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Estimation of Load Model Parameters from Instantaneous Voltage and Current

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***Abstract*— Load modeling is a very important aspect of voltage stability analysis as load characteristics governs voltage behavior. In this paper a compact solution to extract parameters of a load model is presented, which includes estimation of power components based on Improved Recursive Newton Type Algorithm and estimation of parameters of a dynamic Load Model using Genetic Algorithms. The paper demonstrates the influence of the preprocessing of the instantaneous values on the final estimation of load parameters. All tests were carried out using 9-buses P.M.Anderson system built in DIgSILENT.**

Keywords—load modeling, parameter estimation, genetic algorithm, power components

I. INTRODUCTION

Power system loads have a significant impact on system stability. It is known that load dynamic response is one of the key elements driving the system to voltage instability or even to voltage collapse [1], so it is crucial to use appropriate load models within Voltage Stability Assessment applications. Additional difficulty related to power system loads is caused by the constantly changing demand, which means that the characteristics of loads vary in time on daily, weekly, monthly and seasonal basis. It is thus essential not only to estimate load parameters once but also to update them when unacceptable difference between model output and power system response is detected. One of two possible approaches to load modelling is the Measurement-based approach [2-5] which enables updating of load parameters whenever it is necessary by taking new measurements at substation. The method consists in comparing measured post disturbance system response versus load model output and based on that, the model's parameters are adjusted. The second method, Component-based approach [6], consists in modelling different types of loads separately, thus requires specific information about contribution of particular devices (e.g. induction motors, heating devices, lighting devices) and classes of loads (e.g. industrial, commercial, residential). Generally, it is difficult to gather all these information precisely enough to create a reliable load model, hence the Measurement-based approach was adopted in this paper.

Currently, the results of estimation of load parameters presented in the literature are mostly based on the assumption of the availability of the measurements of active and reactive power as well as voltage *RMS* value. It is well known that these values are not directly available from the measurements, but they are a product of Digital Signal Processing based on a variety of existing algorithms capable of extracting signal parameters from instantaneous values of voltage and current. It has been proven that sensitivity of different methods may influence the final result, especially when the signal's frequency deviates from its nominal value [7].

In this paper the estimation of active power, reactive power and voltage *RMS* value has been obtained by using a recursive estimation method – Improved Recursive Newton Type Algorithm (IRNTA) [8]. Then the result of this signal processing has been sent to the input of the algorithm estimating the parameters of the load model, which in this case is a widely used Artificial Intelligence (AI) method called Genetic Algorithms (GA) [2], [4] and [5]. The final result will be compared against an estimation performed on the *RMS* values obtained directly from the simulation software (the estimation of *RMS* values is not applied).

The rest of the paper is organized as follows: first the load model and the signal models are described in Section II, then both estimation methods are presented in Section III, after which the simulation results are presented in Section IV, finally conclusions are given in Section V.

II. MODELS

The first part of this Section contains a description of a dynamic load model, parameters of which are being estimated in the experiment. The second part presents an instantaneous power model developed in [7] which is used to obtain active power P and reactive power Q. This part also includes a description of a traditional sine signal model, which has been used to obtain the *RMS* voltage from the instantaneous signal.

A. *Exponential Recovery Load Model*

Exponential Recovery Load Model (ERLM) is a general load model and it is formulated as a mathematical description of the relationship between voltage and active/reactive power (dynamic, voltage dependent load model). Equations (1)-(4) present the model for both, active and reactive power [1], [9].

