Optimization of Self Excited Induction Generator Using Constrained Particle Swarm Optimization

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Abstract

Induction generators are widely used in various applications since they offer distinct advantages over conventional synchronous machines, resulting in a simplified design and installation at lower capital cost and substantial savings in operation and maintenance expenses. A wind turbine induction generator system is proposed to supply isolated loads under widely varying conditions. With these varying loading conditions there will be some changes in the terminal voltage and frequency. The terminal voltage and frequency is regulated by adapting the value of excitation capacitance required for the excitation of the induction generator. This paper presents a constrained Particle Swarm Optimization (PSO) based procedure for minimizing the power losses in a self excited induction generator with terminal voltage and frequency control under different loading conditions by selecting the suitable capacitance required for the excitation.

Keywords: Self Excited Induction Generator, Particle Swarm optimization, Terminal Voltage Control and Frequency Control.

Nomenclature

R_S, R_R, R_L	per unit stator, rotor, and load resistances, respectively
X_S, X_R, X_M, X_L, X_C	per unit stator, rotor leakage, magnetizing, load and exciting reactances, at base frequency, respectively
Z_L	per unit load impedance
f_S	synchronous frequency
F	per unit frequency
v	per unit rotational speed
Eg, V_T	per unit air gap and terminal voltages, respectively
I_S, I_L	per unit stator and load currents per phase, respectively
N	number of dimensions in a particle
I	number of particles
w	inertia weight factor
t	pointer of iterations
c_1, c_2	accelerating constant
$rand_1$, $rand_2$	uniform random value in the range of [0, 1]
$v\ v_{ij}^{(t)}$	velocity of the j^th dimension for the i^th particle
$p_{ij}^{(t)}$	current position of the j^th dimension for the i^th particle at iteration t

w_{max} and w_{min}	both random numbers, called initial and final weights
t_{max}	maximum number of iterations
t	he current iteration number

1. Introduction

In recent years, new resources have been focused on electricity generation, such as wind energy and photovoltaic power. The Self Excited Induction Generator (SEIG) was used as the electromechanical energy converter in such generation schemes. The advantages of an induction generator are low cost, robustness, absence of moving contacts, and no need for DC excitation. The cost of an induction generator is about 40% - 50% of that of a synchronous generator of the same capacity. The SEIG is capable of generating electrical energy from constant speed as well as variable speed prime movers. Such an energy system can feed electrical energy to isolated locations, which in turn can enhance agriculture production and improve the standard of living in remote areas.

The magnitude of the terminal voltage of a SEIG depends upon the load impedance, excitation capacitance, and speed of the prime mover. The acceptability of such units depends upon the capability of the control system, which will provide constant voltage at different loads and different speeds. Many investigations on the suitability, steady state analysis, and output control of a three phase SEIG have been made [1-5].

Several optimization techniques have been reported in the literature. The suitability of using a normal three-phase induction motor as a capacitor self-excited induction generator has been illustrated [6-8]. For this design procedure, the air gap flux density and the current densities of the rotor and the stator must be specified by the designer [9].

Steady state performance analysis of a capacitor excited induction generator is compared with commercially designed line excited induction generator, operating as SEIG [10]. Steady state analysis using an iterative method for determination of per unit frequency was performed [11]. A simulated Annealing like approach was suggested for solving voltage regulation optimization problems [12].

Constrained Optimization (CO) problems are encountered in numerous applications. Structural optimization, engineering design, economics, allocation, and location problems are just a few of the scientific fields in which CO problems are frequently met [13, 14]. The CO problem can be represented as the following nonlinear programming problem:

$$\min f(x) \tag{1}$$

subject to the linear or nonlinear constraints

$$g_i(x) \leq 0, \; i = 1, \ldots, m \tag{2}$$

The formulation of the constraints in equation (2) is not restrictive, since an inequality constraint of the form $g_i(x) \geq 0$, can also be represented as $-g_i(x) \leq 0$, and an equality constraint, $g_i(x) = 0$, can be represented by two inequality constraints $g_i(x) \leq 0$ and $-g_i(x) \leq 0$.

