Induction Generator Model Parameter Estimation using Improved Particle Swarm Optimization and On-Line Response to a Change in Frequency

P. Regulski, F. González-Longatt, *Senior Member, IEEE*, P. Wall, and V. Terzija, *Senior Member, IEEE*

***Abstract*— An induction generator (IG) is preferred to a synchronous generator in many renewable energy applications. In order to achieve proper control of an induction generator it is important to have accurate knowledge of its model parameters. In this paper, an Improved Particle Swarm Optimization (IPSO) approach is used to estimate the model parameters of an IG. The IPSO is executed based on the response of the active and reactive power flows associated with the IG to a change in the frequency of the external system, which the IG is connected to. This change in frequency is applied when the IG is operating in steady state, to represent the scenario where the IG parameters must be estimated on-line, and during a large disturbance to the system equilibrium. This approach is in contrast to others in the literature that estimate the parameters of an induction machine based on its start-up behavior, or the results of mechanical tests. Therefore, this approach should offer benefits when the parameters of the IG being modeled may vary over time and need to be estimated on-line.**

***Index Terms*-- generator modeling, parameter estimation, particle swarm optimization.**

I. Introduction

An induction generator (IG) is, in principle, an induction motor with torque applied to the shaft, although there may be some modifications made to the machine design to optimize its performance as a generator [1]. IGs are widely used in many applications due to their simple construction and ease of operation. As generators they are more favorable for some renewable energy applications than synchronous generators, because of their lower cost and higher reliability [2]. The suitability of using IGs for power system applications and renewable energy has been reported in several publications [3], [4], [5], [6]. The squirrel-cage rotor type is the most common IG, they are used in several applications such as small-scale hydro [7], micro-turbines (split-shaft type) [8] and the first generation of fixed speed wind turbines [9]-[10].

The performance of an IG depends, among other aspects, on accurate knowledge of the machine parameters. These machine parameters directly affect the operational and control characteristics of the IG. Therefore, it is desirable to have accurate knowledge regarding the value of these parameters for any IG in the system. This data could be obtained from the manufacturer or calculated based on mechanical tests (e.g. no load and locked rotor tests). Unfortunately, these solutions will not always be practical, because mechanical testing requires additional hardware (DC power source, auto-transformer etc) and the IG manufacturer may not be available, or able, to provide a complete set of parameter values when required. The shortcomings of the above methods for finding IG parameters mean that it becomes necessary to apply parameter estimation techniques to the problem. For the purposes of parameter estimation, IGs and induction machines working as motors (IM) can be treated in a very similar fashion.

Nowadays, the problem of parameter estimation for IM is receiving a great deal of attention and numerous schemes for parameter estimation have been proposed. These schemes use the measured response of the IM to a change in voltage to estimate the IM parameters.

A range of techniques have been used to estimate the parameters of an induction machine model. These include: non-linear least squares, Kalman Filters [11], genetic algorithms (GA) [12], [13], [14], [15], local search algorithms (LSA), simulated annealing (SA), differential evolution [16] and various forms of particle swarm optimization (PSO) [12], [17], [18], [19]. Most of these techniques are applied to data gathered during the start-up of the machine [13], [16], [17], [18]. Some approaches do compare the results of the estimated model to data gathered by applying mechanical tests to the machine [12], [15]. PSO has been shown to be an effective parameter estimation tool [12], [13]. It is simple to implement, allows beneficial interaction between different members of its population, and, unlike some other techniques, possesses a memory of the solutions from past iterations [20]. Improved particle swarm optimization (IPSO) modifies the concept of inertia weight, introduced in [21], to become a function of the iteration count, as in [18], [22], [23]. This modification allows an improvement in convergence and accuracy [23].

The parameter estimation schemes introduced above all use data from the IMs response to a change in voltage or its behavior during startup. In contrast, the scheme developed in this paper uses the measured response of an IG to a change in

P. Regulski, F. González-Longatt, P. Wall, and V.V. Terzija are with the School of Electrical and Electronic Engineering, Ferranti Building C14, Sackville Street, Manchester M1 7DN, United Kingdom (e-mail: pawel.regulski@postgrad.manchester.co.uk, fglongatt@ieee.org, peter.wall@postgrad.manchester.ac.uk, vterzija@ieee.org).

978-1-4577-1002-5/11/$26.00 ©2011 IEEE

frequency. The response of the IG is viewed in terms of the active and reactive power flow associated with the IG. Parameter estimation based on the IGs response to a change in frequency is possible as both the active power generated and reactive power consumed is dependent on the frequency of the system that the IG is connected to.

