A FUZZY-PI CONTROLLER FOR WIND TURBINE DRIVEN DFIG OPTIMIZED USING GENETIC ALGORITHMS

Lawrence K. Letting[1], Josiah L. Munda[1] and Yskandar Hamam[1,2]
[1]*Tshwane University of Technology, Pretoria, South Africa*
[2]*ESIEE-Paris, Paris-Est University, LISV, UVSQ, Paris, France*

Keywords: DFIG, Fuzzy-PI control, Optimization, Genetic algorithms.

Abstract: This paper presents the design of optimal TSK-fuzzy PI controller for the rotor side converter (RSC) of a doubly fed induction generator (DFIG) in a grid connected wind generation system. The optimization strategy is based on binary genetic algorithms. The controller is used to regulate the active and reactive power and hence extract maximum energy from the system under varying wind speeds. Pitch angle control is used to regulate the rotor angular speed while the active and reactive power are controlled by the rotor voltage supplied by the RSC. The stator flux oriented reference frame is adopted. A fuzzy-PI controller with a minimum rule base of nine rules is realized. The controller is implemented in C code as a dynamic linked library and simulated using LabVIEW. Simulation results are presented.

1 INTRODUCTION

Wind energy is the fastest growing and the most promising renewable energy source in the world today. It is non-polluting, free and economically viable. In addition, there has been a rapid technological development in wind turbine technology (Munteanu et al., 2008). In the recent past there has been an increased use of DFIG's in small power plants due to their unique capabilities (Abedi et al., 2010). The special features of DFIG are: it can supply power at constant voltage and frequency; the rotor can operate in both sub-synchronous or super-synchronous speeds; the rating of the power converter is approximately 30% of the rated wind turbine power and; the generated active and reactive power can be independently controlled (Abo-Khalil et al., 2007).

To ensure maximum utilization of wind energy in variable speed power plants, the stator active and reactive power are controlled separately by varying the rotor current of the DFIG using a vector control scheme. A power converter is used to control the rotor voltage. The control of power converters connected to the DFIG is traditionally accomplished using proportional and integral (PI) controllers. However, wind energy conversion systems (WECS) are highly nonlinear with time-varying system parameters such as wind speed and reference power values. This makes it difficult to design optimal PI-controller gains using either modern or classical control theory (Abedi et al., 2010).

Artificial intelligence based methods using genetic algorithms, particle swarm optimization (PSO), and fuzzy logic have been introduced in order to improve controller performance in WECS (Elshafei and Azzouz, 2011), (Lin et al., 2011), (Ren et al., 2009), (Leite et al., 2009), (Vieira et al., 2008). (Lin et al., 2011) presents a particle swarm optimized recurrent fuzzy neural network used to track the maximum wind energy with reference values obtained from an adaptive model reference observer. In (Leite et al., 2009) PI controller gains are tuned using PSO with aim of improving DFIG performance under network faults. (Vieira et al., 2008) optimizes the PI-controller gains using genetic algorithms in order to improve active power control and dc-link voltage regulation. (Ren et al., 2009) presents a 49-rule fuzzy controller used to control the rotor speed and is shown to give better performance than PI-control. (Elshafei and Azzouz, 2011) reports the design of a 9-rule adaptive fuzzy controller (AFLC) for regulating the dc-link voltage. The AFLC is shown to give better performance compared to a classical PI controller and a 9-rule non-adaptive FLC. It has therefore been established that fuzzy control offers a great potential in control of WECS.

