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Optimal Identification of Doubly Fed Induction Generator Parameters in Wind Power System using Particle Swarm Optimizationand Artificial Neural Network

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Abstract

Wind energy became one of the techniques that attracted much attention worldwide. The induction generator is used in the exploitation of this energy and converts it into electrical energy because of the advantages that distinguish it from other types of generators. In this paper, an optimal identification of induction generator parameters is proposed. Particle Swarm Optimization technique (PSO) trained using Artificial Neural Network (ANN) is used to identify the main parameters of the induction generator in cases of wind speed change, load change and fault cases.

The simulation results obtained indicate that the particle swarm optimization is suitable for neural networks training for controlling of the voltage, frequency and generated power. The simulation programming is implemented using MATLAB.

Keywords: Wind Energy (WE), Induction Generator (IG), Particle Swarm Optimization (PSO).

تحديد العناصر المثلى للمولد الحثي في منظومة طاقة الرياح بأستخدام أمثلية الحشد الجزيئي والشبكات العصبية الأصطناعية

الخلاصة

يعتبر توليد الطاقة الكهربائية باستخدام المصادر غير التقليدية للطاقة مثل طاقة الرياح من التقنيات الواعدة التي اجتذبت قدرا واسعاً من الاهتمام في السنوات الاخيرة. يستخدم المولد الحثي في منظومات طاقة الرياحلتحويل الطاقة الكهربائية بسبب المزايا التي تميزه عن الأنواع الأخرى من المولدات الكهربائية. تم في هذاالبحث أقتراحاستخدام تقنية أمثلية الحشد الجزيئي(PSO) وتدريبها باستخدام الشبكة العصبية الأصطناعية (ANN)لتحديد عناصرالمولد الحثي ثلاثي الأطوار في حالات تغير سرعة الرياح والحمل وحالات العطل، بينت نتائج المحاكاة التي تم الحصول عليها من هذه التقنية المقترحة فاعليةالتقنية المقترحة في تحديد مخرجات المولد الحثي من خلال السيطرة

على الفولتية والتردد ضمن حدودها المثلى ومن ثم السيطرة على القدرة المتولدة. تم تنفيذ العمل والمحاكاة باستخدام برامجيات المختبر الرياضي (MATLAB).

INTRODUCTION:

Wind energy has proven to be a potential clean, free and renewable source for generation of electricity with minimal environmental impact [1].

In recent years, wind energy has become one of the most important and promising sources of renewable energy, which demands additional transmission capacity and better means of maintaining system reliability. The evolution of technology related to wind systems industry led to the development of a generation of variable speed wind turbines that present many advantages compared with the fixed speed wind turbines. These wind energy conversion systems are connected to the grid through Voltage Source Converters (VSC) to make variable speed operation possible[2, 3].

In this paper, proposed a variable speed wind generation system based on Doubly Fed Induction Generator (DFIG) with introduces the operation and control of a system. This paper describes the effect of electrical parameters of the Double Fed Induction Generator (DFIG) for operation within power system in order to perform stability and turbine control to maximize the power generated with the lowest impact on the grid voltage and frequency during normal operation and under several disturbances, such as a transmission line earth fault. The proposed methods consider wind turbines based on induction generator and a grid-connected converter with constant or variable speed wind turbines. The proposed work is performed within the multiple technologies design tool MATLAB/Simulink.

The performance of DFIG under different operating conditions is investigated and Artificial Intelligence (AI) controllers are proposed to enhance the performance of induction generator parameters in wind energy system during different disturbances conditions. The purpose of the control system is to manage the safe, automatic operation of the turbine, within a framework of optimizing generated power.

Mathematical Model of DFIG:

A doubly fed induction machine is basically a standard, wound rotor induction machine with its stator windings directly connected to the grid and its rotor windings connected to the grid through a converter. The AC/DC/AC Converter is divided to two components: the rotor side converter (RSC) and the grid side converter (GSC) as shown in Figure (1).

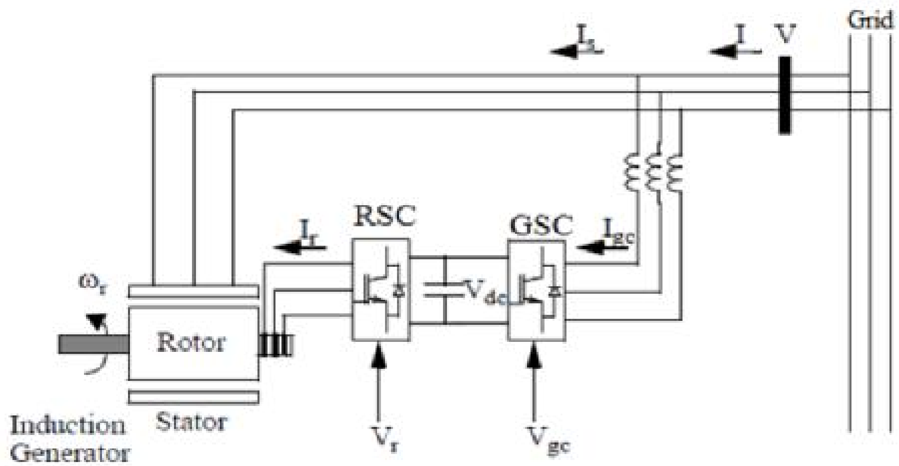

Figure (1) Rotor Side and Grid Side Converters control system

For a doubly fed induction machine, as shown in Figures (2) and (3) the Concordia and Park transformation's application to the traditional a, b, c model allows to write a dynamic model in a d-q reference frame as follows [4, 5, 6]:

