

# Parameter Estimation of Wind Power Plant Equivalent Model through a Hybrid Method

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**Abstract:** Reliable models are vital for dynamic simulations made by electric system operators. Generic models can be adjusted to match certain equipment criteria and provide accurate responses to different faults and disturbances. This paper addresses that issue by proposing a hybrid estimation method to estimate parameters of a wind power plant generic model. At first, the parameters are estimated through the Mean-Variance Mapping Optimization method, a population-based metaheuristic. When the parameters are close enough to their real values, Trajectory Sensitivity method is applied to improve the results and optimize solution. Combining both methods results in a fast and robust estimation approach. The proposed hybrid method was executed using measurement data acquired from PowerFactory and the results show the adequacy of this application.

*Keywords:* Parameters Estimation, Wind Energy, DFIG, MVMO, Trajectory Sensibility.

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## 1. INTRODUCTION

During the last few decades, participation of renewable sources in power generation increased worldwide, led mainly by wind and solar energy. These green technologies provide an alternative to sources based on fossil fuel, reducing environmental impact of energy generation.

In Brazil, wind energy contributed to the energy matrix with 48.5 TWh during 2018, resulting in a participation share of 8.1%. For comparison, Itaipu, Brazil's largest power plant in generation, has produced 96.6 TWh during the same period. Also, while other sources, such as coal and other fossil fuels, had their share reduced, wind energy had the highest increase among sources comparing to 2017 levels, increasing its participation by 14.4% (EPE, 2019).

Regarding installed capacity, Brazil had 14.4 GW of wind turbines operating in 2018 (EPE, 2019). Despite the high participation of wind energy in Brazil's energy mix, the country has a large amount of unexplored yield, specially in the Northeast Region, as shown in do Amarante et al. (2001).

One of the issues concerning wind energy is the lack of reliable models for operational studies, since many manufacturers do not provide complex information about their generators due to industrial secret. Besides, wind farms are composed of multiple turbines, each with different characteristics and technologies, preventing the application of aggregate models to represent such power plants.

In order to allow the expansion of this energy source, many studies have addressed wind generators and power plants modelling. The application of generic models to represent entire wind power plants was discussed and validated in Muljadi and Ellis (2008), Ellis et al. (2011) and Asmine et al. (2011). These models can have their parameters adjusted to represent most wind power plants. Thus,

the modelling problem becomes an optimization problem, focusing on estimating parameters in order to reduce error between model and real system behaviour. Many estimation methods were developed during the years, with metaheuristic and nonlinear methods worth mentioning.

Metaheuristics are methods based mainly on behaviours present in nature, such as evolution, bacteria growth, swarms and flocks, to find a global optimum solution. These methods are able to quickly narrow down the search region, but usually take a long time to find an optimal solution.

Nonlinear methods, on the other hand, rapidly converge to an optimal solution. However, these methods are extremely sensitive to the initial values chosen for parameters, diverging for parameter values far enough from real.

In Erlich et al. (2012), a generic model of equivalent wind power plant was introduced and its parameters were estimated by a metaheuristic known as Mean-Variance Mapping Optimization (MVMO). In Cari et al. (2015), Trajectory Sensitivity Method (TS), a nonlinear method, was applied to estimate the parameter of the same generic model.

The results of the first study show that MVMO had good performance in the beginning of the estimation process, but, as it approaches to the optimal values, the process became slow. In the second study, the applied method quickly converged to a solution, however it presented strong convergence problems when the initial values of the parameters were not close to their optimum.

Therefore, in this paper, a hybrid method based on both MVMO and TS is proposed, resulting in a fast and robust parameter estimation method. At first, the Mean-Variance Method Optimization method, a population-based metaheuristic, will be applied to find a global

optimum. This solution is then refined by the Trajectory Sensitivity method, a nonlinear method based on Newton-Raphson method.

The resulting hybrid method is used to estimate parameters of a wind power plant generic model adapted of the one presented in Erlich et al. (2012). This model is able to represent most Doubly-Fed Induction Generators (DFIG) and Full-Converter Generators, the most common technologies used in wind turbines.

This paper is organized as follows: the next section addresses the hybrid estimation method and the methods that compose it. Section 3 discuss the chosen generic model, its characteristics and the data collected for estimation. Results of the estimation process are shown in Sections 4, followed by the conclusions of this work.

