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Parameter Identification of Doubly Fed Induction Generator (DFIG) using Particle Swarm Optimization (PSO) algorithm

***Abstract**. The objective of this study is to determine the parameters of the doubly fed induction generator (DFIG), which is a crucial first step in wind turbine power generation. This research focuses on understanding the dynamics of the DFIG system and aims to develop more precise control systems for network movement and the exchange of active and reactive energy, especially at high speeds in this domain. This research utilizes the particle swarm optimization (PSO) approach to perform DFIG parametric identification. The model simulation is adapted to the identical settings in the MATLAB/Simulink software environment. The identification findings of the "PSO" method are compared to those of traditional testing and validated based on their accuracy and convergence to the energy source values obtained by the dSPACE panel. The findings obtained using the "PSO" algorithm demonstrate superior effectiveness and performance compared to the conventional identification approach.*

***Streszczenie.** Celem tego badania jest określenie parametrów generatora indukcyjnego z podwójnym zasilaniem (DFIG), który jest kluczowym pierwszym krokiem w wytwarzaniu energii przez turbinę wiatrową. Badania te skupiają się na zrozumieniu dynamiki systemu DFIG i mają na celu opracowanie bardziej precyzyjnych systemów sterowania ruchem sieci oraz wymianą energii czynnej i biernej, szczególnie przy dużych prędkościach w tej dziedzinie. W badaniach tych wykorzystano podejście optymalizacji roju cząstek (PSO) do przeprowadzenia identyfikacji parametrycznej DFIG. Symulacja modelu dostosowana jest do identycznych ustawień w środowisku oprogramowania MATLAB/Simulink. Wyniki identyfikacji metody „PSO" porównuje się z wynikami tradycyjnych testów i waliduje na podstawie ich dokładności i zbieżności z wartościami źródła energii uzyskanymi przez panel dSPACE. Wyniki uzyskane przy użyciu algorytmu „PSO" wykazują wyższą skuteczność i wydajność w porównaniu z konwencjonalnym podejściem do identyfikacji. (**Identyfikacja parametrów generatora indukcyjnego zasilanego dwustronnie (DFIG) przy użyciu algorytmu optymalizacji roju cząstek (PSO)**)*

Keywords: Doubly fed induction generator (DFIG), parameter identification, classic test, Particle Swarm Optimization (PSO)..
Słowa kluczowe: Translation generator indukcyjny z podwójnym zasilaniem (DFIG), identyfikacja parametrów, próba klasyczna, Optymalizacja roju cząstek(PSO)..

Introduction

The doubly fed induction generator (DFIG) is prevalent in the industrial sector due to its durability, lack of a mechanical collector, and cost-effectiveness. In wind energy, the DFIG stands out for its unique feature of having two three-phase windings in the stator and rotor [1]. DFIG is commonly utilized in three modes: monitoring, producing, and plugging. In the driving mode, the stator terminals are linked to a power source, causing the rotor to revolve in the same direction as the stator's magnetic field. Generating mode occurs when the rotor rotates at a speed higher than the synchronous speed, in the same direction as the spinning field of the stator. Plugging mode [2] occurs when the rotor rotates in the opposite direction of the stator spinning field.

The significance of this machine in generating energy through wind turbines necessitates a comprehensive examination of these factors using various methodologies to get the most optimal approaches to the machine model. To acquire a model of a system, three essential steps must be accomplished, selecting the appropriate model structure, determining its parameters, and then verifying its correctness. The parametric identification of a 'DFIG' involves establishing the parameters of its model, which is employed for control purposes, to achieve an accurate depiction of the actual system. The identification of the parameters of the induction motor is difficult because the model is highly nonlinear and rotor fluxes are not accessible for measurements. The parameter estimation is performed using various machine load tests on the steady-state equivalent circuit. Simulations, rather than experimental tests, were performed to estimate the IM parameters in [3].

