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Original articles

Performance analysis of stand-alone six-phase induction generator using heuristic algorithms

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Abstract

The paper exhibits the performance analysis of six-phase self-excited induction generator for stand-alone wind energy generation system. The analysis is based essentially on solving the nonlinear equivalent circuit of the SP-SEIG, which is to find the per-unit frequency F and the magnetizing reactance X_m minimizing the determinant of the nodal admittance matrix Y instead of solving two non-linear equations with two unknowns. Hence, the equation-solving problem is converted to an optimization problem. The obtained minimum yields the adequate magnetizing reactance and frequency which will be used subsequently to compute the self-excitation process requirements in terms of the prime mover speed, the excitation capacitance and the load impedance on the one hand and to predict the generator steady state performance parameters on the other. In this work, the analysis is performed using three different global search algorithms, the genetic algorithm (GA), the particle swarm optimization (PSO) technique and the Taguchi optimization method (TM). A study of some simulation results is carried out using MatLab to compare between these three algorithms in terms of accuracy and guaranteed convergence in finding the minimum of the admittance.

Keywords: Six-phase induction generator; Optimization; Heuristic algorithms; Self-excitation; Wind energy

1. Introduction

As a result of depletion of the fossil fuel in generating electrical power from the conventional power plants, the increase in oil price, and the major interest in obtaining a clean environment, many efforts have been done to produce electrical energy from the renewable energy sources such as photovoltaic systems and wind energy conversion systems [2,12]. Vast amounts of such energy sources are available in remote areas leading to the intensive research and development of isolated power generators that exploits these various friendly environmental and low cost energy sources.

In these applications of wind energy conversion systems, the induction generators are the most commonly used as wind generators over the synchronous generators because of their merits including low cost, robust construction,

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Nomenclature

F	Unit frequency in p.u.
I_L	Load current.
I_m	Magnetizing current.
I_r	Rotor current.
I_s	Stator current.
P_{out}	Output power.
R_{L1}	Load resistance per phase connected to winding set abc.
R_{L2}	Load resistance per phase connected to winding set xyz.
R_r	Per phase rotor resistance referred to stator.
R_{s1}	Per phase stator resistance of winding set abc.
R_{s2}	Per phase stator resistance of winding set xyz.
SEIG	Self-excited induction generator.
SP-SEIG	Six-phase self-excited induction generator.
u	Rotor speed in p.u.
V_g	Air gap voltage.
V_{t1}	Stator terminal voltage per phase of winding set abc.
V_{t2}	Stator terminal voltage per phase of winding set xyz.
X_{c1}	Capacitive reactance connected to set abc.
X_{c2}	Capacitive reactance connected to set xyz.
X_{ls}	Mutual leakage reactance between two sets abc and xyz.
X_m	Per phase magnetizing reactance.
X_r	Per phase rotor leakage reactance referred to stator.
X_{s1}	Per phase stator leakage reactance of winding set abc.
X_{s2}	Per phase stator leakage reactance of winding set xyz.
Z_L	Load impedance.

free maintenance, and high reliability [3,9]. The only requirement for the induction generator, compared to the classical synchronous generator, is an external reactive power source in the form of a capacitor bank which is available for whatever required ratings.

When the induction generator is driven at required speed, the capacitor delivers the reactive current due to the residual magnetization flux and the stator voltage starts to build up. This interaction between the stator circuit and the capacitor bank is known as the self-excitation process. The principle of this process is well described in [18,27] and [23]. The stator voltage continues to build up until it intercepts with the capacitor load line. The value of the obtained stator voltage and the frequency cannot be determined in a straightforward manner since, they are very altered by the values of the equivalent circuit parameters such as the magnetizing characteristic, the rotor speed, the load and the excitation capacitance. Therefore the prediction of the output voltage and the frequency and the other performance characteristics of the induction generator becomes a difficult task. Hence, the analysis of steady state performances of the SEIG is important for ensuring adequate quality power and assessing the suitability of the configuration for a particular application. Six-phase self-excited induction generators SP-SEIG are particularly gaining more popularity among the multi-phase machines, as a result, many theoretical and practical works on the subject have been reported [34].