Performing the parameter estimation based on the frequency response may be of benefit in the case of an IG connected via a weak transmission link, e.g. an offshore wind farm represented by a single equivalent model of an IG. This is because, in the event of a disturbance, the reactive power compensation, that is required when using IGs, would reduce the voltage deviation whilst the frequency deviation would be unaffected. Any improvement in the performance of the parameter estimation would be of benefit to on-line applications dependent on accurate representations of power system components, e.g. intelligent controlled islanding or stability assessments.

The primary focus of this paper is to demonstrate the validity of using IPSO to estimate IG model parameters based on the response of an IG to a deviation in frequency. The paper is organized as follows. Section II describes the mathematical model of the induction generator used for the parameter estimation problem. Section III presents the proposed improved particle swarm optimization algorithm used for parameter estimation of an induction generator model. Section IV shows the results of simulations that confirm the validity of the proposed algorithm. Finally, the advantages of this novel application are discussed in Section V.

II. Formulation of Parameter Estimation for an Induction Generator

A. Induction Generator Model

An IG can, in principle, be viewed as simply an induction machine with torque applied to the shaft. Therefore, a commonly used IM model, described in detail in [24], [25], can be used to represent an IG.

The electrical part of the machine is represented by a fourth-order state-space model and the mechanical part by a second-order system. The following voltage equations for an arbitrary reference at angular velocity ω define the electrical model [25]:

$$\begin{aligned}
\frac{d\lambda_{qs}}{dt} &= v_{qs} - R_s i_{qs} - \omega\lambda_{ds} \\
\frac{d\lambda_{ds}}{dt} &= v_{ds} - R_s i_{ds} + \omega\lambda_{qs} \\
\frac{d\lambda'_{qr}}{dt} &= v'_{qr} - R'_r\, i'_{qr} - (\omega - \omega_r)\lambda'_{dr} \\
\frac{d\lambda_{dr}}{dt} &= v'_{dr} - R'_r\, i'_{dr} + (\omega - \omega_r)\lambda'_{qr}
\end{aligned} \tag{1}$$

where the indices d and q indicate the d-axis and q-axis in the d-q reference frame, respectively. The indices s and r indicate the stator and rotor values and the variable ω_r is the electrical angular velocity.

In the above equations V denotes voltage, i current, R resistance and λ flux linkage. All electrical variables and parameters are referred to the stator, as indicated by the prime notation. The flux linkages are expressed in terms of current and the inductance (L) [25]:

$$\begin{aligned}
\lambda_{qs} &= L_{ls} i_{qs} + L_m \left(i_{qs} + i'_{qr}\right) \\
\lambda_{ds} &= L_{ls} i_{ds} + L_m \left(i_{dr} + i'_{dr}\right) \\
\lambda'_{qr} &= L'_{lr}\, i'_{qr} + L_m \left(i_{qs} + i'_{qr}\right) \\
\lambda'_{dr} &= L'_{lr}\, i'_{dr} + L_m \left(i_{ds} + i'_{dr}\right)
\end{aligned} \tag{2}$$

In the case of a singly excited induction machine with squirrel-cage rotor type, $v'_{qr} = v'_{dr} = 0$. Therefore, the mechanical model is defined by two differential equations in terms of the rotor angular velocity (ω_m) and its angular position (θ_m):

$$\begin{aligned}
\frac{d\theta_m}{dt} &= \omega_m \\
\frac{d\omega_m}{dt} &= \frac{1}{2H}\left(P_m - P_e\right)
\end{aligned} \tag{3}$$

where H is the rotor inertia constant, P_m is the shaft mechanical power, and P_e is the electromechanical torque given by:

$$P_e = v_{ds} i_{ds} + v_{qs} i_{qs} \tag{4}$$

The reactive power is calculated as follows:

$$Q_e = v_{qs} i_{ds} - v_{ds} i_{qs} \tag{5}$$

The model of a symmetrical induction machine using an arbitrary reference is represented by (1)-(5). The reference frame transformation for the stator voltages (*abc*-to-*dq*) is defined by:

$$\begin{bmatrix} v_{qs} \\ v_{ds} \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 2\cos\theta & \cos\theta + \sqrt{3}\sin\theta \\ 2\sin\theta & \sin\theta + \sqrt{3}\cos\theta \end{bmatrix}\begin{bmatrix} v_{abs} \\ v_{bcs} \end{bmatrix} \tag{6}$$