Contemporary heuristic algorithms are regarded as efficient instruments for solving optimization issues. These methods don't need the goal function to be distinct and uninterrupted. Particle Swarm Optimization (PSO) is a technique that may be used for optimizing problems that are nonlinear and non-continuous. The issues about continuous variables have been addressed by developing simpler social models using simulation. This method is more straightforward and less complex to develop compared to other scalable algorithms due to its limited number of adjustable parameters. The electric parameter vector [ϴ]= [Rs Rr M Ls Lr] represents the benefits mentioned above. where: Rs(Ω) – stator resistance, Rr(Ω) – rotor resistance Ls(H) – stator inductance, Lr(H) – rotor inductance, M(H) – mutual cyclic inductance.

In the beginning, we assessed these factors using conventional testing carried out under controlled laboratory conditions. This was conducted to widely comprehend the machine's behavior and establish a dependable basis for subsequent simulations and comparisons with the results of PSO. Subsequently, we presented a thorough mathematical model of the induction machine, encompassing the equations pertaining to flow and torque. In the third section, we also used the PSO technique, utilizing its effectiveness and robustness in this field of identification. In conclusion, we thoroughly examined the obtained results and concluded that the identification process utilizing PSO was very precise and showed superior convergence. The actual testing and measurements for this study were conducted in our laboratory, consisting of two main components:

a. The power source measuring segment of the dSPACE board.

b. The measuring component of the conventional tests the parameters of the Doubly Fed Induction Generator (DFIG).

Fig.1. illustrates the utilization of various equipment, measuring tools, and control instruments during this procedure or: ① Power supply and DC excitation, ② An induction double-fed machine DFIM with a power of 3 kW, ③ A 3 kW independent excitation DC machine, ④ FLUKE type i30S/i30 closed-loop sensors using the Hall effect for current measurements, ⑤ GWINSTEC sensors type GDP-050 (closed loop type sensors using the Hall effect) for voltage measurements, ⑥ Tachometer DT-1236L to measure motor speed, ⑦ DS1104 dSPACE board with these accessories as the external box for connecting analog

and digital inputs/outputs. This card is integrated into a PC, ⑧ The PC is loaded with two software applications. One option is to use Matlab/Simulink to set the inputs/outputs of the DS1104 board by utilizing specified blocks. The second software, ControlDesk, facilitates the loading of program code onto the board, processing of data, and saving it in a format compatible with Matlab for further analysis. It also enables real-time tracking of the evolution of measured or calculated data using graphical or digital displays.

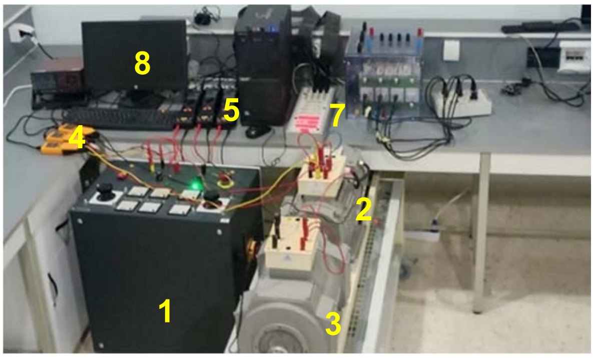

Fig.1. Experimental setup in laboratory

Part of the power of the measurement from the dSPACE board

The power values (voltage-current) of this machine were experimentally measured in the laboratory, as shown in Fig.1 The system is actively managed utilizing a dSPACE DS1104 board that is linked to the programmable PC. The SIMULINK modeling tool is utilized for programming, enabling us to visually represent and evaluate problems through interconnected blocks. The process involved in obtaining and documenting measurements of these variables was as follows.

► The voltage and current sensors have been installed on the three DFIG power circuit phases and are connected to the dSPACE board through analog and digital inputs/outputs in the external box.

► We created a model in Matlab/Simulink and a new project in ControlDesk, for the acquisition and graphical visualization and real-time of the evolution of these variables.

► The machine was subjected to a gradual increase in input voltage, reaching its nominal value of 230v, before measurements were taken. The transient phase was surpassed.

► Record these observations and export them to a Matlab file with the extension (file.mat) for loading and utilization in simulation.

Upon applying a nominal voltage value (230V) to the machine in an empty state, we saw that the current reached a value of (4.85A). The measurements of the machine's voltage and current have been saved as Matlab extension files. These voltage files can be imported and used as a standard power source for models that include the measured and identified parameters and the current files can be used as a reference to compare with the current outputs of these simulated models. This stage also seeks to assess and confirm the forthcoming outcomes derived from this investigation.