Over the past 25 years, many researchers have analyzed the steady state performance of the SEIG. The analysis relies on using the per-phase equivalent circuit of the machine, that is, either loop analysis [13,33] or nodal analysis [4,6,22] will be used to calculate these parameters. Both analytical techniques must go through the derivation of the mathematical equation of the impedance (or admittance) of the equivalent circuit and the segregation of this latter into two equations, one is real part and the other is the imaginary part. The next step consists in using an iterative technique for solving these equations for the two unknowns, magnetizing reactance

X_m and the output frequency F. The Newton–Raphson algorithm is usually used, however, the implementation of this algorithm requires the derivation of the gradient equations for both real and imaginary equations. To alleviate the computation process, the use of equations derived from the nodal analysis can be adopted [1,5]. In other words, an iterative algorithm is applied only to a single equation which is the real part of the admittance equation. This allows getting first the value of F which will be used in the imaginary equation to deduce the value of X_m. However, the two above mentioned approaches have two major drawbacks namely (1) the mandatory passage by the segregation of the impedance equation (or admittance) in real and imaginary parts and (2) the use of an iterative algorithm whose convergence depends on the selection of the initial guess.

Recently, there has been a trend to use the pre-programmed optimization algorithms that are available in the toolboxes of softwares dedicated to engineering computations such as MatLab. These routines can be used for minimizing the impedance (or admittance) without resorting to segregation into imaginary and real parts. The MatLab function "Constr" was used by Allolah and AlKanhal [1] in order to minimize the absolute value of the admittance and obtain optimal values of F and X_m to be used in analyzing the performance of the self-excited induction generator. The MatLab function "fsolve" was used by Haque [8] to minimize the impedance's absolute value and analyze the performance of the machine in various operating conditions, including operations under constant stator voltage or current constraints. The performance analysis principle using the equivalent circuit has been extended to six-phase induction machine by Singh et al. [31,32] where they have used "fmincon" to minimize the absolute value of the overall admittance. The aim was to look for the shunt and series capacitor values required for the self-excitation of the six-phase induction machine as well as regulation of the voltage at its terminals. These built-in functions have proven their effectiveness in minimizing impedance or admittance equations to obtain the optimal values of F and X_m without going through the long and tedious process of separating the equations of impedance or admittance. However, the implementation of these functions requires the use of an appropriate initial guess, which requires a minimum knowledge of the problem to be able to estimate it.

To overcome this, many researchers have proposed different techniques and evolutionary methods to solve the nonlinear equations [8,30], artificial neural network [14,29], genetic algorithm [15,24], particle swarm optimization algorithm [11], direct algorithm [18], artificial bee colony algorithm [26] and flower pollination algorithm [38] [16] that have been used for the performance analysis of SEIG. These techniques have proven their effectiveness in minimizing impedance or admittance equations to obtain the optimal values of F and X_m without going through the long and tedious process of separating the equations of impedance or admittance. However, the convergence of these algorithms requires an appropriate limitation of the search space since their convergence time depends on the width of this latter, the wider is the search space the longer time required to reach the optimal solution.

Among all the aforementioned algorithms, Genetic algorithm (GA) and Particle swarm optimization (PSO) algorithm have been popular in the steady state analysis of the self-excited induction generator mainly because of their ease of implementation and their effectiveness. This present work investigates the application of these two heuristic algorithms and a new optimization method which is Taguchi optimization method (TM) to evaluate the steady state performances of the SP-SEIG and compare between their effectiveness and efficiency based on the fitness achieved, the solution accuracy, the convergence speed and the number of iterations to achieve the minimum cost.

2. Problem formulation and mathematical modeling

Most of the steady state models of SP-SEIG developed by different researchers are based on its per phase equivalent circuit using two basic methods: (i) Loop impedance method and (ii) Nodal admittance method. The steady state model based on nodal admittance approach is presented here. During the analysis, the following assumptions are made:

- The core loss in the machine is neglected.
- All the machine parameters in the equivalent circuit are assumed to be constant except the magnetizing reactance which is assumed to be affected by the magnetic saturation.

For a detailed mathematical modeling during steady state analysis, a schematic block diagram and its per-phase per unit generalized equivalent circuit feeding resistive load, as shown in Fig. 1 and Fig. 2 respectively, are used for this purpose.

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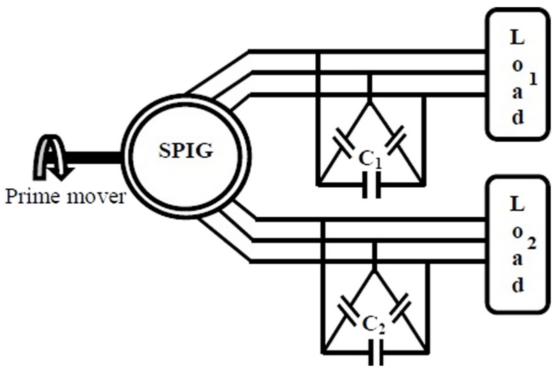

Fig. 1. Schematic diagram of the six-phase self-excited induction generator.

