Variable speed wind turbine based on doubly fed induction generator using genetic algorithms

Turbina eólica de velocidade variável baseada em gerador de indução duplamente alimentado usando algoritmos genéticos

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ABSTRACT
Optimization of the control of doubly fed induction generators (DFIGs) is essential for many applications, such as renewable energy systems, industrial automation, and electric cars. Unfortunately, the dynamic and non-linear character of DFIG frequently makes it difficult for conventional control techniques to adjust, which results in less-than-ideal performance. To overcome these obstacles, this paper presents an optimized fuzzy speed control of a doubly fed induction wind generator using a genetic algorithm, which has more advantages than its counterpart PI speed controller. In this study, the modeling of generator in the Park's frame was presented, as well as its indirect vector control applied to the stator flux. Then, to guarantee tracking of the ideal operating point in real-time and to produce the most electricity possible for varying wind speeds, we used a fuzzy PI speed controller. To improve the sizing operation of this controller, we opted for the genetic algorithm technique combined with one of the local search methods, which facilitated the search and reduced the effort compared to the trial-and-error sizing method. Furthermore, this made it possible for the wind system to track the optimal power point maximum with good performance. The simulation results of the suggested control displayed by MATLAB-Simulink illustrate the effectiveness and adaptability
of the proposed control scheme across different operating conditions. The analysis of the results showed good performance for speed, small voltage and current ripple when using the fuzzy PI speed controller with genetic algorithm technique, offering promising prospects for practical implementation in variable speed wind turbine applications.

**Keywords:** fuzzy PI controller, vector control, asynchronous generator, wind system, genetic algorithms.

**RESUMO**
A otimização do controle de geradores de indução duplamente alimentados (DFIGs) é essencial para muitas aplicações, como sistemas de energia renovável, automação industrial e carros elétricos. Infelizmente, o caráter dinâmico e não linear do DFIG frequentemente dificulta o ajuste das técnicas de controle convencionais, o que resulta em um desempenho abaixo do ideal. Para superar esses obstáculos, este artigo apresenta um controle de velocidade difuso otimizado de um gerador eólico de indução duplamente alimentado usando um algoritmo genético, que tem mais vantagens do que seu controlador de velocidade PI equivalente. Neste estudo foi apresentada a modelagem do gerador no pórtico do Parque, bem como seu controle vetorial indireto aplicado ao fluxo do estator. Então, para garantir o rastreamento do ponto de operação ideal em tempo real e produzir o máximo de eletricidade possível para velocidades variadas do vento, usamos um controlador de velocidade PI fuzzy. Para melhorar a operação de dimensionamento deste controlador, optou-se pela técnica do algoritmo genético combinada com um dos métodos de busca local, o que facilitou a busca e reduziu o esforço em comparação ao método de dimensionamento por tentativa e erro. Além disso, isso possibilitou ao sistema eólico rastrear o ponto de potência máximo ideal com bom desempenho. Os resultados da simulação do controle sugerido exibido pelo MATLAB-Simulink ilustram a eficácia e adaptabilidade do esquema de controle proposto em diferentes condições operacionais. A análise dos resultados mostrou bom desempenho para velocidade, pequena ondulação de tensão e corrente quando utilizado o controlador de velocidade fuzzy PI com técnica de algoritmo genético. Oferecendo perspectivas promissoras para implementação prática em aplicações de turbinas eólicas de velocidade variável.

**Palavras-chave:** controlador fuzzy PI, controle vetorial, gerador assíncrono, sistema eólico, algoritmos genéticos.

**1 INTRODUCTION**
Since the dawn of humanity, energy production has been based largely on fuels such as wood, fossil fuels (coal, oil, gas, etc.), and then uranium [1]. But the major issue associated with the use of these materials is the emission of gases and the massive release of various compounds, which disrupts our planet. Not to mention that this energy resource is not available to everyone for political or financial reasons, its installation is expensive and it can be dangerous ecologically.
Therefore, we need to look for other alternative solutions to produce electricity such as water, sun, and wind. These latter options fit perfectly into the overall effort to reduce CO2 emissions. Our study focuses on one of the developing renewable energies at the moment, which is wind energy [2]-[5]. We will look into the current state of technological advancements that have enabled the construction and proper functioning of wind turbines and their integration into electricity production.