## 2. HYBRID ESTIMATION METHOD

By combining two distinct methods, the resulting hybrid method is expected to provide a suitable parameter vector faster than the methods separately and be less susceptible to divergence. The flowchart in Figure 1 shows how the hybrid method will conduct the estimation process.

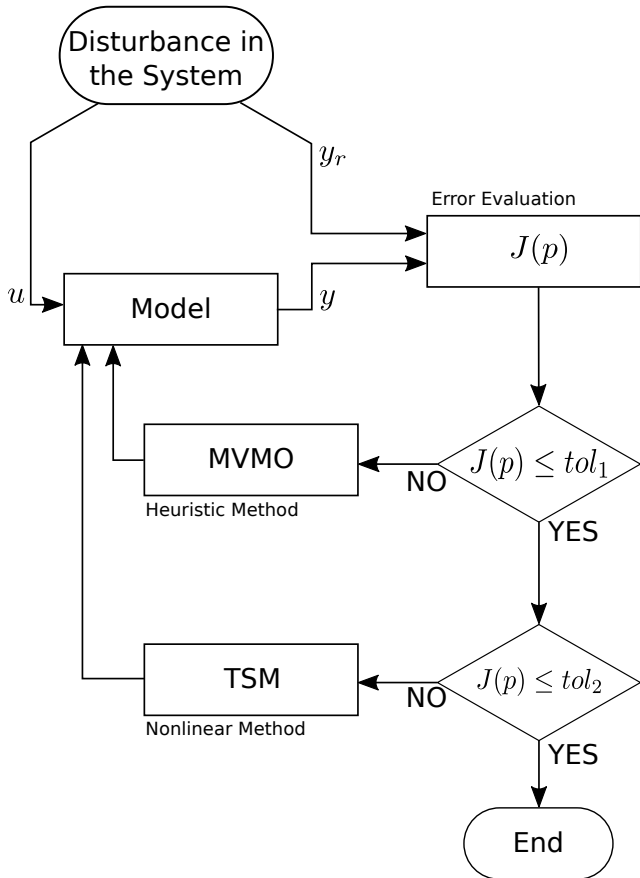


Figure 1. Hybrid estimation method.

Measurement data obtained during a disturbance in the system is used both as input for the model,  $u$ , and as output of the real system,  $y_r$ . The adequacy of the model is evaluated by the  $l^2$ -norm of the error vector, as shown in equation (1).

While the error function  $J$  is above a predetermined tolerance  $tol_1$ , MVMO is used to improve the model behaviour by searching for a global optimum solution. When  $J$  is reduced to a level below  $tol_1$ , TS is used to provide a fine-tuning on the parameters values. These adjustments are carried out until the error is lowered below a tolerance  $tol_2$ , when the resulting model with estimated parameters is considered capable of representing the real system with desired accuracy.

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

Each method is discussed individually in the following subsections. With both methods combined, the time spent on exploitation by MVMO is reduced, since, when it reaches this stage, the method is switched to TS. On the other hand, MVMO provides a more reliable initial parameter vector for TS to start from, preventing it to diverge. This is crucial when standard parameter values are not well-defined.

### 2.1 MVMO

First presented in Erlich et al. (2010), the Mean-Variance Mapping Optimization method is a population-based metaheuristic. The main difference between this algorithm and others based in evolution of populations is the mutation and offspring generation steps. MVMO uses a mapping function based on populational statistics to generate new individuals, inserting a memory effect to the evolutionary process. The mapping function improves search performance, allowing MVMO to perform as fast as other metaheuristics with a relative small population.

For the sake of analogy, the authors use the terms ‘gene’ and ‘individual’ instead of ‘parameter’ and ‘parameter vector’, respectively, to explain MVMO process. At the start, individuals are randomly generated to compose the initial population. These individuals are evaluated and ranked according to their error and the fittest individual is then selected to generate new individuals.

The offspring are cloned from the fittest individual and suffer a mutation on some predetermined genes. During the mutation process, the selected genes receive a random value in the interval  $[0, 1]$ . The value is then plugged into a transformation function that returns the new value of the genes. The transformation function depends on the mean and variance values of the gene inside the population. Figure 2 depicts an example of the transformation function.

The offspring are evaluated and included to the population, that is then reranked according to the error of individuals. The worst individuals are then discarded in order to maintain the original size of the population. This process goes on until the stop criterion are met.

The main advantages of this algorithm are its low computational cost, good performance with small populations and constrained search region. The effects of population size on method performance are also addressed in this paper.

