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Research Article

Genetic Algorithm-Optimized Fuzzy Control for Doubly-Fed Asynchronous Generator in Variable-Speed Wind Turbines

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ABSTRACT

Optimization of Doubly Fed Induction Generator (DFIG) control is crucial for applications such as renewable energy systems, industrial automation, and electric vehicles. However, the dynamic and nonlinear nature of DFIGs often challenges conventional control methods, leading to suboptimal performance. To address these limitations, this paper proposes an optimized fuzzy speed control strategy for a DFIG-based wind generator using a genetic algorithm (GA), offering superior performance compared to traditional PI controllers. The study begins with the modeling of the generator in Park's reference frame and its indirect vector control applied to stator flux orientation. To ensure real-time tracking of the optimal operating point and maximize power extraction under varying wind speeds, a fuzzy PI speed controller is implemented. Further, the genetic algorithm—combined with a local search method—is employed to optimize the controller's parameters, significantly reducing the tuning effort compared to trial-and-error approaches. This optimization enhances the wind system's ability to track the maximum power point (MPP) with high efficiency. MATLAB/Simulink simulations demonstrate the effectiveness and adaptability of the proposed control scheme under diverse operating conditions. The results exhibit excellent speed regulation, reduced voltage and current ripples, and robust performance, highlighting the potential of this approach for practical implementation in variable-speed wind turbine systems.

Keywords: Doubly fed induction generator (DFIG), Fuzzy control; Variable speed wind system, Genetic algorithms, Speed control.

INTRODUCTION

Historically, energy production has relied on combustible resources, including wood, fossil fuels, and nuclear power, but these sources present significant environmental challenges such as greenhouse gas emissions and pollution, contributing to climate change and ecological damage. Their high costs, geopolitical issues, and safety concerns also limit accessibility and sustainability. Consequently, a global shift towards renewable energy sources, such as hydropower, solar, and wind, is crucial for reducing carbon emissions and ensuring a cleaner future. Wind energy is a rapidly growing renewable source, and this study focuses on Doubly Fed Induction Generators (DFIGs), commonly used in modern wind turbines due to their cost-effectiveness, robustness, and low maintenance. DFIGs are versatile and suitable for applications in robotics, aerospace, household appliances, renewable energy systems, ship propulsion, and electric vehicles.

Despite their advantages, DFIGs pose control challenges due to their nonlinear dynamics and strong coupling between electrical and mechanical variables. Conventional control methods, like vector control, aim to decouple stator and rotor currents for simpler regulation, similar to DC motor behavior. However, this approach is sensitive to disturbances, difficult to tune, and lacks robustness. Traditionally, fixed-gain PI and PID controllers have been used for DFIG regulation because of their simplicity and wide applicability. However, these controllers rely heavily on manual tuning, often requiring extensive trial-and-error adjustments to achieve optimal dynamic response in stator current and rotor speed, making this method inefficient and potentially unable to guarantee optimal performance. To address these limitations, intelligent optimization techniques, such as genetic algorithms (GAs), have become effective tools for automatically tuning controller gains and ensuring superior performance under varying operating conditions.

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This paper proposes an optimized fuzzy speed control strategy for DFIG-based wind turbines using a genetic algorithm. Key contributions include the development of an efficient fuzzy-PI controller with GA-based tuning for enhanced dynamic response; improved system performance across different operating modes, ensuring stability under wind speed fluctuations; robust and precise control, minimizing errors despite system uncertainties; and validation through MATLAB/Simulink simulations, demonstrating the controller's effectiveness in real-time operation. The paper is organized as follows: Section 2 covers modeling of the wind energy conversion system, Section 3 details the design of the proposed speed controller, Section 4 presents simulation results and performance analysis, and Section 5 concludes and outlines future research directions

WIND ENERGY CONVERSION SYSTEM

Wind Turbine Modeling

The modeling of a wind turbine aims to characterize the extractable mechanical power as a function of wind speed and operational parameters. This analysis enables the determination of the aerodynamic torque** applied to the turbine's low-speed shaft [3].

