WIND EQUIVALENT MODEL PARAMETER ESTIMATION THROUGH MEAN-VARIANCE MAPPING OPTIMIZATION AND TRAJECTORY SENSITIVITY METHOD

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ABSTRACT

Wind energy is a renewable source of vital importance and is constantly growing. In this scenario, it is imperative to carry out studies through mathematical models. However, the mathematical representation becomes excessively complex when considering the number of wind turbines present in a wind farm. This paper proposes the estimation of parameters in a wind farm equivalent model using two different approaches. The first method is responsible for performing a global search over a wide interval, thus providing an intelligent initial parameter. The values estimated by this first method are then used in the second method, which will be responsible for performing the final estimation. Simulation results show that the combination of the two methods was adequate to obtain the parameters of the wind farm equivalent model.

Keywords: Wind energy. Mathematical model. Parameter estimation.

1. INTRODUCTION

In recent years, several countries around the world have increased the integration of renewable energy sources into their electrical grids. In this growth, it becomes essential to perform several studies to assess the impact of wind energy on electrical systems. All these studies need an accurate representation of wind farms through mathematical models. However, obtaining these models is a considerable challenge due to the large number of wind turbines available, coming from different manufacturers, featuring various technologies, sizes, and characteristics (ERLICH, SHEWAREGA, FELTES, KOCH, and FORTMAN, 2012). Moreover, due to confidentiality issues, manufacturers provide limited information about the modeling of their wind turbines. Therefore, models presented by IEEE and WECC, validated in previous works (MULJADI and ELLIS, 2008; ELLIS, MULJADI, SANCHEZ, and KAZACHKOV, 2011), are frequently employed for parameter estimation.

The parameter estimation of a wind farm equivalent model is based on metaheuristic algorithms or nonlinear programming. The former has the advantage of finding optimal solutions in a wide search space. Nonlinear programming algorithms offer the advantage of

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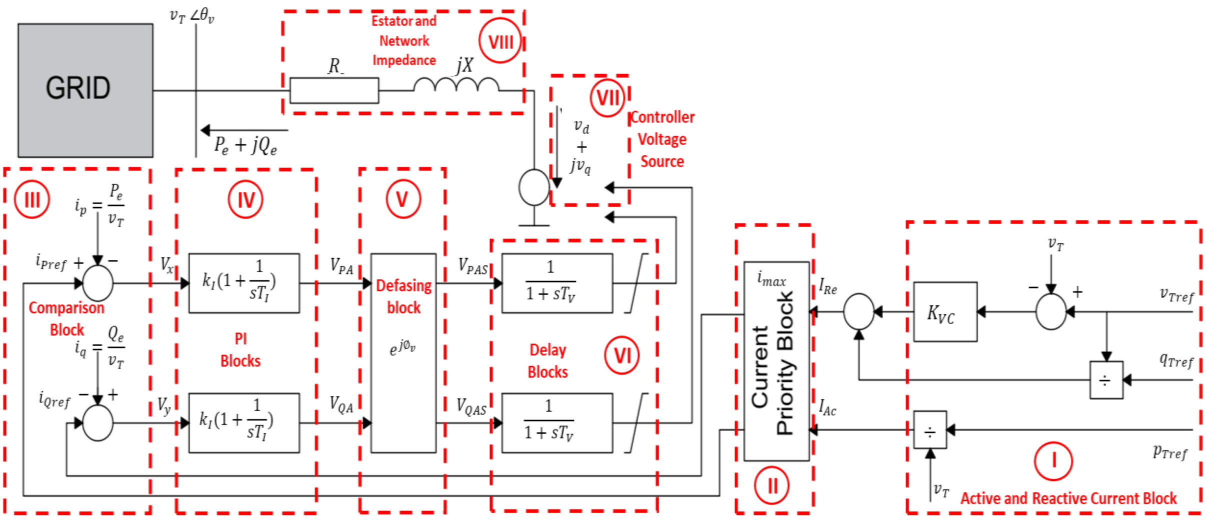
fast convergence, reducing processing time. However, requires an initial parameter estimate close enough to the real values to guarantee convergence.