$$V_{ds} = R_s I_{ds} + \frac{d}{d_t}\psi_{ds} - \omega_s \psi_{qs} \quad \ldots (1)$$

$$V_{qs} = R_s I_{qs} + \frac{d}{d_t}\psi_{qs} + \omega_s \psi_{ds} \quad \ldots (2)$$

$$V_{dr} = R_r I_{dr} + \frac{d}{d_t}\psi_{dr} - (\omega_s - \omega_r)\psi_{qr} \quad \ldots (3)$$

$$V_{qr} = R_r I_{qr} + \frac{d}{d_t}\psi_{qr} + (\omega_s - \omega_r)\psi_{dr} \quad \ldots (4)$$

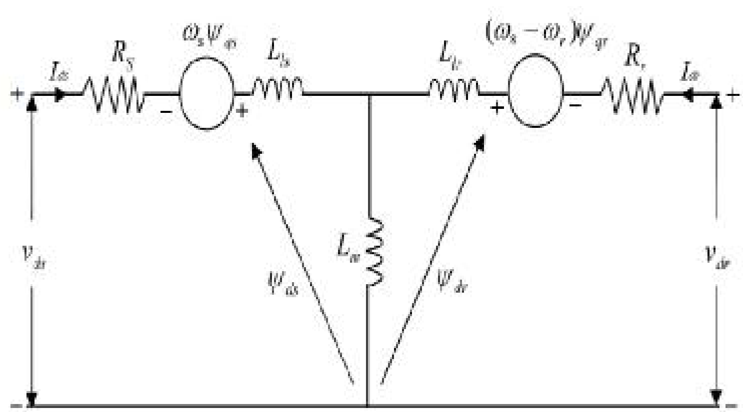

Figure (2) Dynamic d axis circuit

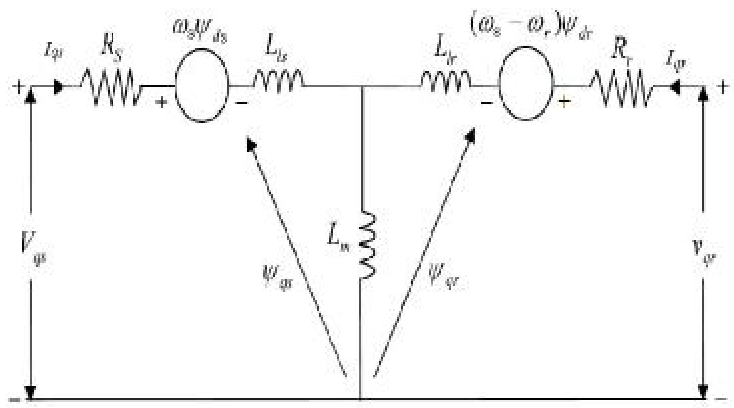

Figure (3) Dynamic q axis circuit

Where$V_{ds}, V_{qs}, V_{dr}, V_{qr}$are the q and d-axis stator and rotor voltages, respectively. $I_{ds}, I_{qs}, I_{dr}, I_{qr}$are the q and d-axis stator and rotor currents, respectively. $\psi_{ds}, \psi_{qs}, \psi_{dr}, \psi_{qr}$are the q and d-axis stator and rotor fluxes, respectively. $\omega_s$is the angular velocity of the synchronously rotating reference frame. $\omega_r$is rotor angular velocity, $R_s$andR_r are the stator and rotor resistances, respectively. The stator and rotor fluxes can be expressed:

$$\psi_{ds} = L_s I_{ds} + L_m I_{dr} \quad \ldots (5)$$
$$\psi_{qs} = L_s I_{qs} + L_m I_{qr} \quad \ldots (6)$$
$$\psi_{dr} = L_r I_{dr} + L_m I_{ds} \quad \ldots (7)$$
$$\psi_{qr} = L_r I_{qr} + L_m I_{qs} \quad \ldots (8)$$

Where$L_s, L_r,$ and$L_m$are the stator, rotor, and mutual inductances, respectively, with and: being the self-inductance of stator and being the self-inductance of rotor.

