Optimal Fuzzy Logic-based Adaptive Controller equipped with DFIG Wind Turbine for Frequency Control in Stand Alone Power System

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***Abstract*—This paper deals with an adaptive controller design by an optimal fuzzy logic of doubly fed induction generator (DFIG) wind turbine for frequency control in the stand alone power system. Since the DFIG wind turbine has the ability of active power control, this makes the possibility of system frequency control contribution by DFIG. The optimal fuzzy logic adapts the control parameters of the supplement controller equipped with the DFIG wind turbine so that the active power output can be controlled to alleviate the frequency deviation due to load changes. In the fuzzy logic design, the membership function and the control rules are automatically optimized by the particle swarm optimization. Simulation study confirms that the control effect and robustness of the proposed adaptive controller is superior to that of the conventional controller with fixed parameters against various random load changes and system parameters variation.**

***Index Terms*--Doubly fed induction generator wind turbine, fuzzy control, frequency control, particle swarm optimization.**

I. INTRODUCTION

Currently, the wind power generation has been installed extensively in the remote areas which cannot access to the power grid. In general, the hybrid wind power and diesel generator have been used to supply electrical power to loads in such stand alone power systems. On the contrary, the load demand always changes and results in frequency deviation. To overcome this problem, the load-frequency controller (LFC) has been used to reduce the frequency deviation by the control of governor and turbine. However, since the response of governor and turbines is not fast enough to handle the abrupt load change. This may cause the large fluctuation of system frequency [1].

Among wind generators, a doubly fed induction generator (DFIG) has been paid attentions significantly. With the ability of active and reactive power controls of DFIG, the DFIG wind turbine is expected to provide any contribution to the system such as system frequency regulation [2,3]. In general, the emulating inertia from wind turbine can be applied to support the primary frequency control [4]. The required power for frequency control is obtained from the kinetic energy stored in the rotating mass of the turbine blades. In [5,6], the supplementary control loop is equipped with the DFIG wind turbine for emulating inertia. This study shows that the DFIG wind turbines equipped with the proportional control with fixed parameters are able to contribute the frequency control effect. Even the proportional control in [5,6] provides the satisfactory effect, it may fail to deal with the system uncertainties such as system parameters variation, random wind and load changes etc. The controller with robustness against such uncertainties is highly expected.

This paper proposes an optimal fuzzy logic-based adaptive controller equipped with the DFIG wind turbine for frequency control in the stand alone power system. The Sugeno type fuzzy logic is applied to adapt the control parameters of the supplementary controller of DFIG so that the emulating inertia from wind turbine can be used to reduce the frequency fluctuation. The particle swarm optimization (PSO) is used to tune the membership function and rule bases of the fuzzy control design automatically. Simulation study in a linearized system confirms the superior control effect and robustness of the proposed adaptive control.

The organization of this paper is described as follows. First, section II explains the study system and modeling. Next, the optimization technique of the Sugeno fuzzy controller is explained in section III. Subsequently, section IV shows the simulation results and discussions. Finally, the conclusion is provided in section V.

II. STUDY SYSTEM AND MODELLING

A. Study System

Fig.1 shows the stand alone power system which is used as the study system. This system consists of DFIG wind turbine, generator, and loads. The DFIG wind turbine is equipped with the adaptive controller with optimal fuzzy Sugeno type control. It is assumed that the load change causes the frequency fluctuation problem in this system.

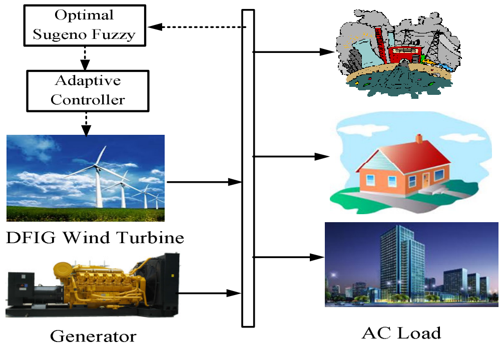

Fig. 1 Study stand alone power system.

B. System Modeling

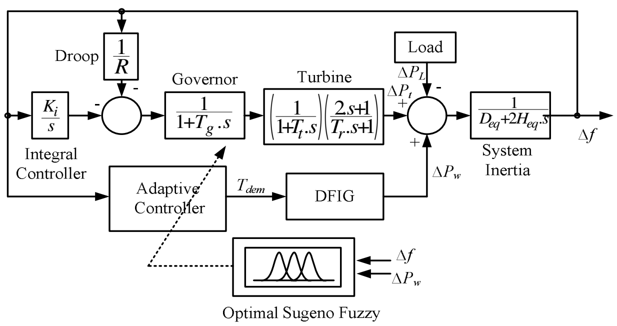

Fig. 2 Linearized system.