$$T_P \dot{z}_P = \left(\frac{V}{V_0}\right)^{\alpha_s} - z_P \left(\frac{V}{V_0}\right)^{\alpha_t} \quad (1)$$

$$P_d = z_P P_0 \left(\frac{V}{V_0}\right)^{\alpha_t} \tag{2}$$

$$T_Q \dot{z}_Q = \left(\frac{V}{V_0}\right)^{\beta_s} - z_Q \left(\frac{V}{V_0}\right)^{\beta_t} \tag{3}$$

$$Q_d = z_Q Q_0 \left(\frac{V}{V_0}\right)^{\beta_t} \tag{4}$$

where z_P and z_Q are the state variables, T_P and T_Q are the recovery time constants, whereas V_0, P_0 and Q_0 are the pre-disturbance voltage, active and reactive power, respectively. P_d and Q_d are the load power demands, α_s and β_s are the static exponents and α_t and β_t are the transient exponents. Vectors of unknown parameters to be estimated are as follows (5-6):

$$\theta_P = [\alpha_s, \alpha_t, T_P] \tag{5}$$

$$\theta_Q = [\beta_s, \beta_t, T_Q] \tag{6}$$

Since the load model for active power is not mathematically related to the reactive power, the unknown parameters can be grouped into two vectors and the estimation process can be performed separately (or in parallel). Maintaining the Integrity of the Specifications

B. Signal Model

Extraction of the *RMS* values (P, Q and V) required by the load model is crucial since its quality will directly influence the final accuracy of the estimated load model. In this paper it is not assumed that the *RMS* values are readily available, instead the instantaneous signals of voltage and current are used (7-8):

$$v(t) = V_{\mathrm{m}} \cos\left(\omega t + \varphi_v\right) \tag{7}$$

$$i(t) = I_{\mathrm{m}} \cos\left(\omega t + \varphi_i\right) \tag{8}$$

where V_m and I_m are the voltage and current magnitudes, respectively, φ_v and φ_i are voltage and current phase angles, respectively and ω is the system angular frequency.

Based on [7] the instantaneous power model is described as follows (9):

$$p(t) = v(t) \cdot i(t) = V_{\mathrm{m}} I_{\mathrm{m}} \cos\left(\omega t + \varphi_v\right) \cos\left(\omega t + \varphi_i\right) \tag{9}$$

which after some mathematical manipulations yields (10):

$$p(t) = \frac{1}{2} V_m I_m \cos\varphi + \frac{1}{2} V_m I_m \cos(2\omega t + \varphi) = \\ = P + S\cos(2\omega t + \varphi) \tag{10}$$

where P is the active power, S is the apparent power and φ is the power angle (phase difference between voltage and current).

Now IRNTA can be applied to (10) and both P and S can be directly extracted from the instantaneous power signal. Q can be simply obtained by applying the following formula (11):

$$Q = \sqrt{S^2 - P^2} \tag{11}$$

The vector of unknown parameters for the instantaneous power model consists of (12):

$$\theta_{IP} = [P, S, \omega, \varphi] \tag{12}$$

By treating ω as an unknown parameter, the model becomes insensitive to system frequency deviations, which is increasing the overall quality of the estimation [7].

Similarly, V_{RMS} can be easily obtained by applying IRNTA directly to (7) to extract V_m, which is related to V_{RMS} in the following way (13):

$$V_{RMS} = \frac{V_m}{\sqrt{2}} \tag{13}$$

and the vector of unknown parameters is defined as (14):

$$\theta_V = [V_m, \omega, \varphi_v] \tag{14}$$

Here also ω is estimated together with the amplitude, which makes this signal model insensitive to possible deviations of system frequency.

The next Section presents the estimation methods (IRNTA and GA) and explains in detail how the load model and the signal models are related in this experiment.

III. Parameter Estimation Methods

There are two optimization tasks in this experiment. The first one is related to extraction of the *RMS* values of P, Q and V from the instantaneous signals $v(t)$ and $i(t)$ and the second one is the estimation of load model parameters based on the previously extracted *RMS* values. An overall picture of this process is shown in fig. 1.

Both stages of the whole procedure can be defined as a curve fitting problem where the task is to minimize the difference between the output of the model and the 'measured' value with respect to the vector of unknown parameters, which in general can be expressed by (15).