This paper proposes an automated strategy for tuning two fuzzy controllers used in regulation of ac-

K. Letting L., L. Munda J. and Hamam Y..
A FUZZY-PI CONTROLLER FOR WIND TURBINE DRIVEN DFIG OPTIMIZED USING GENETIC ALGORITHMS.
DOI: 10.5220/0003601403480353
In *Proceedings of 1st International Conference on Simulation and Modeling Methodologies, Technologies and Applications* (SIMULTECH-2011), pages 348-353
ISBN: 978-989-8425-78-2

tive and reactive power in the rotor side converter of WECS. The FLCs are based on the first order Takagi-Sugeno-Kang (TSK) model with two inputs: error and integral of error. This proposed method shows that it is possible to optimize a fuzzy-PI controller and meet the desired performance with a minimum rule base of only 9 rules. An optimized fuzzy-PI controller gives performance similar to a classical PI controller with adaptive gains.

2 SYSTEM CONFIGURATION

The system is configured as shown in Fig. 1. The stator of the induction machine is directly connected to the three- phase grid while the rotor winding is supplied through the back-to-back converters. The system is implemented with PI control in LabVIEW control design and simulation module (NI LabVIEW, 2009). A master controller is used to regulate the rotor angular speed by varying the pitch angle in order to the ensure operation is maintained at an optimal tip-speed ratio. The generator controller uses PI controllers to regulate the active and reactive power. Vector control scheme is applied using the stator flux oriented reference frame (Pena et al., 1996). The dc-link voltage is fixed while the rotor side converter is modeled as a voltage source. Grid-side converter control is therefore not considered.

(NI LabVIEW, 2009) presents a WECS control system model where the rotor-side converter regulates the the stator active and reactive power through rotor voltage components V_{qr} and V_{dr} which are independently controlled by PI controllers. In this paper the same model is adopted and the PI controllers are replaced by two fuzzy-PI controllers as shown in Fig. 2. FLC1 controls the rotor d-axis voltage while FLC2 controls the q-axis voltage. The two fuzzy controller outputs V_{dr}^* and V_{qr}^* are used as the reference values for the PWM controller connected to the rotor side converter.

Detailed modeling of the DFIG and the vector control scheme is available in (Pena et al., 1996). The modeling of the wind-turbine and calculation of the maximum active power reference values can be found in (NI LabVIEW, 2009).

3 fuzzyPI CONTROLLER STRUCTURE

The structure of the fuzzy-PI controller is presented in Fig. 3. It comprises of four parts: fuzzification,

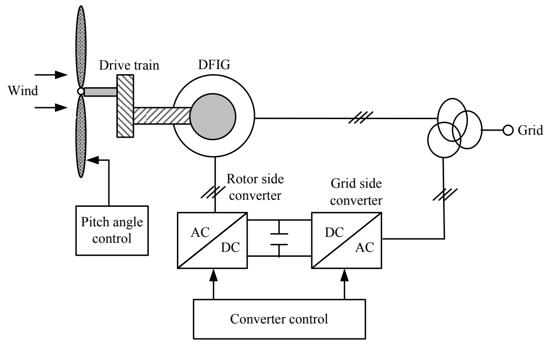

Figure 1: DFIG wind turbine configuration.

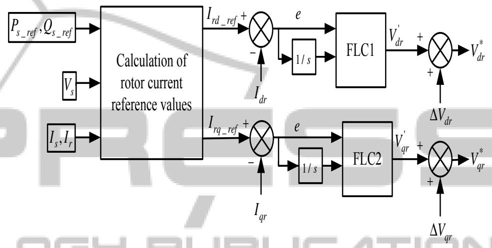

Figure 2: DFIG vector control scheme using fuzzy logic.

knowledge base, inference engine, and defuzzification. There are two input variables, error $e(t_k)$, and the integral of error $ie(t_k)$ at the k_{th} simulation step defined as:

$$e(t_k) = i_{ref}(t_k) - i(t_k) \tag{1}$$

$$ie(t_k) = e(t_{k-1}) + \int_{t_{k-1}}^{t_k} e(t)dt \tag{2}$$

where $i_{ref}(t_k)$ and $i(t_k)$ are the reference and actual values of the rotor dq-currents respectively.