The power captured by the wind turbine is derived from aerodynamics and can be expressed as:

$$P_v = \frac{1}{2}\rho S V^3 \tag{1}$$

Where:

ρ is the air density and the wind speed is V. The aerodynamic power at the turbine rotor level is written in the following form [2]:

$$P_T = C_p P_v$$
(2)

The power coefficient Cp represents the aerodynamic efficiency of the wind turbine and depends on the turbine's characteristics. The tip-speed ratio is defined as the ratio between the linear speed of the blades and the wind speed:

$$\lambda = \frac{\Omega_t R}{V} \tag{3}$$

The gain multiplier allows for adjusting the mechanical quantities (speeds and torques) of the turbine and the generator, which are expressed by the following mathematical equation:

$$\begin{cases} \Omega_t = \frac{\Omega_e}{G} \\ T_g = \frac{T_{aer}}{G} \end{cases} \tag{4}$$

Where:
T_g is the effect of the turbine torque on the generator shaft. By bringing back the mechanical parameters of the turbine to the generator shaft, we obtain the model defined by the following relationship:

$$J\frac{d\Omega_e}{dt} + D\Omega_e = T_g - T_{em} \tag{5}$$

Where:
J and D are the inertia and friction coefficient of the generator shaft, respectively. Based on the previously presented equations, the Figure 1 [5] can define a physical model of the turbine with inputs such as the blade angle, wind speed, and the torque.

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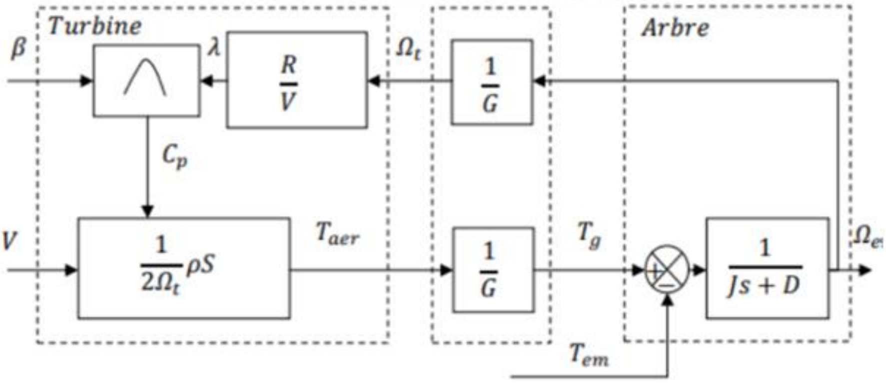

Fig.1. Block diagram of the turbine model [5].

Vector Control of DFIG

Vector control, a technique applied to electric devices, achieves decoupled operation by strategically positioning current and flux vectors [7]. This approach allows a DFIG machine to emulate the behavior of a DC machine, in which armature current and electromagnetic torque are directly proportional. The machine model in the Park reference frame is employed to control the stator flux orientation:

$$\begin{cases} V_{ds} = R_s i_{ds} + \frac{d\phi_{ds}}{dt} - \varpi_s \phi_{qs} \\ V_{qs} = R_s i_{qs} + \frac{d\phi_{qs}}{dt} - \varpi_s \phi_{ds} \end{cases} \tag{6}$$

$$\begin{cases} V_{dr} = R_r i_{dr} + \frac{d\phi_{dr}}{dt} - (\varpi_s - \varpi)\phi_{qr} \\ V_{qr} = R_r i_{qr} + \frac{d\phi_{qr}}{dt} - (\varpi_s - \varpi)\phi_{dr} \end{cases} \tag{7}$$

We orient the stator flux along the d-axis so that the component along the g-axis is constantly zero, and the machine model will be simpler as presented below:

$$\begin{cases} V_{ds} = R_s i_{ds} + \frac{d\phi_{ds}}{dt} \\ V_{qs} = R_s i_{qs} - \varpi_s \phi_{ds} \end{cases}$$
(8)

$$\begin{cases} V_{dr} = R_r i_{dr} + \frac{d\phi_{dr}}{dt} - (\varpi_s - \varpi)\phi_{qr} \\ V_{qr} = R_r i_{qr} + \frac{d\phi_{qr}}{dt} - (\varpi_s - \varpi)\phi_{dr} \end{cases}$$
(9)

The expression of the rotor flux will be:

$$\begin{cases} \phi_{dr} = L_r \sigma i_{dr} + \frac{M}{L_s}\phi_{ds} \\ \phi_{qr} = L_r \sigma i_{qr} \end{cases} \tag{10}$$