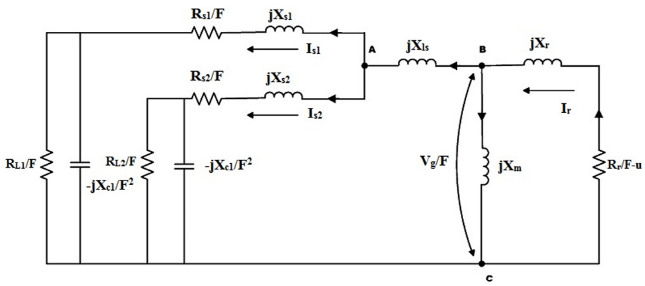

Fig. 2. Per-phase per-unit generalized equivalent circuit of SP-SEIG feeding a resistive load.

The analysis of self-excited induction generator performance characteristics consists in the computing of the output parameters of the generator, such as the stator voltage, output power, efficiency, for a given operating condition determined by the rotor speed, the load impedance and the excitation capacitance. Usually, the analysis starts by finding out the required conditions without which the self excitation process cannot take place. These conditions are quantified in terms of minimum rotor speed, minimum excitation capacitance and minimum load impedance.

Using nodal admittance method based on inspection, the matrix equation is derived from the equivalent circuit shown in Fig. 2 as follows:

$$[Y][V] = [I_s] \tag{1}$$

where,
$[Y]$ is the nodal admittance matrix (given in Eq. (2))
$[V]$ is the node voltage matrix
$[I_s]$ is the source current matrix

$$Y = \begin{bmatrix} Y_1 + Y_2 + Y_3 & -Y_3 & 0 & 0 \\ -Y_3 & Y_3 + Y_4 + Y_5 & -Y_5 & -Y_4 \\ 0 & -Y_5 & Y_5 + Y_8 + Y_9 & 0 \\ 0 & -Y_4 & 0 & Y_4 + Y_6 + Y_7 \end{bmatrix} \tag{2}$$

where

$$Y_1 = \frac{1}{R_r/(F-u) + jX_r} \qquad Y_2 = \frac{1}{jX_m} \qquad Y_3 = \frac{1}{jX_{ls}}$$

$$Y_4 = \frac{1}{R_{s1}/F + jX_{s2}} \qquad Y_5 = \frac{1}{R_{s1}/F + jX_{s1}} \qquad Y_6 = \frac{-jX_{c2}}{F^2}$$

$$Y_7 = \frac{1}{R_{L2}/F^2} \qquad Y_8 = \frac{1}{-jX_{c1}/F} \qquad Y_9 = \frac{1}{R_{L1}/F}$$

Since the circuit contains no current sources, therefore $[I_s] = 0$ and Eq. (1) reduces to Eq. (3).

$$[Y][V] = 0 \tag{3}$$

For a successful voltage build up, $[V] \neq 0$, and therefore from Eq. (3) $[Y]$ should be a singular matrix i.e.

$$\det[Y] = 0 \tag{4}$$

The analysis consists in solving Eq. (4) for F and X_m which will be used subsequently to determine the performance characteristics of the self-excited induction generator.

In classical analysis, solving Eq. (4) implies that both the real and imaginary components of $\det[Y]$ should be independently zero, which will result in two nonlinear equations with two unknowns. Then, iterative algorithm should be used to solve these two equations, this latter requires calculation of the Jacobian and an initial guess to start the iteration process.

In the optimization-based analysis, solving Eq. (4) is finding the minimum of the absolute value of the determinant of Y, which can be converted thereby into a multivariable nonlinear constrained optimization problem as described:

$$\min(\det[Y]) \tag{5}$$

subject to:
$0 \leq F \leq u$ (input rotor speed)
$0 \leq X_m \leq X_o$ (unsaturated value)

– The output frequency F must be less than or equal to the input rotor speed in pu.
– The magnetizing reactance X_m must be less than or equal to its unsaturated value X_o.

In this paper, genetic algorithm GA, particle swarm optimization technique PSO and Taguchi optimization method TM are used to solve Eq. (5) for F and X_m with three external parameters, speed, capacitance and varying load impedance. Once these two key parameters are identified, V_g/F can be evaluated using the magnetizing curve of the machine approximated by a polynomial Eq. (12) given in the Appendix. Knowing the value of V_g/F the performance of the generator (voltage, current, and power at various points of the circuit) can then be computed.

