Scientific Papers of the
Institute of Electrical Power Engineering of
Wrocław University of Technology

PRESENT PROBLEMS OF POWER SYSTEM CONTROL

No 2

Wrocław 2012

*load modeling, parameter estimation,
particle swarm optimization, composite load model*

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ESTIMATION OF COMPOSITE LOAD MODEL PARAMETERS USING IMPROVED PARTICLE SWARM OPTIMIZATION

Power system loads are one of its crucial elements to be modeled in stability studies. However their static and dynamic characteristics are very often unknown and usually changing in time (daily, weekly, monthly and seasonal variations). Taking this into account, a measurement-based approach for determining the load characteristics seems to be the best practice, as it updates the parameters of a load model directly from the system measurements. To achieve this, a Parameter Estimation tool is required, so a common approach is to incorporate the standard Nonlinear Least Squares, or Genetic Algorithms, as a method providing more global capabilities. In this paper a new solution is proposed - an Improved Particle Swarm Optimization method. This method is an Artificial Intelligence type technique similar to Genetic Algorithms, but easier for implementation and also computationally more efficient. The paper provides results of several experiments proving that the proposed method can achieve higher accuracy and show better generalization capabilities than the Nonlinear Least Squares method. The computer simulations were carried out using a one-bus and an IEEE 39-bus test system.

1. INTRODUCTION

Power system loads have a significant impact on the system stability. It is known that the load dynamic response is one of the key elements driving the system into dangerous voltage instability or even to catastrophic voltage collapse [3]. Some of the power systems studies, including studies of interarea oscillations, voltage stability and long-term stability, often require consideration of dynamic loads. Taking also into account that typically motors consume 60 to 70 % of the total energy supplied by a power system, Induction Motors (IM) have become one of the crucial elements to be modeled [6]. On the other hand, due to technological progress, nowadays more and

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more Intelligent Electronic Devices are deployed in power systems, including newly emerging Wide Area Monitoring Systems (WAMS), which are capable of providing huge amounts of data in real-time. To take the advantage of this fact, it seems that the measurement-based approach to Load Modeling might be a more convenient and efficient option [1,7,8,9]. This technique is utilizing previously captured data for the purpose of estimation of load models' parameters by minimizing the difference between the measurements and the model's output. Such method can efficiently increase the quality of modeling by updating the parameters whenever inacceptable mismatch is detected.

Selection of appropriate load model is probably the most challenging task, thus it needs a special consideration. Designers have to consider which phenomena are of interest in particular case. Load being a combination of heating and lighting devices will require a model with slowly recovering power, therefore a simple Exponential Recovery Model [2] would be suitable in this case. On the other hand, when Induction Motors are the dominant element of a load mix, which is assumed to be the case in this paper, then a Composite Load Model (CLM) [1,7,8] should be selected. A CLM is simply an Induction Motor model supported by a Static Load (SL) model, which takes into account any non-dynamic devices. In Section II the CLM adopted in this paper will be in detail described.

Most of the dynamic load models are highly nonlinear, thus making the estimation process difficult and challenging. Traditionally, the Nonlinear Least Squares (NLS) method has been used as a basic tool for obtaining the model's parameters. However, researchers also have demonstrated a huge interest in Artificial Intelligence (AI) based methods, which could overcome the 'local' limitation of the standard NLS method. So far Genetic Algorithms (GA) [7], [9] have been successfully introduced to the field of load modeling and in this paper the authors would like to propose an interesting alternative to GA, another AI technique called Improved Particle Swarm Optimization (IPSO) [5]. Both methods give similar results, however IPSO is easier for implementation and computationally more efficient. Moreover, the technique can achieve better accuracy than the NLS method, which will be demonstrated in this paper.