By integrating the equations of the stator currents and rotor fluxes into the set (9), the machine model becomes:

$$\begin{cases} V_{ds} = \frac{R_s}{L_s}\phi_{ds} - \frac{R_s}{L_s} M i_{dr} + \frac{d\phi_{ds}}{dt} \\ V_{qs} = -\frac{R_s}{L_s} M i_{qs} + \varpi_s \phi_{ds} \end{cases} \tag{11}$$

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$$\begin{cases} V_{ds} = R_r i_{dr} + L_r \sigma \frac{di_{dr}}{dt} + e_d \\ V_{qs} = R_r i_{qr} + L_r \sigma \frac{di_{qr}}{dt} + e_\phi + e_q \end{cases} \tag{12}$$

With:

$$\begin{cases} e_d = -R_r \varpi_g \sigma i_{qr} + \frac{M}{L_s} \frac{di_{dr}}{dt} \\ e_\phi = \frac{M}{L_r} \varpi_g \phi_{ds} \\ e_q = L_r \varpi_g \sigma i_{dr} \end{cases} \tag{13}$$

On the other hand, the expression of the electromagnetic torque becomes:

$$T_{em} = -\frac{3pM}{2L_s} \phi_{ds} i_{dr} \tag{14}$$

In the two-phase benchmark, the stator active and reactive powers of the machine are expressed by the following equations:

$$\begin{cases} P_s = -\frac{3}{2} V_s \frac{M}{L_s} i_{qr} \\ Q_s = \frac{3}{2} \left(\frac{V_s^2}{L_s \varpi_s} - \frac{M}{L_r} V_s i_{dr} \right) \end{cases} \tag{15}$$

Basic Structure of a Speed Controller

Fuzzy logic is employed to control the speed of a doubly fed induction machine. Due to the highly non-linear nature of speed profile tracking, a non-linear regulator, such as a fuzzy logic regulator, is needed to achieve high-performance control. The Mamdani architecture, used here, comprises four key components:

- The fuzzification interface (fuzzifier)
- The knowledge base
- The inference mechanism (rule evaluation)
- The defuzzification interface

Fuzzy Logic Speed Control Principle

The fuzzy speed controller uses speed error (e) and its fluctuation (de) as inputs, as these are the important quantities for control. The controller then outputs the increment of the control signal, which represents the reference torque value, to be applied to the controlled process. The speed loop configuration is shown in Figure 2 [3].

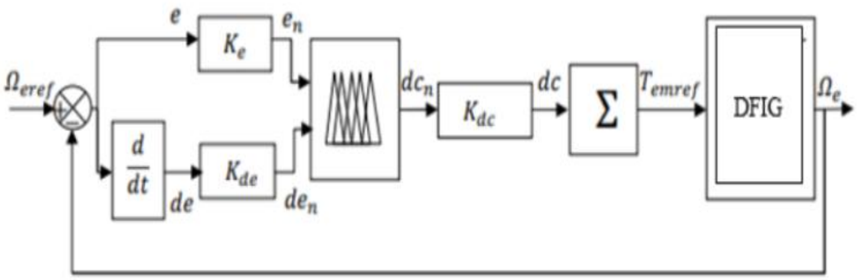

Fig.2. Block diagram of a fuzzy speed controller [3].

The speed error is expressed by:

$$e(k) = \Omega_{eref}(k) - \Omega_e(k) \tag{16}$$

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The variation of the speed error is expressed by:

$$de(k) = e(k) - e(k-1) \tag{17}$$

de: the increment of the command at the output of the controller; ke, kde, kdc: gains associated with e, de, and dc respectively.

Genetic Algorithms

Genetic algorithms (GAs) are optimization methods based on genetics and natural selection. They evaluate the fitness of potential solutions (chromosomes), and use selection, crossover, and mutation to generate new, improved solutions [12]. This process repeats until a good solution is found, simplifying manual trial-and-error optimization. For wind turbine speed controllers, GAs minimize the quadratic error of the normalized rotation speed of the double-fed asynchronous generator in steady state, to find the optimal solution of an objective function [3]

$$f_{obj} = \frac{1}{(\Omega_{eref})^2}\int_0^{t_f}\left(\Omega_e - \Omega_{eref}\right)^2 dt \tag{18}$$

The genetic algorithm's parameters were set as follows to obtain the best results: population size at 20, stochastic uniform selection, a crossover probability of 0.8 with multiple crossovers, a mutation probability of 0.001 with uniform mutation, and 200 generations.