The following relationship describes the reference frame transformations (*dq*-to-*abc*) for the stator currents:

$$\begin{bmatrix} i_{as} \\ i_{bs} \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ \dfrac{-\cos\theta + \sqrt{3}\sin\theta}{2} & \dfrac{-\cos\theta + \sqrt{3}\sin\theta}{2} \end{bmatrix}\begin{bmatrix} i_{qs} \\ i_{ds} \end{bmatrix} \tag{7}$$

where $i_{cs} = -i_{as} - i_{bs}$, this is the case as the machine windings are connected in a three-wire Y configuration, so, there is no homopolar (0) component. This property justifies the fact that only the two line-to-line input voltages are used inside the model instead of the three line-to-neutral voltages. In the preceding equations, θ is the angular position of the arbitrary reference. A rotating reference frame with angular velocity $\omega=\omega_s$, is suitable for computer simulations where the system frequency, f_s, is changing ($\omega_s = 2\pi f_s$). The use of a rotating reference frame with variable speed is vital to the application presented in this paper. As without it, it would be impossible to capture the system's frequency behavior in the model.

B. Formulation of the Parameter Estimation Problem

The fundamental principle behind parameter estimation is the comparison of the response of the real system and the response of an estimated parameter model, to the same input. Based on this comparison, the parameter vector $\boldsymbol{\theta}$, which defines the model variables, is then adjusted to minimize a predefined error function ε.

For the non-linear model used for an IG in this paper there are six parameters that cannot be measured directly; therefore, the parameter vector contains six unknown variables that must be estimated:

$$\boldsymbol{\theta} = [H, R_s, L_{ls}, R'_r, L'_{lr}, L_m]^T \tag{8}$$

The initial values of the states of the induction machine model are obtained by solving the model with respect to the initial (pre-disturbance) frequency. Determining the initial values in this way reduces the dimension of the problem and therefore increases the speed of convergence and accuracy of the final solution.

Parameter estimation can be transformed into an optimization problem, where the task is formulated as a curve fitting problem in which the following *objective function* is minimized:

$$\min \varepsilon(\boldsymbol{\theta}) = \min \frac{1}{n}\sum_{k=1}^{n}\left[\left(P_{mk} - \hat{P}_{mk}\right)^2 + \left(Q_{mk} - \hat{Q}_{mk}\right)^2\right] \tag{9}$$

where P_m and Q_m are the measured active and reactive power from the real system, respectively, $\hat{P}_m$ and $\hat{Q}_m$ correspond to the estimated parameter model response, and n is the number of samples simultaneously processed in the estimation process. The same objective function will be used to formulate the IPSO in the next section.

III. Improved Particle Swarm Optimization

Kennedy and Eberhart [20] originally proposed Particle Swarm Optimization in 1995, they were inspired by the social interactions that occur between animals that move in large groups. This technique is based on producing a number of *particles*, which will then be moved around the searching space to find the best solution. The procedure for executing the method is depicted in a block diagram in Fig. 1.

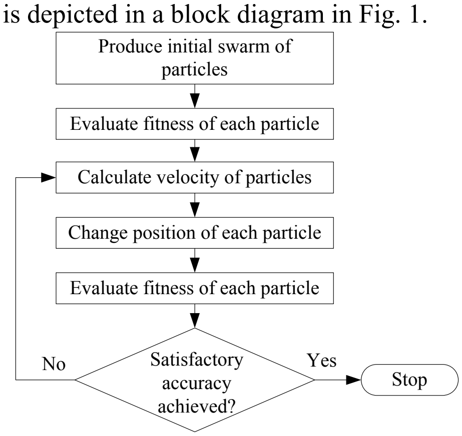


Fig. 1. Flowchart of PSO algorithm.

The method is initialized by populating a number of particles to create a *swarm*. Each particle is simply a parameter vector $\boldsymbol{\theta}$ 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, where fitness is a quantity indicating the accuracy of the solution represented by a particle. The fitness should increase with the accuracy, so the reciprocal of the objective function (9) is used.