TABLE I SYSTEM PARAMETERS

Parameters of Generator Model	
Synchronous Capacity	40.78 GW
Total equivalent inertia, H_{eq}	3.11Mw s/Hz
Damping constant, D_{eq}	1MW/Hz
Governor time constant, T_g	0.2 s
Turbine time constant, T_t	0.3 s
Turbine re-heat time constant, T_r	12.0 s
Speed regulation, R	11 Hz/puMW
Integral control gain, K_i	0.35
Parameters of Wind Turbine Model (2MW)	
Wind Turbine Capacity	2 MW
Stator resistance, R_s	0.00491 pu
Rotor resistance, R_r	0.00552 pu
Stator reactance, X_{ls}	0.09273 pu
Rotor reactance, X_{lr}	0.1 pu
Magnetizing reactance, X_m	3.96545pu
Lumped inertia constant, H	4.5 s
Performance of wind turbine, η	95 %
Proportional control gain, K_p	0.5
Integral control gain, K_i	0.5
Total Wind Turbine Capacity	19.4 GW
Total number of Wind Turbine	9700
Frequency Response Control Model	
Washout time constant, T_w	1 s
Transfer function time constant, T_f	20 s

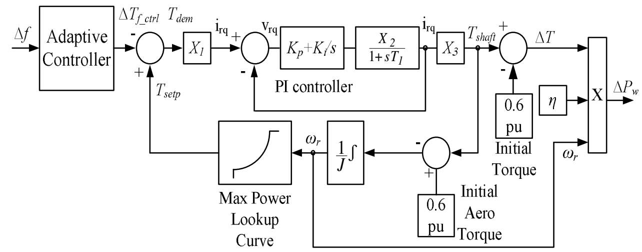

Fig. 3 DFIG wind turbine model with adaptive control.

Fig.2 depicts the linearized system for frequency control study. The system consists of the LFC, governor, turbine and DFIG wind turbine. System parameters and definition are given in Table I. The simplified DFIG wind turbine model can be shown in Fig.3 [5]. Note that $X_1 = L_{ss}/L_m$, $X_2 = 1/R_r$, $X_3 = L_m/L_{ss}$, and $T_1 = L_0/w_sR_r$.

III. PROPOSED ADAPTIVE CONTROL

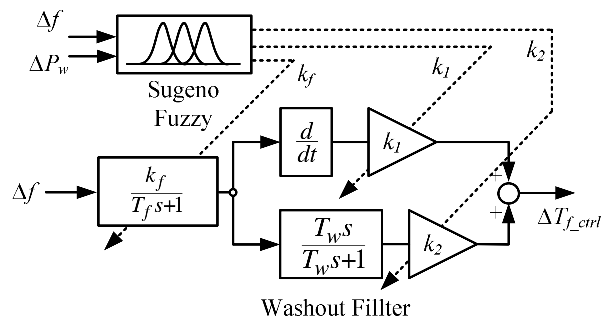

Fig. 4 Adaptive control by Sugeno Fuzzy.

Fig.4 shows the adaptive controller based on the Sugeno fuzzy. This controller is aim to change the frequency deviation input signal to the torque deviation for compensation of load change. The Sugeno fuzzy adapts the parameters k_1, k_2, and k_f, so that the generated torque deviation can follow the load changes. Note that

- k_1 gives an emulation of the inertia of the wind turbine. It acts on the rate of change of frequency deviation signal, and represents the initial response from the wind turbine.
- k_2 is used to give an additional shaping response provided by the 'washout' filter with washout time constant T_w.
- k_f is the transfer function gain between the frequency deviation (Δf) and the torque deviation (ΔT_{f_ctrl}).
- T_f is the time delay.

As a result, the system frequency deviation can be alleviated by the adaptive control.

The Sugeno fuzzy control design can be explained as follows [7]. The input of Sugeno fuzzy consists of frequency deviation and wind power deviation (ΔP_w). The output of Sugeno fuzzy can be considered from the following condition.