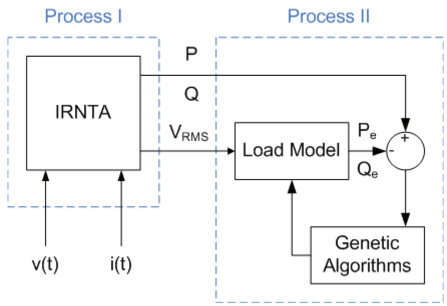

Figure 1. Block diagram of the optimization procedure

$$\min \varepsilon(\theta) = \min \frac{1}{n}\sum_{k=1}^{n}\left(y(k) - M(\theta,k)\right)^2 \tag{15}$$

where *y(k)* is the 'measurement' and $M(\theta,k)$ is the model output, θ is the vector of unknown parameters, and *n* is the number of samples in the data set.

In this paper IRNTA has been incorporated to extract the *RMS* values of the required signals (find optimal θ_{IP} and θ_V) and GA are used to obtain the parameters of the assumed load model (find optimal θ_P and θ_Q). Both methods are described in the following subsections.

A. Genetic Algorithms

GA have become popular in the estimation of load model parameters because of their ability to find a global solution. The method is based on the evolution theory and it is imitating such mechanisms as natural selection, mating of individuals in a population and mutation of genes [4]. The algorithm starts by producing an initial population of individuals, where each individual is vector of unknown parameters θ with randomly selected values. Then, so called fitness is calculated for each individual in the following way (16):

$$f = \frac{1}{\varepsilon(\theta)} \tag{16}$$

which means that fitness is simply a reciprocal of the model error formulated by (15) and this indicates the accuracy of the optimization represented by each individual in the population (the smaller the error the higher the fitness). After identifying the strongest individuals (with the highest fitness) the next generation is bred by applying one of the genetic operators called crossover. In this process the information carried by two selected individuals is exchanged to create two new individuals. The selection of individuals for the crossover is such that the individual with higher fitness have better chance to take part in the process (imitation of mating). The last stage in producing of the next generation is application of the second genetic operator – mutation. This is accomplished by introducing small random changes to randomly selected parameters contained in an individual undergoing a mutation.

The process is repeated until the maximum number of generations is reached or a satisfactory accuracy is achieved. The whole procedure is illustrated in fig. 2.

To improve the overall performance of GA the mutation level is adjusted according to achieved accuracy. At the start of the algorithm, mutations make significant changes to selected parameters contained in an individual, but when the procedure gets closer to the solution, the level of the changes is smaller. This improves the exploration of the searching space at the beginning as well as the fine tuning of the final solution.

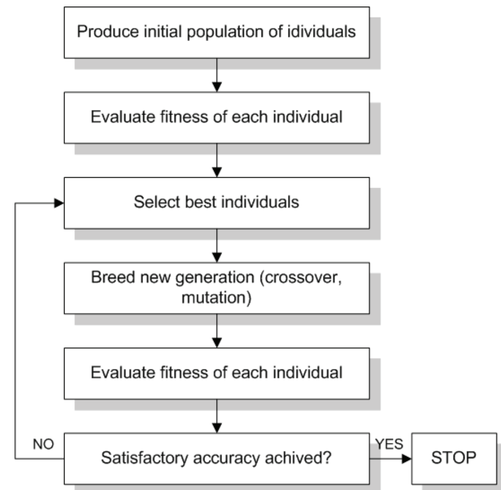

Figure 2. Block diagram of GA procedure

B. Improved Recursive Newton Type Algorithm

IRNTA is a recursive variation of the traditional Newton-type algorithm proposed in [8]. The method has several advantages over the classical algorithm because it can be easily applied in real-time applications and it does not require inversion of the Jacobian matrix. The method is formulated in the following way (17-18):

$$\theta_{k+1} = \theta_k + \mathbf{P}_{k+1}\mathbf{j}_{k+1}\left(y(k+1) - M\left(\theta_k,k\right)\right) \tag{17}$$

$$\mathbf{P}_{k+1} = \frac{1}{\lambda_{k+1}}\left(\mathbf{P}_k - \frac{\mathbf{P}_k\mathbf{j}_{k+1}\mathbf{j}_{k+1}^T\mathbf{P}_k}{\lambda_{k+1} + \mathbf{j}_{k+1}^T\mathbf{P}_k\mathbf{j}_{k+1}}\right) \tag{18}$$