Part of the classical DFIG parameter tests.

Traditional approaches often prioritize the determination of certain characteristics, such as inductance, resistance, and magnetic flux. Nevertheless, this method fails to account for many imperfections that may exist in the consolidated system, such as time delays, power losses in inverters, intervals of inactivity, wiring issues, and inaccuracies measurements in this second part, the following steps were followed :

► Measurement of Stator (Rs) and Rotor (Rr) Resistance from Hot Volt-Ampere Method.

► Finding the stator's cyclic inductance (Ls), the mutual inductance between the stator and rotor (Msr), and the transformation ratio (m1) from a...[4]

- Vacuum test.
- Determination of the total resistance returned to the stator.
- Open rotor test.

► Determination of the cyclic inductance of the rotor (Lr), the mutual inductance rotor/stator (Mrs), and the transformation ratio (m2) from:

- Open stator test
- Determination of the electrical parameters returned to the stator.

The machine rating plate provided the nominal values that were utilized in these traditional tests. The findings of these assessments are condensed in Table 1.

Table 1. The parameters were measured by conventional tests.

Rs [Ω]	Rr [Ω]	M [H]	Ls [H]	Lr [H]
2.25	3.25	0.208	0.235	0.255

These experimental values are introduced for the purpose of comparison and validation of this approach.

The DFIG mathematical model

Nonlinear systems widely exist in industries and practical implementations. General linear mathematical models usually ignore nonlinear factors in actual systems, so linear mathematical models can not completely describe the actual physical systems [5]. The most accurate depiction of an induction motor in terms of its physical characteristics is the transformer-type scheme. This scheme is defined by five electrical parameters, namely Rs, Rr, Ls, Lr, and M.

It is presumed that the power supply for the machine is perfect, suggesting that the three-phase voltages are symmetrical sine waves with a constant amplitude and frequency [6]. The mathematical representation of the Doubly Fed Induction Generator (DFIG) in the park repository, in terms of the d-axis and q-axis, is described by the following equations:

Electrical equations

The electrical equations of the DFIG in the synchronous frame are written as follows [7]:

$$(1)\quad \begin{cases} Vsd = Rs.isd + \frac{d}{dt}\varphi sd - \omega s.\varphi sq \\ Vsq = Rs.isq + \frac{d}{dt}\varphi sq + \omega s.\varphi sd \\ Vdr = Rr.ird + \frac{d}{dt}\varphi rd - (\omega s - \omega).\varphi rq \\ Vrq = Rr.irq + \frac{d}{dt}\varphi rq + (\omega s - \omega).\varphi rd \end{cases}$$

$$(2)\quad \omega r = (\omega s - \omega)$$

$$(3)\quad \omega = p\Omega$$

where: : $Vs,Vr(d,q)$ – stator and rotor voltages in the reference of park , $(\varphi s,\varphi r(d,q))$ – stator and rotor flux in the reference of park , $(is,ir(d,q))$ – stator and rotor current in the reference of park , (ωs) – pulse of the stator electrical quantities ,(ωr) – pulse of the rotor electrical quantities , $(\omega\ )$

– pulse glissement , (Ω) – the mechanical rotor speed , *(p)* – number of pole pairs of the machine.

Expression of the stator and rotor flux

The stator and rotor flux equations [7]:

$$(4)\qquad \begin{cases} \varphi sd = Ls.isd + M.ird \\ \varphi sq = Ls.isq + M.irq \\ \varphi rd = Lr.ird + M.isd \\ \varphi rq = Lr.irq + M.isq \end{cases}$$

Electromagnetic torque Expressions

In [8], The electromagnetic torque is given by:

$$(5)\qquad \mathrm{Tem} = M.p.(ird.isq - irq.isd)$$

Rotor dynamics equation

the mechanical equation:

$$(6)\qquad \mathrm{Tem} = \frac{\mathrm{J}d\Omega}{dt} + f\Omega + Tr$$

where: Tem – the electrical torque, Tr –the sum of the resistant torque, J – the coefficient of inertia of the rotating masses, f – the load friction coefficient.