If Input 1 = A and Input 2 = B

then Output $k_1 = C$, $k_2 = D$, $k_f = E$

where *A, B, C, D* and *E* are membership functions of fuzzy logic control.

Here, the optimization of membership functions and control rules are performed by time simulation under the load pattern 1 in Fig. 5. To minimize the system frequency deviation, the optimization problem is formulated as follows.

$$\text{Minimize} \quad IAE = \int_0^T (|\,\Delta f(t)\,|)dt. \qquad (1)$$

Where *IAE* is the integral absolute error of frequency deviation, *T* is the time simulation. This problem is solved by PSO [8]. The PSO procedures are provided as follows.

Step 1: Generate randomly the initial populations of *n* particles. Here, *n* = 50. These initial populations are feasible solutions that satisfy the constraints.

Step 2: Set *NP* = 0 where *NP* is the iteration number.

Step 3: The initial populations are substituted in the Sugeno fuzzy parameters. These values will be verified in the system.

Step 4: Select the fittest particle (P_{best}). Set $P_{best} = P_{old}$, where P_{old} is the best selected value from the previous iteration.

Step 5: Check the stopping criterion. If *NP* = 400, terminate the search. If not, go to next Step.

Step 6: Update both velocity and location in each particle. After that, the new values are substituted in the Sugeno fuzzy parameters. These values will be verified in the system again.

Step 7: Set *NP* = *NP*+1.

Step 8: Select P_{best}.

Step 9: If $P_{old} < P_{best}$, then $P_{old} = P_{best}$. Next, go to Step 5.

Step 10: If $P_{old} > P_{best}$, then $P_{old} = P_{old}$. Next, go to Step 5.

IV. SIMULATION RESULTS

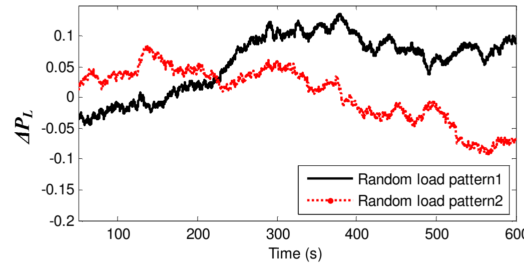

Fig. 5 Random load.

After the optimization by PSO, the optimal rule bases are given in Table I and the membership functions of input 1 and input 2 are shown in Figs.6 and 7, respectively. As a result, the optimal surfaces of k_1, k_2, and k_f with respect to the variation of input 1 and input 2 are depicted in Figs. 8,9,10 respectively.

TABLE I OPTIMAL MEMBERSHIP FUNCITONS

		Input 1				
		NM	NS	ZO	PS	PM
		$k_1\,k_2\,k_f$	$k_1\,k_2\,k_f$	$k_1\,k_2\,k_f$	$k_1\,k_2\,k_f$	$k_1\,k_2\,k_f$
Input 2	NB	mf1,mf7,mf5	mf4,mf2,mf6	mf4,mf2,mf4	mf6,mf4,mf4	mf7,mf6,mf2
	NM	mf4,mf6,mf3	mf1,mf6,mf6	mf5,mf2,mf1	mf3,mf5,mf3	mf4,mf1,mf6
	NS	mf5,mf2,mf4	mf5,mf3,mf5	mf7,mf1,mf5	mf6,mf2,mf6	mf3,mf7,mf5
	ZO	mf1,mf6,mf4	mf2,mf2,mf5	mf3,mf1,mf2	mf1,mf3,mf4	mf5,mf1,mf6
	PS	mf6,mf7,mf6	mf3,mf6,mf3	mf2,mf1,mf5	mf1,mf5,mf5	mf2,mf2,mf6
	PM	mf2,mf5,mf1	mf6,mf2,mf3	mf5,mf6,mf2	mf1,mf2,mf6	mf2,mf6,mf4
	PB	mf7,mf2,mf1	mf1,mf6,mf4	mf3,mf2,mf5	mf1,mf3,mf2	mf6,mf2,mf1

