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Fault Diagnosis and Rectification an a DFIG using Multi-Layer Perceptron Control Strategy

Harshit Singa, Ch Sai Ram, R B R Prakash, P Srinivasa Varma

Abstract: This paper presents the direct power control of a doubly fed induction generator with grid connected by using multilayer perceptron controller, A physical fault is given to analyse the grid conditions under fault. The direct power control strategy where the input variables are rotor speed, stator, reactive powers, their respective errors and these are considered as control variables. The controlled variables are the direct and quadrature axis rotor voltage . Digital simulation is carried out in MATLAB to analyse the grid conditions.

NOMENCLATURE

R_s, R_r	Resistances of stator and rotor windings
l_s, l_r	Inductances of stator and rotor windings
l_m	Main inductance
V_{ds}, V_{qs}	Direct and Quadrature components of the space phasors of the stator and voltages
V_{dr}, V_{qr}	Direct and Quadrature components of the space phasors of the rotor voltages
i_{ds}, i_{qs}	Direct and Quadrature components of the space phasors of the stator and currents
i_{dr}, i_{qr}	Direct and Quadrature components of the space phasors of the rotor currents
Φ_{ds}, Φ_{qs}	Direct and Quadrature components of the space phasors of the stator flux
Φ_{dr}, Φ_{qr}	Direct and Quadrature components of the space phasors of the rotor flux

I. INTRODUCTION

Doubly fed induction generator is used here because it has the favour of controlling its flux as slated in [1],[2].DFIG has an added advantage because it can control the stator power flux using rotor voltage[3] and due to this it has low power factor involved which makes it available for high power applications. The needed rotor voltage which is derived from stator power errors can be determined by using the proportional-integral controllers [4],[5].

There are various techniques like direct power control (DPC), direct torque control (DTC) and vector control which can be used to get dynamic performance from the active and reactive stator power controls. The techniques DPC and DTC for the induction motor are presented in respectively. In the strategies mentioned the controller generates switching signals for the SVM converter by using rotor voltages. Comparison of different strategies like DPC, vector control and DTC of DFIG are compared and presented in [9].From the comparison it is known that DPC is better suited and superior due to the fact that the complexity of model is medium , low settling time and robustness is high.

The control variables d- and q-axes rotor voltages can be determined by using different controllers like fuzzy-logic controller, neuro-fuzzy PI and ANN. The neuro fuzzy controller which is proposed to determine control variables gives some good results but the implementation has more number of neurons with at least three neural networks which is a disadvantage. The neuro-fuzzy PI is proposed in [11] which it has the capability to achieving the system response fastly, less settling time, no steady state error and with negligible overshoot. Generally Artificial neural network (ANN) is used to predict the wind speed from a certain amount of data that can help in achieving maximum power. So another controller based on ANN is proposed in which has some advantages than the PI controller like faster response , lower peaks during transition and requires lower number of blocks which reduces the complexity.

Based on the comparison of different control strategies of DFIG and different controllers, here a DPC strategy is proposed and multilayer perceptron controller which is based on ANN is implemented. This MLP controller gets the reactive and active stator powers, rotor speed and respective power errors as inputs. These five inputs are used to get the output which consists of d-axes and q-axes rotor voltages. Digital simulation is conducted in to analyse the conditions of grid which is connected to the dfig.

II. MODELLING OF DFIG

DFIG model:

The equations of DFIG are written in the form of direct and quadrature axes and are mentioned below

The voltages of dq in terms of ds and qs

$$V_{qs} = V_{qs}^{s} \cos\theta_e - V_{ds}^{s} \sin\theta_e$$

$$V_{ds} = V_{qs}^{s} \sin\theta_e + V_{ds}^{s} \cos\theta_e$$

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Harshit Singa, Department of EEE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P, India.

Ch Sai Ram, Department of EEE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P , India.

R B R Prakash, Department of EEE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P, India.

P Srinivasa Varma, Department of EEE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P, India.

