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Hybrid Parameter Estimation Method for Load Model Disturbed by OLTC

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Abstract. In this paper, a hybrid approach is used to estimate the parameters of Z-IM Load Model from on-line measurements obtained from on load tap changes. The approach proposed applies heuristic (Mean Variance Mapping Optimization) and nonlinear (Trajectory Sensitivity) methods in cascade to optimize convergence. The estimation method was applied on six different sets of disturbances obtained by simulation. The averaged parameters behaviour was compared to the real system. The results obtained show the adequacy of the hybrid method for identifying the load model. The entire process took, on average, 6 minutes to converge. All algorithms used for this work were developed in Python 2.7.

Keywords. Parameter Estimation. Load Model. OLTC. Trajectory Sensitivity. MVMO.

1 Introduction

Load model identification was the focus of many works, but, due to the diverse and changing nature of loads, accurate load models have been hard to be obtained. One of the solutions for this problem is to use measurements obtained during grid disturbances to estimate the model parameters [1]. In [2] is shown that not only big disturbances, such as faults, can be used to estimate the model parameters, but also small voltage changes, such as tap changes in transformers. Since those occur frequently, load models can be updated on an hourly basis, improving the accuracy of simulations. Also, these disturbances are natural to the grid, not representing a damage to its operation. In [3] and [4], the identification of load model using disturbances from tap changing was used in an exponential load model succesfully.

In this paper, the parameter estimation of a load model using a hybrid method based on Mean-Variance Mapping Otimization (MVMO) and Trajectory Sensitivity Method (TSM) is done. Measurements obtained through simulations of tap changes are used to estimate the model parameters. The model chosen is Z-IM Load Model (differently than

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in [3] and [4]), composed of an impedance in parallel with a third-order induction motor, representing static and dynamic loads, respectively. The choice for this type of model was made due to its short number of parameters combined with its accurate results [1]. Since the magnitude of the disturbance is relatively small, the model equations were linearized around an initial value.

The MVMO, first presented on [5], is a metaheuristic method that relies on a random population evolution to identify the model. This method, as for most heuristic methods, reduces the error significantly in its first generations, but, as it approaches the real values, it slows down. In addition, that method constrains the parameters values on a chosen region, preventing it to diverge. TSM is a nonlinear approach based on Newton-Raphson Method. This method converges rapidly, as long as the initial values of the parameters are in the vicinity of the real values. In this work, the MVMO is used to provide a "smart" initial set of parameters for TSM. This combination provides a robust method that minimizes the error rapidly and constrains the parameters to a certain region.

This paper is a ongoing work of [6], where estimation was performed for one set of distrubance. This work is organized as follows: Section 2 details the hybrid method. Section 3introduces the Z-IM Load Model. Section 4 explains how data was obtained and displays the results of hybrid method. Section 5 depicts the work's conclusions.

2 Hybrid Method for Parameter Estimation

Consider the dynamic nonlinear system as (1):

$$\begin{aligned} \dot{x} &= f(x,\, u,\, p) \\ y &= g(x,\, u,\, p) \end{aligned} \tag{1}$$

where $x \,\epsilon\, \Re$ is the state vector of the model, $y \,\epsilon\, \Re$ is the output vector, $u \,\epsilon\, \Re$ is the input vector, $p \,\epsilon\, \Re$ is the vector of parameters to be estimated and f and g are implicit nonlinear functions. The proposed parameter estimation process is formulated as a nonlinear optimization problem. For this purpose an objective function is defined as (2). This function measures the proximity of the actual system output y_r, obtained from measures sampled, in relation to the output of the mathematical mode y, resulted from the simulation of (1).

$$\begin{gathered} min\, J(p) = \frac{1}{2}\int_0^T (y_r - y)\cdot(y_r - y)dt \\ subject\ to\ p_{i_{min}} < p_i < p_{i_{max}} \end{gathered} \tag{2}$$

where T is the sampling period and $p_{i_{min}}$ and $p_{i_{max}}$ are the lower and upper boundaries of p, which define the search region. Therefore, those parameter limits must be equal to the lower and higher possible values, roviding optimal search region. On the other hand, convergence problems must be presented in those cases for nonlinear methods and large processing time for heuristic approaches. Thus, a hybrid method is used to circumvent the problem. At first, MVMO is used to get a short, feasible parameter region. Then, the method is switched to TSM, in order to obtain the local optimum parameter set.