By replacing the flow expressions (4), in the voltage equations (1), the machine model becomes [4]:

$$\begin{bmatrix} Vsd \\ Vsq \\ Vrd \\ Vrq \end{bmatrix} \begin{bmatrix} Rs + Ls.D & -ws.Ls & M.D & -ws.M \\ ws.Ls & Rs + Ls.D & ws.M & M.D \\ M.D & -M.wr & Rr + Lr.D & -Lr.wr \\ M.wr & M.D & Lr.wr & Rr + Lr.D \end{bmatrix} \begin{bmatrix} isd \\ isq \\ ird \\ irq \end{bmatrix}$$

This DFIG state model can be represented in the following discrete form.

$$(7)\qquad DX = \mathrm{A.X} + B.U$$

where: D – the differential operator d/dt.
$X = [isd\ isq\ ird\ irq]^T$ – the state variable vector.
$U = [Vsd\ Vsq\ Vrd\ Vrq]^T$ – the input variable vector.
A – Must be an n-by-n matrix, where (n) number of states
B – Must be an n-by-m matrix, where (m) is the number of inputs

$$A = \begin{bmatrix} -a1 & a2.w & a3 & a4.w \\ -a2.w & -a1 & -a4.w & a3 \\ a5 & -a6.w & -a7 & -w/\sigma \\ a6.w & a5 & w/\sigma & -a7 \end{bmatrix}, B = \begin{bmatrix} b1 & 0 & b2 & 0 \\ 0 & b1 & 0 & b2 \\ b2 & 0 & b3 & 0 \\ 0 & b2 & 0 & b3 \end{bmatrix}$$

where:

$$\sigma = \frac{1-M\text{^}2}{Ls.Lr}, \quad a1 = \frac{Rs}{Ls.\sigma}, \quad a2 = \frac{1-\sigma}{\sigma}, \quad a3 = \frac{Rr.M}{Ls.Lr.\sigma},$$

$$a4 = \frac{M}{Ls..\sigma}, \quad a5 = \frac{Rs.M}{Ls.Lr.\sigma} \quad a6 = \frac{M}{Lr.\sigma} \quad a7 = \frac{Rr}{Lr.\sigma},$$

$$b1 = \frac{1}{Ls.\sigma}, \quad b2 = \frac{-M}{Ls.Lr.\sigma}, \quad b3 = \frac{1}{Lr.\sigma},$$

Identification by PSO

Particle swarm optimization (PSO) is a type of optimization algorithm that was created by Russell Eberhart and James Kennedy in 1995. It falls under the category of meta-heuristic optimization methods. Driven by the social behavior and collective intelligence of a flock of birds or school of fish in their quest for food [9]. In the Particle Swarm Optimization (PSO) algorithm, individual animals are represented as particles, each with specific velocities and locations inside the search space. A collection of particles is categorized as a swarm. The swarm typically starts with a population that is initiated randomly, with each individual particle traversing the search space and retaining its best position encountered thus far. The particles engage in communication and, using the most optimal positions discovered, dynamically modify the search position and relative velocity of the swarm. Consequently, the swarm will navigate towards more favorable outcomes [11]. Every particle attempts to alter its location based on the subsequent information [10]:

- The current position and the current velocity,
- The distance between the current position and Pbest,
- The distance between the current position and Gbest.

The new velocity and position of each particle are calculated using the following PSO dynamic equations :

$$(8)\qquad v_i(t+1) = K\left(w_i \times v_i(k) + c_1.rand_1.\left(pbest_i - x_i(k)\right) + c_2.rand_2.\left(gbest - x_i(k)\right)\right)$$

$$(9)\qquad \boldsymbol{x_i(k+1)} = x_i(k) + v_i(k+1)$$

where: c_1, c_2 – two positive learning rates, $rand_1$, $rand_2$, – two random numbers between 0 and 1.
x_i– the position of particle I, v_i– the velocity of particle i, ***best***,– the best previous position of xi, ***get*** – the best previous position among the members of the population chosen at random as informants , k – 1,2…number of iterations , [$c_1.\mathrm{rand}_1.\left(pbest_i - x_i(k)\right)$] – Corresponds to the component of personal influence, [$c_2.\mathrm{rand}_2.\left(gbest - x_i(k)\right)$] corresponds to social influence, w – the inertia weighting factor or :

$$(10)\qquad w = \mathrm{wmax} - \frac{w\mathrm{max} - \mathrm{wmin}}{\max it\acute{e}ration} * k$$