2. COMPOSITE LOAD MODEL

Composite Load Model is a voltage dependant dynamic model represented by an Induction Motor model connected in parallel with a Static Load model. A clear and thorough derivation of the most commonly used IM model is given in [6]. For representation in power system stability studies, stator transients are neglected, which results in the following three dynamic equations describing the *load model*:

$$\begin{aligned}
\frac{dv_d^{'}}{dt} &= -\frac{1}{T_0^{'}}\left[v_d^{'} + (X - X^{'})i_{qs}\right] + \frac{d\theta_r}{dt}v_q^{'} \\
\frac{dv_q^{'}}{dt} &= -\frac{1}{T_0^{'}}\left[v_q^{'} - (X - X^{'})i_{ds}\right] - \frac{d\theta_r}{dt}v_d^{'} \\
\frac{d\omega_r}{dt} &= \frac{1}{2H}(T_e - T_m)
\end{aligned} \tag{1}$$

and two algebraic equations representing the stator current:

$$\begin{aligned}
i_{ds} &= \frac{1}{R_s^2 + X^{'}}\left[R_s(v_d - v_d^{'}) + X^{'}(v_q - v_q^{'})\right] \\
i_{qs} &= \frac{1}{R_s^2 + X^{'}}\left[R_s(v_q - v_q^{'}) - X^{'}(v_d - v_d^{'})\right]
\end{aligned} \tag{2}$$

where *d* and *q* indices indicate the d-axis and q-axis of the d-q reference frame, respectively, *s* and *r* indices indicate the stator and rotor values, v' is the voltage behind the transient reactance, in pu, H is the motor inertia constant, in s, ω is the rotor speed, in pu, T'_0 is the transient open circuit time constant (3), in s, X' is the transient reactance (4), in pu, R_S is the stator resistance, in pu, X is a sum of the stator reactance X_S and the magnetizing reactance X_m, in pu, T_e is the electromagnetic torque, in pu, T_m is the load torque, in pu and $d\theta_r/dt$ is the slip speed (5), in rad/s.

$$T_0^{'} = \frac{X_r + X_m}{R_r\omega_s} \tag{3}$$

$$X^{'} = X_s + \frac{X_m X_r}{X_m + X_r} \tag{4}$$

$$\frac{d\theta_r}{dt} = \omega_s - \omega_r \tag{5}$$

where R_r and X_r are the rotor resistance and reactance, respectively, in pu, ω_s and ω_r are the synchronous and rotor speed, respectively, in rad/s. It should be noted that in (1) ω_r is expressed in pu.

The electromagnetic and load torques are calculated as follows:

$$T_e = v_d^{'}i_{ds} + v_q^{'}i_{qs} \tag{6}$$

$$T_m = (A\omega_r^2 + B\omega_r + C)T_0 \tag{7}$$

where T_0 is the nominal torque at nominal speed, in pu, *A*, *B* and *C* donate the torque coefficients: proportional to the square of the speed, proportional to the speed and constant coefficient, respectively. In addition the coefficients obey the following equality:

$$T_m = (A\omega_r^2 + B\omega_r + C)T_0 \tag{8}$$

The active and reactive powers are calculated as follows:

$$P_{IM} = v_d i_d + v_q i_q \tag{9}$$

$$Q_{IM} = v_q i_d - v_d i_q \tag{10}$$

The static part of the model can be described using the well known Exponential Load Model (ELM) [3]:

$$P_S = P_0 \left(\frac{V}{V_0} \right)^{\alpha} \tag{11}$$

$$Q_S = Q_0 \left(\frac{V}{V_0} \right)^{\beta} \tag{12}$$

where V_0 is the pre-disturbance voltage, in pu, P_0 and Q_0 are the pre-disturbance active and reactive power, respectively, in W and var. P_S and Q_S are the static load power demands, respectively, in W and var, α and β are the static exponents.

The total power output of the CLM is described as follows:

$$P_{CLM} = S_b P_{IM} + P_S \tag{13}$$

$$Q_{CLM} = S_b Q_{IM} + Q_S \tag{14}$$

where S_b is the induction machine power base, in VA.

To obtain an output from the above presented model, the following vector with 13 unknown parameters needs to be determined:

$$\theta = [H, R_s, T_0, T_0^{'}, X, X^{'}, S_b, A, B, \alpha, \beta, P_0, Q_0] \tag{15}$$

The initial values of the 3 states of the IM model, v'_d, v'_q and ω_r, are obtained by solving the model with respect to the initial (pre-disturbance) voltage. Such approach reduces the dimension of the problem by 3 and therefore speeds up the convergence and increases the accuracy of the final solution.