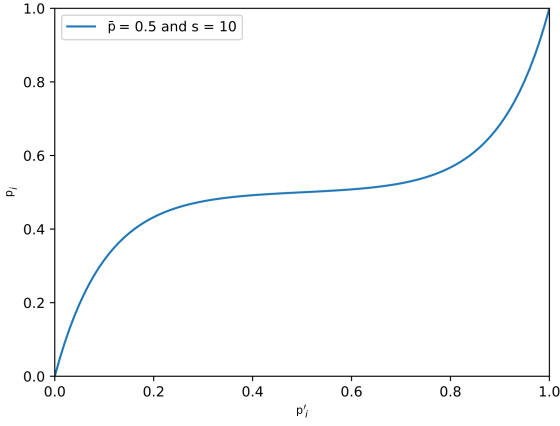


Figure 2. Example of MVMO transformation function.

## 2.2 Trajectory Sensitivity

In order to minimize the error  $J(p)$ , one must find a parameter vector  $p^*$  so that:

$$G(p^*) = \frac{\partial J(p^*)}{\partial p} = 0 \quad (2)$$

The derivative  $G(p^*)$  can be rewritten as:

$$G(p) = - \int_0^{T_0} \left[ \frac{dy(p)}{dp} \right]^T [y_r - y(p)] dt \quad (3)$$

Expanding the Taylor series of  $G(p)$  and truncating it on the first-order term results in (4).

$$G(p^*) = G(p) + \Gamma(p)(p^* - p) \quad (4)$$

The matrix  $\Gamma(p)$  is the jacobian matrix of  $g$  and can be calculated by the following approximation.

$$\Gamma(p) = \frac{\partial G(p)}{\partial p} \approx \int_0^{T_0} \left( \frac{dy}{dp} \right)^T \left( \frac{dy}{dp} \right) dt \quad (5)$$

Based on (2) and (4), the parameter vector after the  $n$ -th iteration can be obtained by:

$$p^{n+1} = p^n + \Gamma^{-1}(p^n) \cdot G(p^n) \quad (6)$$

In order to facilitate the calculations of  $G(p)$  and  $\Gamma(p)$ , the derivatives  $\frac{dy}{dp}$  were approximated using its definition, given by:

$$\frac{dy(p)}{dp} = \lim_{h \rightarrow 0} \frac{f(p+h) - f(p)}{h} \quad (7)$$

Consider two parameter vectors  $p$  and  $p^\epsilon$ , where  $p^\epsilon$  is obtained by adding a small perturbation  $\epsilon p_i$  to the  $i$ -th element of  $p$ , as shown in (8).

$$p = \begin{bmatrix} p_1 \\ \vdots \\ p_i \\ \vdots \\ p_n \end{bmatrix}; \quad p^\epsilon = \begin{bmatrix} p_1 \\ \vdots \\ p_i + \epsilon p_i \\ \vdots \\ p_n \end{bmatrix} \quad (8)$$

With  $\epsilon$  sufficiently small, the partial derivative with respect to the parameter  $p_i$  can be approximated by the difference shown in (9).

$$\frac{\partial y(x, p, u)}{\partial p_i} \approx \frac{y(x, p^\epsilon, u) - y(x, p, u)}{\epsilon p_i} \quad (9)$$

The value of  $\epsilon = 0.1 \times 10^{-3}$  have shown great results for most cases. Using the approximation of the partial derivatives allows Trajectory Sensitivity method to be applied on both differentiable and non-differentiable systems, as shown in Benchluch and Chow (1993).

The Trajectory Sensitivity method has fast convergence characteristics and can be applied directly to nonlinear problems, not requiring linearization. Also, by analyzing the sensitivities, the method is able to provide information about identifiability of parameters.

However, this method is extremely sensitive to initial value of parameter. Thus, if the initial values are too far from the real values, the method may diverge (Benchluch and Chow, 1993).

## 3. WIND POWER PLANT EQUIVALENT MODEL

The model chosen to represent wind turbines and wind farms is an adaptation of the model presented in Erlich et al. (2012). This model represents a wind power plant by its Thevenin equivalent, where the voltage source is controlled by PI controllers and saturation blocks. The Thevenin equivalent is connected to an infinite bus representing the entire power grid. The chosen model is able to simulate the dynamic behaviour of the most common types of wind turbines composing wind farms. Figure 3 depicts the block diagram of this model.