When addressing several optimization issues, it is not possible to use the same parameter configuration for all of them. Therefore, the selection of parameter values dictates the behavior of the adaptive Particle Swarm Optimization (PSO) method in addressing a particular optimization issue.

The inertia factor "w" effectively regulates the range of particle search. When the value of "w" is high, the PSO algorithm exhibits a robust capacity to search globally but a limited ability to search locally. And when the value of "w" is low, it is advantageous for precise local investigation. Typically, the inertia weight "w" is considered to be constant. It can attain favorable, optimum outcomes. The PSO method has strong global and local search capabilities, which may be tailored by adjusting the coefficients. Consequently, it allows for a reduction in the number of iterations required to find an optimal solution with high precision.

Description The PSO system, problem, and algorithm

The PSO (Particle Swarm Optimization) identification system, is a specialized implementation of the PSO algorithm designed to address parametric identification challenges in machinery and dynamic systems. The parameter estimation problem is considered in the first phase by utilizing nonlinear differential equations. The process involves comparing the actual outputs of the system with the outputs of the identified sound model. The goal is to minimize a quadratic criterion that represents the sum of the squared differences between the actual results of the process and those obtained from the model. Both the actual machine and its model are stimulated by the same input. Our PSO identification process is demonstrated in Fig.2.

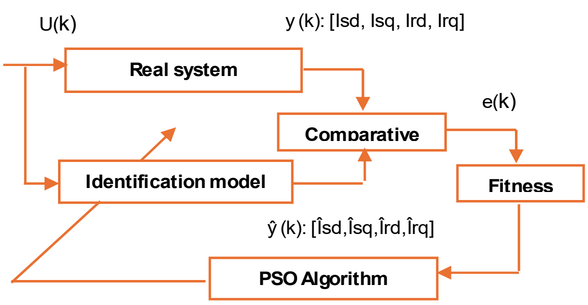

Fig.2. PSO identification system principle

Thus, one can compare the response of the real system $y(k)$ and the response of the model of estimation $\hat{y}(k)$ by a comparative defined by the expression:

$$e(k) = y(k) - \hat{y}(k) \tag{11}$$

The disparity between the desired system output and the present system output may be quantified as [12]:

$$f(\Theta) = \int_{t1}^{t2} e^T e \, dt \tag{12}$$

This represents the time constant of the system, which governs the behavior of any non-linear system. The goal function was derived using the discrete variant of the quadratic error minimization approach:

$$F(\Theta) = \sum_{k=1}^{N} \{[Y(k) - \hat{Y}(k)]^T [Y(k) - \hat{Y}(k)]\} \tag{13}$$

N – corresponding sample number

The identification technique employed in this study relies on an iterative approach that utilizes the discrepancy between the actual machine's outputs and the outputs of its model, as described in the repository (d q) [13]. The model's measured and predicted currents are compared to assess the fitness function, which is used by the optimization process to decide the chosen criterion for expression in this study:

$$F(\Theta) = \sum_{k=1}^{n} \{w_1 (Isd(k) - \hat{I}sd(k))^2 + w_2(Isq(k) - \hat{I}sq(k))^2 + w_3(Ird(k) - \hat{I}rd(k))^2 + w_4(Irq(k) - \hat{I}rq(k))^2\} \tag{14}$$

where: : w_1, w_2, w_3, w_4 – are appropriate weights, $Is, Ir(d,q)$ – the stator and rotor current outputs of the actual machine in reference (d,q) , Îs,Îr(d,q) – the stator and rotor current outputs of the model estimated in reference (d,q).

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The PSO algorithm

Fig.3. flowchart is a basic illustration of the 'PSO' algorithm [14], encompassing the principal stages. The primary purpose of the PSO method is to minimize the physical condition value of the objective function through optimization. The parameter estimate values can be determined by calculating the minimal value of the fitness function [8].