3. Overview of GA, PSO and TM

3.1. Genetic algorithm (GA)

The genetic algorithm GA is one of the basic population based evolutionary algorithms that simulates the evolution on a genotype level. This algorithm uses in its work three main operators: crossover, mutation, and selection [25].

The method simply relies on representation of the solution candidates by means of chromosomes, via which the relevant objective function is evaluated. The solution candidates constitute a population, which will be evolved throughout the generations. Performing these evaluations and considering the fitness of each solution candidate, it is decided which candidates deserve to survive and to be transferred to the next generation. Diversity is added by means of some operators such as crossover and mutation.

The genetic algorithm is implemented as follows:

1 **Initialization**: a population of N_{pop} individuals (chromosomes) is randomly generated within a search space, which is the space of all feasible solutions.
2 **Selection**: survival of the fittest translates into discarding the chromosomes with the highest cost, only the best are selected to continue, while the rest are deleted. The number of chromosomes that are kept each generation is

$$N_{keep} = X_{rate} \times N_{pop} \tag{6}$$

where X_{rate} is the selection rate.
3 **Pairing**: two chromosomes are selected from the mating pool of N_{keep} chromosomes to produce two new offspring. Pairing takes place in the mating population until $N_{pop} - N_{keep}$ offspring are born to replace the discarded chromosomes.

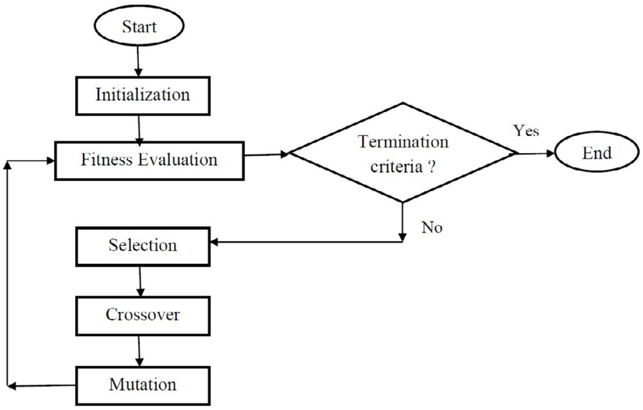

Fig. 3. Flowchart of GA.

4 **Crossover**: it is the process used to create one or more offspring from the selected parents; it is analogous to reproduction and biological crossover, upon which genetic algorithms are based.
5 **Mutation**: mutation is the second way a GA explores a cost surface. It can introduce traits not in the original population and keeps the GA from converging too fast before sampling the entire cost surface. Increasing the number of mutations tends to distract the algorithm from converging on a popular solution.
6 **Replacement**: after the initial population gets decimated, the surviving parents get selected to mate. Thus, new offspring are created through process of crossover. These new offspring replace the perished members of the initial population. Random mutation takes place, and alters some chromosomes (except the elite chromosomes). As a result of this process, a new generation is created.

All this methodology is summarized in the GA's flowchart given in Fig. 3.

3.2. Particle Swarm Optimization technique (PSO)

Particle swarm optimization PSO technique was first proposed by Kennedy and Eberhart in 1995 [17]. It aimed at the description of birds' behaviors by graphic method. Later on, it was developed as a general heuristic exploration technique, which performs effective exploration through memory and feedback. With the imitation of the behavior of bio-community, it enjoys a rapid calculation and a sound global exploration when applied in a large-scale optimization [7].

PSO shares many similarities with Genetic algorithms. The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. In PSO, each single solution is a "bird" in the search space, it is called "particle". All the particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two best values. The first one is the best solution the particle has achieved so far. This value is called p_{best}. Another best value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called g_{best}.

After finding the two best values, the particle updates its velocity and positions as follows:

$$v_{new} = v_{old} + c_1 r_1 (p_{best} - p_{old}) + c_2 r_2 (g_{best} - p_{old}) \tag{7}$$