It is important to notice that dynamic responses of wind turbines occur during a considerably short amount of time. Thus, the wind speed in these instants can be considered constant, not impacting on the model behaviour.

The point of interconnection to the grid is represented by the bus between grid and Thevenin equivalent, and  $v_T$  and  $\phi_V$  stand for its voltage magnitude and angle, respectively. The active and reactive power generated by the wind farm are represented by  $P_e$  and  $Q_e$ , respectively. Those four variables are the inputs of the chosen model and their data is crucial to the estimation process. Thevenin equivalent resistance  $R$  and reactance  $X$  represent the line impedances connecting the turbines to the point of interconnection. The equivalent voltage source is decomposed into direct ( $v_d$ ) and quadrature ( $v_q$ ) components.

The block diagram controlling the voltage source simulates the controllers of a real wind turbine. At first, the reference values of active and reactive components of current are obtained by the following equations.

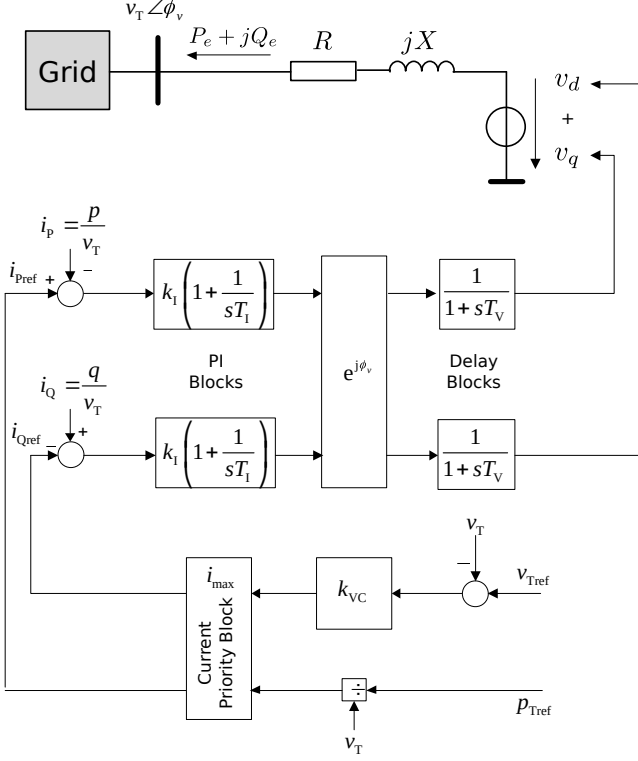


Figure 3. Block diagram of chosen model.

$$\begin{cases} I_{Ac} = \frac{P_{Tref}}{v_T} \\ I_{Re} = k_{VC}(v_{Tref} - v_T) \end{cases} \quad (10)$$

Those reference currents are inserted into the current priority block. This block checks terminal voltage magnitude and current magnitude to decide whether the priority is active power injection or voltage control. In case of voltage sag, reactive power injection must be prioritized in order to sustain the bus voltage. During normal conditions, the wind turbine must focus on injecting the maximum active power possible into the grid.

The following PI blocks represent all turbine controllers (blade pitch, gearbox, converters). The following equations describes the PI blocks behaviour.

$$\begin{cases} V_{PA} = k_I[(i_{Pref} - \frac{P_e}{v_T}) + \frac{1}{T_I} \int_0^t (i_{Pref} - \frac{P_e}{v_T}) dt] \\ V_{QA} = k_I[(\frac{Q_e}{v_T} - i_{Qref}) + \frac{1}{T_I} \int_0^t (\frac{Q_e}{v_T} - i_{Qref}) dt] \end{cases} \quad (11)$$

The following phase-shifting block adequates the obtained values to the direct-quadrature reference used in the voltage source. The block performs the transformation displayed in (12).

$$\begin{cases} V_{PAS} = -V_{PACos}(\phi_v) - V_{QASin}(\phi_v) \\ V_{QAS} = V_{PASin}(\phi_v) - V_{QACos}(\phi_v) \end{cases} \quad (12)$$

Finally, a delay block simulating the delay effects of converters and electrical machine (mechanical, electrical and magnetic delays) composing the wind turbines. Their effects are summarized by the following equations:

$$\begin{cases} \dot{v}_d = \frac{1}{T_V}(v_d - V_{PAS}) \\ \dot{v}_q = \frac{1}{T_V}(v_q - V_{QAS}) \end{cases} \quad (13)$$