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

$$\mathbf{V}_i^{k+1} = \omega\mathbf{V}_i^k + c_1 r_1(\mathbf{P}_i^k - \boldsymbol{\theta}_i^k) + c_2 r_2(\mathbf{P}_g^k - \boldsymbol{\theta}_i^k) \tag{10}$$

where $\mathbf{V}_i^k$ and $\mathbf{V}_i^{k+1}$ are the current and next step velocity of the ith particle, respectively, ω is the inertia weight, $\mathbf{P}_i^k$ is the best previous position of the ith particle, $\mathbf{P}_g^k$ is the best global position, $\boldsymbol{\theta}_i^k$ is the actual ith particle position, c_1 and c_2 are the acceleration coefficients usually equal to 2.0 and r_1 and r_2 are random numbers ranging from 0.0 to 1.0.

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

$$\boldsymbol{\theta}_i^{k+1} = \boldsymbol{\theta}_i^k + \mathbf{V}_i^{k+1} \tag{11}$$

This process is usually terminated after reaching either a maximum number of iterations or a satisfactory fitness.

The Improved Particle Swarm Optimization proposed in [18] offers an increase in both the precision, and speed of the convergence. This improvement has been achieved by changing the inertia weight, ω, from a predefined constant into a variable. The function modulating ω is as follows:

$$\omega = \left\{\frac{(iter_{\max} - iter)^n}{(iter_{\max})^n}\right\}(\omega_{initial} - \omega_{final}) + \omega_{final} \tag{12}$$

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 the current iteration and n is the nonlinear modulation index. Inertia weight, defined in such a way, decreases with each iteration, consequently reducing the contribution of the current velocity when calculating the velocity of the next iteration. This improves the accuracy and convergence in the final stage of the estimation.

IV. Simulation Results

To verify the effectiveness of the parameter estimation procedure, simulations have been carried out. In these simulations, the dynamic model of the induction generation described by (1)-(5) is employed. The parameter estimation procedure is carried out using the IPSO. In all cases the swarm size of the IPSO algorithm is equal to 30, the maximum number of iterations (generations) is equal to 10 and the remaining two parameters are defined as follows: $\omega_{initial} = 0.9$ and $\omega_{\mathrm{final}} = 0.01$. A computer program was developed in MATLAB® to execute this algorithm.

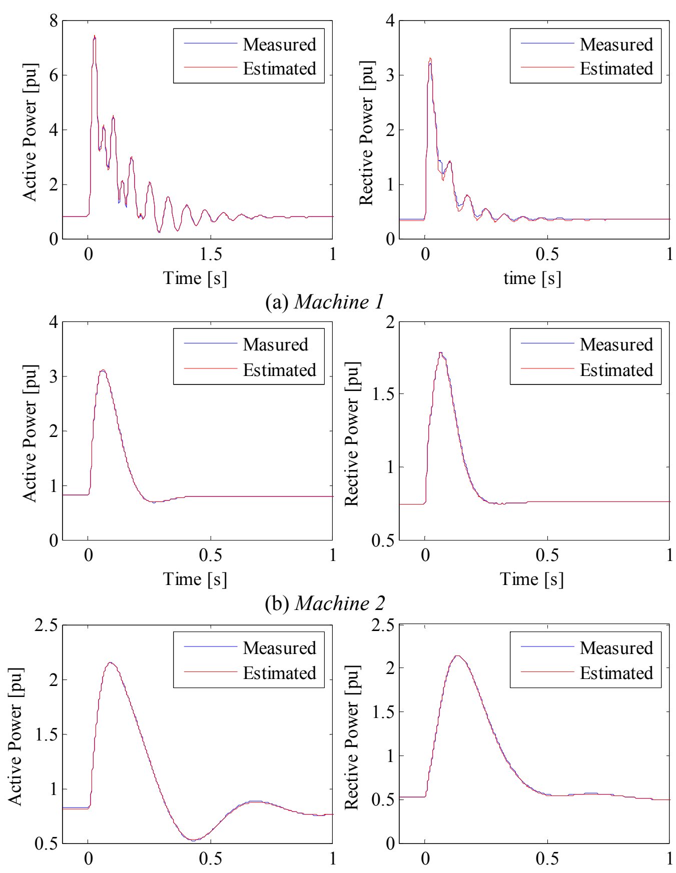
. The test procedure involves maintaining the stator voltage and mechanical power constant at their steady state operating points. The frequency is then changed in some way to produce the necessary variation in the active and reactive power flow associated with the IG. Two case studies have been examined. In the first case, a step change in frequency is simulated. In the second case, a time series representing the frequency response of a synchronous generator during a load step change was used. This time series of frequency was obtained from a simulation performed with DIgSILENT® PowerFactory™. Three induction generators with squirrel-cage rotors, typically employed in fixed speed wind turbine applications, have been used in each test case, the parameters of these are given in Table I.