This paper introduces an innovative approach to parameter estimation in a wind farm equivalent model with doubly fed induction generators (DFIG) to overcome the limitations of metaheuristic and nonlinear programming algorithms. This approach performs the combination of two distinct algorithms: the Mean-Variance Mapping Optimization (MVMO) (ERLICH, VENAYAGAMOORTHY, and WORAWAT, 2010), which provides an intelligent initial estimate, and the nonlinear programming algorithm Trajectory Sensitivity (TSM) (BENCHLUCH and CHOW, 1993), responsible for the final estimation based on the values provided by MVMO.

2. WIND FARM EQUIVALENT MODEL

A simplified generic model applicable to both Doubly Fed Induction Generators (DFIG) and Full-Converter based wind turbines, as proposed in Erlich, et al., (2012), was selected. This model represents the wind farm equivalent and was developed using a Thevenin equivalent, where the Thevenin voltage source takes into account the effects of all components of the wind generator, as illustrated in Figure 1.

Figure 1: Wind farm equivalent model.



The point of interconnection (POI) between the electrical grid and the Thevenin equivalent is established through a bus, where v_T and $\emptyset_v$ represent the magnitude and angle of the voltage, respectively. The active and reactive power generated by the wind farm is denoted as P_e and Q_e. The line impedances connecting the turbines to the POI are represented by the Thevenin equivalent resistance (R) and reactance (X). The equivalent voltage source is subdivided into direct (v_d) and quadrature (v_q) components. Initially, the reference values of active and reactive current components are obtained by Eq. 1 and Eq. 2.

$$I_{Ac} = \frac{P_{Tref}}{v_T} \tag{1}$$

$$I_{Re} = K_{VC}.\left(v_{Tref} - v_T\right) + \frac{Q_{Tref}}{v_{Tref}} \tag{2}$$

Those reference currents are introduced into the current priority block. This block assesses both the voltage magnitude at the terminal and the current magnitude to determine whether the priority is active power injection or voltage control. In situations of voltage drop, the priority is directed towards injecting reactive power to maintain the voltage at the bus. However, under normal conditions, the wind turbine focuses on injecting the maximum active power into the electrical grid. The PI blocks represent the controllers of the wind turbines, encompassing elements such as the gearbox and converters. The behavior of these controllers is described by Eq. 3 and Eq. 4.

$$V_{PA} = k_I.[\left(i_{Pref} - \frac{P_e}{v_T}\right) + \frac{1}{T_I}.\int_0^T \left(i_{Pref} - \frac{P_e}{v_T}\right).dt] \tag{3}$$

$$V_{QA} = k_I.[\left(\frac{Q_e}{v_T} - i_{Qref}\right) + \frac{1}{T_I}.\int_0^T \left(\frac{Q_e}{v_T} - i_{Qref}\right).dt] \tag{4}$$

At this moment, the model operates in terminal voltage-oriented coordinates. To operate in the electrical grid reference, it is necessary to incorporate a dephasing block, as represented by Eq. 5 and Eq. 6.

$$V_{PAS} = V_{PA}\,.\cos\theta_v - V_{QA}\,.\sin\theta_V \tag{5}$$

$$V_{QAS} = V_{PA}\,.\sin\theta_v + V_{QA}\,.\cos\theta_V \tag{6}$$

Finally, the delay block simulates the effects of the delays of the converters and the electrical machine (mechanical, electrical, and magnetic delays) that make up the wind turbines, the effects of which are described by Eq. 7 and Eq 8.

$$\dot{v_d} = \frac{1}{T_V}.(V_{PAS} - v_d) \tag{7}$$

$$\dot{v_q} = \frac{1}{T_V}.(V_{QAS} - v_q) \tag{8}$$

The active and reactive power generated from the wind farm are described by Eq. 9 and Eq. 10.

$$P_e = \frac{R\left(v_{Td}.V_d + v_{Tq}.V_q - v_T^2\right) + X(v_{Td}.V_q - v_{Tq}.V_d)}{R^2 + X^2} \tag{9}$$

$$Q_e = \frac{X\left(v_{Td}.V_d + v_{Tq}.V_q - v_T^2\right) - R.(v_{Td}.V_q - v_{Tq}.V_d)}{R^2 + X^2} \tag{10}$$

3. PARAMETER ESTIMATION PROCESS

The parameter estimation process employed in this study utilizes two distinct approaches to parameter estimation. For this purpose, a dynamic system is modeled using a differential algebraic equation (DAE) represented by Eq. 11.

$$\begin{aligned} \dot{x} &= f(x, y, p, c, u) \\ y &= g(x, p, c, u) \end{aligned} \tag{11}$$