The fuzzy control algorithm was developed in C++ based on first order TSK-inference system. The TSK fuzzy model is more compact with a computationally efficient representation than a Mamdani system (Bose, 2002). The input membership functions are encoded as shown in Fig. 4 using trapezoidal membership functions. Each input is fuzzified using three membership functions: Negative (N), Zero (Z), and Positive(P). The FLC has nine rules and the output of each rule is given by (3).

$$v(t_k) = K_P \cdot e(t_k) + K_I \cdot ie(t_k) + K_0 \tag{3}$$

Where K_P, K_I, and K_0 are constants to be determined for each output MF in the inference engine of Fig. 3.

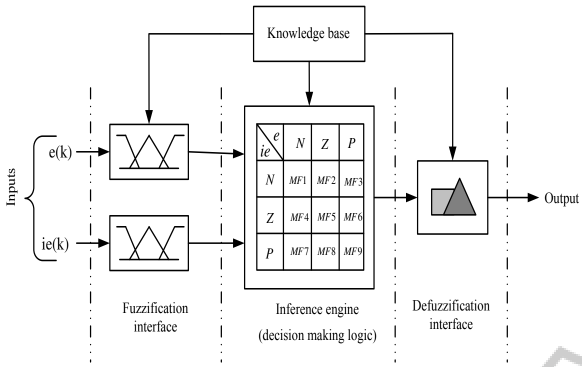

Figure 3: Structure of the fuzzy-PI controller.

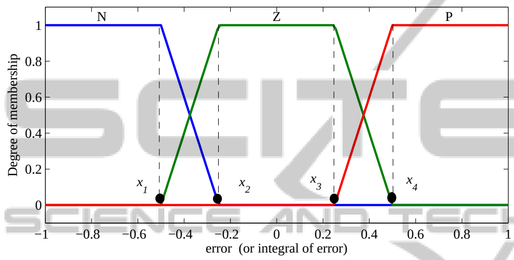

Figure 4: Encoding of input membership functions.

4 OPTIMIZATION OF fuzzyPI CONTROLLER

The conventional design of membership functions and rule base of a fuzzy inference system is based on expert knowledge. However, expert knowledge alone is not enough to design a robust fuzzy controller for a complex system such as WECS. In this design a fixed rule base size and and input MF type were selected as explained in section 3. The total number of variables that need to be optimized for each FLC are summarized in Table 1. The variable limits were identified by performing initial simulation runs in open-loop mode. Each FLC has 35 optimization variables.

During optimization using GA, each FLC is modeled as single chromosome with 35 genes where each gene represents a parameter in Table 1. The initial

Table 1: Optimization variables.

Parameter	No.of variables	Min.	Max.
e	4	-30	30
ie	4	-10	10
K_P	9	-1	1
K_I	9	-1	1
K_0	9	-1	1

Table 2: GA parameters.

Parameter	Value
Population	70
Number of iterations	50
No. of bits	8
Selection rate	0.5
Mutation rate	0.2

population is randomly generated using the parameters of Table 2. At the end of each iteration the cost of each chromosome is evaluated and ranking is done. An elitist strategy is adopted such that 50% of the individuals with the least cost are selected to form the next population. The remaining members are reproduced through mating of the selected individuals. Parents for mating are selected using rank-weighting and the offspring is generated using single-point crossover. Random mutations are carried out on the population with a mutation rate of 20%. Mutations ensure that the entire cost surface is explored. The best chromosome is not mutated due to elitism.