In order to better harness wind resources for different wind conditions, this study focuses on the Doubly Fed Induction Generator (DFIG), which forms the core of a large portion of wind turbines [4]. Indeed, these machines have several advantages such as lower cost, robustness, and reduced maintenance. These are suitable candidate in practical applications and good option for real-world applications requiring high performance, like robotics actuations, aerospace applications, household appliances, renewable energy, ship propulsion, and vehicles.

However, the absence of natural decoupling between the different input and output variables imposes a non-linear model on the asynchronous machine [6]-[8], which is strongly coupled to its structural simplicity, leading to great difficulty in its control. The complexity of controlling the asynchronous machine has led to the development of several control strategies, the most popular of which is vector control [7]. Its principle is to eliminate the coupling between the inductor and the rotor of the asynchronous machine, thus allowing for operation comparable to that of a direct current machine, but it offers few acceptable results, due to some drawbacks including disturbance, difficult parameter tuning, and decreased robustness.

Generally, these machines can be controlled by the traditional fixed gain PI, PID controllers [9],[10] which have been used in most practical applications because of their applicability and simplicity [10]. However, this technique depends on the control gains to achieve the high performance such as a faster dynamic of the stator current and the mechanical speed. The empirical tuning approach is typically used to establish control gains [11]. This approach involves running a number of experiments to identify the gains values that produce the required performance, but it is difficult and not always effective the best result. Indeed, it seems necessary to use stochastic search methods such as genetic algorithms to
generate the appropriate gains. Some studies have previously demonstrated the effectiveness of such strategies in producing the best outcomes for the optimum gains [12], [13].

This paper presents an optimized fuzzy control of a DFIG used in a wind turbine system using genetic algorithm for speed regulation. Furthermore, the guarantee of an accurate determination of control gains, assuring the required performances. In fact, the suggested algorithm is based on a simple technique compared to the earlier works published in [12], [13]. Through Simulink, we were able to validate the system's behavior under various conditions, providing a comprehensive view of its dynamic response.

In light of the above, the main objectives of this article can be summarized as follows:

- Develop and analyze an optimized fuzzy control of a DFIG used in a wind turbine system using genetic algorithm.
- Improving system performance in different operating modes.
- Ensuring dependable performance with minimal error, enhancing the system’s stability and responsiveness during wind speed fluctuations.
- Maintaining steady performance and precise control despite system flaws.

The presented work is structured in five sections, Section 2 gives the modelling of the wind conversion chain. Then, the Section 3 contains the basic structure of a speed controller, and the section 4 comprises a simulation result to show the effectiveness of the proposed system. Finally, some conclusions are drawn in Section 5.

2 WIND CONVERSION CHAIN
2.1 WIND TURBINE MODELING

Modeling the wind turbine involves expressing the extractable power as a function of wind speed and operating conditions, which allows for determining the wind torque applied to the wind turbine’s slow shaft [3]. This modeling is based on literature reviews or information extracted from brochures of different manufacturers. Previously, we have seen that wind power is expressed by:

\[ P_v = \frac{1}{2} \rho SV^3 \]  

(1)
Where:

\( \rho \) 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]:

\[
P_t = C_p P_v
\]

The power coefficient \( C_p \) 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:

\[
\lambda = \frac{\Omega R}{V}
\]

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:

\[
\begin{align*}
\Omega &= \frac{\Omega_G}{G} \\
T_g &= \frac{T_{gen}}{G}
\end{align*}
\]

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:

\[
J \frac{d\Omega}{dt} + D\Omega = T_g - T_{em}
\]

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.
2.2 VECTOR CONTROL OF DFIG