The active and reactive power generated by the wind power plant are described by:

$$\begin{cases} P_e = \frac{R(v_{Td}v_d + v_{Tq}v_q - v_T^2) + X(v_{Tq}v_d - v_{Td}v_q)}{R^2 + X^2} \\ Q_e = \frac{X(v_{Td}v_d + v_{Tq}v_q - v_T^2) - R(v_{Tq}v_d - v_{Td}v_q)}{R^2 + X^2} \end{cases} \quad (14)$$

Thus, this model can be represented by the following equation system:

$$\begin{cases} \dot{x} = f(x, p, u) \\ y = g(x, p, u) \end{cases} \quad (15)$$

where the states  $x$ , inputs  $u$ , outputs  $y$  and parameters  $p$  are described by (16), (17), (18) and (19), respectively.

$$x = [v_d, v_q]^T \quad (16)$$

$$u = [v_T, \phi_v, P_e, Q_e]^T \quad (17)$$

$$y = [P_e, Q_e]^T \quad (18)$$

$$p = [R, X, k_I, T_I, T_V, k_{VC}, i_{max}]^T \quad (19)$$

The parameters presented above are, respectively, the resistance and reactance obtained via Thevenin equivalent, gain and time constant of the PI block, time constant of the delay block, voltage gain and maximum rated current. These will be the parameters estimated in order to reduce the error between the model output and the data collected.

The initial values of  $x$  can be easily calculated based on the data collected during the initial instants and considering the equations below, where  $V_t^*$  is the complex conjugate of the terminal voltage.

$$\begin{cases} v_d(0) = Re \left[ V_t(0) + \frac{P(0) - jQ(0)}{V_t^*(0)}(R + jX) \right] \\ v_q(0) = Im \left[ V_t(0) + \frac{P(0) - jQ(0)}{V_t^*(0)}(R + jX) \right] \end{cases} \quad (20)$$

Notice that the initial values of the states depend on the values of the parameters  $R$  and  $X$ . Therefore, after every change in those parameters, the values of  $v_d(0)$  and  $v_q(0)$  must be reevaluated.

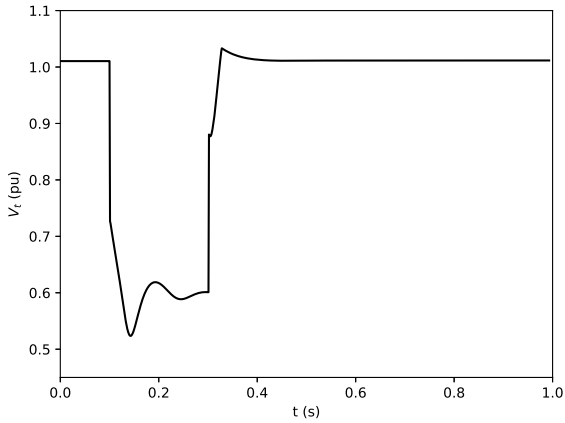


Figure 4. Voltage at wind power plant bus.

### 3.1 Collected data

The data used in the estimation process addressed in this paper was the same used in Cari et al. (2015), where the authors apply only the Trajectory Sensitivity Method to estimate the parameters of the model presented in this section.

In that study, a test system composed of a wind power plant connected to a infinite bus by a transmission line was simulated using PowerFactory 14. A short-circuit was applied to the infinite bus with fault impedance of  $Z_F = 3 + j9 \Omega$  and lasted for 0.2 s. The entire simulation lasted for 1 s and the sampling rate was 1 kHz. Figure 4 depicts the voltage behaviour observed at the wind power plant bus.

## 4. RESULTS

Based on the parameter values found in Cari et al. (2015), the search region used in MVMO was defined, as displayed in Table 1. At every generation, three parameters of the fittest individual in the population would suffer mutation in order to generate one new individual. This method would halt if either reached the 5000<sup>th</sup> generation or the fittest individual presented an error level below  $tol_1 = 0.5$ .

Table 1. MVMO search region

Parameter	Lower boundary	Upper boundary
R	0.027	0.040
X	0.16	0.24
$k_I$	5.58	8.37
$T_I$	0.028	0.043
$T_V$	0.22	0.32
$k_{VC}$	1.60	2.40
$i_{max}$	0.88	1.32

Estimation through Trajectory Sensitivity takes place afterwards, using the fittest individual found by MVMO as its starting point. This method was set to find a solution with error level below  $tol_2 = 5 \times 10^{-4}$  in seven or fewer iterations. Estimations that eventually take longer than that are considered to result in divergence and can be discarded.