Applying reverse method

$$V_{qs}^{s} = V_{qs}\cos\theta_e + V_{ds}\sin\theta_e$$

$$V_{qs}^{s} = V_{ds}\cos\theta_e - V_{qs}\sin\theta_e$$

Stator voltage

$$V_{ds} = R_s i_{ds} + w_s \Phi_{qs}$$

$$V_{qs} = R_s i_{qs} + w_s \Phi_{ds}$$

Rotor voltage

$$V_{dr} = R_s i_{dr} - s w_s \Phi_{qr} + \frac{d\Phi_{dr}}{dt}$$

$$V_{qr} = R_r i_{qr} - s w_s \Phi_{dr} + \frac{d\Phi_{qr}}{dt}$$

Flux linkage

$$\Phi_{ds} = l_s i_{ds} + l_m i_{dr}$$

$$\Phi_{qs} = l_s i_{qs} + l_m i_{qr}$$

$$\Phi_{dr} = l_s i_{dr} + l_m i_{ds}$$

$$\Phi_{qr} = l_s i_{qr} + l_m i_{qs}$$

Stator active and reactive power

$$P_S = V_{ds} i_{ds} + V_{qs} i_{qs}$$

$$Q_S = V_{qs} i_{ds} + V_{ds} i_{qs}$$

Rotor active and reactive power

$$P_r = V_{dr} i_{dr} + V_{qr} i_{qr}$$

$$Q_r = V_{qr} i_{dr} + V_{dr} i_{qr}$$

Electromagnetic torque

$$T_e = \frac{3}{2}\frac{P}{2}\left(\Phi_{ds} i_{qs} - \Phi_{qs} i_{ds}\right)$$

MLP controller:

A multilayer perceptron is a class of feed forward artificial neural network. .A MLP controller generally consists of three types of layers. There are input layer, hidden layer and output layer. The input layer consists of one or multiple nodes depending upon the application. These nodes are used to take the input from the outside. After information is given into input layer, it will pass it to the hidden layer. Similarly like input layer, the hidden layer consists of one or multiple nodes. The hidden layer is not connected to outside world and the information is taken from the input layer. Since they are not connected to outside world they are considered as hidden layer. After performing the calculation the result is given to the output layer. The output layer consists of one or multiple nodes. The output layer is used to convey the result or the output to the outside world. The output is collected from the hidden layer. The number of neurons in the input or the output layer depends on the application. The number of hidden neurons does not have specific rules and more or less the number of neurons may decrease the capability of the network. To find the number of hidden neurons, training need to be done . The property of approximating the non-linear applications is the main advantage of the multilayer perceptron controller.

III. PROPOSED MLP CONTROLLER

The use of MLP is that it has the capability to generate the v_{dr} and v_{qr} rotor voltages.The advantage of MLP is that it give the rotor voltages without using estimation blocks and PI controllers.In the mentioned MLP there are five inputs given to the input layer. The five inputs are Q_S^*,P_S^*,ΔQ_S,ΔP_S,ω_r.The output layer consists of two neurons v_{dr} and v_{qr} . The hidden layers are chosen to be consisted of five neurons based on feasibility, efficiency and a training will be carried out.

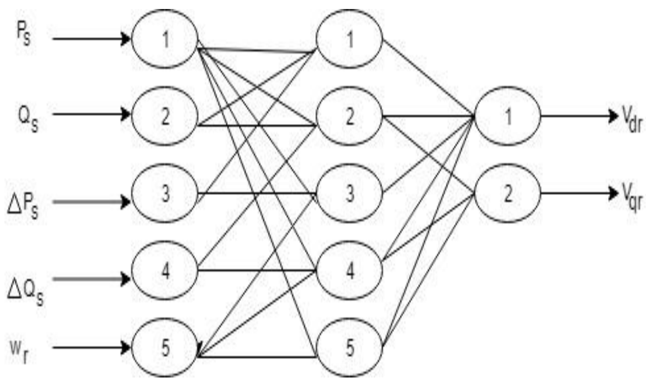

Fig:1 Architecture of neural network

Training process

Calculation of total number of weights.

$$W_1^1 = w_1 a_1 + w_2 a_2 + \cdots \ldots\ldots\ldots\ldots\ldots\ldots + w_n a_n - 10$$

Where,w= weights

a=activation

Our output partly depends on the weights and biases because the activation rate for the next neuron depends on weights. So we have to calculate each weights and biases for our whole neural network system further we have to calculate what will be the activation rate of the hidden layer neuron.