Simulation Results

Vector control simulations of a doubly fed induction generator in a variable speed wind turbine system were performed using Matlab/Simulink. The turbine model and control structures were created in this environment. Results are presented for a 1.5 MW turbine, with parameters given in Table 1 [3].

Table 1. Parameters of the 1.5 MW wind conversion chain [3].

Meaning	Numerical value	Meaning	Numerical value
Stator resistance (Ω)	$R_s = 0.012$	Optimal specific speed	$\lambda_{op} = 0.012$
Rotor resistance (Ω)	$R_r = 0.021$	Multiplier gain	$G = 90$
Mutual inductance (H)	$M = 0.0135$	Wind turbine radius	$R = 35.25$
Stator inductance (H)	$L_s = 0.0137$	Power coefficient	$C_p = 0.5$
Rotor inductance (H)	$L_r = 0.0136$	Coefficient of friction	$D_e = 0.0024$

Figure 3a and 3b show the desired speed and the turbine rotation speed. To show the performance obtained by the optimized fuzzy-PI controller, the simulation results obtained in this case are represented by Figure 4.

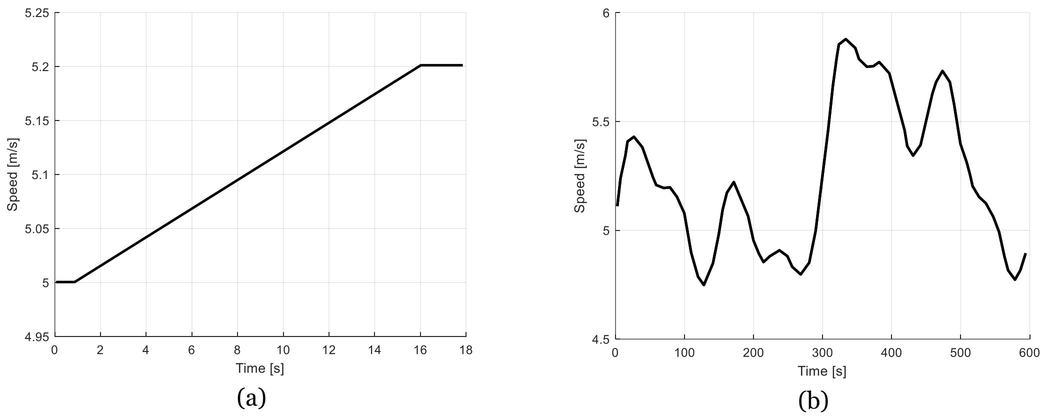

Fig.3. Wind speed, (a) evolution of wind speed applied to the wind turbine, (b) random wind profile applied to the wind turbine.

The simulation results indicate that the fuzzy-PI controller performs slightly better than the classical PI controller, particularly in dynamic conditions. As shown in the specific speed (A) and power coefficient (Cp) figures, the fuzzy-PI controller returns to optimal or maximum values much faster after a speed change than the classical PI controller [7]. Consequently, the Cp and A figures for fuzzy-PI control are more stable and closer to optimal values. Figure 4c

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demonstrates that the tracked rotation speed closely follows the optimal reference and matches the applied speed profile. Furthermore, active power production occurs at a unity power factor due to the phase opposition between voltage and machine current. Reactive power is zero, as illustrated in Figure 4f, because the machine operates at a unity power factor.

