage–armature current curve with the machine unloaded and unexcited, and the open-circuit characteristics are determined twice; one on the stator and the other on the rotor, to determine the stator and rotor leakage inductance saturation characteristics in Fig. 5(b) and (c), respectively. This main flux path saturation has been represented in the generator model by modifying the unsaturated magnetizing inductance corresponding to the magnetizing current using imFig.5 (a). In order to take the leakage flux saturation into account, the unsaturated stator and rotor leakage inductances in the machine model have been modified employing the stator and rotor leakage inductance saturation characteristics in Fig. 5(b) and (c), respectively.

B. Maximum Power Point Tracking:

The output power changes as a function of the wind speed as well as the generator speed as shown in Fig.6. To track the maximum power point, a lookup table is generated based on Fig. 6 for wind speeds less than 12 m/s and saved into the neuro-fuzzy vector controller. Wind speeds higher than 12 m/s are beyond the scope of this research. Although measuring the wind speed may have some drawbacks, it is the most accurate and easy way to change the generator speed in order to maximize the power generation.

Major wind turbine manufacturers such as Vestas and Nordex have ultrasonic wind sensors in their V90-3.0 MW modeland N90/2500 kW model, respectively. The speed information from the sensor can be used for maximum power point tracking.

C. Sub- and Super-Synchronous Operations of the DFIG:

The performance of the system employing the proposed neuro fuzzy gain tuner is examined under different operating conditions, as shown in Figs. 7 and 8.Two cases are considered in this project. The first case investigates the sub synchronous operation where the wind speed changes from 7 to 8 m/s at t = 1s. According to Fig. 6, for the maximum power generation of 0.96 kW at a wind speedof8m/s, the generator set speed increases from1200to1400 rpm. The second case investigates the super-synchronous operation where the wind speed changes from9 to 11 m/s at t = 1s.

The generator set speed increases from 1600 to 1900 rpm according to the maximum power point curve in Fig. 6, where the corresponding power output is 1.86 kW at a wind speed of 11 m/s. For both cases, the proposed neuro-fuzzy gain scheduler is employed. The speed response, stator current, rotor line voltage, and rotor current for sub synchronous operation are shown in Fig. 7,while, for the super-synchronous operation, they are shown in Fig. 8.

Experimental Determination Of The Dfig Performance Using The Proposed Controllers:

The main objective is to validate the simulation results obtained in the previous section as well as investigate the performance of the DFIG when using different controllers. The types of controllers considered are: adaptive gain scheduler, fuzzy logic, and neuro-fuzzy. The performance of the DFIG system using the above-mentioned controllers is compared to that of the conventional PI controller with constant gains.

While the system stability analysis employing these controllers is not the focus of this project, the controllers were developed with system stability in mind and it was observed that the system was stable during all experiments. As frequent and rapid changes of the controller gains may lead to instability, there is a limit as to how often and how fast the controller gains can be changed.

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The conventional PI controller has a proportional gain of 45 and an integral gain of 22.5. The DFIG used in this experiment is coupled to a dc motor (Fig. 9). The dc motor can be used as a prime-mover in wind turbine applications to adjust speed and deliver the required torque.

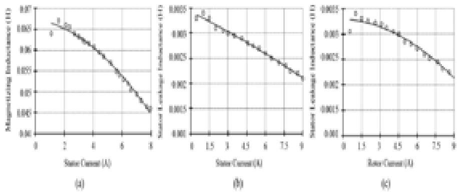


Fig 5: Saturation characteristics of the DFIG. (a) Magnetizing inductance. (b) Stator leakage inductance. (c) Rotor leakage inductance.

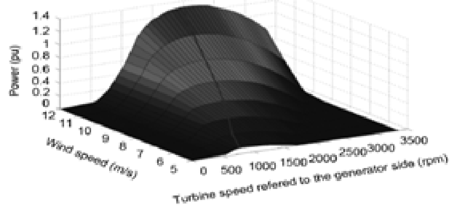


Fig.6. Typical wind turbine power curves for different wind speeds showing maximum power point curve.

Numerous cases were considered and, for illustration purposes, two were chosen and will be demonstrated. For the ease of comparison, these two cases are chosen to be same as the two described in the simulation section. The first case investigates the sub synchronous operation of the DFIG with different controllers while the second case investigates the super-synchronous operation.The selected gate driver is IRS2186 from IRF. It is capable of providing 4 A for the MOSFET gate.