where $\mathbf{j}_k = \left[j_1, j_2, \ldots, j_m\right]$ is the k-th row of the Jacobian matrix, λ is the forgetting factor and $\mathbf{P}$ is a matrix through which the inversion of the Jacobian matrix is carried out in a recursive way. The forgetting factor λ is a nonlinear function defined as follows (19):

$$\lambda_{k+1} = g\left(\lambda_{\min}, \lambda_{\max}, R_0, R_{k+1}\right) = \lambda_{\min} + \left(\lambda_{\max} - \lambda_{\min}\right)e^{-R_{k+1}/R_0} \tag{20}$$

where $\lambda_{\min}$, $\lambda_{1\max}$, ($\lambda_{\min} \le \lambda_{\max}$) and R_0 are the tuning parameters and R_{k+1} is the sum of absolute values of residual errors (21-22):

$$R_{k+1} = \sum_{p=k+1-L}^{k+1} |r_p| \tag{21}$$

$$r_{k+1} = y(k) - M(\theta_k) \tag{22}$$

where L is the size of the data window.

As it can be seen from (17) that at each discrete time step k the method is giving a new estimation of the unknown parameters defined in vector θ. This means that the algorithm has to start from an initial guess θ_0 provided by the user at the start of the procedure.

IV. Simulation Results

This section is divided into two parts: first the result of the estimation of the RMS values is presented, then in the second part this result is used to obtain parameters of the assumed load model. The simulation data was obtain from DIgSILENT software, where the well known 9-buses P.M.Anderson network [10] was built, and the mathematical analysis of the results were carried out in MATLAB. The simulated event was a loss of a line (causing a sudden voltage drop across the system) and the measurements (v(t) and i(t)) were taken at a bus, where a dynamic load was connected.

A. Signal Processing

Figs. 3 and 4 present the measurements of *v(t)* and *p(t)* (according to (9)), respectively. These signals were used directly to estimate P, Q and V by applying IRNTA. This result is compared against the same signals obtained directly for the simulation software (figs. 5-7).