$$p_{new} = p_{old} + v_{new} \tag{8}$$

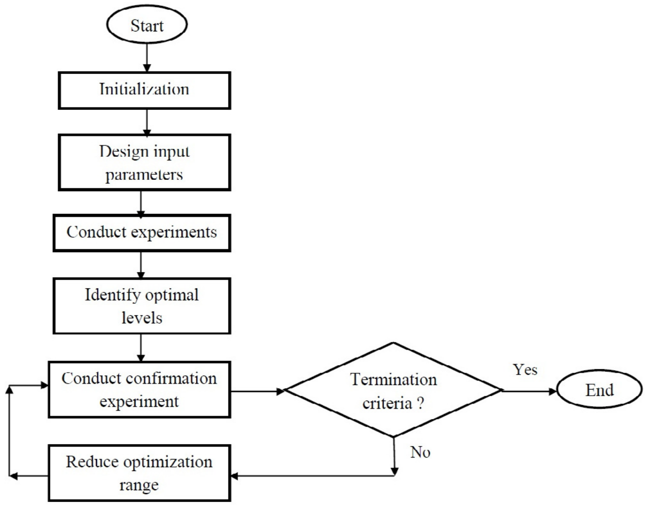

Fig. 4. Flowchart of PSO.

where,
v : particle velocity.
p : particle position.
r_1, r_2 : independent uniform random numbers.
c_1, c_2 : learning factors.
p_{best} : best local solution.
g_{best} : best global solution.

The PSO's flowchart is as given in Fig. 4 as follows.

3.3. Taguchi optimization method (TM)

Taguchi method was mainly introduced by Dr. G.Taguchi in 1985, he has introduced several new statistical tools and concepts of quality improvement that depend heavily on the statistical theory of design of experiments. These methods of design optimization developed by Taguchi are referred to as a "Taguchi optimization method". The Taguchi method provides a systematic and efficient approach for finding the near-optimum combination of design parameters such that the product is functional, exhibits a high level of performance, and is robust to noise factors [37], it has been applied successfully in various engineering problems [21,35]. The major tools used in the Taguchi method are signal to noise ratio *SNR* and orthogonal arrays *OA*. These tools are used to measure the quality of solution and to study many decision variables simultaneously.

3.3.1. Orthogonal Arrays (OA)

It is a method of setting up experiments according to the number of factors and their levels. The experiment combinations are chosen to provide sufficient and relevant information to determine the effects of each factor's level. By knowing the number of factors and their levels, one can use the available programmed codes to generate the suitable Orthogonal Array or directly grab the appropriate one from *OA* databases or libraries [36]. A matrix A of N rows and k columns with entries from S (S is a set of s symbols or levels) is said to be an *OA* with s levels and strength t $(0 \leq t \leq k)$ if in every $N \times t$ subarray of A, each *t-tuple* based on S appears exactly the same number of times as a row. The notation $OA(N, k, s, t)$ is used to represent an *OA*. To help understand the *OA* definition, Table 1 shows an orthogonal array $OA(9, 2, 3, 2)$, which has 9 rows and 4 columns. Each entry of the array is selected from a set $S = 1, 2, 3$, thus, this is a three level OA. Pick any arbitrary two columns $(t = 2)$ and one may see nine possible combinations as a row: $(1, 1), (1, 2), (1, 3), (2, 1), (2, 2), (2, 3), (3, 1), (3, 2), (3, 3)$. It can be simply verified that each combination has the same number of occurrences as a row, i.e. three times. This is the meaning of *orthogonal* in the definition, which ensures a balanced and fair selection of parameters in all possible combinations [10,20].

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Table 1
Orthogonal array $OA(9, 2, 3, 2)$.

	Elements			
Experiments	1	2	3	4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

3.3.2. Signal to Noise Ratio (SNR)

The procedure after the experimental runs is analyzing data and identifying the optimal levels for all the parameters. This analysis starts by computing the tendency of the fitness function for each factor using what is called signal to noise ratio. Three different signal to noise ratios are mostly used in optimization [19], which are: nominal-the-best, larger-the-better and smaller-the-better. Following the purpose of optimization, one can choose the appropriate ratio. In this paper, the objective is to minimize the determinant's absolute value of the total admittance matrix Y, the smaller-the-better ratio seems to be more appropriate and it is given as:

$$\eta = -10\log_{10}(|\bar{Y}|) \tag{9}$$

The higher the SNR the smaller the cost function's value will be. The obtained results allow constructing a response table by determining the average *SNR* for each factor and each level.

A fundamental implementation procedure of the Taguchi optimization method is given as follows:

1 **Initialization**: the optimization procedure starts with the problem initialization, which includes the selection of a proper *OA* and the design of a suitable fitness function. The selection of an $OA(N, k, s, t)$ mainly depends on the number of optimization parameters.