The mean-square-error (MSE) defined in (4) and (5) is used as the fitness function for FLC1 and FLC2 respectively. Equations (4) and (5) measure the deviation from the desired reactive (Q) and active power (P) respectively. The optimization variables for the two fuzzy-PI's are encoded in one matrix where each row represents the parameters of FLC1 and FLC2 which are used to run the system during one iteration. The fitness of each row of the population is given by the sum of the cost obtained in (4) and (5). Optimization is carried out off-line before the start of the next iteration. The simulation steps are illustrated in the the flowchart of Fig. 5.

$$J_d = \frac{1}{T}\int \left(Q_{ref}(t) - Q(t)\right)^2 dt \qquad (4)$$

$$J_q = \frac{1}{T}\int \left(P_{ref}(t) - P(t)\right)^2 dt \qquad (5)$$

5 SIMULATION RESULTS

Optimal parameters for the fuzzy controllers is obtained from the best chromosome at the end of the simulation. The optimized input MFs for FLC1 and FLC2 are presented Fig. 6 and Fig. 7 respectively. The rule surface for FLC1 and FLC2 are shown in Fig. 8 and Fig. 9 respectively. The contour maps are shown at the bottom of each surface plot. The performance of the fuzzy-PI was tested using the wind profile of Fig.10. It is observed in Fig. 11 and Fig. 13 that the proposed controller is able to track the maximum

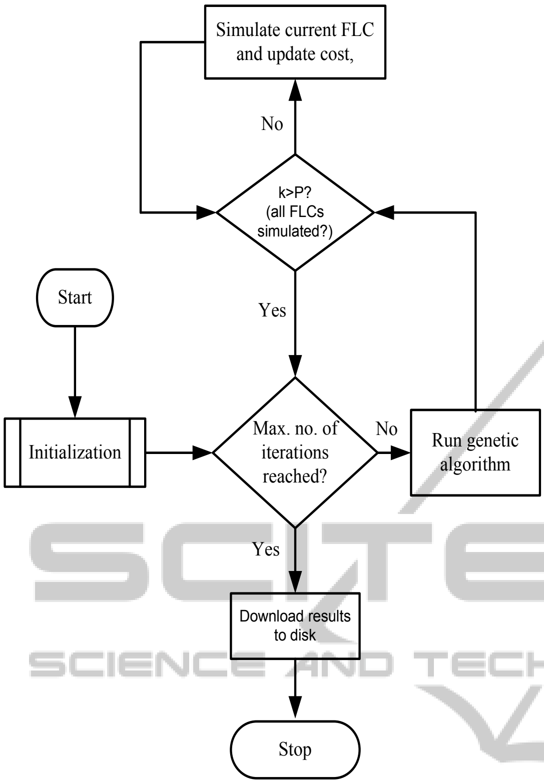

Figure 5: Illustration of optimization procedure.

energy from the wind and maintain the stator reactive power close to zero. The reference active power is obtained from the rotor current q-axis reference component ($I_{qr_{ref}}$).

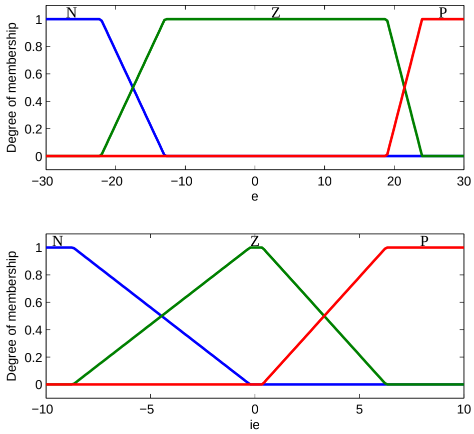

Figure 6: Optimized input MFs for FLC1.

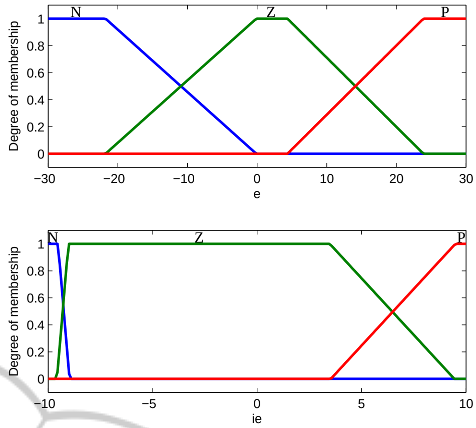

Figure 7: Optimized input MFs for FLC2.