2.1 Mean-Variance Mapping Optimization

The MVMO is a metaheuristic approach that uses a mapping function based on mean and variance of a population (set of parameters vectors) to generate a new individual (parameter vector) [5]. MVMO can be summarized as:

Step1: Definition of the inputs u and outputs y of system (1), and likewise definition of the vector of parameters p. In this phase, the limits of the parameters to be estimated and the stop criteria (tolerance, tol_1, and number of generations, N_{gen}) are defined.

Step2: With the defined vector p, the set of current individuals is evaluated and ranked from best to worst.

Step3: The stop criteria is checked using the objective function, $J(p)$. If the best individual in the population has an objective function below the tol_1 the method is terminated. Otherwise, the following steps should be taken:

a) Generate new individuals. The parameters values of new individuals is obtained using a mapping function based on mean and variance of current population;

b) The population is evaluated according to its objective function and the individuals, including the new ones, are reranked. The worst individuals of this new classification are discarded and return to step 3.

At the end of this procedure, a set of paremeters (p_{opt1}) is found. Further details of the MVMO can be found in [5].

2.2 Trajectory Sensitivity Method

To use the Trajectory Sensitivity Method to optimize (2), the problem is changed to find the roots of (3).

$$G(p^*) = \frac{\partial J(p^*)}{\partial p} = 0 \tag{3}$$

The process is performed iteratively from initial values (p_{opt1}), which was obtained previously from MVMO, until the stop criteria (tol_2) is met. At the n^{th} iteration:

$$p^{n+1} = p^n - \Gamma^{-1}(p^n)G(p^n) \tag{4}$$

where $\Gamma(p)$ is the Jacobian matrix of $G(p)$, and can be approximated as:

$$\Gamma(p) = \frac{\partial G(p)}{\partial p} \approx \int_0^T \left(\frac{\partial y}{\partial p}\right)^T \left(\frac{\partial y}{\partial p}\right) dt \tag{5}$$

When the stop criteria is achieved ($J(p) \leq tol_2$), the optimal parameter set, p_{opt2}, will be estimated.

The partial derivatives $\frac{\partial y}{\partial p_i}$ can be approximated to:

$$\frac{\partial y(t)}{\partial p_i} \approx \frac{y^1(t) - y^0(t)}{\Delta p_i} \tag{6}$$

where y^1 is the output for a given parameter vector p^1, y^0 is the system outputs for a vector p^0 and $\Delta p_i = p_i^1 - p_i^0$.

Figure 1 shows the application of the hybrid approach.

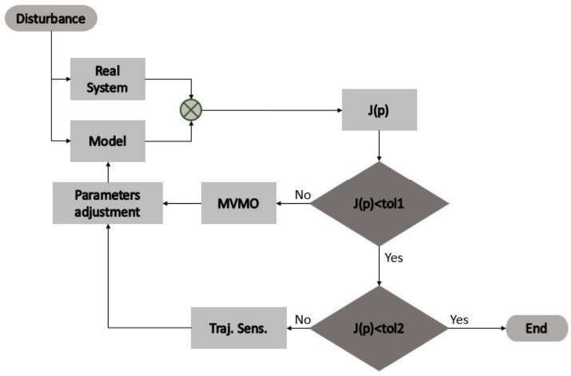

Figure 1: Hybrid approach

3 Linearized Z-IM Load Model

In this work, the model chosen to represent electrical loads was a linearization of Z-IM Load Model, composed of a impedance in parallel with a third-order induction motor (IM). According to [1], this model results in low error levels for both active and reactive power, alongside having a smaller parameter vector when compared with other models. The linearization is needed due to the magnitude of disturbance caused by tap changes.