The mechanical and electromagnetic torques is expressed with the following equations:

$$T_m = T_e + J\frac{d\omega}{dt} + f\omega \quad \ldots (9)$$
$$T_e = -P\frac{L_m}{L_s}\left(\psi_{qs} I_{dr} - \psi_{ds} I_{qr}\right) \quad \ldots (10)$$

The active and reactive powers at the stator are defined as:

$$P_S = v_{ds} I_{ds} + v_{qs} I_{qs} \quad \ldots (11)$$
$$Q_S = v_{qs} I_{ds} - v_{ds} I_{qs} \quad \ldots (12)$$

Also the active and reactive powers at the rotor:

$$P_r = v_{dr} I_{dr} + v_{qr} I_{qr} \quad \ldots (13)$$
$$Q_r = v_{qr} I_{dr} - v_{dr} I_{qr} \quad \ldots (14)$$

Wind Farm DFIG Model Description

9-MW wind farm turbine with the parameters values of DFIG used as shown in Appendix connected to a 33kV distribution system exports power to a 132-kV grid through a 30-km, 33kV feeder. A 2300V, 2-MVA plant consisting of a motor load (1.68 MW induction motor at 0.93 PF) and of a 500-kW resistive load is connected at bus B400 as shown in Figure (4).

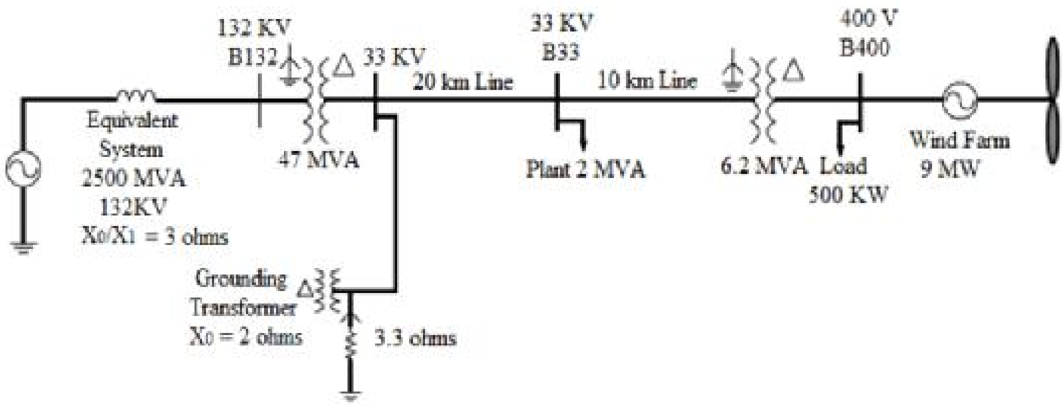

Figure (4) Single-line diagram of the wind farm connected to a distribution system

PI Controller:

]The PI controller has been widely used in industry due to simple implementation, low coast and the ability to apply in a wide range of application. It also improves the dynamic response of the system as well as reduces or eliminates the steady state error and the error sensibility. This is achieved by providing a proportional gain (K_p) for the error input term with an integral component correction (K_i) [7].

Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) algorithm is a population-based stochastic optimization technique developed by Eberhart and Kennedy in 1995. It is inspired by the natural animal social behavior such as bird flocking and fish schooling. It has been fo und to be robust in solving continuous nonlinear optimization problems. PSO becomes a focus these days due to its simplicity and ease to implement [7].

A modified PSO was introduced in 1998 to improve the performance of the original PSO. A new parameter called inertia weight is added [8].

In PSO, each single solution is a “bird” in the search space; this is referred to as a “particle”. The swarm is modeled as particles in a multidimensional space, which have positions and velocities. These particles have two essential capabilities: their memory of their own best position and knowledge of the global best. Members of a swarm communicate good positions to each other and adjust their own position and velocity based on good positions [8].

The particles are updated according to the following equations [7, 8]:

$$v(k+1)_{i,j} = w.v(k)_{i,j} + c_1 r_1\left(gbest - x(k)_{i,j}\right) + c_2 r_2 (pbest - x(k)_{i,j} \quad \ldots (15)$$

$$x(k+1)_{i,j} = x(k)_{i,j} + v(k+1)_{i,j} \quad \ldots (16)$$

Where

v_{ij} : Velocity of particle i and dimension j.
$x_{i,j}$: Position of particle i and dimension j.
c_1, c_2 : Known as acceleration constants.
w : Inertia weight factor.
r_1, r_2 : Random numbers between 0 and 1.
Pbest : Best position of a specific particle.
Gbest : Best particle of the group.

The PSO tuning algorithm for gains can be illustrated with flow chart as shown in Figure (5).