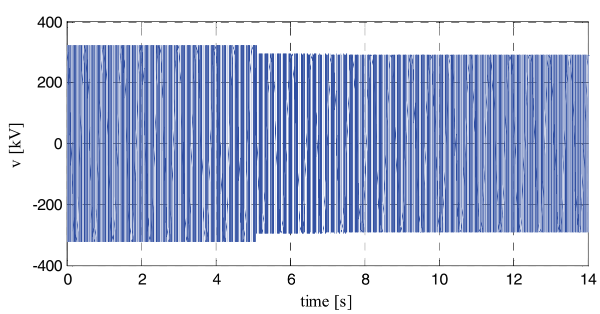

Figure 3. Instantaneous voltage

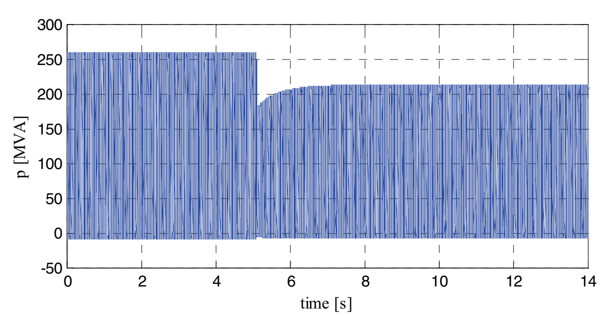

Figure 4. Instantaneous power

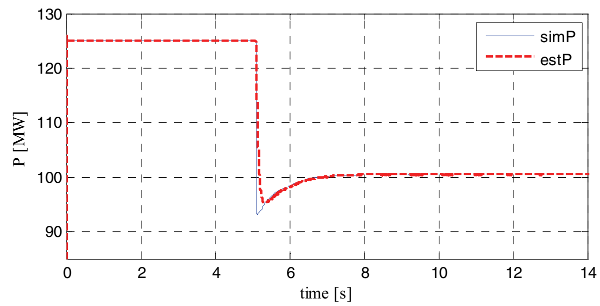

Figure 5. Simulated P versus estimated P

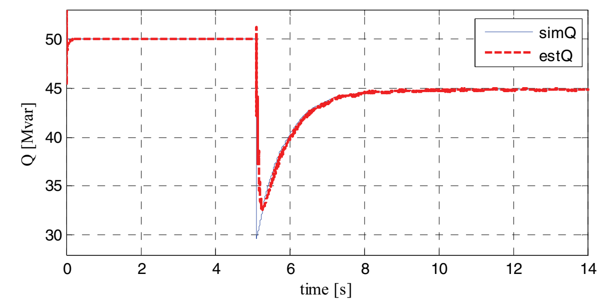

Figure 6. Simulated Q versus estimated Q

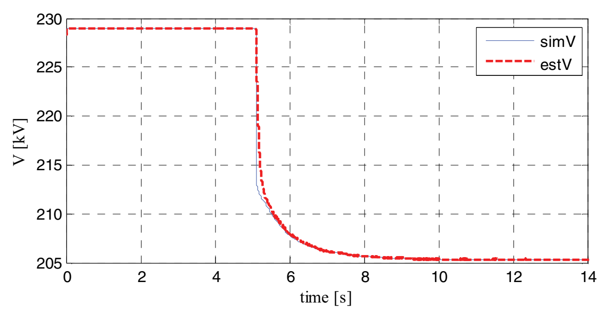

Figure 7. Simulated V versus estimated V

From figs. 5-7 it is clear IRNTA gives a very good estimation of the electrical quantities despite the frequency deviation, which occurs right after the loss of a line at t = 5s. As expected, in the steady state the method gives an error practically equal to zero and during the dynamic state the algorithm produces an error related to the convergence properties of the method, which are considerably good.

In the following subsection these results will be used to obtain parameters of the load model to investigate the influence of the dynamic error introduced during the estimation of the *RMS* values of P, Q and V.

B. Estimation of Load Model Parameters

In this part of the experiment the estimation has been carried out by GA. To ensure that the accuracy of the result is optimal, in each case the algorithm has been apply 10 times to obtain mean value and standard deviation of each estimated parameter.

In the first case original simulated P, Q and V (*simP*, *simQ* and *simV* in fig. 5, 6 and 7, respectively) has been used to perform the estimation of unknown parameters defined in (5) and (6). The results are presented in tab. I and II and the corresponding plots are shown in fig. 8 and 9.

TABLE I. ESTIMATED PARAMETERS RELATED TO ACTIVE POWER

	α_s	α_t	T_P
mean	1.9991	4.2302	0.3426
std dev	0.0004	0.0282	0.0048

TABLE II. ESTIMATED PARAMETERS RELATED TO REACTIVE POWER

	β_s	β_t	T_Q
mean	0.9848	7.8145	0.2453
std dev	0.0019	0.0226	0.0017

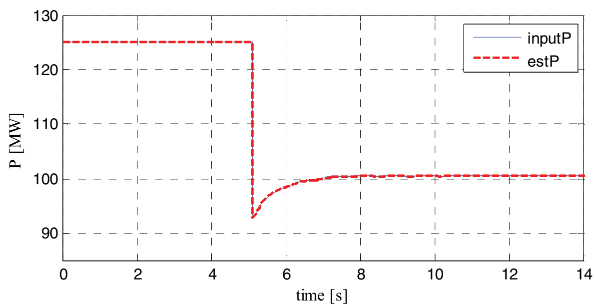

Figure 8. Load model response (active power)

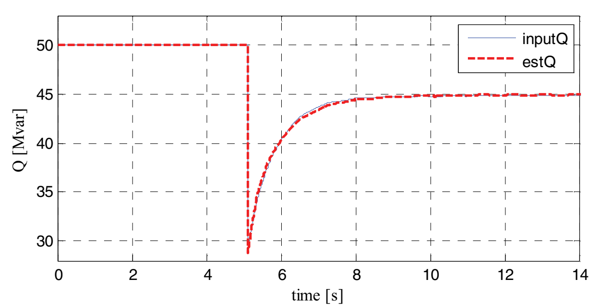

Figure 9. Load model response (reactive power)

From figs. 8 and 9 it can be noted that the quality of estimation is considerably high, which confirms that the algorithm is suitable for this task.