3. PARAMETER ESTIMATION

Traditionally, to estimate the parameter vector (13) of the Composite Load Model, the Nonlinear Least Squares method has been incorporated. For this purpose the task was formulated as a curve fitting problem in which the following *objective function* has to be minimized:

$$\min \varepsilon(\theta) = \min \frac{1}{n}\sum_{k=1}^{n}\left[\left(P_{mk} - P_{CLMk}\right)^2 + \left(Q_{mk} - Q_{CLMk}\right)^2\right] \tag{16}$$

where P_m and Q_m are the measured active and reactive power, respectively, in W and var and n is the number of samples simultaneously processed in the estimation process. Note that the same objective function will be used to formulate the Improved Particle Swarm Optimization below.

Originally, Particle Swarm Optimization was proposed by Kennedy and Eberhart [4] in 1995 and it was inspired by bird flocks' social behaviors. The idea of this technique is to produce a number of *particles*, which will then move around the searching space to find the best solution. The procedure of the method is depicted in a flowchart in Fig. 1.

The method starts with populating a number of particles to create a *swarm*. In fact, each particle is simply a parameter vector (13) with randomly selected values (limited by a certain range particular to each parameter). The value of each particle indicates its *position* in the swarm, based on which a particle's *fitness* can be calculated, whereas fitness is a quantity indicating the accuracy of the solution represented by each particle. The fitness should increase with the accuracy, so to achieve this, a reciprocal of the objective function (16) is used.

To change the position of a particle its *velocity* needs to be calculated as follows:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - \theta_i^k) + c_2 r_2 (P_g^k - \theta_i^k) \tag{17}$$

where V_i^k and V_i^{k+1} are the actual and next step velocity of i^th^ particle, respectively, ω is the inertia weight, P_i^k is the best previous position of i^th^ particle, P_g^k is the best global position, θ_i^k is the actual i^th^ particle position, c_1 and c_2 are the acceleration coefficients usually equal to 2 and r_1 and r_2 are random numbers ranging from 0 to 1.

After obtaining the velocity of a particle, the position can be updated:

$$\theta_i^{k+1} = \theta_i^k + V_i^{k+1} \tag{18}$$

The process is usually terminated after reaching either maximum number of iterations or satisfactory accuracy of the result.

The Improved Particle Swarm Optimization proposed in [5] offers an increase in both, the precision and the speed of convergence.

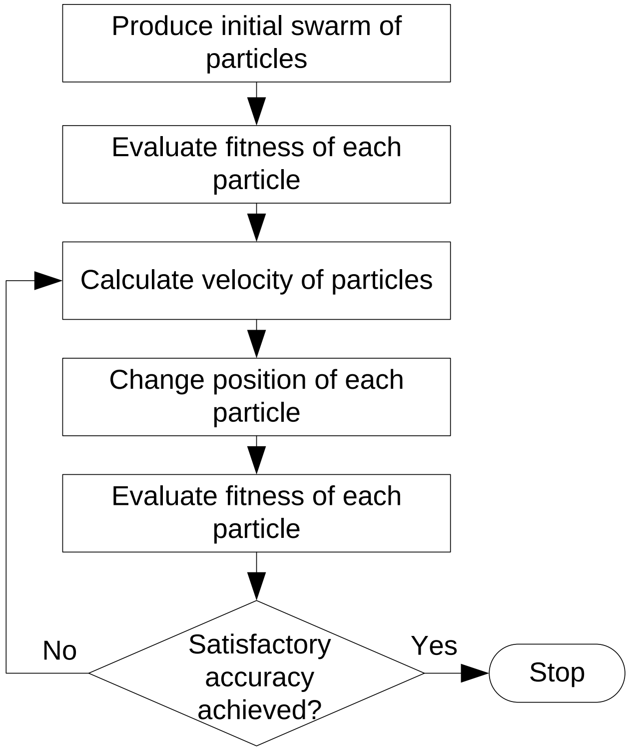

Fig. 1. Flowchart of PSO

The improvement has been achieved by introducing a variable inertia weight ω, whereas originally it was a predefined constant. The function modulating ω is as follows:

$$\omega = \left\{ \frac{(iter_{\max} - iter)^n}{(iter_{\max})^n} \right\} (\omega_{initial} - \omega_{final}) + \omega_{final} \tag{19}$$

where $\omega_{initial}$ is the initial inertia weight, ω_{final} is the final inertia weight, $iter_{max}$ is the maximum number of iterations, $iter$ is the number of current iteration and n is the nonlinear modulation index. Inertia weight defined in such way is decreasing with each iteration, consequently reducing the contribution of previous velocity in calculating the new one. This improves the accuracy and convergence in the final stage of the estimation.

The following section provides a comparison of the introduced method against the traditional NLS.

4. SIMULATION RESULT

In order to provide the most reliable results, two case studies have been examined. The data was obtained from two separate network models built in DIgSILENT Power Factory software. To expose the dynamics of an IM a voltage variation at the machine's terminal needs to occur, thus in the first case a voltage step change was simulated, while in the second case a fault was incepted. All the data was exported to Matlab environment at the sampling rate of 1600 Hz.

4.1. VOLTAGE STEP CHANGE

The first test network consists only of a programmable voltage source feeding a single cage IM through one busbar. The intention was to star with a simple case and a simple IM (single cage IM is a machine which can be modeled with fewest parameters, thus it should be easier to estimate its response) and then move to more sophisticated tests.

To obtain the results using NLS, the Optimization toolbox in Matlab has been used. It offers an implementation of the Levenberg-Marquardt algorithm for solving curve-fitting problems.

The methodology of presenting results in both case studies is the same: few data sets were obtained and then one set was used to estimate the parameters of the model and the others were used as cross-validation data; such test was repeated for each data set.

The first study case consist of 4 data sets obtained by simulating a step change with pre-disturbance voltage equal to 1 pu and post-disturbance voltage equal to 0.9, 0.8, 0.7 and 0.6 pu. Figure 2 presents the results IPSO (0.7 step change).

The summary of this case study is given in Fig. 3. The first two bars in each experiment present the error of the estimation, whereas the remaining two bars show an average error obtained during a cross-validation test. This cross-validation technique provides information about generalization capabilities of the model and the estimation method.

It can be clearly seen from the plots that IPSO shows better performance than NLS method. One needs to keep in mind that the total performance of a method is based on the sum of active and reactive power error, because this is how the objective function (16) is formulated. IPSO also has better generalization capabilities, which can be assessed based on the average error. What is interesting is that this average error is decreasing for higher voltage deviations, which means that more general solution can be obtained. Higher voltage step change provides more information about the speed-torque characteristic of the model, thus better result can be reached. It seem that the NLS method do not take advantage of this fact.