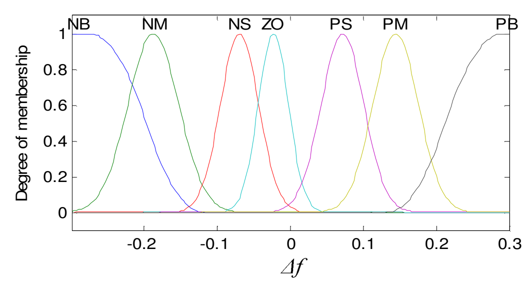

Fig. 6 Optimal membership function of input 1

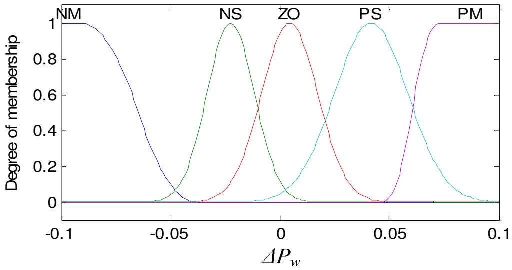

Fig. 7 Optimal membership function of input 2

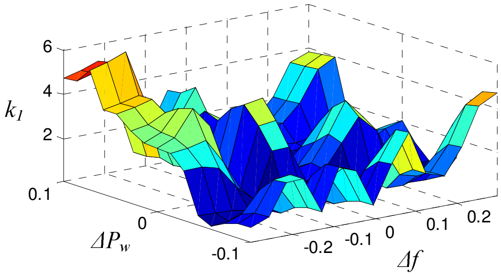

Fig. 8 Optimal surface of k_1

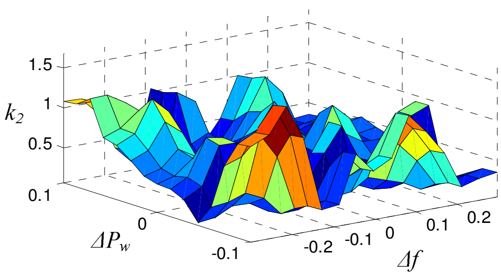

Fig. 9 Optimal surface of k_2

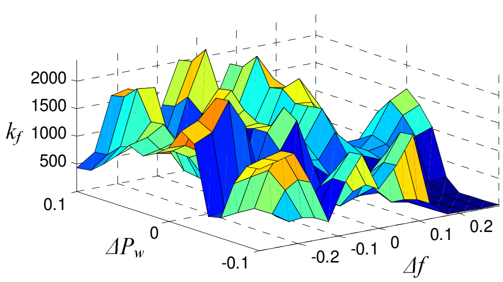

Fig. 10 Optimal surface of k_f

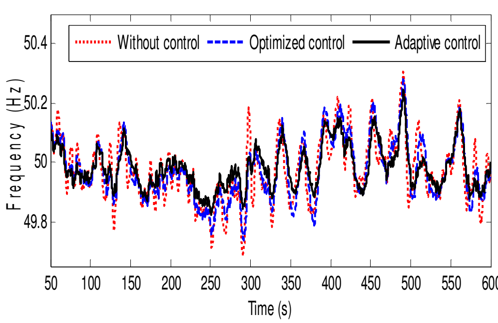

Fig. 11 Frequency deviation in case of random load change 1.

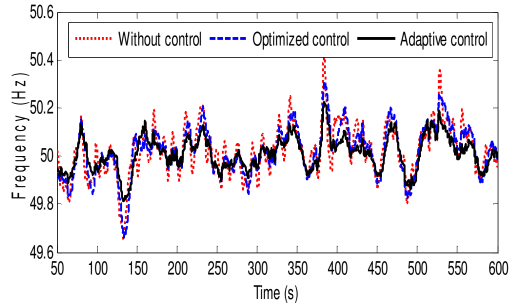

Fig. 12 Frequency deviation in case of random load change 2.

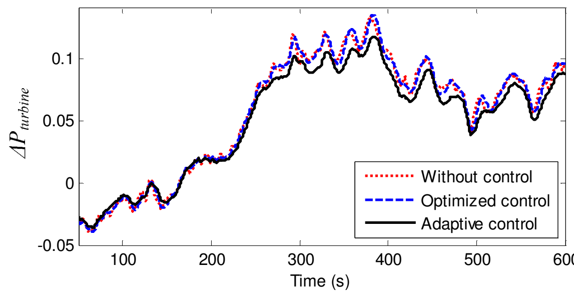

Fig. 13 Turbine power deviation in case of random load change 1.

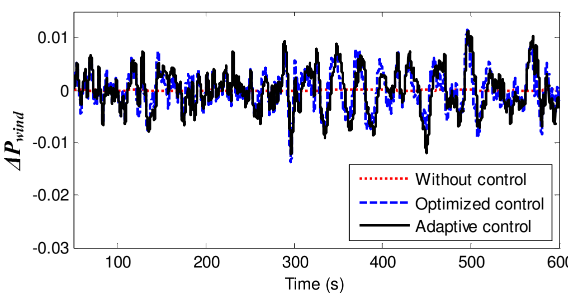

Fig. 14 Wind power deviation in case of random load change 1.