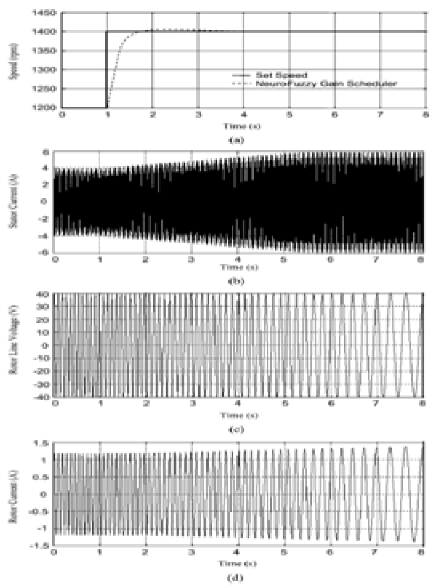


Fig.7: Calculated responses for sub synchronous operation. (a) Speed response. (b) Stator current. (c) Rotor line voltage. (d) Rotor current.

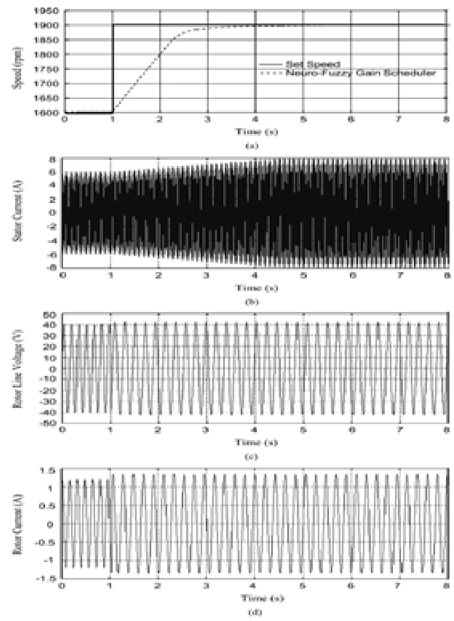
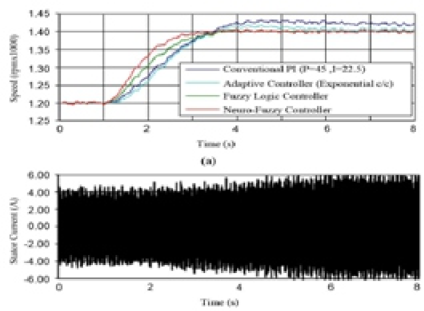


Fig 8: Calculated responses for super-synchronous operation. (a) Speed response. (b) Stator current. (c) Rotor line voltage. (d) Rotor current.

After selecting the components, the next stage is to build the circuit and fabricate the printed circuit board (PCB). Al-tium Designer was used to perform this task for its powerful capabilities in designing the routes and massive component library. All stator and rotor currents are experimentally measured and recorded using a Tektronix TDS1002 digital storage oscilloscope. The sampling frequency is 1.25 kHz.

B. Sub synchronous Operation of the DFIG:

In this case, the generator speed changes from 1200 to 1400 rpm. The resulting speed change for each controller is illustrated in Fig. 9(a).



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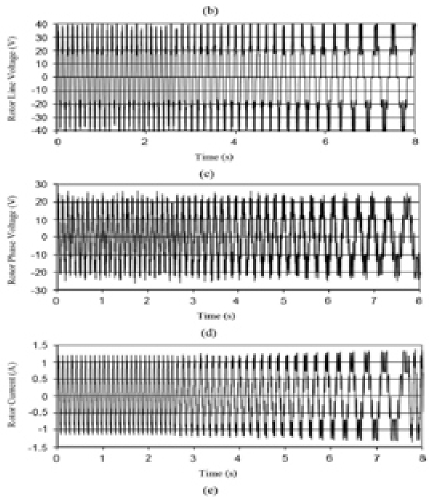

Fig 9: Measured Responses For Sub Synchronous Operation. (A) Speed Response. (B) Stator Current. (C) Rotor Line Voltage. (D) Rotor Phase Voltage. (E) Rotor Current.