2 **Design input parameters using *OA***: the input parameters are selected to conduct the experiments. When the *OA* is used, the corresponding numerical values for the levels of each input parameter should be determined. In the first iteration, the value for a certain level is selected at the center of the optimization range. Values of the remaining levels are calculated by subtracting/adding the value of the selected level with a variable called level difference (LD). The level difference in the first iteration (LD_1) is determined by the following equation:

$$LD_1 = \frac{max - min}{\text{number of levels} + 1} \tag{10}$$

Where max is the upper bound of the optimization range and min is the lower bound of the optimization range. Thus, the three levels are uniformly distributed in the optimization region.

3 **Conduct experiments and build a response table**: after determining the input parameters, the fitness function for each experiment can be calculated. These results are then used to build a response table for the first iteration and so on.

4 **Identify optimal level values and conduct confirmation experiment**: finding the largest fitness value in each column of the response table can identify the optimal level for that parameter. When the optimal levels are identified, a confirmation experiment is performed using the combination of the optimal levels identified in the response table. This confirmation test is not repetitious because the OA-based experiment is a fractional factorial experiment, and the optimal combination may not be included. The fitness value obtained from the optimal combination is regarded as the fitness value of the current iteration.

5 **Conduct experiments and build a response table**: after determining the input parameters, the fitness function for each experiment can be calculated. These results are then used to build a response table for the first iteration and so on.

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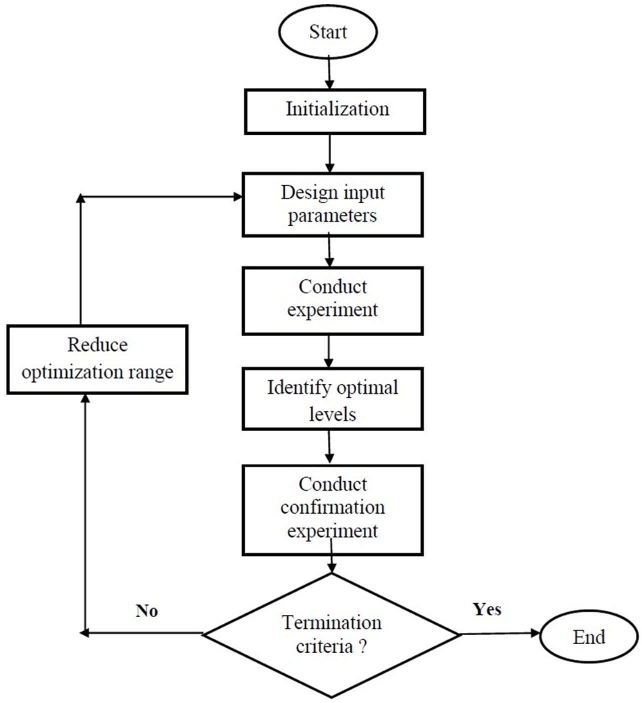

Fig. 5. Flowchart of TM.

6 **Updating level values**: if the results of the current iteration do not meet the termination criteria, the optimal level values of the current iteration are used as central values for the next iteration. To reduce the optimization range for a converged result, the LD_i is multiplied with a reduced rate to obtain LD_{i+1} for the $(i+1)th$ iteration.

7 **Check the termination criteria**: when the number of iterations is large, the level difference of each element becomes smaller. Hence, the level values are close to each other and the fitness value of the next iteration is close to the fitness value of the current iteration. The following equation may be used as a termination criterion for the optimization procedure:

$$\frac{LD_i}{LD_1} \leq \text{converged value}$$

The steps of the Taguchi method are summarized in the flowchart depicted in Fig. 5.

4. Steady state analysis of SP-SEIG using GA, PSO and TM

Usually, the analysis starts by finding out the required conditions without which self excitation process cannot take place. These conditions are quantified in terms of minimum rotor speed, minimum excitation capacitance and minimum load impedance. If the minimum capacitance required for self-excitation process is sought X_c and F are chosen as unknown variables. If the objective is to compute the induction generator steady state performances, X_m and F are used as independent variables. In the optimization process, the variables X_m and F or X_c and F are allowed to vary only within their upper and lower limits so as to let the cost function achieve its minimum value.

The flowchart in Fig. 6 gives the computing procedure to determine the generator performances.

The computing procedure depicted in Fig. 6 is summarized as follows:

1 Define all the constants of the induction generator equivalent circuit.
2 Set the value of the speed and the capacitance. Limit the search space for the unknowns X_m and F.
3 Within a loop, call the procedures GA, PSO or TM which will minimize the determinant of the total admittance matrix Y to determine X_m and F. The number of iterations is limited by the load impedance variation, Z_L.