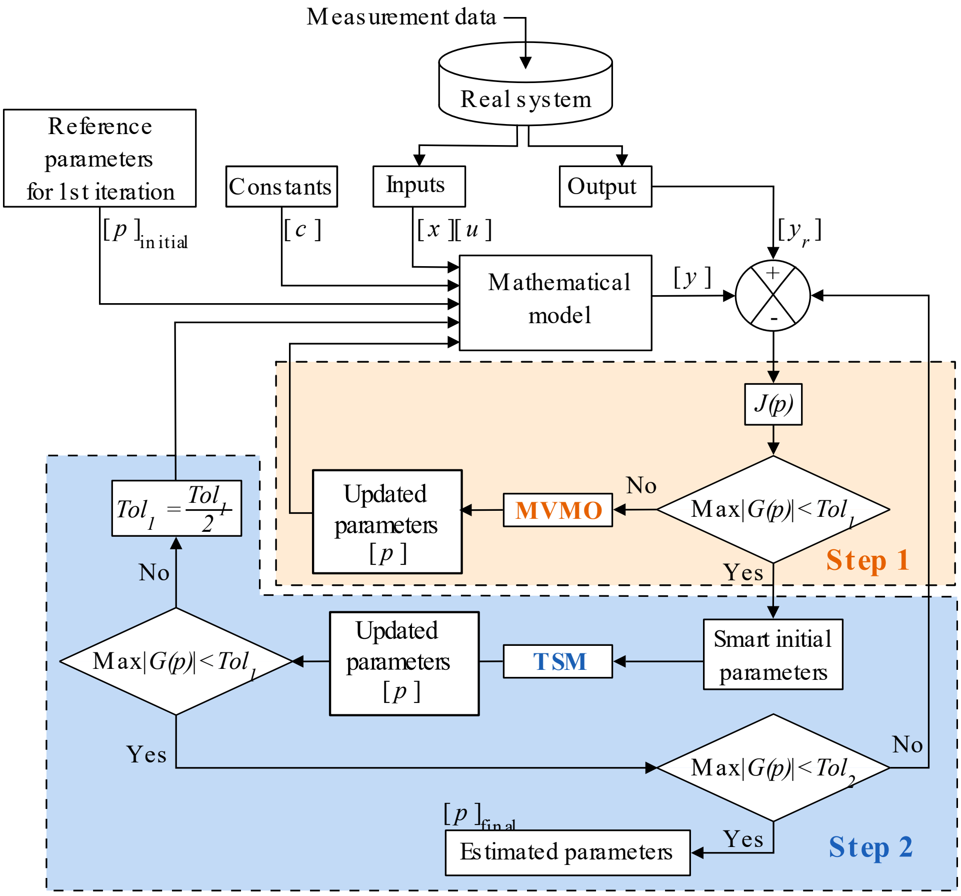
Where $x \in R^m$ is the state variable vector, $y \in R^r$ is the output variable vector, $u \in R^l$ is the input variable vector, $c \in R^{nc}$ is the constants variable vector, and $p \in R^{np}$ is the parameter variable vector. Let p_i be the i-th component of p. The functions f and g will be differentiable concerning each p_i, $i = 1,2,\dots,r$. The parameter estimation error is defined between the available measurement y_r and the mathematical output y, which is formulated through a minimization problem of the objective function represented by Eq. 12.

$$J(p) = \frac{1}{2}\int_0^{T_0} (y_r - y)^T.(y_r - y).dt \tag{12}$$

Where T_0 is the sampling period of the measurements. To avoid convergence problems, long processing times or estimation errors, the methodologies proposed in this paper solve Eq. 12 in two steps, as illustrated in Figure 2, where in the step 1, initially, the MVMO algorithm obtains an intelligent initial estimate by exploring a large parameter space. In the step 2, based on the intelligent initial guess provided by MVMO, the TSM is employed to find the local minimum. This algorithm is applied iteratively until $J(p)$ falls below a predetermined threshold (Tol_2). When these steps are completed, the parameters are accurately determined. In Figure 2, $G(p)$ is the derivative of the objective function $J(p)$ concerning the parameter vector, Tol_1 and Tol_2 are predetermined tolerances for MVMO and

TSM, respectively. To prevent divergence of TSM, the maximum value of $G(p)$ should be less than Tol_1. Otherwise, Tol_1 should be halved, and MVMO should be re-executed with this updated tolerance.