Calculation of the activation rates,

$$a_0^{(1)} = \sigma(w_{0,0} a_0^{(0)} + w_{0,1} a_1^{(0)} + \cdots .... + w_{0,n} a_n^{(0)} + b_0$$

The above equation can be written in matrix form as:-

$$a_0^{(1)} = \sigma\left(\begin{bmatrix} w_{0,0} & w_{0,1} & \cdots & w_{0,n} \\ w_{1,0} & w_{1,1} & & w_{1,n} \\ \vdots & & \ddots & \vdots \\ w_{k,0} & w_{k,1} & \cdots & w_{k,n} \end{bmatrix} \begin{bmatrix} a_0^{(0)} \\ a_1^{(0)} \\ \vdots \\ a_n^{(0)} \end{bmatrix} + \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_n \end{bmatrix}\right)$$

Where k = number of weights ,a= number of activations.
The above matrix can be minimized as:-

$$a^1 = \sigma(W_a^0 + b)$$

Training parameters

Neural Networks is an attempt to replicate the working of the human brain in order to make things more intelligent. There are two types of learning methods. Forward-Propagation is making a guess about the answer whereas Back-Propagation is a process of minimizing the error between the actual answer and guessed answer. The training examples are processed through a backward pass and forward pass which is called as an epoch. Batch size is can be defined as the number of examples which are trained in forward or backward pass. The higher the batch size, more memory space that is needed. Minimum Performance Gradient is a value that can be set which represents when training has to stop. It means if training performance result is below Minimum Performance Gradient value, training will stop. As already mentioned, an epoch describes the number of times the algorithm sees the entire data set. So an epoch will be done when the whole dataset has processed .If a batch of training examples is passed through a network it is called as iteration. So every time a batch of data is passed through the ANN, iteration is completed. Learning rate defines direction of weights to an extent such that it reaches the optimization . Training will take ample of time if the rate of learning is low because the minimum loss function is small if the rate of learning is high, it can miss the minimum or maximum training areas. The change in weights play a crucial role because it will have an impact on the results making it worse.

IV. Results

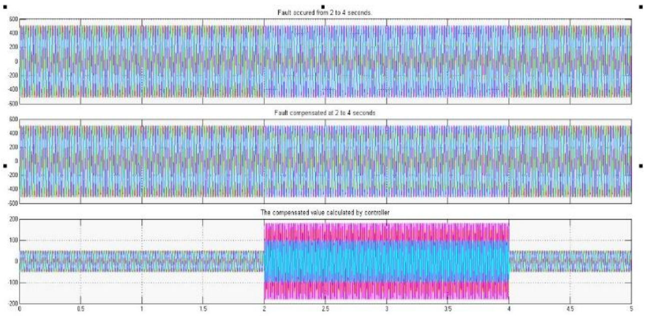

Fig.2. Voltage compensation during fault

Here the fault has been applied for 2 seconds and i.e. [2, 4] seconds and as we can see that the fault has been analyzed and compensated in 2 seconds. The above graphs represents the fault, compensated value and the cleared fault.

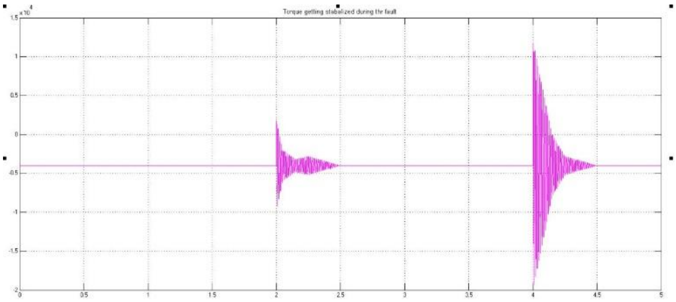

Fig.3. Torque transients at 2 and 4 seconds

Here the torque during the fault has fluctuated and the controller controlled and rectified the fault in 2 seconds.