TABLE I
INDUCTION MACHINES PARAMETERS USED IN THE SIMULATIONS

Machine	*1*	*2*	*3*
V_n [V]	690 V	690 V	660 V
P_n [kW]	2000 kW	500 kW	330 kW
f [Hz]	50.0	50.0	50.0
H [s]	1.1877	3.2000	3.0000
R_s [pu]	0.0010	0.0035	0.0071
L_{ls} [pu]	0.0100	0.0474	0.0762
R'_r [pu]	0.0010	0.0098	0.0076
L'_{lr} [pu]	0.0100	0.0619	0.2329
L_m [pu]	3.0000	1.4760	3.4498

A. *Case I: Step Frequency Change -2Hz*

This test system is a network which consists of a programmable voltage source feeding a single squirrel-cage induction generator through one busbar. A step change of 2Hz is then applied to the system frequency to represent a disturbance i.e. the pre-disturbance frequency is equal to 50Hz and the post-disturbance frequency is equal to 48Hz. This disturbance was simulated to verify the effectiveness of the parameter estimation when exposed to a large frequency excursion. The data sets of active and reactive power measurements and the results for the parameter estimation performed by the IPSO are shown in Fig. 2.



(a) *Machine 1*
(b) *Machine 2*
(c) *Machine 3*

Fig. 2. Results with IPSO: Case I.

In this case study, *Machine 1* possessed the most complex frequency response and thus a considerably higher P and Q error, when compared to the other two cases. It should be noted, however, that the accuracy of the estimated machine parameters is comparable in all cases (Table II).

TABLE II
SUMMARY OF RESULTS FOR CASE I

Machine	*1*		*2*		*3*	
	real	*estimated*	*real*	*estimated*	*real*	*estimated*
P_e error [%]	2.0950		0.4009		0.3262	
Q_e error [%]	8.4823		0.3773		0.7232	
H [s]	1.1877	1.1999	3.2000	3.1507	3.0000	3.0635
R_s [pu]	0.0010	0.0013	0.0035	0.0025	0.0071	0.0098
L_{ls} [pu]	0.0100	0.0116	0.0474	0.0507	0.0762	0.0746
R'_r [pu]	0.0010	0.0010	0.0098	0.0096	0.0076	0.0078
L'_{lr} [pu]	0.0100	0.0081	0.0619	0.0586	0.2329	0.2316
L_m [pu]	3.0000	3.1193	1.4760	1.4733	3.4498	3.4139

The results prove the estimation method to be capable of reaching satisfactory accuracy for all three different generators. The precision of the estimation will satisfy the needs of stability analysis.

B. *Case II: System Frequency change*

Here, as in Case I, a programmable voltage source has been used to excite a single squirrel-cage induction generator; however, the frequency disturbance used is the response of a synchronous generator to a load step change. Fig. 3 shows the frequency time series applied to the three IGs, the parameters of which are shown in Table I.

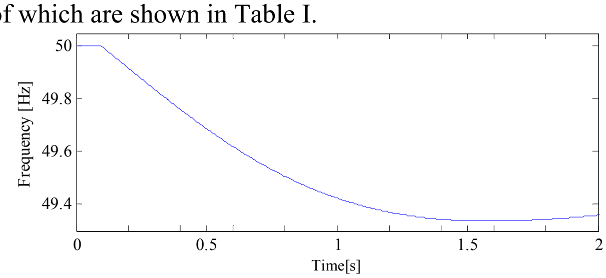


Fig. 3. System frequency response of synchronous generator during load step change.