Figure 2: Parameter estimation methodology.



3.1 Mean-Variance Mapping Optimization (MVMO)

MVMO is a metaheuristic method based on the use of mapping functions to mutate new generations by considering the mean and variance of the best population. The evolution of MVMO populations shares characteristics with other evolutionary algorithms. However, the method differs as it induces mutations in offspring to diversify populations (GOMES and CARI, 2020). Consequently, the MVMO method updates the mathematical model parameter from Eq. 11 around the best solution and reduces the fitness function from Eq. 12 in each iteration. Therefore, MVMO is considered a robust method as it combines mapping functions with intelligent search techniques. More information about the MVMO algorithm stages can be found in Erlich, et al., (2010).

The main advantage of the MVMO compared to traditional metaheuristic methods such as GA (ZHOU, ZHAO, and LEE, 2018) and PSO (ZHOU, HSIEH, and LEE, 2019) lies in its superior performance when dealing with small populations (ERLICH, VENAYAGAMOORTHY, and WORAWAT, 2010). This characteristic makes the MVMO an ideal choice for optimizing problems that involve a limited number of individuals. It is for this reason that we have chosen to use the MVMO in this paper. However, it is important to note that, like any metaheuristic method, MVMO can become more time-consuming as it approaches local minima. To overcome this limitation, it introduces the TSM.

3.2 Trajectory Sensitivity Method (TSM)

TSM is a well-established methodology for estimation purposes. When compared to other nonlinear programming algorithms, it generally exhibits faster convergence, as it takes advantage of the Hessian of the objective function $J(p)$ to find the solution. This is a reason for using it in this paper. However, it is important to note that, like any nonlinear programming method, TSM is highly sensitive to the initial parameter estimates. To solve this problem, MVMO was employed in the process of obtaining an accurate initial estimate, as explained in the previous section. The estimation process can be formulated as an optimization approach, which allows the vector p that minimizes the objective function to be found. The optimization condition ($\frac{\partial J(p)}{\partial p} = 0$) is given by Eq. 13.

$$G(p) = \frac{\partial J(p)}{\partial p} = -\int_0^{T_0} \left(\frac{\partial y}{\partial p}\right)^T . (y_r - y). dt = 0 \tag{13}$$

The Newton-Raphson method can be employed to solve the nonlinear Eq. 13. Beginning with an initial parameter guess $p^0 = p_0$, the parameter fitting at the k^{th} iteration is determined by Eq. 14, where Γ is the Jacobian of $G(p)$, expressed by Eq. 15.

$$p_{k+1} = p_k - \Gamma(p_k)^{-1}. G(p_k) \tag{14}$$

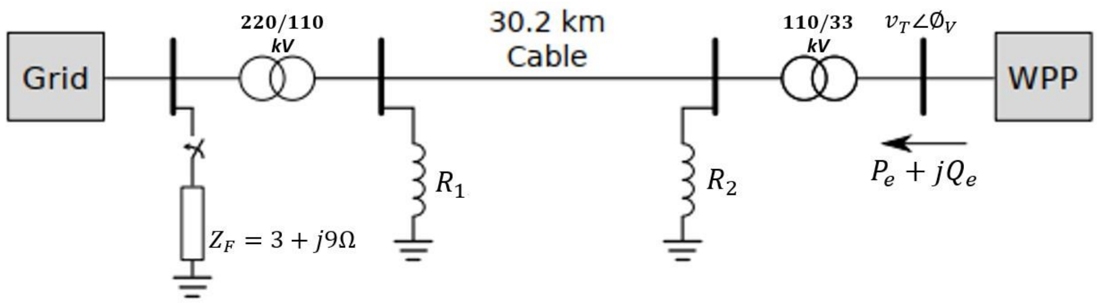
$$\Gamma(\mathrm{p}) \approx \int_0^{T_o} \left(\frac{\partial y}{\partial p}\right)^T . \left(\frac{\partial y}{\partial p}\right). dt \tag{15}$$

Where $\frac{\partial y}{\partial p}$ is the sensitivity function, which is the partial derivative of the output regarding p_i. More information about TSM can be found in Cari, et al., (2013); Cari, et al., (2015); Gomes, et al., (2020).