Simulation and validation of results

a. Simulation and Discussion

The simulation was performed in Matlab/Simulink Environment. First, the simulated modules are powered by the actual voltage that we saw and measured in section 1 (matte file). Consists of applying the PSO approach to estimate the parameters of our machine using the experimental data in Table 1, the efficiency and performance of the PSO algorithm heavily rely on the careful selection and adjustment of various parameters, such as the iteration number, inertia coefficient w, and acceleration coefficients c1 and c2. The convergence of the PSO algorithm is greatly influenced by the choice of these parameters, which can either lead to successful convergence or divergence of the algorithm. Through a series of iterative simulations, we systematically varied the value of one coefficient at a time while keeping the others constant. As a result, we identified the PSO parameters that consistently led to the objective function converging towards the best solution.

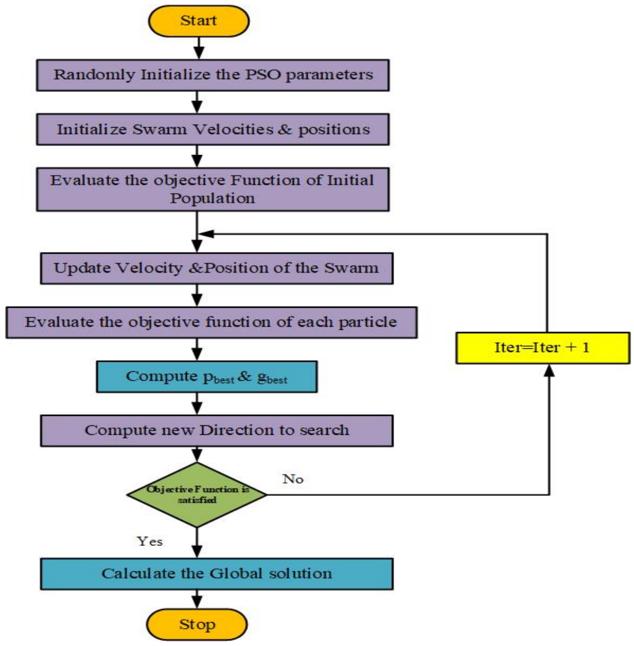

Fig.3. PSO Organizational Chart

Table 2. The PSO parameters.

Parameters	value
swarm size	20
max iteration	50
max	0.9
win	0.4
coefficients c1=c2	1.5

The optimization results for the machine parameters are displayed in Table 3.

Table 3. Parameters identified by PSO

Parameters	Rs [Ω]	Rr [Ω]	M [H]	Ls [H]	Lr [H]
value	2.53	3.25	0.20	0.15	0.35

Fig.4. illustrates the progression of these parameters' values with respect to the number of iterations, as well as the speed at which this PSO algorithm achieves the optimal and more satisfactory values for its objective function.

However, in the Fig.5. graph that depicts the relationship between the fitness function and the number of iterations, it is observed that the value of the function decreases as the iterations go. When the process reaches 30 iterations, the fitness function value becomes extremely small at 1.5047e-04, while the error remains nearly unchanged. The value of the goal function varies in accordance with the number of repetitions. The ideal value of the intended Doubly Fed Induction Generator (DFIG) parameters is determined to be the best answer from the previous rounds.

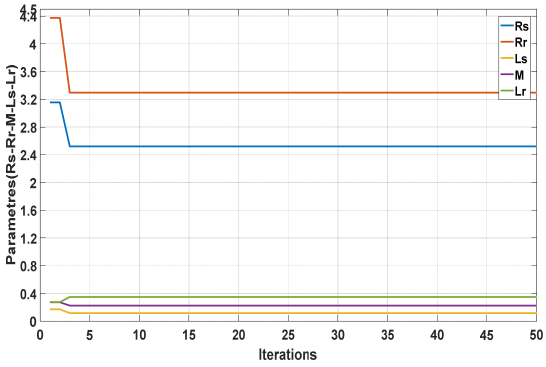

Fig.4. Variation of parameters according to the number of iterations.