The most common approach for solving CO problems is the use of a penalty function. The constrained problem is transformed to an unconstrained one, by penalizing the constraints and building a single objective function, which in turn is minimized using an unconstrained optimization algorithm [13, 14].

In this paper, selection of the value of the excitation capacitor required for exciting SEIG is performed in order to minimize power losses, and control the voltage and the frequency of the SEIG at different loading conditions, using constrained PSO.

2. Steady State Analysis of Self-Excited Induction Generators

Figure 1 shows the per-phase equivalent circuit commonly used for SEIG supplying resistive load. A three-phase induction machine can be operated as a SEIG if its rotor is externally driven at a suitable speed and a three-phase capacitor bank of a sufficient value is connected across its stator terminals. When the induction machine is driven at the required speed, the residual magnetic flux in the rotor will induce a small electromotive force in the stator winding. The appropriate capacitor bank causes this induced voltage to continue to increase until an equilibrium state is attained due to magnetic saturation of the machine.

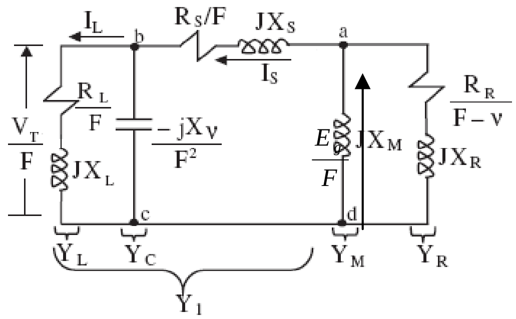

Figure 1 Per-phase equivalent circuit of a SEIG

When a SEIG is loaded, both the magnitude and frequency of the induced electromotive force are affected by the prime mover speed, the capacitance of the capacitor bank used for excitation and the load impedance.

The steady-state per-phase equivalent circuit of a SEIG, supplying a balanced resistive load, is shown in Figure 1. From Figure 1, the total current at node a may be given by:

$$E_1(Y_1 + Y_M + Y_R) = 0 \qquad (3)$$

Therefore, under steady-state self-excitation, the total admittance must be zero, since:

$$E_1 \neq 0 \text{ so}$$
$$(Y_1 + Y_M + Y_R) = 0 \qquad (4)$$

Equation 4 is divided into real and imaginary parts as:

$$\Re(Y_1 + Y_M + Y_R) = 0 \qquad (5)$$
$$\Im(Y_1 + Y_M + Y_R) = 0 \qquad (6)$$

Where

$$Y_1 = \frac{(Y_L + Y_C)Y_S}{Y_L + Y_C + Y_S}$$
$$Y_C = \frac{1}{-j(X_C / F^2)}$$
$$Y_L = \frac{1}{(R_L / F + jX_L)}$$
$$Y_S = \frac{1}{(R_S / F) + jX_S}$$
$$Y_M = \frac{1}{jX_M}$$
$$Y_R = \frac{1}{\frac{R_R}{F-V} + jX_R}$$

Equations 5 and 6 are nonlinear for the four unknowns F, X_M, X_C and v. Two of these unknowns should be specified. The other two unknowns can be found by solving the two nonlinear equations. Different values of rotational speed v and the controlled value of the capacitance X_C are determined to control the output voltage. Then, the frequency and X_M are calculated.

Based on the analysis introduced in Alghuwainem [15], Alolah and Alkanhal [16], a fifth order polynomial independent of X_M is extracted to calculate the frequency. Then, the values of X_M are calculated at different loading conditions.