4. APPLICATION AND RESULTS

The electrical power system considered for this paper consists of a 5 MW wind farm equivalent model, as illustrated in Figure 3. In this power system, a short-circuit disturbance with a fault impedance $Z_f = 3 + 9\mathrm{j}$ was simulated using PowerFactory 14 software. The data collected during the simulation were subsequently used to estimate the system parameters. The system simulation lasted for 1 second, with measurements taken every 0.001 second, and was promptly cleared by the protection devices of the electrical system at 0.3 seconds.

Figure 3: Electric power system for testing.



To compare the estimation results provided by the combination of MVMO and TSM, the parameters obtained in Cari, et al., (2015); Gomes, et al., (2020) were used as a reference values, as presented in Table 1. In this paper, a computer with a Core i5 processor and 16 GB of RAM memory capacity was used.

Table 1: Benchmark for parameters.

Parameters	R	X	K_i	T_i	T_v	K_{vc}	i_{max}
Value	0.0336	0.1986	6.6339	0.0357	0.2574	1.9990	1.1011

The results obtained by combining these two algorithms are presented in Table 2. The values obtained from MVMO, using a tolerance ($Tol_1 = 0.001$), were used as an intelligent initial guess for TSM (gray columns), allowing the parameters to converge to the reference values in a total time of 13 minutes. Figure 4 and Figure 5 show the results obtained from this combination of algorithms, where P_e and Q_e are the output signals of the real system compared with the calculated mathematical model. The results were quite similar, achieving a correct estimate.

Table 2: Parameter estimation results.

		Search Region	Tol1	Estimated values	Reference values	Error (%)	Time (min)
MVMO (Step 1)	R	$0.0101 \leq R \geq 0.0571$	10^{-3}	0.0438	0.0336	30.4	12.02
	X	$0.0596 \leq X \geq 03376$		0.2512	0.1986	26.5	
	K_i	$1.9902 \leq K_i \geq 11.2776$		4.9239	6.6339	25.8	
	T_i	$0.0107 \leq T_i \geq 0.0607$		0.0336	0.0357	5.88	
	T_v	$0.0772 \leq T_v \geq 0.4376$		0.1901	0.2574	26.1	
	K_{VC}	$0.5997 \leq K_{VC} \geq 3.3983$		2.0046	1.9990	0.28	
	i_{max}	$0.3303 \leq i_{max} \geq 1.8719$		1.1010	1.1011	0.01	
		Intelligent Ini. Guess By MVMO	Tol2	Estimated values	Reference values	Error (%)	Time (s)
TSM (Step 2)	R	0.0438	10^{-8}	0.0336	0.0336	0.0	2.15
	X	0.2512		0.1988	0.1986	0.1	
	K_i	4.9239		6.4459	6.6339	2.8	
	T_i	0.0336		0.0349	0.0357	2.2	
	T_v	0.1901		0.2510	0.2574	2.4	
	K_{VC}	2.0046		1.9988	1.9990	0.0	
	i_{max}	1.1010		1.1005	1.1011	0.1	

Figure 4: Active power from estimated parameters.