The state and output equations of this model are shown in (7) and (8), respectively. Some of the equations terms are detailed in (9).

$$\begin{cases} \dot{\Delta E'} = \frac{-1}{T_o X'}[X\Delta E' + (X - X')V_0 \sin\delta_0 \Delta\delta] + \frac{(X-X')\cos\delta_0}{T_0 X'}\Delta V \\ \dot{\Delta\delta} = \frac{(X-X')V_0}{T_0 X' E_0'} \cdot \left(\frac{\sin\delta_0 \Delta E'}{E_0'} - \cos\delta_0\Delta\delta\right) + \Delta\omega - \frac{(X-X')\sin\delta_0}{T_o X' E_0'}\Delta V \\ \dot{\Delta\omega} = \frac{-V_0}{MX'}(\sin\delta_0 \Delta E' + E_0'\cos\delta_0\Delta\delta) - \frac{E_0'\sin\delta_0}{MX'}\Delta V \end{cases} \tag{7}$$

$$\begin{cases} \Delta P = \frac{-V_0}{X'}(\sin\delta_0\Delta E' + E_0'\cos\delta_0\Delta\delta) + \left(2G_s V_0 - \frac{E_0'\sin\delta_0}{X'}\right)\Delta V \\ \Delta Q = \frac{-V_0}{X'}(\cos\delta_0\Delta E' + E_0'\sin\delta_0\Delta\delta) + \left(2B_s V_0 + \frac{2V_0 - E_0'\cos\delta_0}{X'}\right)\Delta V \end{cases} \tag{8}$$

$$\begin{cases} X = X_s + X_m \\ X' = X_s + \frac{X_m X_r}{X_m + X_s} \\ T_o = \frac{X_r + X_m}{\omega_s R_r} \end{cases} \tag{9}$$

where the terms $\Delta E'$ and $\Delta\delta$ represent the variation on voltage magnitude and angle at the motor terminals, $\Delta\omega$ is the variation on stator speed, in rad/s. X_m, X_s and X_r are the magnetizing, stator and rotor reactances, respectively, R_r stands for the rotor resistance,

Table 1: Parameters used as real system

	X	X'	T_o	M	G_s	B_s	E_0'	δ_0
p_r	0.2089	0.0446	0.0963	0.0139	4.1358	2.8004	1.0750	-0.3689

ω_s is the synchronous speed, T_o represents the open-circuit transient time constant, M is the motor inertia and V_0 is the voltage on the load terminals before the disturbance. Therefore, the system can be rewritten as the nonlinear dynamic system of (1), where x is the state vector, defined as $x = [\Delta E', \Delta\delta, \Delta\omega]^T$, y is the output vector, defined as $y = [\Delta P, \Delta Q]^T$, u is the input vector, defined as $u = [\Delta V]$. Since the initial values of x are needed to calculate the system behaviour, these are also treated as parameters. Thus, the parameters vector p is given as $p = [T_o, X, X', M, G_s, B_s, E_0', \delta_0, \omega_0]^T$.

4 Results and Discussions

The measurement data were obtained via simulation using the parameters p_r shown in Table 1. A set of disturbances (tap changes) were applied to the real system to generate the disturbance data. The strategy for parameter estimation and validation was split in two stages:

Stage 1: Disturbance for parameter estimation purpose: It were generated six measurements data (set #1 to set #6 of Table 2) for estimation purpose. For each, measurements, the parameter of the load model was obtained and at end, the average of the estimation parameter will be used for comparison purpose.

Stage 2: Disturbance for Validate purpose: It was generated one measurement date (set #7 of Table 2) for validation purpose (using as a real system output). The validation was executed comparing the output of the "real system" with model output generated with the average parameter estimated in stage 1.

The tap changes of the transformer applied to the load and its initial voltage V_0 on every set is shown on Table 2. The sign of the tap value tells if the tap change increased (+) or decreased (-) voltage and the number represents the number of taps changing. For example, on the fifth set, the initial voltage of 0.75 pu was decreased in 0.032 pu.