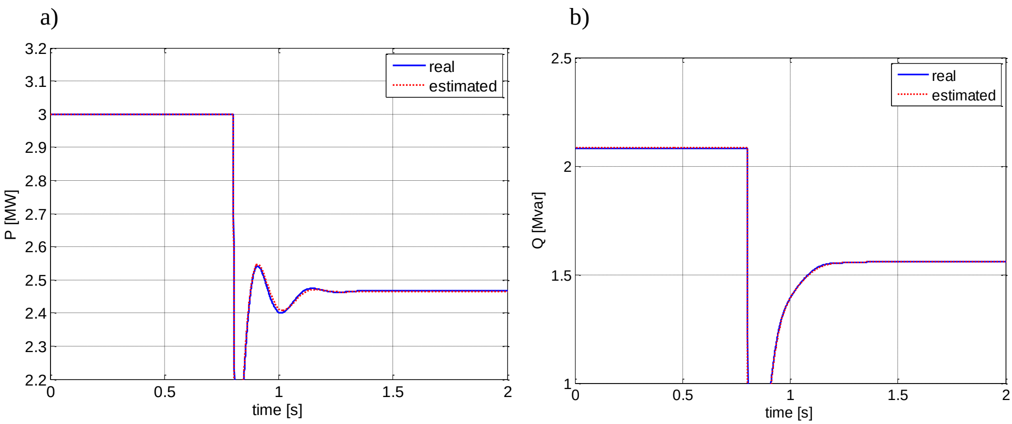

Fig. 2. Active a) and reactive b) power estimation with IPSO

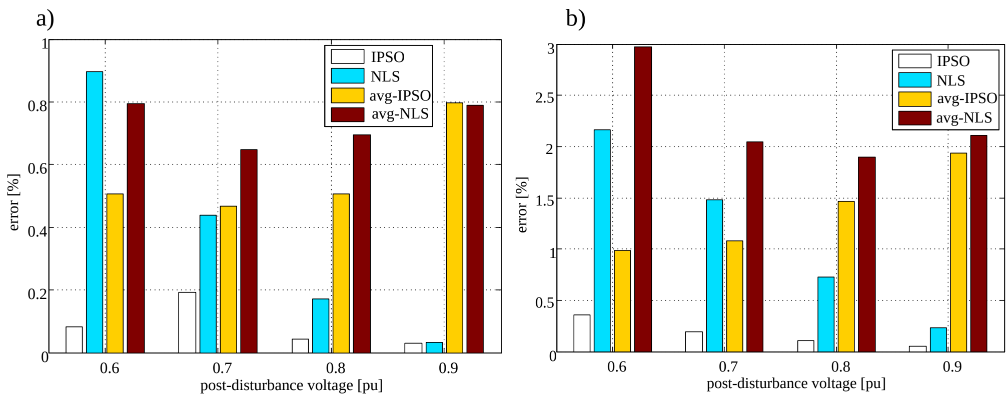

Fig. 3. Summary of active a) and reactive b) power estimation

4.2. FAULT TEST

In the second case study an IEEE 39-bus test network has been used (Fig. 4). The system provides more realistic approach also because of a double cage IM connected at bus 4. Voltage variation was caused by a fault incepted at bus 16 and lasting 0.2s. Different data sets were obtained by setting the fault resistance to 5, 0.5 and 0.05 Ω.

Figure 5 presents results for the 5 Ω fault resistance data set and Fig. 6 provide a summary of this case study.

In this case study IPSO also shows better performance, especially in terms of reactive power error. It also has to be noted that the double cage IM is more complex then the single cage IM used in previous case. The purpose of using more complex model to produce the test data in this case was to investigate the ability of a Composite Load

Model to approximate different IM, which might be an essential feature, since it is not known what kind of machines might be connected to a node in a power system.

Generalization capabilities again are considerably better in case of IPSO; the average reactive power error is always at least 3 times lower than in case of NLS. Average active power error is not so dramatically different, but still its value is lower when IPSO is used.