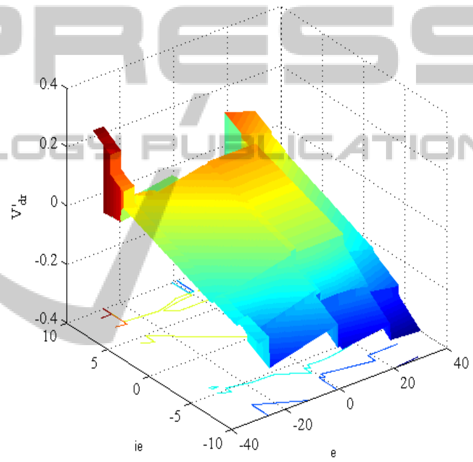

Figure 8: Optimized rule surface for FLC1.

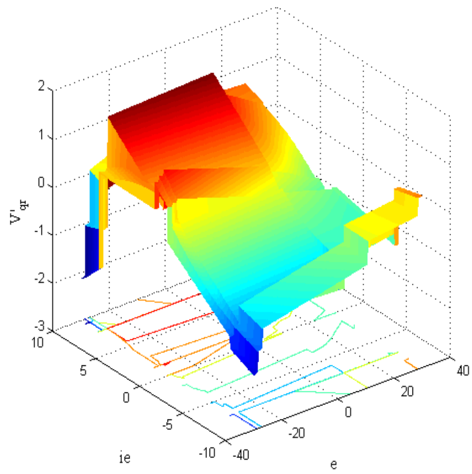

Figure 9: Optimized rule surface for FLC2.

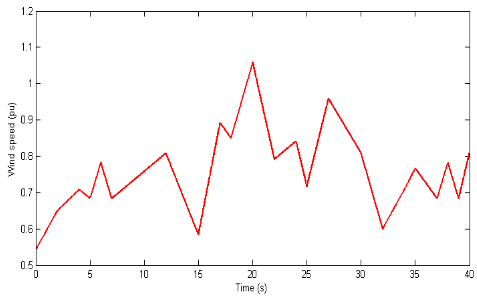

Figure 10: Wind profile (base speed 12m/s).

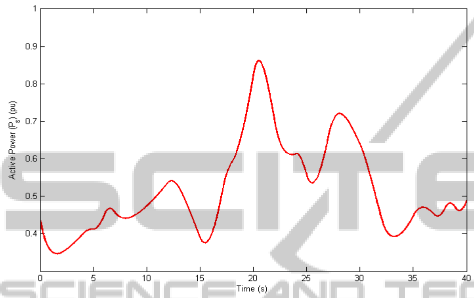

Figure 11: DFIG active power (P_s).

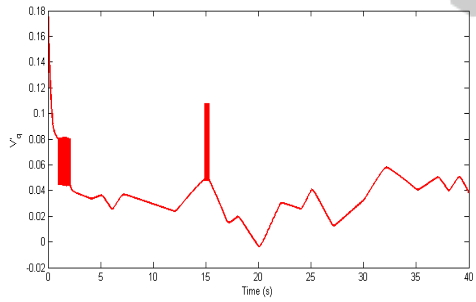

Figure 12: Control signal (V_q').

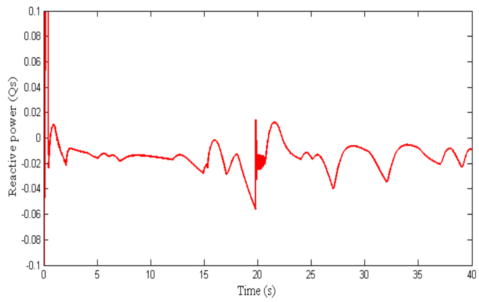

Figure 13: DFIG reactive power (Q_s).