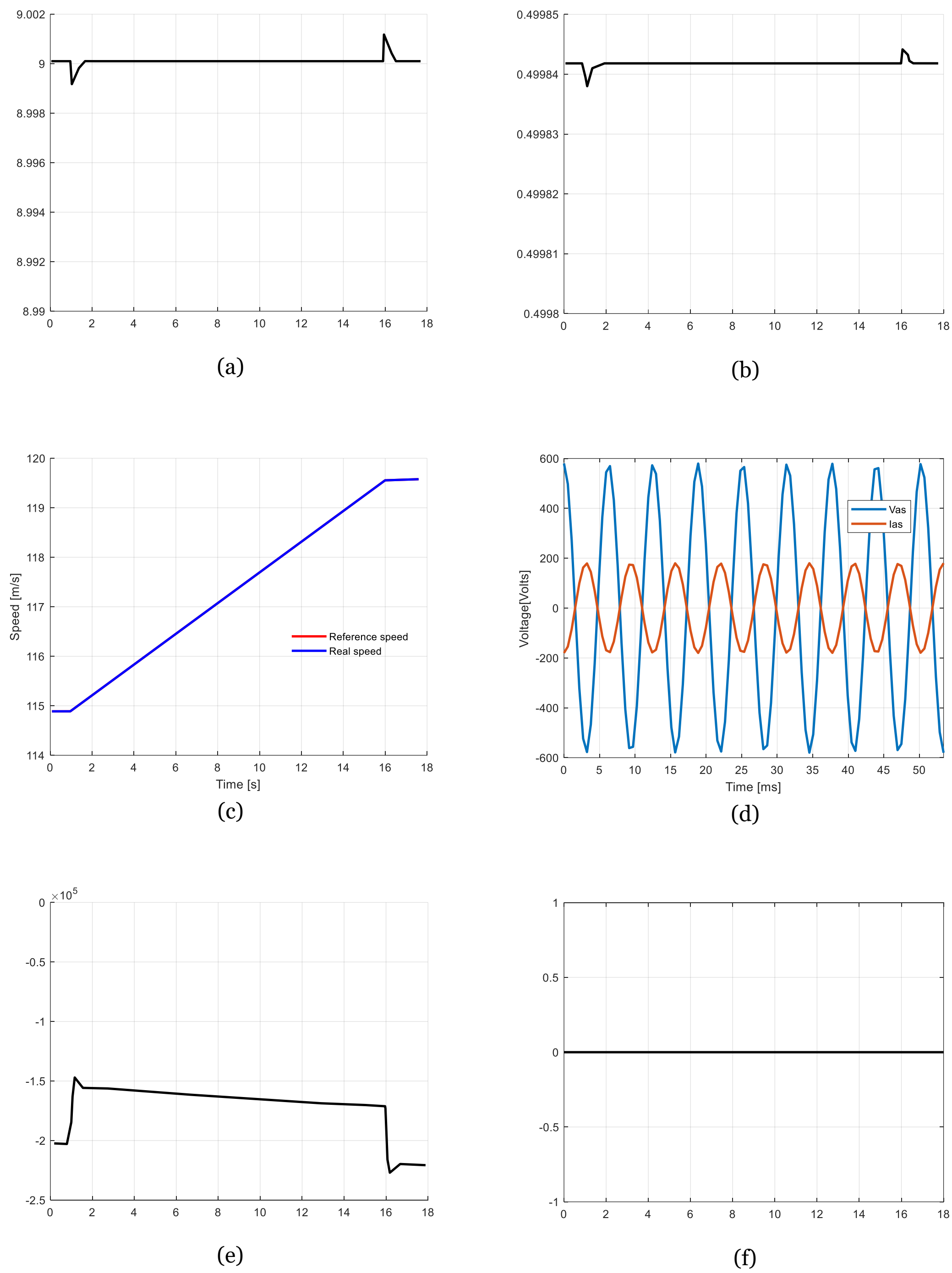

Fig.4. Simulation results of the double-fed asynchronous wind turbine with variable wind speed on the ramp, (a) the specific speed A, (b) power coefficient Cp, (c) DFIG speed, (d) Vas voltage and las current, (e) active power on the rotor side, (f) reactive power on the rotor side

To assess the fuzzy control system's tracking and operational performance, a random wind profile was applied to the reduced model. The results, shown in Figure 5, indicate that the specific speed (À) and the power coefficient (Cp) fluctuate only slightly around their optimal values. The wind power and DFIG speed curves closely follow the applied wind profile. Additionally, the stator voltage and current, and the active and reactive power delivered by the DFIG, were analyzed. Overall, the fuzzy PI controller provides satisfactory tracking, and unity power factor operation is

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maintained. This is evidenced by the phase opposition between stator voltage and current, resulting in the production of purely active power.