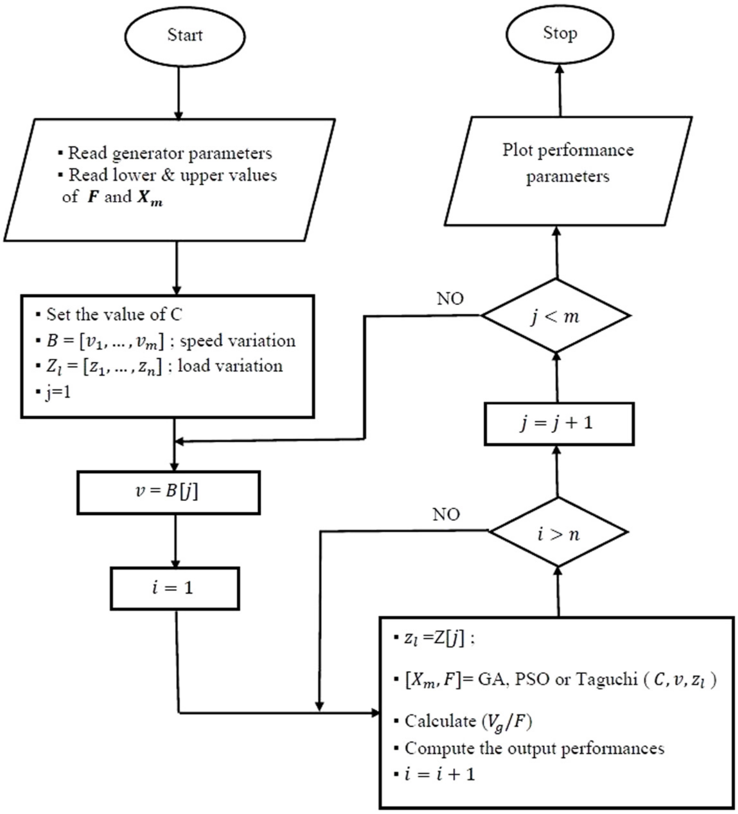

Fig. 6. Procedure of SEIG performance analysis using GA, PSO or TM.

4 Once X_m and F are known for each value of Z_L, deduce the corresponding Vg/F according to the magnetizing curve using Eq. (12).
5 Calculate the corresponding output performances such as, stator current, load voltage and output power for each value of load impedance.
6 Repeat steps (2)–(5) for other values of prime mover speed.

4.1. Selection of simple shunt capacitance

The flowchart depicted in Fig. 6 is applied to determine the required values of the excitation capacitance to ensure self-excitation, i.e. a voltage appearing across the load connected to the generator terminals.

Based on the per phase equivalent circuit of SP-SEIG, two modes of excitation will be investigated: (a) excitation capacitor connected across one single three-phase winding set, and (b) excitation capacitor bank connected across both the three-phase winding sets. The minimum value for self excitation is taken as the value corresponding to rated terminal voltage of $1.0pu$ at rated speed of $1.0pu$. The curves showing the variation of no load terminal voltage for different values of excitation capacitance and speed are plotted using MatLab.

4.1.1. Capacitor bank connected across one single winding set 'abc'

Fig. 7 shows the variation of no load terminal voltage V_t for different values of excitation capacitance C_e. It is found that the allowable capacitor value corresponding to the no load terminal voltage of $1.0pu$ is 70 µF at synchronous speed using the three algorithms.

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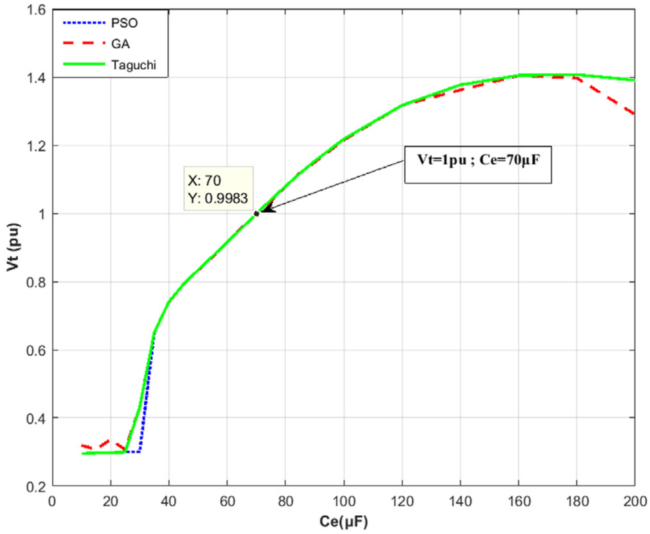

Fig. 7. Variation of terminal voltage with excitation capacitance when capacitor bank is connected to winding set *abc* at no load.