It Can Be Seen From This Figure And Table IV That The Conventional PI Controller With Constant Gain Has A Rise Time Of 2.8 S With 2% Overshoot And 1.5% Steady-State Error While The Adaptive PI Gain Scheduler Employing An Exponential Characteristic Has A Rise Time Of 2.5 S And A Settling Time Of 6 S With 1% Overshoot And No Steady-State Error. On The Other Hand, The Fuzzy PI Gain Scheduler Has A Rise Time Of 2 S And A Settling Time Of 3 S With No Overshoot And No Steady-State Error While The Neuro-Fuzzy PI Gain Scheduler Has A Rise Time Of 1.5 S And A Settling Time Of 2.8 S With No Overshoot And No Steady-State Error.

Table IV:Controllers Performance For Sub-synchronous Operation

Controller	Rise time (s)	Settling time (s)	Overshoot (%)	S.S. error (%)
Conv. PI	2.8	∞	2.0	1.5
Adaptive	2.5	6.0	1.0	0.0
Fuzzy Logic	2.0	3.0	0.0	0.0
Neuro-Fuzzy	1.5	2.8	0.0	0.0

For the same case, the change in speed increased the stator active power production from 0.78 to 0.96 kW while the reactive power produced is kept constant at 0.80 kVAR. This rise in power production increased the stator current as shown in Fig. 9(b). At the rotor side, the increase in speed required an increase in the rotor current and rotor line voltage which are shown in Fig. 9(c)–(e), respectively.

In order to increase the active power generation from 0.78 to 0.96 kW, an increase in the q-axis component of the rotor current iqris required. However, there is no change in the d-axis component of the rotor current idrsince the reactive power generation has been kept constant. This increase in iqr has resulted in an increase in the rotor current.

C.Super-Synchronous Operation of the DFIG:

In the second case, the generator speed changes from 1600 to 1900 rpm. The resulting speed change for each controller is illustrated in Fig. 10(a). It can be seen from this figure and Table V that the conventional PI controller with constant gain has a rise time of 3.8 s and a settling time of 4.5 s with no overshoot and no steady-state error. The adaptive PI gain scheduler with an exponential characteristic also yielded similar results. On the other hand, the fuzzy PI gain scheduler has a rise time of 2.5 s and a settling time of 4.5 s with 0.6% overshoot and no steady-state error while the neuro-fuzzy PI gain scheduler has a rise time of 2.8 s and a settling time of 4.5 s with no overshoot and steady-state error. Although the fuzzy PI gain scheduler has a shorter rise time than that of the neuro-fuzzy PI gain scheduler in this case, it has the largest overshoot among the compared gain scheduler. For this case, the change in speed increased the stator active power production from 1.32 to 1.86 kW while the reactive power production is kept constant at 1 kVAR. This increase in power production increased the stator current as shown in Fig. 15(b). At the rotor side, the increase in speed required an increase in the rotor current and rotor line voltage which are shown in Fig. 10(c)–(e), respectively.

D. Comparison of the Results:

It can be seen from Figs. 7 and 8 that the speed and stator and rotor quantities calculated by employing the neuro-fuzzy controller in Section IV-C are in good agreement with the experimentally measured ones shown in Figs. 9 to 10. This indicates the accuracy of the proposed control system. The neuro-fuzzy PI gain scheduler enables proportional and integral gains within the vector control scheme to be changed depending on the operating conditions. It can also be seen that using the proposed neuro-fuzzy controller, the dynamic response can be improved and more precise control is achieved in comparison to PI, adaptive, and fuzzy logic controllers.

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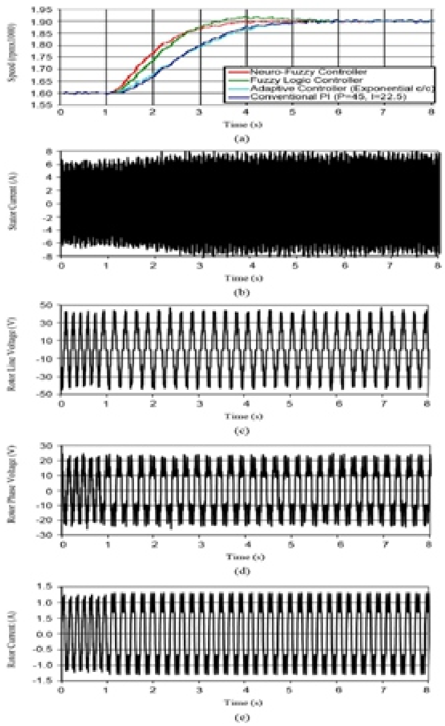

Fig.10: Measured responses for super-synchronous operation. (a) Speed response. (b) Stator current. (c) Rotor line voltage. (d) Rotor phase voltage. (e) Rotor current.