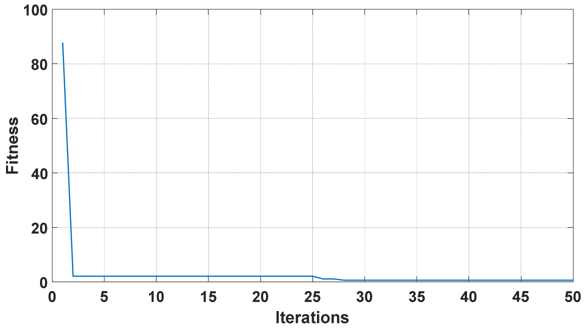

Fig.5.Evolution of the fitness function according to the number of iterations.

By analyzing Fig.4. and Fig.5. we can observe that the PSO algorithm exhibits a significant initial peak at the beginning of the cycle, occurring around the third iteration. This peak gradually decreases until approximately the thirtieth iteration, as depicted in Fig.5. of the objective function. The values then converge to those of the best fitness, indicating that the algorithm enables rapid adaptation of all particle swarms to the best visited position.

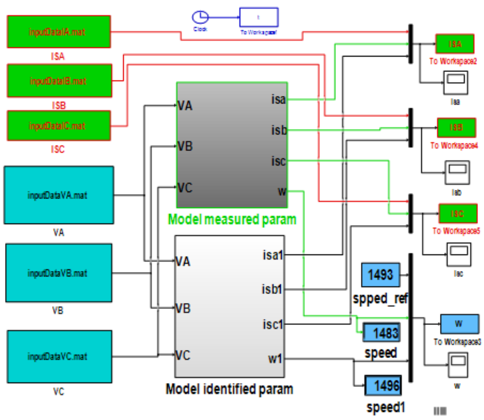

Fig.6. Validation results model

Validation of DFIG Identification Results

The result validation is a process that assesses the accuracy of a model by comparing the outputs of the real system with those of the model using the data used during the identification phase. The goal is to identify the model that most accurately represents the physical behavior of the system. The validation process was conducted using the Matlab/Simulink environment, involving the creation and simulation of a model depicted in Fig.6.

The objective of this operation is to provide the two models with the measured and simulated parameters from Fig.6. using the same nominal voltage of the machine recorded by the dSPACE board. The purpose is to compare the current outputs (isa, isb, etc) with the actual current curves recorded by the dSPACE map, to determine which model accurately replicates the behavior of the system.

The 'ISA' current was chosen, and the simulation result of this step is represented in Fig.7.

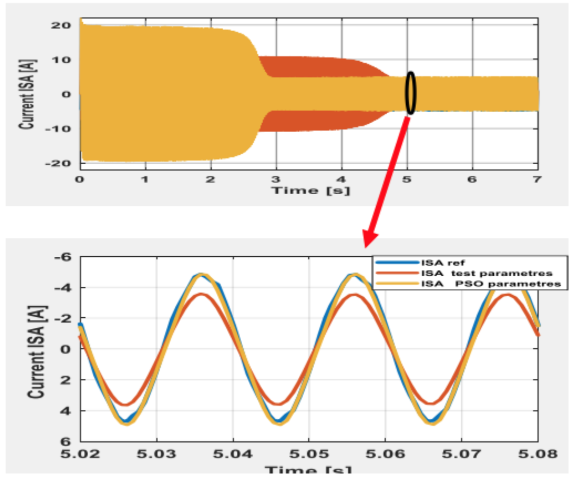

Fig.7. Zoom current shape "ISA

In the most recent figure, we observe that the output of the current 'ISA' from the model, which was identified using 'PSO', is more similar to that of the actual machine. Conversely, the current of the model simulated with parameters obtained from classical tests shows a significant deviation from the reference. This indicates that the parameters derived from the PSO approach exhibit a high degree of adaptability to real-world conditions. From this step, we can conclude that classical tests for identification require specific conditions and are unable to accurately determine the parameters. This is because the measurements are influenced by various factors such as temperature, noise, and nonlinearities. Additionally, there are uncertainties associated with the measurement equipment and the laboratory environment, which can introduce further noise. This is particularly evident in the measurements of inductances (L_s and L_r), as indicated by the percentage of error in relation to the measured results presented in Table 4. and Fig.8. The table provides a comparison between the parameters obtained through classical tests and the parameters estimated using PSO.