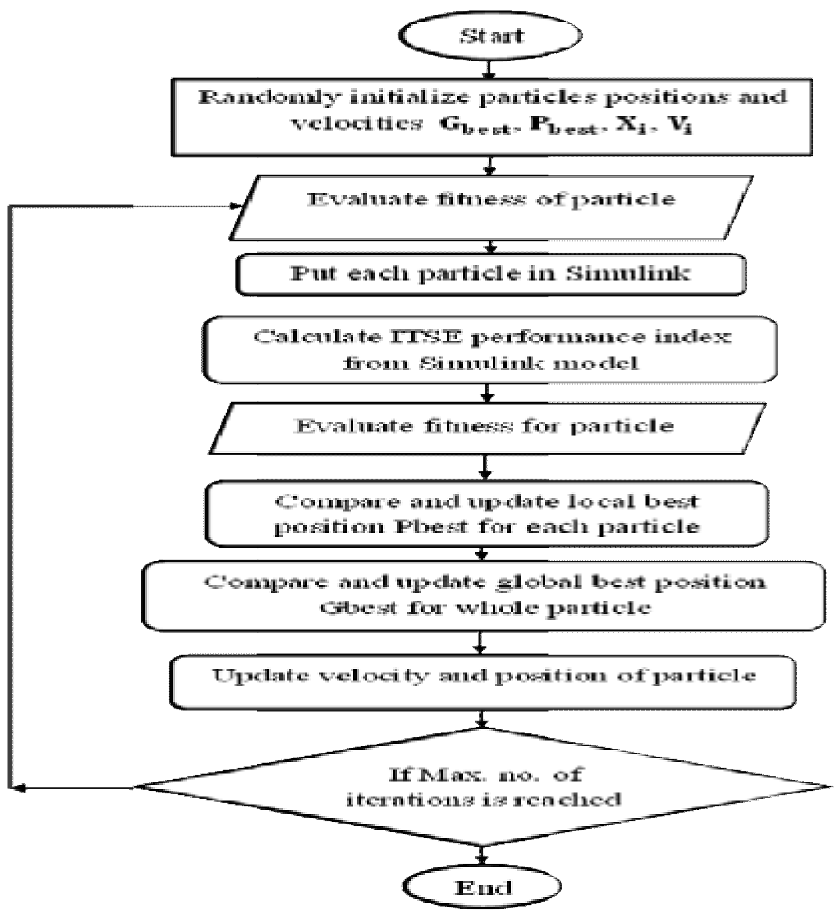

Figure (5) Flow chart of PSO algorithm

The PSO algorithm is implemented in the following iterative procedure to search for the optimal solution [7].

1) Initialize a population of particles with random positions and velocities of N dimensions in the problem space.

2) Define a fitness measure function to evaluate the performance of each particle.

3) Compare each particle's present position (xi) with its (xpbest) based on the fitness evaluation. If the current position xi is better than (xpbest), then set (xpbest = xi).

4) If (xpbest) is updated, then compare each particle's (xpbest) with the swarm best position (xgbest) based on the fitness evaluation. If (xpbest) is better than (xgbest), then set (xgbest = xpbest).

5) At iteration k, a new velocity for each particle is updated by equation (15).

6) For each particle, change its position according to the equation (16).

7) Repeat steps (2)-(6) until a criterion, usually a sufficiently good fitness or a maximum number of iterations is achieved. The final value of (xgbest) is regarded as the optimal solution of the problem.

Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are a data processing system consisting of a large number of simple, highly interconnected processing elements inspired by the biological system and designed to simulate neurological processing ability of human brain [9, 10].

A generic Artificial Neural Network (ANN) can be defined as a computational system consisting of a set of highly interconnected processing elements, called neurons, which process information as a response to external stimuli. An artificial neuron is a simplistic representation that emulates the signal integration and threshold firing behavior of biological neurons by means of mathematical equations. Like their biological counterpart, artificial neurons are bound together by connections that determine the flow of information between peer neurons. Stimuli are transmitted from one processing element to another via synapses or interconnections, which can be excitatory or inhibitory. If the input to a neuron is excitatory, it is more likely that this neuron will transmit an excitatory signal to the other neurons connected to it. Whereas an inhibitory input will most likely be propagated as inhibitory [10].

The artificial neuron is composed of a summer (net), which just likes the linear equation of the linear regression model, and a transfer function, which is linear or non-linear.The summing block is directly connected with the input vector $(a_1, a_2, \ldots, a_n)$ from outside of the neuron. There is a weight $(w_1, w_2, w_3, \ldots, w_n)$ on each connection (path) between each input and the neuron. In addition, a bias which input value is 1 is also associated with the neuron, a threshold value 'θ' that has to be reached or extended for the neuron to produce a signal, a nonlinear function "F " acts on the produced signal "net" and an output "T " after the nonlinearity function [6].

The basic model of an artificial neuron is shown in Figure (6).

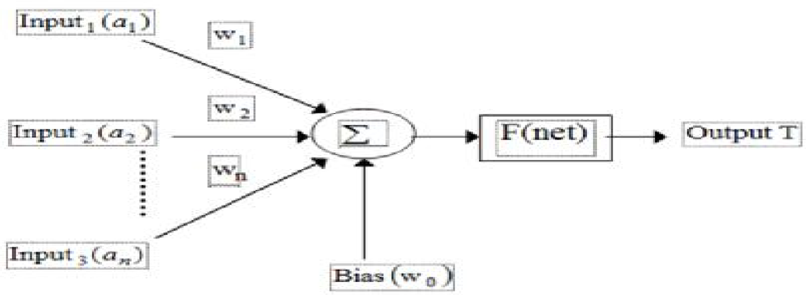

Figure (6) Basic neural model

The following relation describes the transfer function of the basic neuron model [9].

$$T = F(net) \quad \dots (17)$$

Where

$$net = w_0 + \sum_{i=1}^{n} a_i w_i \quad \dots (18)$$

And the function firing condition is:

$F(net) \geq \theta$ [For nonlinear activation function].