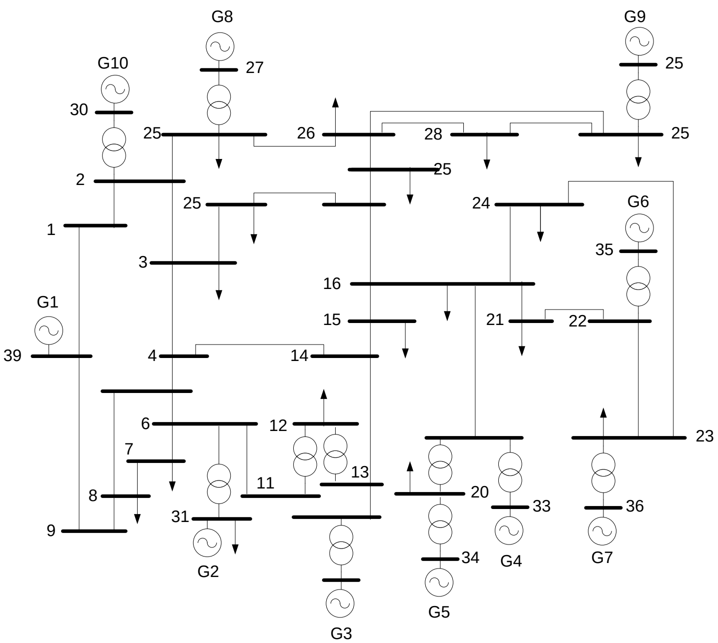

Fig. 4. Diagram of the IEEE 39-bus test system

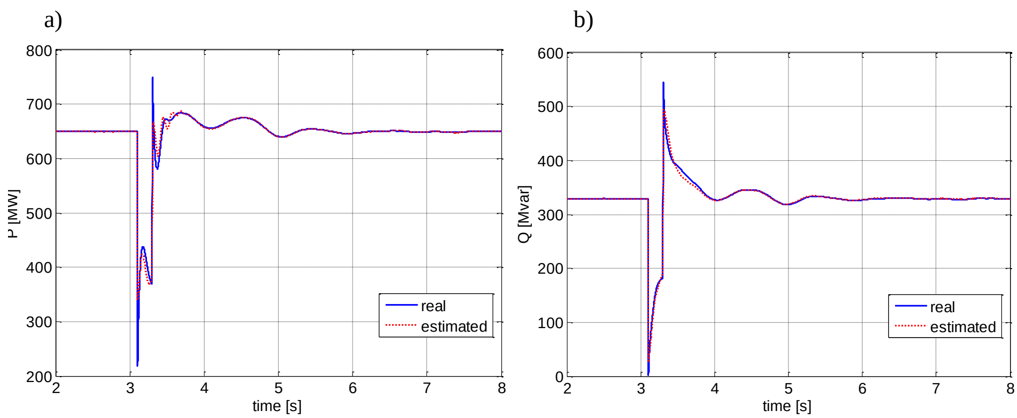

Fig. 5. Active a) and reactive b) power estimation with IPSO

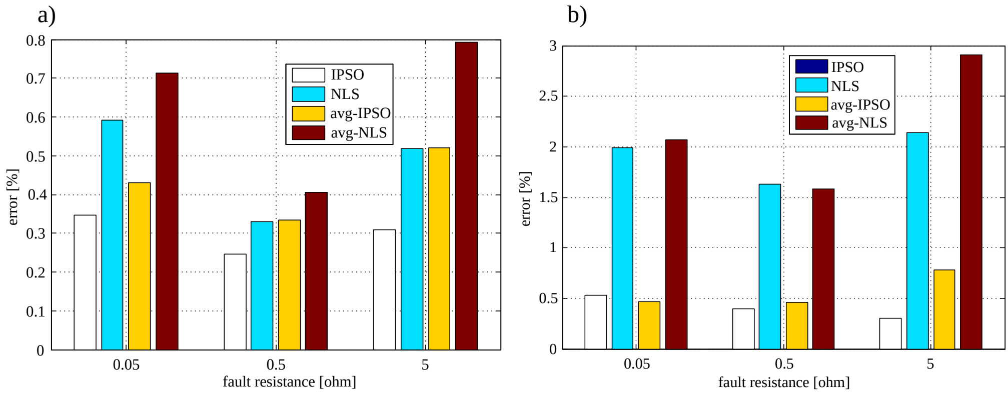

Fig. 6. Summary of active a) and reactive b) power estimation

5. CONCLUSION

In this paper the Improved Particle Swarm Optimization method is presented. It was demonstrated that it can be very practical and efficient for estimation of parameters of the Composite Load Model. It was shown that the accuracy of this new technique is very high and the cross-validation test proved its excellent generalization capabilities. Compared to the standard NLS method, the new one requires a longer computationally time, which is rather typical to Artificial Intelligence type techniques. Having in mind the availability of modern fast computers, efficient implementation of the method is not seen as an issue.

Contrary to the NLS method, the IPSO is not critical in terms of determining the starting point (initial estimate of the vector with unknown parameters). The IPSO just requires a definition of a range of the searching space, which is usually known. For the same reason the Genetic Algorithms were introduced to assist NLS in solving the problem. The idea was to use GA to find the initial guess for the NLS method, which could usually reach better accuracy in shorter time. The results presented here prove that IPSO, having the same global abilities as GA, can also give very accurate results. For offline studies IPSO can be a very good alternative to both, GA and NLS.

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