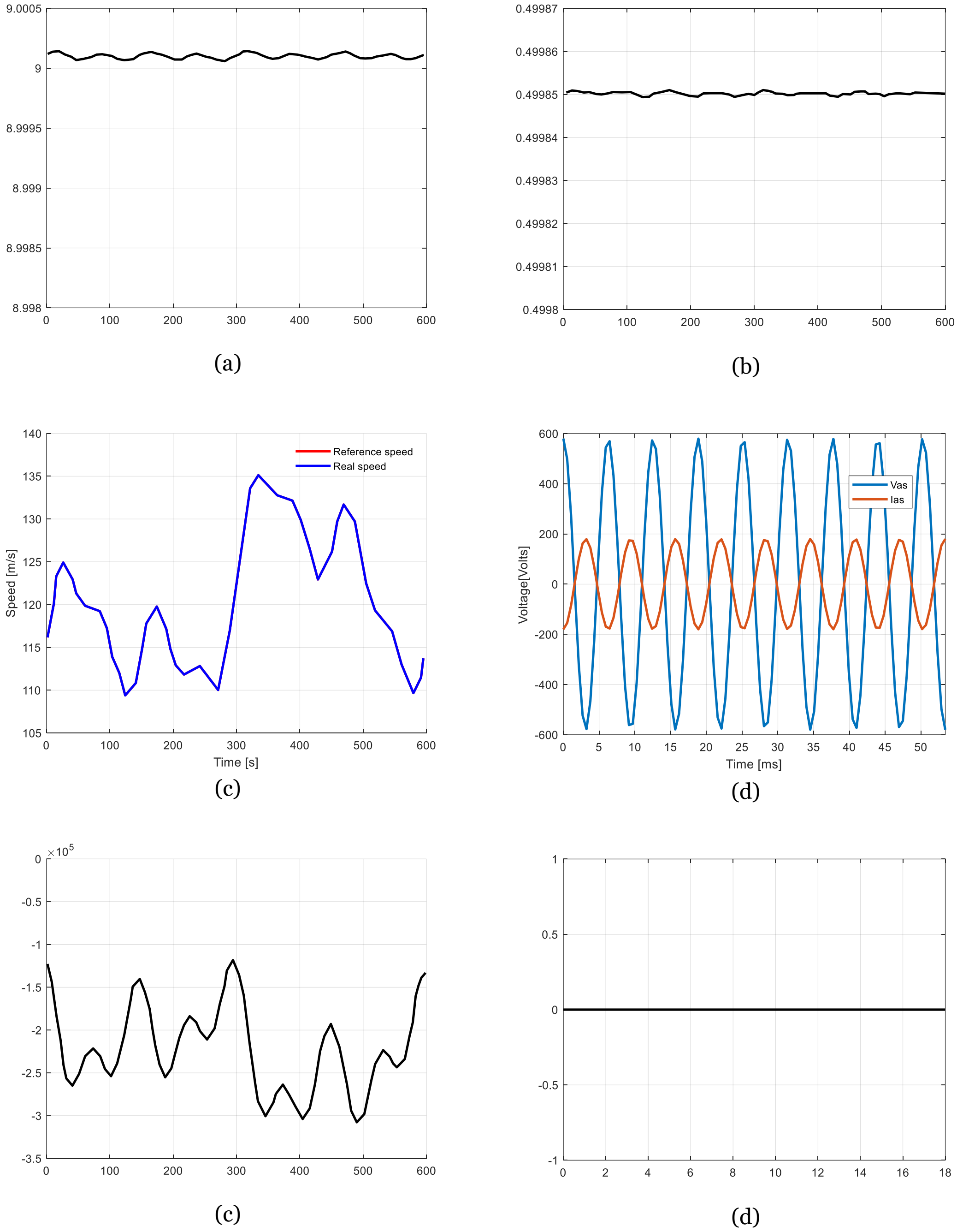

Fig.5. Simulation results of the double-fed asynchronous wind turbine with variable wind speed on the ramp, (a) the specific speed A, (b) power coefficient Cp, (c) DFIG speed, (d) Vas voltage and Ias current, (e) active power on the rotor side, (f) reactive power on the rotor side

CONCLUSIONS

This dissertation examined the modeling and optimization of fuzzy control systems for doubly fed induction generators in variable speed wind applications. The research demonstrated that fuzzy control approaches simplified the design process while producing highly effective speed controllers, highlighting the benefits of optimization-based design methodologies. The findings provide practical guidance for implementing advanced control strategies and identify promising directions for continued research.

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A key contribution of this work is the comprehensive testing conducted across varied operating conditions, which substantially advances our understanding of variable speed wind turbines utilizing doubly fed induction generators. The study's primary limitations include its simulation-based approach and the use of specific generator parameters. Future research directions should focus on experimental validation, improved genetic algorithms, real-time implementation strategies, and comprehensive disturbance response testing.

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