### 4.1 MVMO population size

As mentioned in Section 3, the effects on population size on the speed of MVMO were evaluated prior to the estimation itself. Five different population sizes were chosen and 35 estimations were executed for each one of them. The estimations were made using only MVMO (settings used were the same described above) and each one was timed. The mean duration of estimation for each population size can be seen in Table 2.

Table 2. Effects of population size in MVMO performance

# of individuals	Mean duration (s)
5	15.62
10	11.08
20	13.02
50	17.84
100	29.00

It is possible to observe that for considerably small populations (five or less individuals), MVMO takes more time searching for fit individuals, due to the lack of good candidates in the first population. On the other hand, very large populations (over 50 individuals) usually present good candidates in their first generation. However, these populations take a good amount of time just to create and evaluate all of their first individuals. As depicted in Table 2, the optimal population size for this estimation problem would be between 10 and 20 individuals.

### 4.2 Parameter estimation

Based on the results depicted in the previous section, the size of MVMO population was set to 15 individuals. The hybrid estimation method proposed was then applied considering all settings described in the beginning of this section. The estimation took 8.11 seconds in total, with 4.19 seconds for MVMO and 3.92 for TS. The final error between data collected and modelled behaviour was  $1.5 \times 10^{-4}$ . The values estimated for each parameter are displayed in Table 3.

Table 3. Estimated values of parameters

Parameter	Estimated value
R	0.034
X	0.198
$k_I$	6.333
$T_I$	0.0348
$T_V$	0.246
$k_{VC}$	1.999
$i_{max}$	1.100

The comparison between the real system and modelled behaviour are presented for both active and reactive power in Figures 5 and 6, respectively. In both figures, it can be seen that the modelled behaviour fits almost exactly to the curve obtained from the collected data. Thus, the model with the estimated parameters can be used to simulate the behaviour of the same wind power plant in similar disturbances.

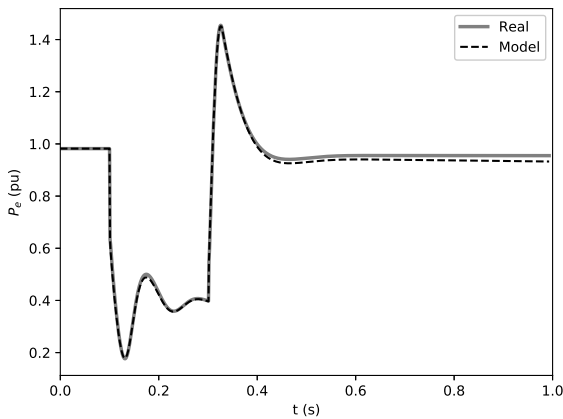


Figure 5. Comparison between active power behaviour.

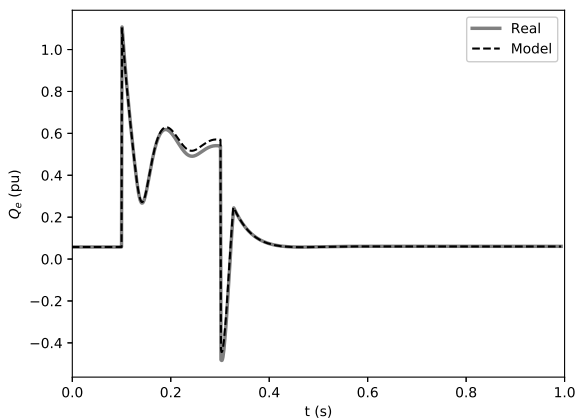


Figure 6. Comparison between reactive power behaviour.

## 5. CONCLUSION

In this paper, a hybrid estimation method combining metaheuristic and nonlinear methods is applied to estimate parameters of a wind power plant equivalent model. Disturbance data, obtained via fault simulation of a simplified system using PowerFactory 14, was used as model input and for output comparison. The first stage of estimation is executed by MVMO, a population-based metaheuristic, in order to find good solutions near global optimum. Trajectory Sensitivity is then applied to refine the results. An assessment on MVMO population size was performed to observe the impacts of it on the estimation process, culminating in a optimum range for this problem of 10-20 individuals. Estimation applying the hybrid method was executed and the results obtained provided a model with error level lower than  $2 \times 10^{-4}$ .

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