Or

$\sum_{i=1}^{n} a_i w_i \geq \theta$ [For linear activation function]

The neurons are assumed arranged in layers, and the neurons in the same layer behave in the same manner. All the neurons in a layer usually have the same activation function. Various multilayer Neural Networks (NN) types have been developed. Feed forward neural networks such as the standard multilayer Neural Networks (NN), functional link NN and product unit NN receive external signals and simply propagate these signals through all the layers to obtain the result (output) of the Neural Networks (NN). The architecture of a multilayer neural network is shown in Figure (7).

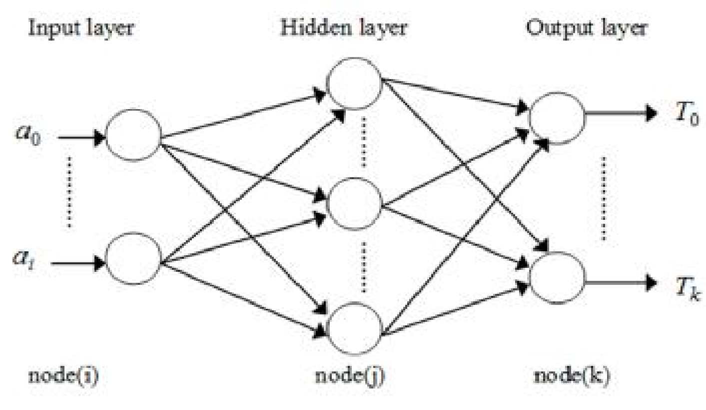

Figure (7) Multilayer neural network

The most important characteristic of an artificial neural network is its ability to learn. Learning is a process in which the network adjusts its parameters the (synaptic weight) in response to input stimuli, so that the actual output response converges to the desired output response [10].

The training procedure used in each network can be summarized in the following steps:

1) Simulation model of DFIG using MATLAB.
2) Generation input/output data for different operating conditions and save them in files.
3) Feed the data to the proposed neural network.
4) Select ANN topology with number of Layers
5) For each input data set, an output data is calculated.
6) Comparing output data with the desired output data to derive the error pattern.
7) Repeat the above steps with each set of input/output data pattern until the error for the entire training set converges below the desired threshold value.
8) After completion of the training process, a test program is performed with arbitrary input data to ensure the successful training.

Figure (8) shows the flow chart for Artificial Neural Network (ANN) training.

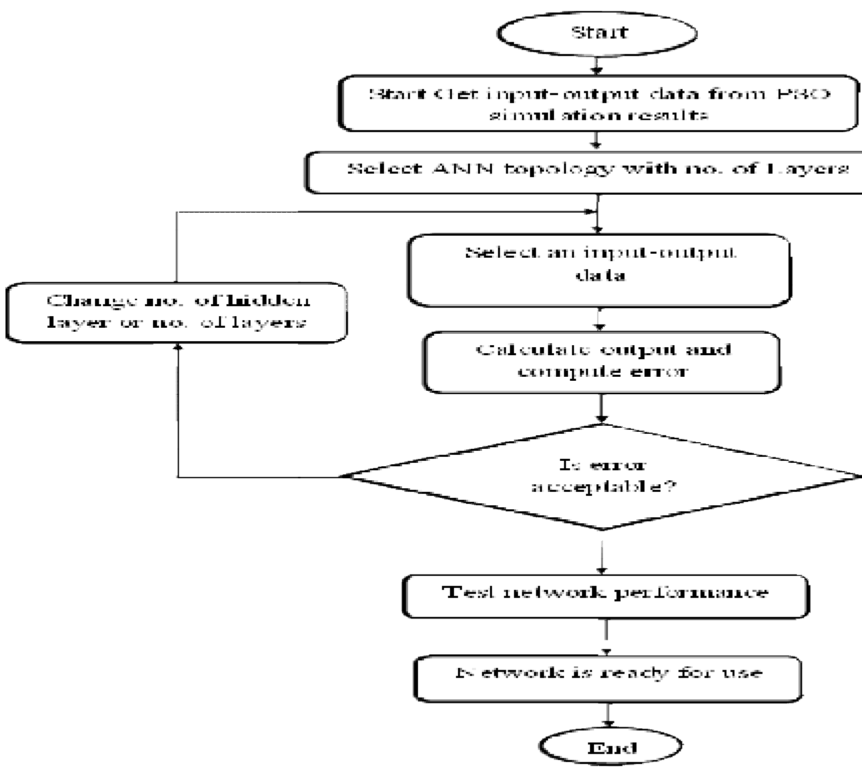

Figure (8) Flow chart for artificial neural network training

ANN based on PSO controller

The simulation of the complete model with PI controller is shown in Figure (9).