Table 2: Set of disturbances

Set	V_0 [pu]	tap	purpose
#1	1.0	+1	estimation
#2	1.0	+2	estimation
#3	1.0	-1	estimation
#4	0.8	+1	estimation
#5	0.75	-2	estimation
#6	1.2	-1	estimation
#7	0.95	+1	validation

The range within the parameters were constrained are shown in (10).

$$\begin{aligned} X: &\quad from \quad 0,0 \quad to \quad 0,5 \\ X': &\quad from \quad 0,0 \quad to \quad 0,2 \\ T_o: &\quad from \quad 0,0 \quad to \quad 1,0 \\ M: &\quad from \quad 0,0 \quad to \quad 1,0 \\ G_s: &\quad from \quad 0,0 \quad to \quad 7,0 \\ B_s: &\quad from \quad 0,0 \quad to \quad 5,0 \\ E_0': &\quad from \quad 0,8 \quad to \quad 1,2 \\ \delta_0: &\quad from \quad -0,5 \quad to \quad 0,5 \end{aligned} \tag{10}$$

The stop criteria chosen for MVMO was $tol_1 = 1$ and maximum generation number $N_{gen} = 50,000$. For TSM, the stop criteria chosen was $tol_2 = 5 \times 10^{-4}$ and maximum number of iterations $N_{it} = 50$.

The results of the estimation process are presented in this section. On average, the converged occured after 6 minutes, with MVMO converging in 6 minutes and 3 seconds and TSM in one second. The quickest estimation took 51 seconds, for set #4, on a 2.9GHz i5 desktop. The parameters estimated during stage 1 and their average values $\bar{p}$ are shown on Table 3. Note that the values of G_s and B_s have higher standard deviation due to the low sensitivity of the outputs in relation to these parameters. For validation purposes, set

Table 3: Estimated parameters for each measurement set

	Set #1	Set #2	Set #3	Set #4	Set #5	Set #6	$\bar{p}$
X	0.20887	0.20883	0.20886	0.20864	0.20861	0.20881	0.20877
X'	0.04460	0.04460	0.04460	0.04460	0.04460	0.04460	0.04460
T_o	0.09628	0.09625	0.09628	0.09614	0.09614	0.09627	0.09623
M	0.01390	0.01390	0.01390	0.01390	0.01390	0.01390	0.01390
G_s	4.13861	4.13993	4.13365	4.16165	4.12036	4.15779	4.14200
B_s	2.80190	2.80011	2.80264	2.79699	2.79706	2.81481	2.80225
E_0'	1.07500	1.07502	1.07502	1.07508	1.07505	1.07494	1.07494
δ_0	-0.36891	-0.36891	-0.36891	-0.36894	-0.36894	-0.36890	-0.36892

#7 was used to compare the outputs of real system and model with the average parameter $\bar{p}$. Figure 2 displays the behaviours of both systems. The final error $J(p)$ obtained was below 1×10^{-5}, confirming that the resulting parameters are able to describe the system behaviour.

5 Conclusion

A hybrid approach combining MVMO and Trajectory Sensistivity methods was used to estimate the parameters of a Z-IM Load Model. MVMO, a metaheuristic method, is able to confine parameters in a given range, preventing divergence. TSM is used to accelerate convergence to local optimal result. Linearized Z-IM Load Model was chosen

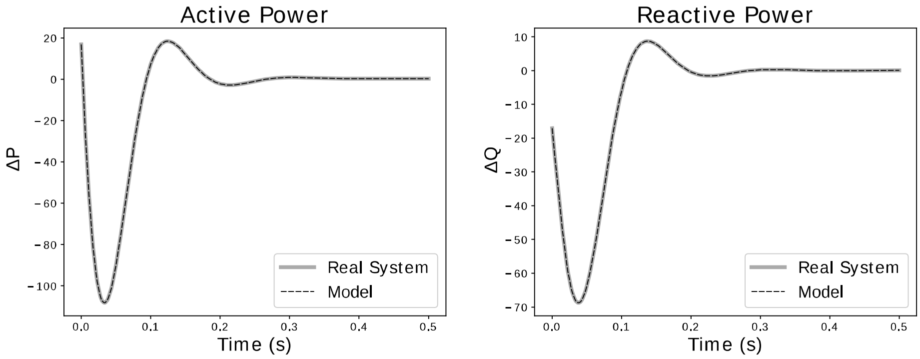

Figure 2: Model and real system behaviour

due to its reduced parameters vector and good results representing loads. The data used to identify the model was obtained from OLTC simulation. The hybrid method was applied to estimate the parameters of load for six tap changes on different conditions and took, on average, six minutes to converge in a 2,9 GHz i5 desktop. The averaged value of parameters was validated when comparing its behaviour to the real system. All algorithms were developed in Python 2.7. Validation using real measurement data will be subject of future research.

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