The relationship between the magnetizing reactance X_M and the air-gap voltage Eg/F of the machine based on Alghuwainem [15] is given by:

$$E_1 = \frac{E_g}{F} = 1.12 + 0.078X_M - 0.146X_M^2 \quad (7)$$

After calculating the air gap voltage E_1, the stator I_s and load currents I_L can be calculated as

$$I_s = E_1 \times Y_1 \quad (8)$$

$$I_L = I_s \frac{Y_L}{Y_L + Y_c} \quad (9)$$

Then, the input and output power can be calculated as:

$$P_{in} = 3|E_1 \times Y_R|^2 \times \frac{R_R}{F - V} \quad (10)$$

$$P_{out} = 3|I_L|^2 \times \frac{R_L}{F} \quad (11)$$

The difference between the input and output power is the losses of the SEIG will be

$$P_{Loss} = P_{in} - P_{out} \quad (12)$$

3. Particle Swarm Optimization (PSO) Method

PSO is a stochastic global optimization method which is based on simulation of social behavior. As in a genetic algorithm, PSO exploits a population of potential solutions to probe the search space. In contrast to the aforementioned methods in PSO, no operators inspired by natural evolution are applied to extract a new generation of candidate solutions. Instead of mutation, PSO relies on the exchange of information between individuals, called particles, of the population, called a swarm. In effect, each particle adjusts its trajectory towards its own previous best position, and towards the best previous position attained by any member of its neighborhood [17]. In the global variant of PSO, the whole swarm is considered as the neighborhood. Thus, global sharing of information takes place and particles profit from the discoveries and previous experience of all other companions during the search for promising regions of the landscape. To visualize the operation of the method, consider the case of the single objective minimization case; promising regions in this case possess lower function values compared to others, visited previously.

Let x and y denote a particle coordinates (position) and its corresponding flight speed (velocity) VV_x in the x direction and VV_y in the y direction. Modification of the individual position is realized by velocity and position information.

PSO algorithm for N-dimensional problem formulation can be described as follows. Let P be the particle position and VV is the velocity in a search space. Consider i as a particle in the total population (swarm). The i^{th} particle position can be represented as P_i= (P_{i1}, P_{i2}, P_{i3}, P_{iN}) in the N-dimensional space. The best previous position of the i^{th} particle is recorded and represented as P_{besti}= (P_{besti1}, P_{besti2}, P_{besti3}, P_{bestij}). The index of the best particle among all the particles in the group is represented by g_{best}. The velocity i^{th} particle is represented as: VV_i = (VV_{i1}, VV_{i2}, VV_{i3},..., VV_{ij}). The modified velocity and position of each particle can be calculated using the current velocity and the distance from P_{best} to g_{best} as indicated in following formulas

$$V_{ij}^{(t+1)} = w*V_{ij}^{(t)} + c_1 * rand_1 * (P_{best_{ij}} - P_{best_{ij}}^{(i)}) + c_2 * rand_2 * (g_{best_i} - P_{best_{ij}}^{(i)}) \quad (13)$$

$$p_{ij}^{(t+1)} = p_{ij}^{(t)} + v_{ij}^{(t+1)} \quad (14)$$

$i = 1,\ 2,...,\ I$ and $j = 1,\ 2,...,\ N$

Inertia weighting factor w has provided improved performance when using the linearly decreasing [17]. Its value is decrease linearly from about 1.2 to 0.1 during a run. Suitable selection of w provides a balance between global and local exploration and exploitation, and results in fewer iterations on average to find a sufficiently optimal solution. Its value is set according to the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} * t \quad (15)$$

In equation (13), the first term indicates the current velocity of the particle. The second term represents the cognitive part of PSO, where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge [17].

4. The Penalty Function Approach

The search space in constrained problems consists of two kinds of points: feasible and unfeasible. Feasible points satisfy all the constraints, while unfeasible points violate at least one of them. The Penalty Function technique solves the problem through a sequence of unconstrained optimization problems [18]. Currently, no other method for defining pertinent penalty functions, other than trial and error, exists [13].