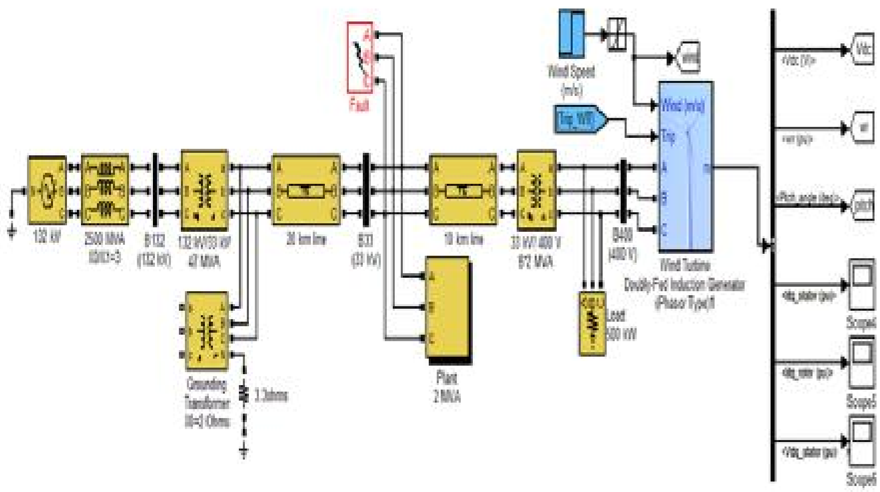

Figure (9) Doubly fed induction generator model

A proposed Artificial Neural Network (ANN) controller with gains was optimized by PSO technique is used in order to enhance the controller performance. The major advantage of ANN is that it has no mathematical model so the computational time is reduced.

Artificial Neural Network (ANN) consists of highly interconnected simple processing units designed in a way to model how human brain performs a particular task. It is essentially a mathematical model of a non-linear statistical data modeling tool and is a powerful and simple algorithm to approximate nonlinear functions or to solve problems where the input-output relationship is neither well defined nor easily computable

Training parameters of the grid side controller are illustrated in Table (3). And the simulation model of the parameters controller for DFIG with ANN control system based on PSO connected to the GSC as shown in Figure (10).

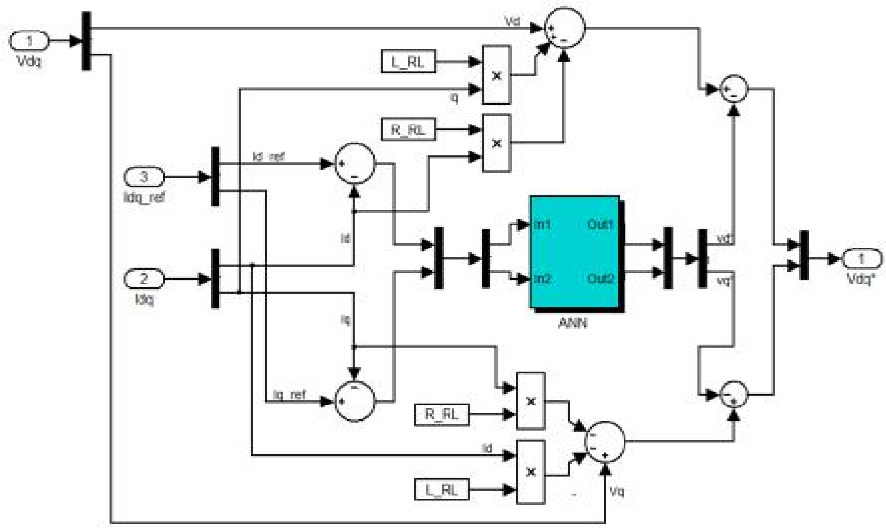

Figure (10) Grid side converter current control system

Training parameters of the rotor side controller are illustrated in Table (4). And the Simulation model of the parameters controller for DFIG with ANN control system based on PSO is connected to the RSC controller as shown in Figure (11).

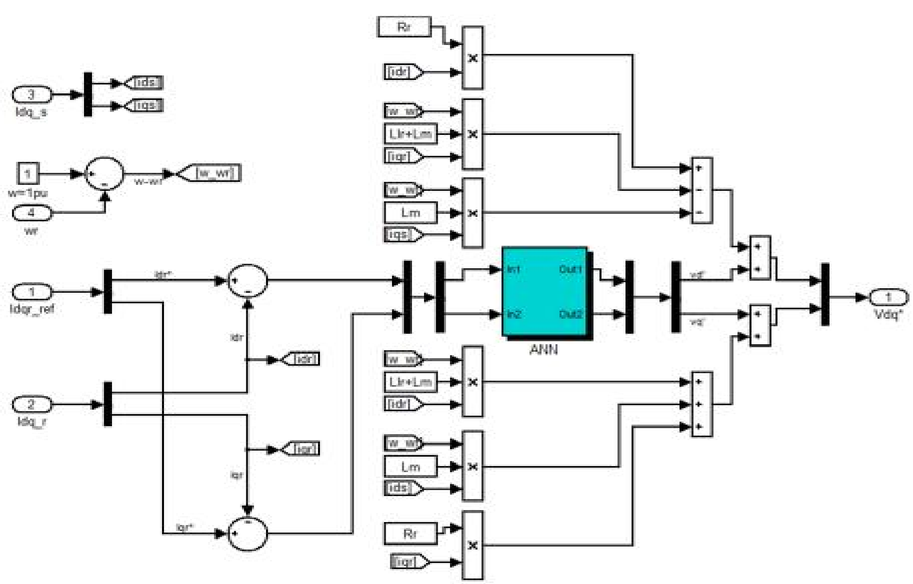

Figure (11) Rotor side converter current control system

Simulation results of DFIG

A comparison between different controllers for the active power of the DFIG based on GSC and RSC control with different conditions is explained as follows:

Case 1: Turbine response to a change in wind speed:

Figure (12) show the generated active power starts increasing smoothly (together with the turbine speed) to reach its rated value of 9MW in approximately 14s with PI controller tuned by trial and error and ANN controller with gains tuned by PSO method is shown below.