One control technique used with electric devices is vector control. By placing the current vectors and consequent flux vectors in the best possible positions, it enables us to create a decoupled operating mode [7]. As a matter of fact, it enables us to integrate the behavior of a DFIG machine with that of a DC machine, in which the armature current and electromagnetic torque are proportionate. To orient the stator flux, we use the machine model in the park reference frame:

\[
\begin{align*}
V_{ds} &= R_i i_{ds} + \frac{d\phi_{ds}}{dt} - \omega \phi_{qs} \\
V_{qs} &= R_i i_{qs} + \frac{d\phi_{qs}}{dt} - \omega \phi_{ds} \\
V_{dr} &= R_i i_{dr} + \frac{d\phi_{dr}}{dt} - (\omega_s - \omega) \phi_{qr} \\
V_{qr} &= R_i i_{qr} + \frac{d\phi_{qr}}{dt} + (\omega_s - \omega) \phi_{dr}
\end{align*}
\]

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

\[
\begin{align*}
\phi_{ds} &= L_s \sigma_i_{ds} + \frac{M}{L_s} \phi_{ds} \\
\phi_{qr} &= L_s \sigma_i_{qr}
\end{align*}
\]

(10)

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

\[
\begin{align*}
V_{ds} &= \frac{R}{L_s} \phi_{ds} - \frac{R}{L_s} M i_{dr} + \frac{d \phi_{ds}}{dt} \\
V_{qs} &= -\frac{R}{L_s} M i_{qs} - \omega_s \phi_{ds}
\end{align*}
\]

(11)

\[
\begin{align*}
V_{dr} &= R_i_{dr} + L_s \sigma \frac{di_{dr}}{dt} + e_d \\
V_{qr} &= R_i_{qr} + L_s \sigma \frac{d \phi_{qr}}{dt} + e_\phi + e_q
\end{align*}
\]

(12)

With:
\[
\begin{align*}
e_d &= -L_r \omega_s \sigma_{q_r} + \frac{M}{L_s} \frac{d\phi_{st}}{dt} \\
e_\phi &= \frac{M}{L_r} \omega_s \phi_{st} \\
e_q &= L_r \omega_s \sigma_{i_{dr}}
\end{align*}
\]

(13)

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

\[
T_{em} = -\frac{3 p M}{2 L_s} \phi_{st} i_{dr}
\]

(14)

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

\[
\begin{align*}
P_s &= -\frac{3}{2} V_s M \frac{i_{qr}}{L_s} \\
Q_s &= \frac{3}{2} \left( \frac{V_{i_{dr}}^2}{L_s \omega_s} - \frac{M}{L_r} V_i \right)
\end{align*}
\]

(15)

3 BASIC STRUCTURE OF A SPEED CONTROLLER

This section is all about applying fuzzy logic to control the speed of the doubly fed induction machine. We’re dealing with tracking a speed profile with a strong non-linearity, which requires us to control it using a non-linear regulator such as the fuzzy logic regulator to achieve high-performance control system. The Mamdani architecture consists of four essential parts, namely:

- The fuzzification interface (the fuzzifier),
- The knowledge base,
- The inference mechanism or rule evaluation,
- The defuzzification interface.

3.1 FUZZY SPEED CONTROLLER

The process observation reveals that the speed error and its fluctuation are the important quantities to be controlled. As a result, these two characteristic
values, designated as e and de, will be used as the fuzzy controller’s inputs. Its output, which reflects the reference torque value, is the increment of the control signal to be applied to the process that needs to be controlled. Figure 2 shows the configuration of the speed loop [3].

Figure (2) Block diagram of a fuzzy speed controller [3].

The speed error is expressed by:

\[ e(k) = \Omega_{eref}(k) - \Omega_e(k) \]  (16)

The variation of the speed error is expressed by:

\[ de(k) = e(k) - e(k - 1) \]  (17)

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

3.2 GENETIC ALGORITHMS

Genetic algorithms (GAs) are genetic and natural selection-based optimization methods. They function by assessing the relative performance (fitness) of a population of viable solutions (chromosomes) at the beginning. Using the basic evolutionary operators of selection, crossover, and mutation, a new population of viable solutions is generated based on these performances [12]. This cycle is repeated until a good solution is found. By using the genetic algorithm as an optimization tool, the manual process of trial and error is made easier, the sizing of the speed controllers of the wind turbine passes through the minimization of the quadratic error of the normalized rotation speed of the double-fed asynchronous
generator in steady state, allowing for the search for the optimal solution of the following objective function [3]:

\[
    f_{obj} = \frac{1}{(\Omega_{eref})^2} \int_0^t (\Omega_e - \Omega_{eref})^2 dt
\]  

(18)

The best results were obtained using genetic algorithms, with the following parameters:
- Population size of 20,
- Stochastic uniform selection,
- Multiple crossovers with a probability of 0.8,
- Uniform mutation with a probability of 0.001,
- 200 generations.