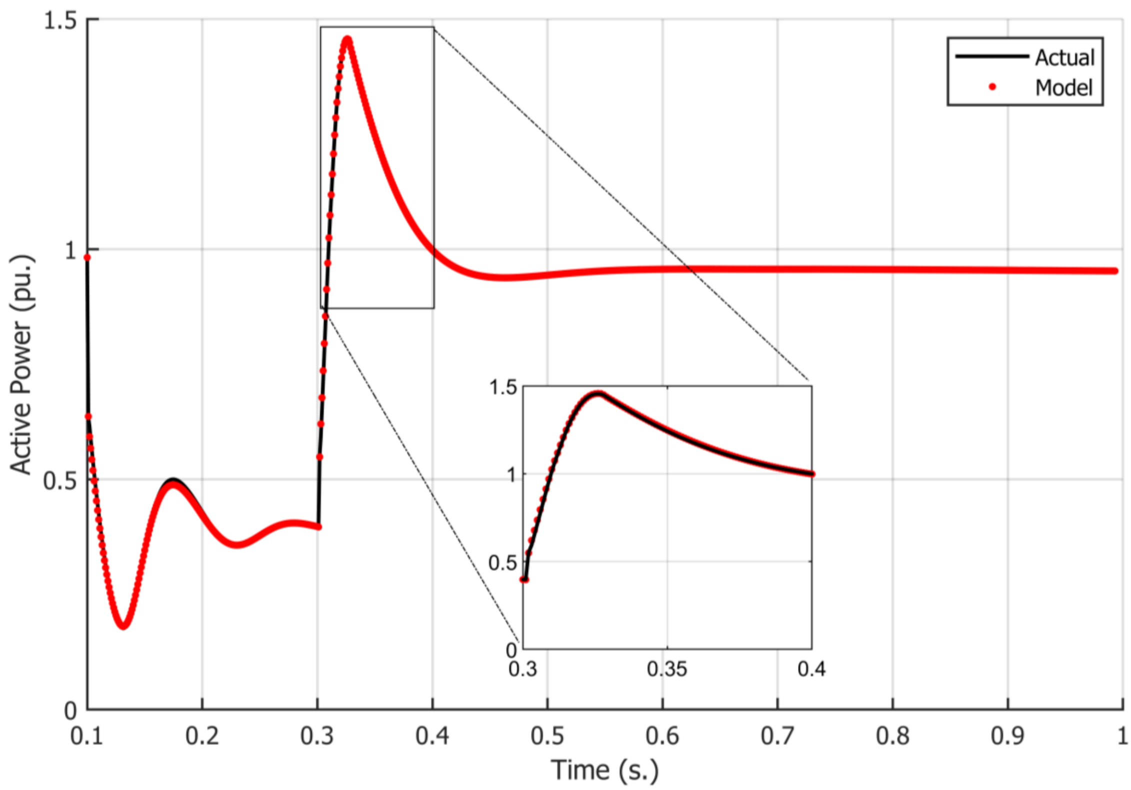
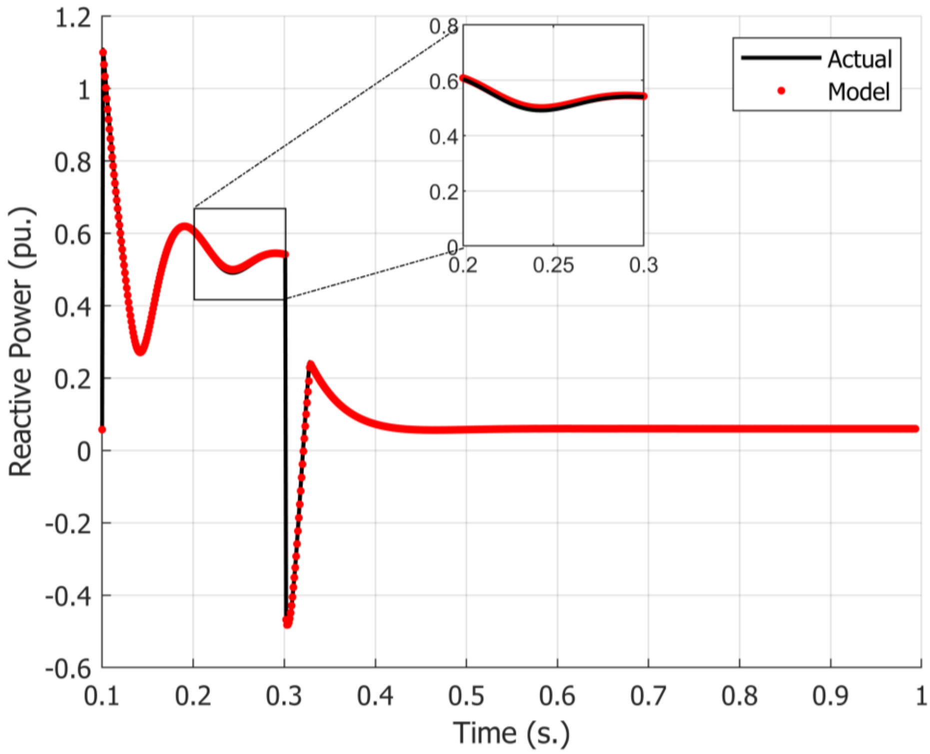


Figure 5: Reactive power from estimated parameters.



5. CONCLUSIONS

The MVMO algorithm and the TSM were proposed for parameter estimation of the wind farm equivalent model based on DFIG wind turbines. The estimation process was carried out in two steps. Initially, the metaheuristic algorithm was executed to provide an intelligent initial estimate for the second algorithm. Then, a nonlinear programming method was applied using the initial estimate to find the local minimum. The results demonstrated that the parameters were correctly estimated, ensuring convergence. This parameter estimation process proved to be robust and reliable achieving errors to reference parameters between 0 to 2.8%.

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