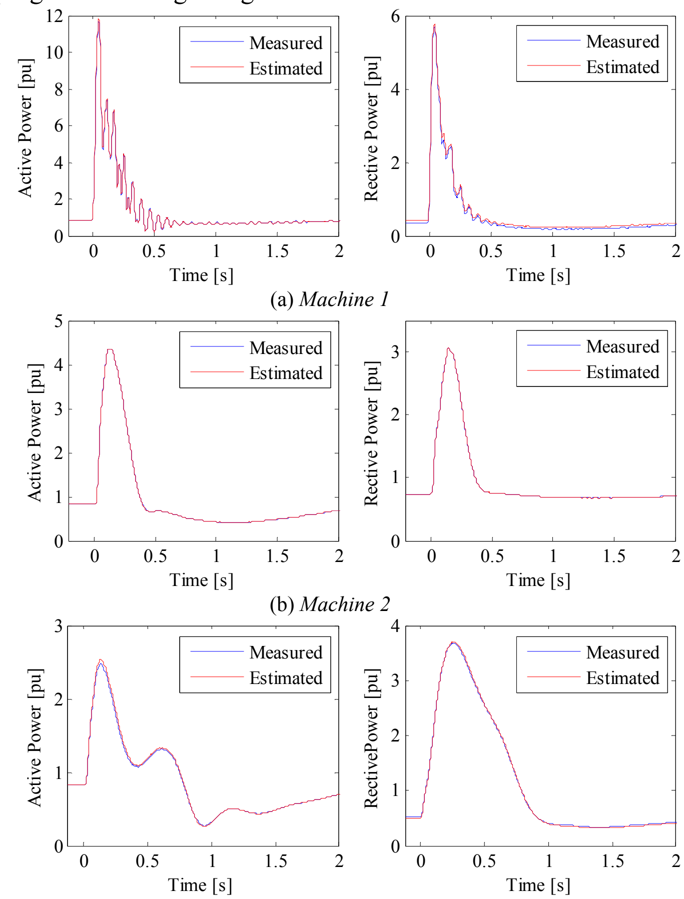
The data sets of active and reactive power measurements and the results of the parameter estimation produce by the IPSO are shown in Fig. 4. In this case *Machine 1* again proved to have the most complex response, in terms of performing parameter estimation; however the obtained parameters are still within acceptable range (Table III).

TABLE III
SUMMARY OF ESTIMATIONS, CASE B

Machine	*1*		*2*		*3*	
	real	*estimated*	*real*	*estimated*	*real*	*estimated*
P_e error [%]	2.5505		0.1650		1.8954	
Q_e error [%]	16.4683		0.1850		3.3857	
H [s]	1.1877	1.2058	3.2000	3.1900	3.0000	3.0251
R_s [pu]	0.0010	0.0009	0.0035	0.0034	0.0071	0.0042
L_{ls} [pu]	0.0100	0.0078	0.0474	0.0478	0.0762	0.0745
R'_r [pu]	0.0010	0.0010	0.0098	0.0097	0.0076	0.0074
L'_{lr} [pu]	0.0100	0.0119	0.0619	0.0620	0.2329	0.2309
L_m [pu]	3.0000	2.5819	1.4760	1.4776	3.4498	3.6265

Two of the three test machines had a higher estimation error than that seen in Case I. However, despite this the IPSO was still capable of producing acceptable estimates of the machine parameters, for this more complex frequency disturbance.

Fig. 5 shows the typical convergence curves of the IPSO for the machines tested in Case B. The plots show how the objective function (9) is minimized once the algorithm has progressed through 10 generations.



(a) *Machine 1*

(b) *Machine 2*

(c) *Machine 3*

Fig. 4. Results with IPSO: Case B.

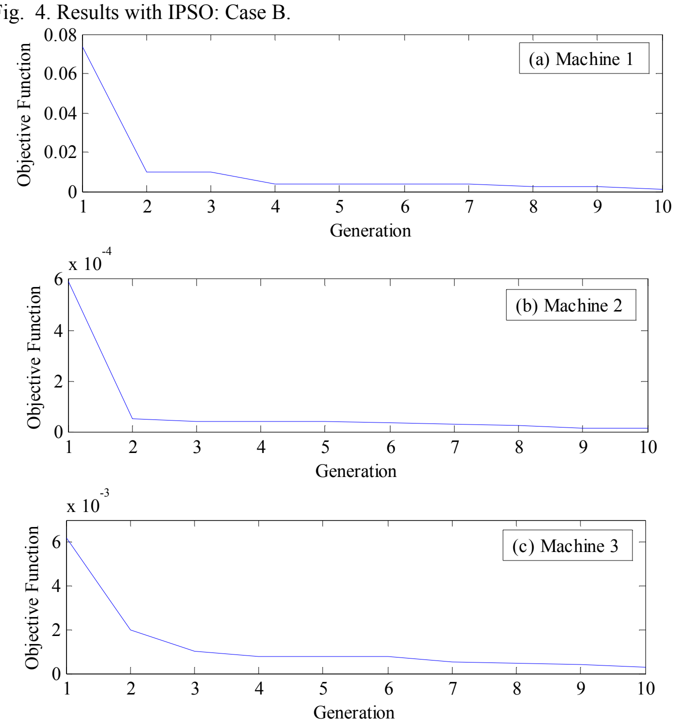


Fig. 5. Typical convergence curve for Case II.