4 SIMULATION RESULTS

In order to show the results obtained from vector control simulation of a doubly fed Induction generator used in a variable speed wind turbine system. The turbine model as well as all control structures are done in Matlab/Simulink. The simulation results that we are going to present have been done for a 1.5 MW turbine with parameters given in the Table 1 [3].

<table>
<thead>
<tr>
<th>Meaning</th>
<th>Numerical value</th>
<th>Meaning</th>
<th>Numerical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stator resistance (Ω)</td>
<td>Rs=0.012</td>
<td>Optimal specific speed</td>
<td>(\lambda_{op}=9)</td>
</tr>
<tr>
<td>Rotor resistance (Ω)</td>
<td>Rr=0.021</td>
<td>Multiplier gain</td>
<td>G=90</td>
</tr>
<tr>
<td>Mutual inductance (H)</td>
<td>M=0.0135</td>
<td>Wind turbine radius</td>
<td>R=35.25</td>
</tr>
<tr>
<td>Stator inductance (H)</td>
<td>Ls=0.0137</td>
<td>Power coefficient</td>
<td>(C_p=0.5)</td>
</tr>
<tr>
<td>Rotor inductance (H)</td>
<td>Lr=0.0136</td>
<td>Coefficient of friction</td>
<td>(D_e=0.0024)</td>
</tr>
</tbody>
</table>

Source: BEKAKRA, Y., BEN ATTOUS, D.

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.
From the simulation results obtained, we can note at first glance that the fuzzy-PI controller has practically slightly better performance than the classical PI controller, especially in dynamic conditions. It's clear on the two figures of the specific speed $\lambda$ and the power coefficient $C_p$ that the time required to return to optimal or maximum values after a speed change is very short compared to that of the classical PI control [7]. This is why the figures of $C_p$ and $\lambda$ by fuzzy PI are more stable and closer to the optimal values compared to the other. Figure 4c shows the tracking of the rotation speed captured at its optimal reference and has the same shape as the applied speed profile. In addition, it can be noticed that the production of active power is done at a power factor of one due to the phase opposition between the voltage and the machine's current. The reactive power is zero since the machine operates at a power factor of one as shown in figure 4f.
Similarly, using the reduced model, we apply a random wind profile to see how well the fuzzy control system can track and operate. Figure 5 presents the results obtained for this application. The specific speed $\lambda$ and the power coefficient $C_p$ fluctuate slightly around their optimal values, while the wind power and the DFIG speed curves evolve in a similar manner to the wind profile applied to the system. Other variables, such as the stator voltage and current, active and reactive powers delivered by the DFIG. Overall, it is observed that the tracking controlled by the fuzzy PI controller is satisfactory and that operation with a unity power factor is maintained, as indicated by the phase opposition between the stator voltage and current, leading to the production of purely active power.
5 CONCLUSIONS

The main goal of this dissertation was the modeling and optimized fuzzy control of a doubly fed induction generator, as well as its potential contribution to a variable speed wind system. A simulation using a fuzzy controller was carried out to adjust the speed of a linearized induction machine. According to the simulation results, it was observed that this technique helped to reduce the trial-and-error design effort and quickly obtain efficient speed controllers, demonstrating the usefulness of optimization-based design for these controllers. These results provide valuable insights into the practical implementation of advanced control strategies and pave the way for further research and development in this area.
On the other side, we believe that the amount of conducted tests under various operating points and working conditions are unique and bring significant contribution over the available solutions on the researched variable speed wind turbine based on doubly fed induction generator. The study's limitations include reliance on simulation-based validation and doubly fed induction generator parameters, which may not generalize to all generators. Future work should focus on experimental validation, enhancing genetic algorithms, real-time implementation, and comprehensive disturbance testing.
REFERENCES