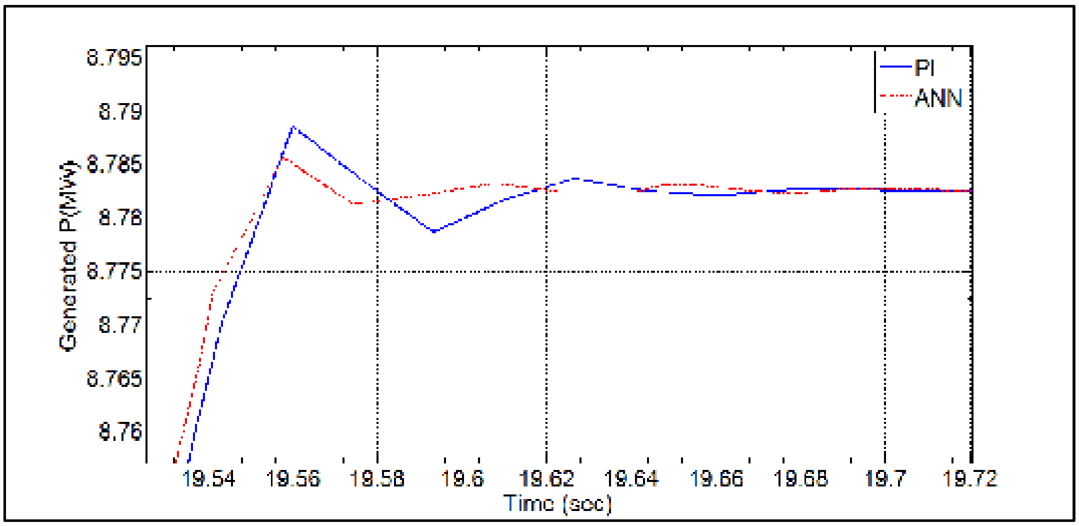

Figure (12) Active power of wind turbine

A comparison between different controllers for the active power of the DFIG based on GSC and RSC control under change of wind conditions are illustrated in Table (1).

Table (1) DFIG responses of change in wind speed

Wind speed (m/s)	Initial value		Final value
	8		14
Rated value of Active Power in Wind Turbine (MW)			8.7825
Active Power in Wind Turbine (MW)	Over shoot	under shoot	Settling time (sec) 5%
PI controller	8.7900	8.778	19.60
ANN controller	8.7857	8.781	19.56

Case 2:Simulation of three phase-to-ground fault

In this case, three phase to ground fault occurring on the 33 kV line.

The transient response analysis is used for these comparisons. At the end of the analysis, the maximum overshoots of the control system which is optimized with ANN controller are as small as about 24% of PI controller. Finally, it may be said that the ANN controller gets better performance than the other population based optimization algorithms.

Figure (13) show that PI controller which is tuned by trial and error and to improve performance of system PSO algorithm is applied for optimal tuning of PI controller which reduces the settling time and using ANN controller based on PSO for optimal control.

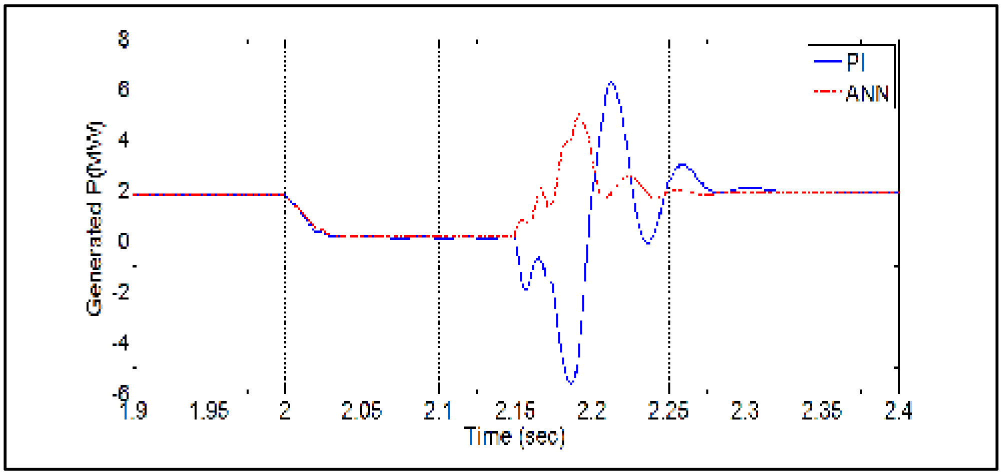

Figure (13) Active power of wind turbine at bus B400

A comparison between different controllers for the active power of the DFIG under three phase-to-ground fault conditions are illustrated in Table (2).