It is clear that in this particular case the number of generations could be reduced to around 4 without any significant loss of accuracy, this means that the estimation time could also be reduced. As expected, the value of the objective function is highest for *Machine 1* (most complex frequency response) and lowest for *Machine 2* (least complex frequency response). The largest progress toward minimizing the error of the estimation occurs during the earlier stages of the procedure for all three machines.

V. Conclusion

In this paper, a novel application of the IPSO algorithm has been proposed for parameter estimation of an induction generator. This application is based on the response of the active and reactive power flows, associated with an induction generator, to a frequency deviation during steady state operation. This is in contrast to the use of start up data or other direct mechanical testing that is necessary in other approaches. The increasing deployment of wide area monitoring devices, such as PMUs, means that data of this nature will be increasingly available in the future. The frequency deviations used to validate this approach are a simulated step change and the response of a synchronous generator to a load step change. These deviations were chosen to demonstrate that the proposed algorithm can operate successfully for both large frequency deviations and for the more intricate fluctuations that will occur in real power systems.

The parameter estimation technique presented in this paper demonstrates a high quality of performance in terms of both convergence and accuracy. In all cases the method was capable of converging to a global minimum with an acceptable precision. Executing IPSO, like other Artificial Intelligence techniques, is time consuming; however, this is not a concern for offline applications. A useful feature of the IPSO, when applying it to this problem, is that the algorithm simply requires an estimate of the likely range of the model parameters, and not an initial estimate of the sate vector. Simple implementation and good accuracy make the IPSO a good alternative to other widely used estimation methods, like Nonlinear Least Squares or Genetic Algorithms.

VI. References

[1] N. Jenkins, R. Allan, P. Crossley, D. Kirschen, and G. Strbac, *Embedded generation* London, United Kingdom: The Institution of Engineering and Technology, 2000.

[2] J. Machowski, J. W. Bialek, and J. R. Bumby, *Power System Dynamics - Stability and Control (2nd Edition)*, 2nd ed.: Wiley-IEEE Press, 2008.

[3] F. P. de Mello, J. W. Feltes, L. N. Hannett, and J. C. White, "Application of Induction Generators in Power Systems," *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-101, pp. 3385-3393, 1982.

[4] M. Godoy-Simoes and F. A. Farret, *Renewable Energy Systems-Design and Analysis with Induction Generators*, 2nd ed. vol. I. New York: CRC Press, 2002.

[5] M. Godoy-Simões and F. A. Farret, *Alternative Energy Systems: Design and Analysis with Induction Generators*, 2nd ed. New York: CRC Press, 2007.

[6] L. L. Lai and T. F. Chan, "Distributed Generation - Induction and Permanent Magnet Generators," John Wiley & Sons, 2007.

[7] J. B. Ekanayake, "Induction generators for small hydro schemes," *Power Engineering Journal,* vol. 16, pp. 61-67, 2002.

[8] S. Li, K. Tomsovic, and T. Hiyama, "Load following functions using distributed energy resources," in *Power Engineering Society Summer Meeting, 2000. IEEE*, 2000, pp. 1756-1761 vol. 3.

[9] J. G. Slootweg, "Wind Power: Modelling and Impact on Power System Dynamics " in *Electrical Power System Laboratory*. vol. PhD Thesis Delft, Netherlands: Delft University of Technology, 2003.

[10] T. Ackermann, *Wind Power in Power Systems*: John Wiley & Sons Inc, 2005.

[11] P. Marino, V. Mungiguerra, F. Russo, and F. Vasca, "Parameter and state estimation for induction motors via interlaced least squares algorithm and Kalman filter," in *Power Electronics Specialists Conference, 1996. PESC '96 Record., 27th Annual IEEE*, 1996, pp. 1235-1241 vol.2.

[12] D. C. Huynh and M. W. Dunnigan, "Parameter estimation of an induction machine using a dynamic particle swarm optimization algorithm," in *Industrial Electronics (ISIE), 2010 IEEE International Symposium on*, 2010, pp. 1414-1419.

[13] K. S. Huang, Q. H. Wu, and D. R. Turner, "Effective identification of induction motor parameters based on fewer measurements," *Energy Conversion, IEEE Transactions on,* vol. 17, pp. 55-60, 2002.

[14] R. R. Bishop and G. G. Richards, "Identifying induction machine parameters using a genetic optimization algorithm," in *Southeastcon '90. Proceedings., IEEE*, 1990, pp. 476-479 vol.2.