The proposed neuro-fuzzy PI gain scheduler achieved faster system response with almost no overshoot, shorter settling time and no steady-state error.

Table V: Controllers Performance For Super-Synchronous Operation

Controller	Rise time (s)	Settling time (s)	Overshoot (%)	S.S. error (%)
Conv. PI	3.8	4.5	0.0	0.0
Adaptive	3.8	4.5	0.0	0.0
Fuzzy Logic	2.5	4.5	0.6	0.0
Neuro-Fuzzy	2.8	4.5	0.0	0.0

For DFIG operation in the entire speed range, it is well understood that the speed and frequencies of induction machines are such that the stator frequency is equal to the rotor electrical speed combined with the rotor frequency. It can be seen from Figs. 8 and 10 that the relation holds true for the super-synchronous mode of operation. Referring to Figs. 7(a) and (b) and 9(a) and (b), for sub synchronous mode, it is seen that the rotor speed settles to the new set point of 1400 rpm approximately at 4 s and the stator current has constant frequency of 60 Hz during the entire event; however, Figs. 7(c) and (d) and 9(c) and (d) show that the frequency of the rotor quantities decrease even after the speed has settled. Current research is underway to identify and resolve this apparent discrepancy.

SIMULATION RESULTS

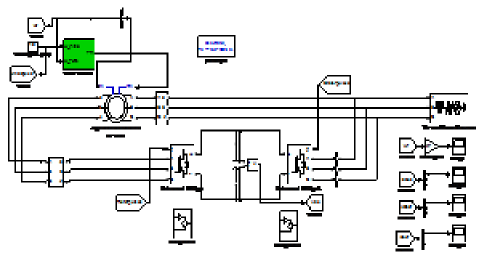

Fig 11: Simulation circuit

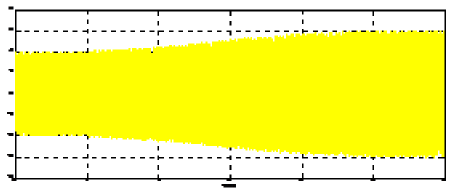

Fig 12: Stator current wave form

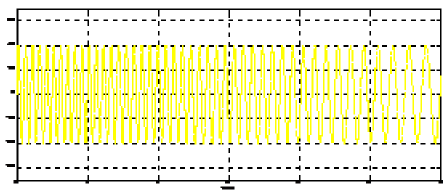

Fig 13:Rotor line voltage wave form

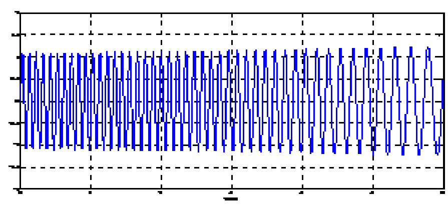

Fig 14: Rotor currents wave form

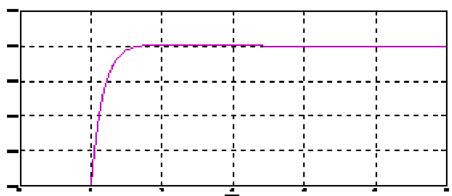

Fig 15: Speed Response wave form

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CONCLUSION:

This paper presents a control method to maximize power generation of a wind-driven DFIG considering the effect of saturation in both main and leakage flux paths. This is achieved by applying vector control techniques with a neuro-fuzzy gain scheduler. The overall DFIG system performance using the proposed neuro-fuzzy gain tuner is compared to that using the conventional PI controllers. The generator speed response as well as the stator and rotor currents and the rotor voltages in response to a sudden change in the wind speed are presented.The main findings of the project can be summarized in the following points: 1) Traditional vector control schemes that employ a conventional PI controller with fixed proportional and integral gains give a predetermined response and cannot be changed. However, the proposed neuro-fuzzy PI gain scheduler enables proportional and integral gains within the vector control scheme to be changed depending on the operating conditions.2) It is demonstrated that, using the proposed controller, the system response can be improved and more precise control is achieved.3) The proposed neuro-fuzzy PI gain scheduler achieves faster system response with almost no overshoot, shorter settling time, and no steady-state error.

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