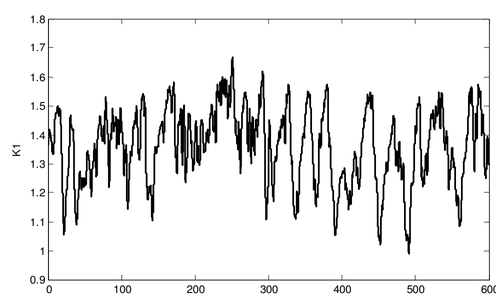

Fig. 15 Variation of k_1 in case of random load change 1.

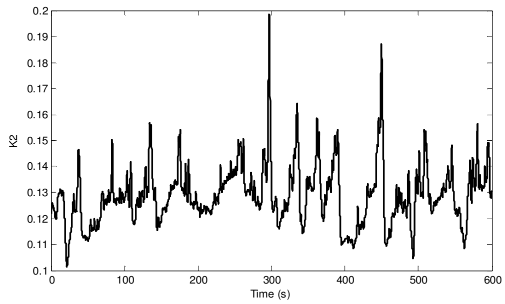

Fig. 16 Variation of k_2 in case of random load change 1.

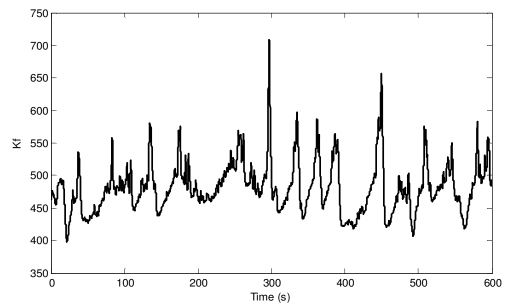

Fig. 17 Variation of k_f in case of random load change 1.

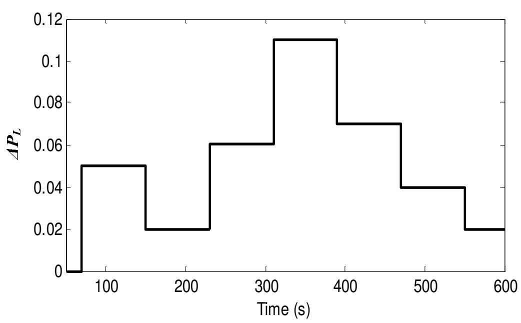

Fig. 18 Frequency deviation in case of step load change.

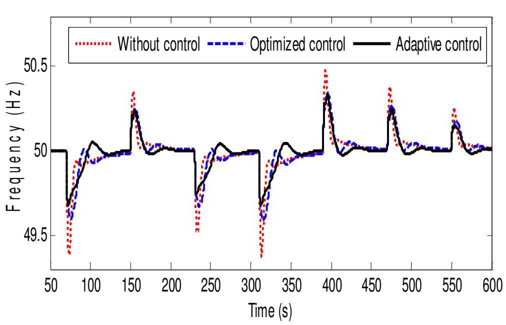

Fig. 19 Frequency deviation in case of step load change.

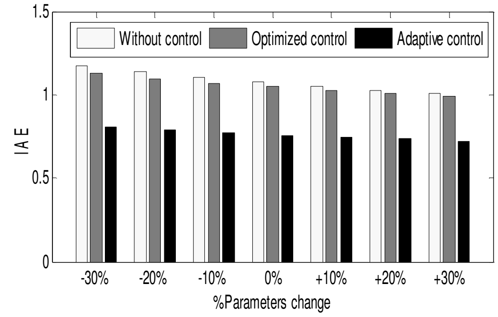

Fig. 20 Variation of IAE in case of random load pattern 1.

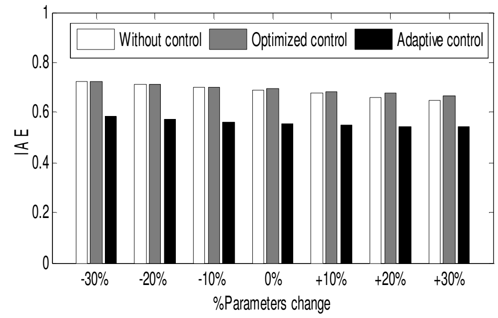

Fig. 21 Variation of IAE in case of step load change.