Penalty functions are distinguished into two main categories: stationary and non-stationary. Stationary penalty functions use fixed penalty values through-out the minimization, while in contrast, in non-stationary penalty functions, the penalty values are dynamically modified. In the literature, results obtained using non-stationary penalty functions are almost always superior to those obtained through stationary functions.

A penalty function is, generally, defined as [13],

$$F(x) = f(x) + h(k)H(x) \quad (16)$$

where *f(x)* is the objective function to be minimized of the constrained optimization problem in equation (1); h(k) is a dynamically modified penalty value, where k is the algorithm's current iteration number; and H(x) is a penalty factor, defined as:

$$h(x) = \sum_{i=1}^{m} \theta(q_i(x))q_i(x)^{\gamma(q_i(x))} \quad (17)$$

where $q_i(x) = \max\{0, g_i(x)\}$, $i = 1,\ldots,m$. The function $q_i(x)$ is a relative violated function of the constraints; $\theta(q_i(x))$ is a multi-stage assignment function $\gamma(q_i(x))$ is the power of the penalty function; and $g_i(x)$ are the constraints described in equation (2). The functions h(k), $\theta(q_i(x))$ and $\gamma(q_i(x))$, are problem dependent by trial and error as will be indicated.

In this paper, a non-stationary multi-stage assignment penalty function was used.

5. SEIG optimization using CO-PSO

CO-PSO is used to optimize the power losses in the SEIG as follows:

- The objective function to be minimized, *f(x)*, is the power losses defined in equation (12) as a function of the capacitance X_c.

- The constraints used are the voltage and frequency to be at the desired(controlled) values, so equation (2) includes two variables (m = 2):
  $V_T(x) \leq V_{desired}$, $F(x) \leq F_{desired}$

6. Simulation Results

The proposed CO-PSO is tested for the SEIG shown in Figure 1. The data for this SEIG are as follows [2]: *Rs = 0.1 p.u; Xs = 0.2 p.u; Rr = 0.06 p.u; Xr = 0.2 p.u.*

Two different cases are used to test the capability of the proposed method. The first one is pure resistive load and the second one is R-L load.

The desired voltage is $V_{desired}$ = 1 p.u and the frequency required is $F_{desired}$ = 0.6 p.u.

The proposed CO-PSO is used to get the required capacitance for compensating SEIG, with minimizing the power losses, keeping the terminal voltage and frequency at the specified values at different loading conditions.

The PSO's parameters used: $c_1 = c_2 = 2$; *w* was gradually decreased from 1.2 towards 0.1. PSO is varied, imposing a maximum value on the velocity, VV_{max}, to prevent the swarm from exploding. In this search VV_{max} was always fixed, to a value of $VV_{max} = 4$. The size of the swarm was set equal to 100, 100 runs were performed, and the PSO algorithm ran for 1000 iterations, in each case. A violation tolerance was used for the constraints. Thus, a constraint $g_i(x)$ was assumed to be violated, only if $g_i(x) > 10^{-5}$.

Regarding the penalty parameters, the same values as the values reported in [13] were used to obtain these results. The penalty function parameters are:

- if $q_i(x) < 1$, then $\gamma(q_i(x)) = 1$, otherwise $\gamma(q_i(x)) = 2$.
- $h(k) = k\sqrt{k}$
- Moreover,
  if $q_i(x) < 0.001$ then $\theta(q_i(x)) = 10$,
  else,
  if $q_i(x) < 0.01$ then $\theta(q_i(x)) = 20$,
  else,
  if $q_i(x) < 1$ then $\theta(q_i(x)) = 100$,
  otherwise
  $\theta(q_i(x)) = 300$

In the first case, the wind speed is varied from 0.7 to 1.1 p.u, and the load resistance from 1 to 1.5 p.u. Then the exciting capacitance (X_c), required for compensation at minimum power losses, 1 p.u terminal voltage and 0.6 p.u frequency, is depicted in Table 1.