In the second case the parameters of the load model are obtained from the estimated *P*, *Q* and *V* (*estP*, *estQ* and *estV* in fig. 5, 6 and 7, respectively). The results are presented in tab. III and IV and in fig. 10 and 11.

TABLE III. ESTIMATED PARAMETERS RELATED TO ACTIVE POWER

	α_s	α_t	T_P
mean	1.9987	4.1774	0.3518
std dev	0.0031	0.0169	0.0041

TABLE IV. ESTIMATED PARAMETERS RELATED TO REACTIVE POWER

	β_s	β_t	T_Q
mean	0.9845	7.6615	0.2547
std dev	0.0068	0.0909	0.0051

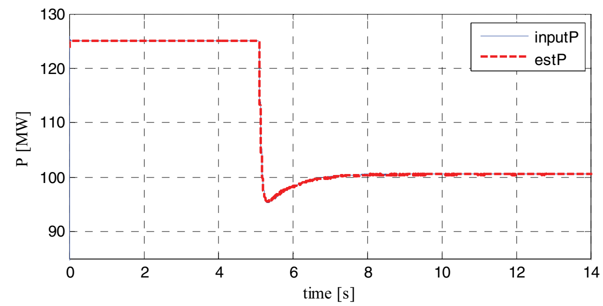

Figure 10. Load model response (active power)

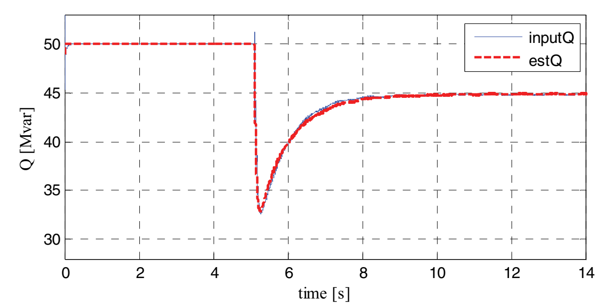

Figure 11. Load model response (reactive power)

In this case GA again confirmed its good performance in this task. By comparing the mean values of the parameters obtained in tab. I and II against the results presented in tab. III and IV, respectively, it is clear that the result is not the same in both cases. Tab. V is summarizing the differences (between mean values) expressed in percents with respect to the original results (mean values in tab. I and II).

TABLE V. DIFFERENCES BETWEEN THE ESTIMATED PARAMETERS

	α_s	α_t	T_P
diff [%]	negligible	1.2482	2.6853
	β_s	β_t	T_Q
diff [%]	negligible	1.9579	3.8320

As expected most affected are parameters governing the dynamic behavior of the model (transient exponents α_t and β_t and recovery time constants T_P and T_Q) whereas the parameters characterizing steady state behavior of the model are practically the same. This result proves that the estimation technique used to obtain the *RMS* values will introduce additional error to the final values of extracted parameters of load model. In this experiment the differences are acceptable, which means that this combination of methods can be efficient and accurate enough to be used in Measurement-based approach to load modeling.

V. CONCLUSIONS

A compact procedure for obtaining parameters of a load model based on instantaneous measurements has been proposed in this paper. The method has been tested in two stages using 9-buses P.M.Anderson test system. Firstly the quality of extracted RMS values has been presented (IRNTA), followed by the estimation of parameters of a dynamic load model performed by GA. The procedure returned considerably good results proving that the combination of both methods is suitable for this task. In the next step the algorithm should undergo extensive testing using more simulated cases and finally its performance should be tested on real data captured by recording equipment in the power system.

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