Table 4. Comparison between measured and identified parameters.

Parameters	measured	identified	error
Rs [Ω]	2.25	2.53	12.44 %
Rr [Ω]	3.25	3.25	0 %
M [H]	0.208	0.20	3.84 %
Ls [H]	0.235	0.15	36.17 %
Lr [H]	0.255	0.35	37 %

The speed of rotation of this machine was also measured by a digital indicator on the permanent phase of operation, and the value of 1493 rpm was found. This value was considered as a reference and represented in the simulation model by a constant as seen in Fig.6.

The following Fig.9. shows the evolution of the speed outputs of the models simulated with the measured and identified parameters and compares it with the reference.

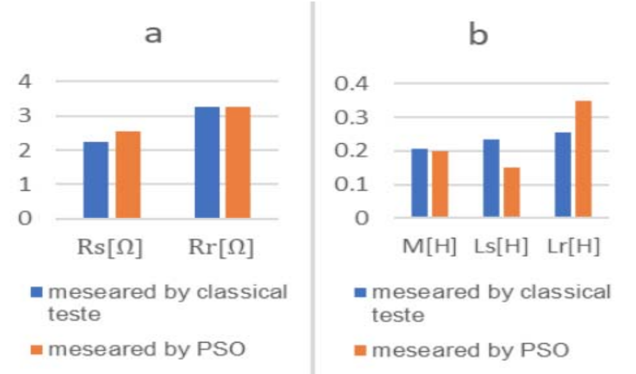

Fig.8. Simulation and experimental results with DFIG parameter's. (a) Rs and Rr [Ω]. (b) M, Ls and Lr[H].

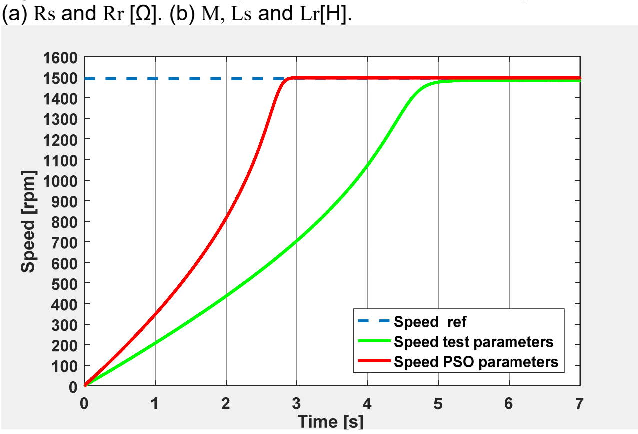

Fig.9. Experimental and simulated speed shape (rpm)

These curves demonstrate that the curve generated using the parameters determined by 'PSO' closely matches the reference rate and reaches a value of 1496 rpm in a shorter response time compared to the curve generated using the parameters measured by the tests, which only reaches a value of 1483 rpm. Hence, it is evident that the PSO algorithm demonstrates enhanced convergence speed and yields superior results in terms of the optimal physical shape. Conventional tests yield electrical parameters, but these results are imprecise due to measurement and reading errors on the devices. To address this, we employed the 'PSO' algorithm, which minimizes a quadratic criterion to identify the parameters. This demonstrates the effectiveness of the PSO method in handling restrictions and its ability to efficiently identify precise parameters with adequate performance.

Conclusion

This study presents the meta-heuristic approach 'PSO' for parameter identification of the induction machine. The method utilizes the mathematical model of the machine and focuses on minimizing the dynamic error between the real model and the estimated model. The simulation findings, when compared to the results of conventional testing, demonstrate that this approach is a robust research tool for accurately identifying parameters with a high degree of efficiency, particularly in situations where noise or flaws affect machine operation. The efficiency of this technique is evident in the parameter vector, which serves as the optimal representation of the machine, as well as in the comparison between the model's current output calculated by this vector and the actual current of the machine. The findings of this comparison validate the benefits of this method.

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