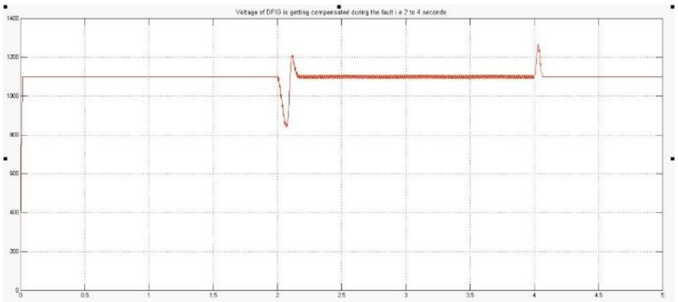

Fig. 4. DC Bus voltage

Because of the fault the voltage (V_{dc}) will also fluctuate So controller controlled the voltage in between the fault calibration time Here if we give the fault for 2 seconds, then all the work of the controller which is rectify the fault and clearing the fault, controlling torque and voltage will be done in these 2 seconds itself.

V. Conclusion

This paper has shown the DPC strategy of DIFG under fault conditions using multilayer perceptron. The assumption of the training data sets and the training process is complex but the other tasks can be made easily. With the help of training data sets the neural network is trained and the strategy is implemented. The results show that the MLP controller is able to isolate the fault when a physical fault is given. Also due to this MLP controller there is a reduction in the PI controller and other estimation blocks. The exhibition of this MLP controller gives out a finite performance, fast responses and shows the capability of the controller

REFERENCES

1. B. H. Chowdhury and S. Chellapilla, “Double-fed induction generator control for variable speed wind power generator,” Electr. Power Syst. Res., vol. 76, no. 4, pp. 786–800, 2006.
2. Saiteja, K., & Prakash, R. B. R, “Power quality improvement using neuro-fuzzy based custom power devices (UPQC) in wind farm connected to weak grid”, International Journal of Applied Engineering Research, 9(20), 7227- 7240, 2014
3. F. Blaabjerg and F. Iov, “Wind power—A power source now enabled by power electronics,” in Proc. Brazilian Power Electr. Conf., 2007, pp. 1–16

4. S. T. Jou, S. B. Lee, Y. B. Park, and K. B. Lee, "Direct power control of a DFIG in wind turbines to improve dynamics responses," J. Power Electron., vol. 9, no. 4, pp. 781–790, 2009.
5. A. Petersson, L. Harnefors, and T. Thiringer, "Evaluation of current control methods for wind turbines using doubly-fed induction machines," IEEE Trans. Power Electron., vol. 20, no. 1, pp. 227–235, Jan. 2005.
6. F. K. de, A. Lima, E. H. Watanabe, P. Rodriguez, and A. Luna, "Controle degerador de inducão duplamente alimentado diante de afundamentos detensão," Eletrôn. Potência, vol. 3, no. 14, pp. 189–199, 2009.
7. Teja, K. S., & Prakash, R. B, "Power quality improvement using custom power devices in squirrel cage induction generator wind farm to weak-grid connection by using neuro-fuzzy control", International Journal of Power Electronics and Drive Systems, 5(4), 477-485, 2015.
8. Narasimha Rao, D., & Srinivas Varma, P, "Performance of DPFC using ANN and comparison with PI controllers" International Journal of Simulation: Systems, Science and Technology, 19(4), 18.1-18.8, 2018.

AUTHORS PROFILE

R B R Prakash working as Associate Professor in Department of Electrical and Electronics Engineering, Koneru Lakshamiah Education Foundation Deemed to be University. He received B. Tech from JNT University, Hyderabad in 2005, M. Tech from AN University in 2008 and currently pursuing Ph.D in Wind Electrical Systems. He has 12 years of teaching as well as Research experience. His areas of interest are Renewable Energy Sources and Energy conservation & Audit. He published many research papers in various national and international conferences and also in scopus indexed journals.