6 CONCLUSIONS

In this paper an optimized fuzzy-PI controller for active and reactive power control in the rotor side converter of a wind energy conversion system is proposed. It is shown that it is possible to design and optimize a fuzzy-PI controller with a minimum rule base of nine rules using genetic algorithms. The advantage of the small rule base is that it requires less memory space with faster execution speed. It is an improvement from the standard fuzzy-PI controllers with 49 rules. Comparison of the performance of the proposed fuzzy-PI and other methods such as classical PI and PI with optimized gains is part of future work.

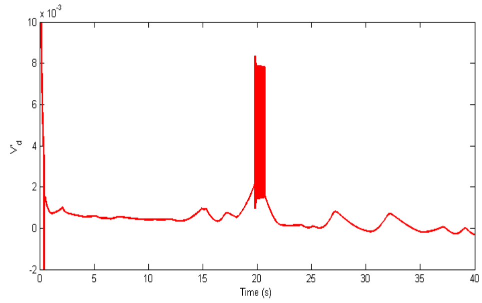

Figure 14: Control signal (V_d').

REFERENCES

Abedi, A., Pishvaei, M., Madadi, A., and Kelk, H. M. (2010). Analyzing vector control of a grid-connected dfig under simultaneous changes of two inputs of control system. *European Journal of Scientific Research*, 45(2):221–231.

Abo-Khalil, A., Lee, D.-C., and Jang, J.-I. (2007). Control of back-to-back pwm converters for dfig wind turbine systems under unbalanced grid voltage. In *Industrial Electronics, 2007. ISIE 2007. IEEE International Symposium on*, pages 2637 –2642.

Bose, B. K. (2002). *Modern Power Electronics and AC Drives*. Prentice-Hall, Inc.

Elshafei, A. and Azzouz, M. (2011). Adaptive fuzzy regulation of the dc-bus capacitor voltage in a wind energy conversion system (wecs). *Expert Systems with Applications*, 38(5):5500 – 5506.

Leite, H., Barros, J., and Miranda, V. (2009). Evolutionary algorithm epso helping doubly-fed induction generators in ride-through-fault. In *PowerTech, 2009 IEEE Bucharest*, pages 1 –8.

Lin, W.-M., Hong, C.-M., and Cheng, F.-S. (2011). Design of intelligent controllers for wind generation system with sensorless maximum wind energy control. *Energy Conversion and Management*, 52(2):1086 – 1096.

Munteanu, I., Bratcu, A. I., Cutululis, N.-A., and Ceangă, E. (2008). *Optimal Control of Wind Energy Systems, Towards a Global Approach*. Springer-Verlag, London.

NI LabVIEW (2009). Designing controllers for a doubly-fed wind power system. http://zone.ni.com/devzone/cda/epd/p/id/6272. Accessed: 1st April 2011: http://zone.ni.com/devzone/cda/epd/p/id/6272.

Pena, R., Clare, J., and Asher, G. (1996). Doubly fed induction generator using back-to-back pwm converters and its application to variable-speed wind-energy generation. *Electric Power Applications, IEE Proceedings -*, 143(3):231 –241.

Ren, Y., Li, H., Zhou, J., An, Z., Liu, J., Hu, H., and Liu, H. (2009). Dynamic performance analysis of grid-connected dfig based on fuzzy logic control. In *Mechatronics and Automation, 2009. ICMA 2009. International Conference on*, pages 719 –723.

Vieira, J., Nunes, M., and Bezerra, U. (2008). Design of optimal pi controllers for doubly fed induction generators in wind turbines using genetic algorithm. In *Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*, pages 1 –7.

APPENDIX

The parameters of the DFIG are given in Table 3.

Table 3: DFIG Parameters.

Parameter	**Value**
Power base	4.8MW
Frequency base	60Hz
Stator resistance	0.003068pu
Rotor resistance	0.006068pu
Rotor leakage inductance	0.05783pu
Stator leakage inductance	0.05783pu
Mutual inductance	1.85068pu
Gear box ratio	55