Table 1 The excited capacitance and the minimum losses at different loading conditions using proposed CO-PSO 1st case

R_L (p.u) \ Speed *V*		0.7	0.8	0.9	1	1.1
1	(Xc (p.u	0.76	0.802	0.841	0.8772	0.9117
	P_{LOSS} (p.u) min	0.2869	0.3014	0.3125	0.3217	0.3354
1.1	(Xc (p.u	0.84	0.89	0.933	0.9788	1.0229
	P_{LOSS} (p.u) min	0.2578	0.2669	0.2580	0.2662	0.2763
1.2	(Xc (p.u	0.91	0.96	1.015	1.071	1.1235
	P_{LOSS} (p.u) min	0.2285	0.2141	0.2176	0.2275	0.2337

Table 1 The excited capacitance and the minimum losses at different loading conditions using proposed CO-PSO 1st case (cont')

R_L (p.u) \ Speed *V*		**0.7**	**0.8**	**0.9**	**1**	**1.1**
1.3	(Xc (p.u	0.96	1.025	1.089	1.1523	1.214
	P_{LOSS} (p.u) min	0.2285	0.1829	0.1880	0.1944	0.2008
1.4	(Xc (p.u	1.012	1.085	1.1553	1.226	1.296
	P_{LOSS} (p.u) min	0.1563	0.1623	0.1651	0.1701	0.1759
1.5	(Xc (p.u	1.06	1.137	1.2147	1.2924	1.3692
	P_{LOSS} (p.u) min	0.1414	0.1434	0.1468	0.1509	0.1550

In the second case, the load impedance is increased gradually from 0.8 to 3.2 p.u at constant power factor of 0.8, then the exciting capacitance (X_c), required for compensation at minimum power losses, 1 p.u terminal voltage and 0.6 p.u frequency, is depicted in Table 2.

Table 2 The excited capacitance and the minimum losses at different loading conditions using proposed CO-PSO 2nd case

Z_L (p.u) \ Speed *V*		**0.7**	**0.8**	**0.9**	**1**	**1.1**
0.8	Xc (p.u)	0.46	0.68	0.6941	0.732	0.8117
	P_{LOSS} (p.u) min	0.421	0.435	0.468	0.562	0.579
1.2	Xc (p.u)	0.68	0.698	0.733	0.802	0.897
	P_{LOSS} (p.u) min	0.401	0.421	0.456	0.543	0.558
1.6	Xc (p.u)	0.732	0.783	0.802	0.843	0.867
	P_{LOSS} (p.u) min	0.394	0.406	0.428	0.487	0.521
2.0	Xc (p.u)	0.821	0.846	0.878	0.899	0.901
	P_{LOSS} (p.u) min	0.366	0.389	0.400	0.456	0.496
2.4	Xc (p.u)	0.8935	0.902	0.911	0.932	0.942
	P_{LOSS} (p.u) min	0.288	0.321	0.366	0.402	0.422
2.8	Xc (p.u)	0.921	0.953	0.932	0.944	0.956
	P_{LOSS} (p.u) min	0.265	0.289	0.302	0.317	0.334
3.2	Xc (p.u)	0.931	0.941	0.962	0.972	0.981
	P_{LOSS} (p.u) min	0.223	0.268	0.299	0.307	0.310

In the second case, the value of the excitation capacitance is increased, as the inductive load, so X_c decreases.

7. Conclusions

This paper described a steady state model for an induction machine in the generating mode, which has the feature of a nonlinear variation in the machine parameters that are dependent on the operating conditions of the machine. The capability of the PSO method to address CO problems was investigated through the optimization and control of SEIG. Results obtained through the use of a non-stationary multi-stage penalty function, imply that PSO is a good alternative for tackling CO problems. It should be mentioned that the results were competitive, as the inequality constraints changed into equality ones. The voltage and frequency are held constant at the desired value, not in certain limits, by the selection of the appropriate capacitors, to achieve minimization of the power losses with different loading conditions.

8. References

[1] T. F. Chan “Steady-state analysis of self excited induction generators” IEEE Trans. on Energy Conversion, Vol. 9, No. 2, pp. 288-296, June 1994.