[15] T. Sag and M. Cunkas, "Multiobjective genetic estimation to induction motor parameters," in *Electrical Machines and Power Electronics, 2007. ACEMP '07. International Aegean Conference on*, 2007, pp. 628-631.

[16] R. K. Ursem and P. Vadstrup, "Parameter identification of induction motors using differential evolution," in *Evolutionary Computation, 2003. CEC '03. The 2003 Congress on*, 2003, pp. 790-796 Vol.2.

[17] A. Karimi, M. A. Choudhry, and A. Feliachi, "PSO-based Evolutionary Optimization for Parameter Identification of an Induction Motor," in *Power Symposium, 2007. NAPS '07. 39th North American*, 2007, pp. 659-664.

[18] G. Chen, W. Guo, and K. Huang, "On Line Parameter Identification of an Induction Motor Using Improved Particle Swarm Optimization," in *Control Conference, 2007. CCC 2007. Chinese*, 2007, pp. 745-749.

[19] C. Picardi and N. Rogano, "Parameter identification of induction motor based on particle swarm optimization," in *Power Electronics, Electrical Drives, Automation and Motion, 2006. SPEEDAM 2006. International Symposium on*, 2006, pp. 968-973.

[20] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Micro Machine and Human Science, 1995. MHS '95., Proceedings of the Sixth International Symposium on*, 1995, pp. 39-43.

[21] G. Yang, "A Modified Particle Swarm Optimizer Algorithm," in *Electronic Measurement and Instruments, 2007. ICEMI '07. 8th International Conference on*, 2007, pp. 2-675-2-679.

[22] M. Senthil Arumugam, A. Chandramohan, and M. V. C. Rao, "Competitive approaches to PSO algorithms via new acceleration co-efficient variant with mutation operators," in *Computational Intelligence and Multimedia Applications, 2005. Sixth International Conference on*, 2005, pp. 225-230.

[23] A. Ratnaweera, S. K. Halgamuge, and H. C. Watson, "Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients," *Evolutionary Computation, IEEE Transactions on,* vol. 8, pp. 240-255, 2004.

[24] P. Kundur, *Power System Stability and Control* Palo Alto , California: McGraw-Hill Inc., 1994.

[25] P. C. Krause, O. Wasiynczuk, and S. D. Sudhoff, *Analysis of Electric Machinery and Drive Systems*, 2nd ed.: Wiley-IEEE Press, 2002.

VII. Biographies

Pawel Regulski obtained the MSc degree in Electrical Engineering from the Wroclaw University of Technology (Poland) in 2008. Currently he is a PhD student at the University of Manchester working on load modeling and voltage stability. His main research interests include development of new estimation techniques and implementation of artificial intelligence techniques in power system applications.

Francisco M. González-Longatt (S'01, M'03, SM' 2009) was born in Cagua-Venezuela, on July 30, 1972. He graduated on Electrical Engineering of Instituto Universitario Politécnico de la Fuerza Armada Nacional, Venezuela (1994), and Master of Business Administration of Universidad Bicentenaria de Aragua, Venezuela (1999) and PhD of Universidad Central de Venezuela (2008). His main area of interest is integration of intermittent renewable energy resources into power grid with special interest on dynamic behavior. He is former associate professor on Electrical engineering Department of Universidad Nacional Politécnico de la Fuerza Armada Nacional, Venezuela. He is currently a Post Doctoral Associate Research School of Electrical and Electronic Engineering, The University of Manchester.

Peter Wall was born in Dorset, England. He graduated from the University of Manchester with a Bachelors degree in Electrical and Electronic Engineering (2008) and with a Masters degree in Power Systems (2009). His main area of interest is power system dynamics and frequency stability. He is currently a PhD student in the School of Electrical and Electronic Engineering, The University of Manchester.

Vladimir Terzija (M'95, SM'2000) is the EPSRC Chair Professor in Power System Engineering in the School of Electrical and Electronic Engineering, The University of Manchester, where he has been since 2006. From 1997 to 1999, he was an Assistant Professor at the University of Belgrade, Serbia. From 2000 to 2006, he was with ABB AG, Germany, working as an expert for switchgear and distribution automation. Dr. Terzija is a convenor of the Cigre WGB5.14 "Wide area protection and control technologies" and a member of several IEEE working groups and task forces. His main research interests are Smart Grid, application of intelligent methods to power system monitoring, control, and protection, switchgear and fast transient processes, as well as DSP applications in power systems.