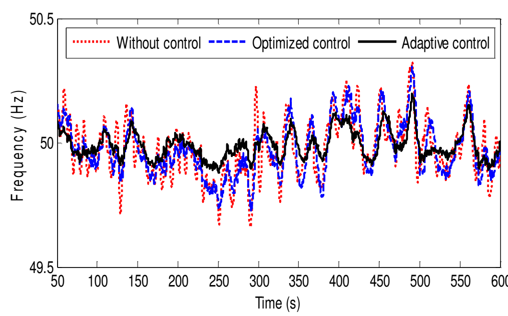

Fig. 22 Frequency deviation in case of random load change 1 with -30% parameters variation.

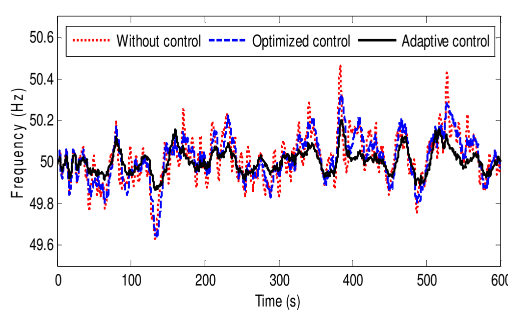

Fig. 23 Frequency deviation in case of random load change 2 with -30% parameters variation.

In the simulation study, MATLAB/SIMULINK is used to design and evaluate the optimal fuzzy-based adaptive controller which is referred to as "Adaptive control". The frequency control effect of the DFIG with the adaptive control is compared with the DFIG with conventional controller with fixed k_1, k_2, and k_f. Note that k_1, k_2, and k_f in case of conventional controller are optimized by PSO based on the same optimization problem (1) under the random load pattern 1. As a result, the optimized k_1, k_2, and k_f of conventional control are 1.8, 1.3, and 500, respectively. The conventional control is referred to as "Optimized control".

Figs. 11 and 12 shows the frequency deviations in case of random load patterns 1 and 2, respectively. Without the supplementary control, the system frequency highly fluctuates. On the other hand, the system frequency can be alleviated by both adaptive control and optimized control. Nevertheless, the frequency control effect in case of adaptive control is better than that of the optimized control.

Figs. 13 and 14 show the turbine power deviation and wind power deviation in case of random load change 1, respectively. Figs. 15, 16, and 17 depict the variation of k_1, k_2, and k_f in case of random load change 1, respectively.

Fig. 18 shows the step load change which is applied to the system. Fig. 19 depicts the system frequency deviation. Clearly, the adaptive control provides the superior effect to the optimized control.

Next, the robustness of the adaptive control and the conventional control is evaluated by the variation of IAE against the change in system parameters. Figs. 20 and 21 show the variation of IAE when the system parameters are varied from -30 % to +30 % of the normal value in case of random load pattern 1 and step load change, respectively. The IAE in case of without control and the optimized control highly changes. This implies that the optimized control is very sensitive to parameters variation. On the other hand, the adaptive controller is very robust against the system parameters variation. The IAE in case of adaptive control is lower and rarely changes.

Figs. 22 and 23 depict the frequency deviation in case of random load changes 1 and 2 with -30% parameters variation, respectively. Clearly, the DFIG with optimized control is very sensitive to the parameters variation. The stabilizing effect of DFIG with optimized control is deteriorated. The frequency fluctuation is very severe. On the other hand, the DFIG with adaptive control is very robust against system parameters variation. The frequency fluctuation is explicitly alleviated. These results confirm the robustness of the DFIG with the proposed adaptive control.

V. CONCLUSION

This paper presents an optimal Sugeno fuzzy logic control based-adaptive controller for DFIG wind turbine for frequency control in the stand alone power system. The adaptive controller is installed with the DFIG generator so that the active power output of DFIG can be controlled and the frequency fluctuation due to load changes can be suppressed. The wind power output and frequency deviation are used as the input signal of the proposed fuzzy control. The output signal of fuzzy control are used to adapt the parameters of the controller. Simulation study confirms that under step and random loads, the frequency control effect of the proposed adaptive controller with proposed fuzzy control is much superior to that of the conventional control. Moreover, the robustness of the adaptive controller is much higher than that of the conventional control.

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