[2] T. F. Chain “Capacitance requirements of self-excited induction generators” IEEE Trans on Energy Conversion, Vol. 8, No. 2, pp. 304-311, June 1993.

[3] C. Chakraborty, S. N. Bhadra and A. K. Chattopadhyay “Excitation requirements for stand alone three-phase induction generator” IEEE Trans. on Energy Conversion, Vol. 13, No. 4, pp. 358-365, December 1998.

[4] E. Muljadi, J. Sallan, M. Sanz and C. P.Butterfield “Investigation of self excited induction generators for wind turbine applications” IEEE Trans. on Energy Conversion, Vol. 12, 2000.

[5] B. Babypriya, R. Anita “Modeling, simulation and analysis of doubly fed induction generator for wind turbines” Journal of Electrical Engineering, Vol. 60, No. 2, 2009, pp. 79–85.

[6] S. P. Singh, B. Singh, and M. P. Jain, "Performance characteristics and optimum utilization of induction generator," IEEE Trans. On Energy Conversion, Vol. 5, No. 5, pp. 679-685, Dec. 1990.

[7] S. P. Singh, B. Singh, and M. P. Jain, "Steady state analysis of self excited induction generator with ac-dc conversion scheme for small scale generation," Electric Power System Research, Vol. 2, No. 2, pp. 95-104, Feb. 1991.

[8] H. Al-Bahrani and N. H. Malik, "Steady state analysis and performance characteristics of three-phase induction generator self excited with single capacitor," IEEE Trans. on Energy Conversion, Vol. 5, No. 4, pp. 725-732, Dec. 1990.

[9] S. I. Kitsis, "Features of the design and calculation of submersible asynchronous self-excited generator," Electrotekhnica, Vol. 57, No. 11, pp. 36-37, 1986.

[10] S. P. Singh, B. Singh, and M. P. Jain, "Comparative study on the performance of a commercially designed induction generator with induction motors operating as self excited induction generators," IEE Proc., Pt. C, Vol. 140, No. 5, pp. 374-380, Sept. 1993.

[11] T. F. Chan, "Analysis of self-excited induction generators using an iterative method," IEEE Trans. on Energy Conversion, Vol. 10, No. 3, pp. 502-507, Sept. 1995.

[12] P. Singh, S. K. Jain, and J. Sharma, "Voltage regulation optimization of compensated self-excited induction generator with dynamic load," IEEE Trans. on Energy Conversion, Vol. 19, No. 4, pp. 724-732, Dec. 2004.

[13] Yang, J.M., Chen, Y.P., Horng, J.T., Kao, C.Y" Applying Family Competition to Evolution Strategies for Constrained Optimization". Lecture Notes in Computer Science, Vol. 1213. Springer - Verlag, Berlin Heidelberg New York (1997) 201-211.

[14] Floudas, C.A., Pardalos, P.M." A Collection of Test Problems for Constrained Global Optimization Algorithms". Lecture Notes in Computer Science, Vol. 455. Springer - Verlag, Berlin Heidelberg New York (1987)

[15] S. M. Alghuwainem, "Performance analysis of a PV powered DC motor driving a three phase self excited induction generator", IEEE Trans., EC-11 (1) (1996), 155–161.

[16] L. A. Alolah and M. A. Alkanhal, "Optimization-based steady state analysis of three phase self-excited induction generator", IEEE Trans., EC-15 (1) (2000), 61–65.

[17] J. Kennedy and R. Eberhart, "Particle swarm optimization," Proc. IEEE Int. Conf. Neural Networks, Vol. IV, pp. 1942–1948, 1995.

[18] Joines, J.A., Houck, C.R." On the Use of Non-Stationary Penalty Functions to Solve Nonlinear Constrained Optimization Problems with GA's" Proc. IEEE Int. Conf. Evol. Comp. (1994), pp. 579-585.