Table (2) DFIG responses of three phase-to-ground fault

Wind speed (m/s)			8	
Rated value of Active Power in Wind Turbine (MW)			1.94	
Active Power in Wind Turbine (MW)	over shoot	Percent ratio (other/ANN)*100	under shoot	Settling time (sec) 5%
PI controller	6.270	124.23%	-5.600	2.319
ANN controller	5.047	100.00%	-0.056	2.259

Case 3: Simulation of a sudden voltage drop in the 132KV system.

There are certain advantages of using Artificial Neural Network (ANN) control when comparing with PI control of DFIG. There are smaller overshoots, which gives a faster response, i.e. the system retakes the regimen in lesser time; and smaller oscillatory behavior. The ANN-based system that estimates the control parameters of the generator showed satisfactory characteristics as was verified in the presented results. It was demonstrated that the reference signals for the grid side and rotor side converters of the DFIG can be obtained using control systems based on ANNs. These can show the superiority of the proposed ANN control of DFIG with the referred advantages.

Figure (14) show the response of Double Fed Induction Generator (DFIG).

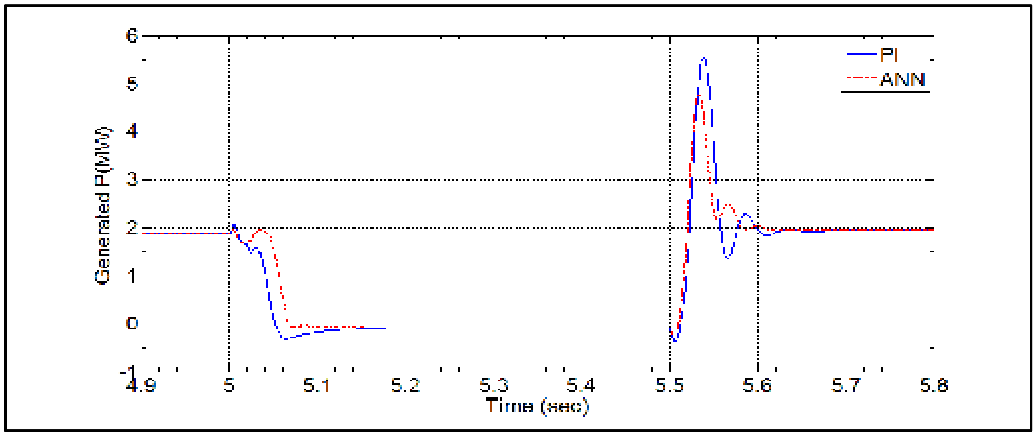

Figure (14) Active power of wind turbine at bus B400

Table (3) illustrates a comparison between the proposed controllers for this case.

Table (3) DFIG responses of voltage drop on the 132 KV system

Wind speed (m/s)			8	
Rated value of Active Power in Wind Turbine (MW)			1.94	
Active Power in Wind Turbine (MW)	over shoot	Percent ratio (other/ANN)*100	under shoot	Settling time (sec) 5%
PI controller	5.56	115.59%	-0.382	5.617
ANN controller	4.81	100.00%	-0.259	5.606

CONCLUSIONS:

In case of steady state, all of PI based on trial and error controllers and PSO have a good performance with steady state error.

When fault is applied after a specified time, the PI controller with gains tuned by trial and error method shows a steady state parameters error that is proportional with the applied load. In case of light load, the DFIG is not too affected, but in the case of higher load such as fault applied to the DFIG the situation is different by higher values of steady state error. The active power response has an oscillation and overshoot in addition to higher value of ripples.

The ANN controller with gains tuned by PSO has minimum steady state error, low overshoot and low ripples.

The final results of the proposed controllers for DFIG show the superiority of the ANN versus the PI controller, which improves the time specification of the response in term of reducing steady state error, overshoot, smoother response and requires less time to reach steady state which makes this controller more robust to the variation in load and wide range of power other than the rest controllers.

The ANN controller designed for DFIG has been connected to a variable speed wind Turbine. The grid-side and rotor-side converters reference voltages are optimization PI parameters. The comparative study between the two controllers shows that ANN is very effective on the stabilization of the system. Processing becomes simpler as computational complexity is reduced.

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Appendix A:
Parameters of Doubly Fed Induction Generator (DFIG)

Table (A) Parameters of Doubly Fed Induction Generator

Pairs of poles (P)	3
Rated Output Power (MW)	9MW (6*1.5)
Rated Voltage V(L-L) (V)	400
Frequency (HZ)	50
Stator winding resistance (R_s) (pu)	0.00706
Stator leakage inductance (L_s) (pu)	0.171
Rotor winding resistance (R_r) (pu)	0.005
Rotor leakage inductance (L_r) (pu)	0.156
Magnetizing inductance (L_m)(pu)	2.9
Rated wind speed at point C (m/s)	12
Power at point C (pu/mechanical power)	0.73
Cut-in speed (m/s)	4
Cut-out speed (m/s)	25
Maximum pitch angle (deg.)	45
Maximum rate of change of pitch angle (deg./s)	2
Nominal DC bus voltage (V)	1200
DC bus capacitor (F)	6*10000e-6
Inertia constant (Kgm^2)	5.04