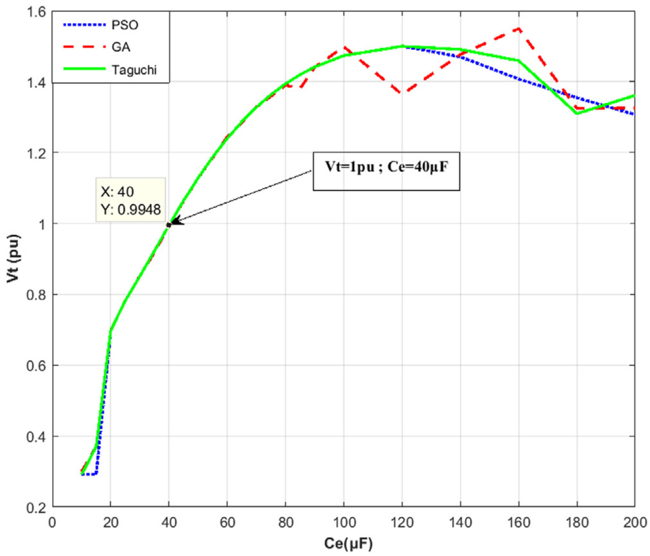

Fig. 8. Variation of terminal voltage with excitation capacitance when capacitor bank is connected to both winding sets '*abc*' and '*xyz*' at no load.

4.1.2. Capacitor bank connected across both winding sets 'abc' and 'xyz'

Variation of no load terminal voltage V_t with excitation capacitance value when excitation capacitor bank is connected across both the three-phase winding sets '*abc*' and '*xyz*' is given in Fig. 8. In this case, the allowable capacitor value is 40 μF for which the terminal voltage and speed are approximately equal to rated value of $1.0pu$.

4.2. Performance analysis

Once the required values of excitation capacitance are determined, the induction generator performance parameters are computed by obtaining first the values of F and X_m. Using these values and the saturation characteristic given by Eq. (12) and Fig. 18 of the machine under study (see Appendix), the values of the magnetizing voltage

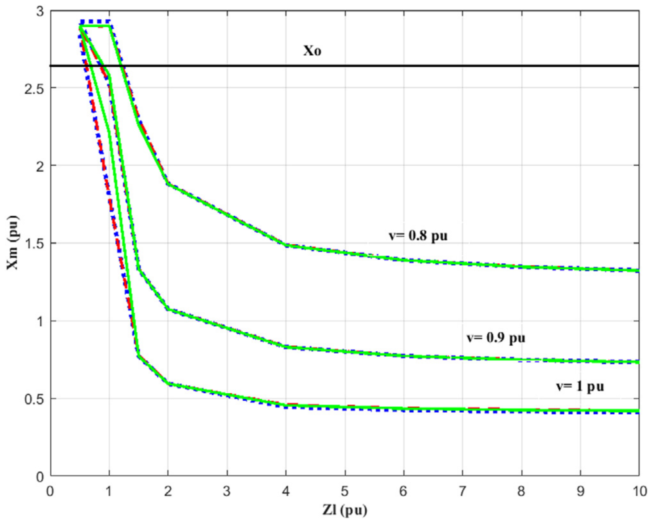

Fig. 9. Magnetizing reactance X_m versus load for different speeds and $C_{e1} = C_{e2} = 45$ µF.

V_g are computed. Finally the performance of the generator (voltage, current, and power at various points of the circuit) can be determined.

In order to assess the accuracy of the optimization algorithms GA, PSO and TM in solving the SEIG analysis; the input parameters altering both self-excitation process and output parameters of self-excited induction generator are varied. That is, the optimizer should give the adequate values of F and X_m (global optimum solution) to be used in the computation of the performance parameters. To this, two loops are run at the same time in which the external one is the rotor speed or the excitation capacitance loop while the inner loop concerns the load impedance variation. For each combination of the three external values rotor speed, excitation capacitance and load impedance, the three algorithms are called to solve Eq. (5) for F and X_m. Computation of F and X_m with high accuracy is of great importance as the calculation of all the performance parameters depends on these two key values.

4.2.1. Variation of rotor speed and load impedance

The first analysis concerns the variation of the rotor speed of the self-excited induction generator that is also the wind turbine speed times the gearbox ratio. The procedure of the analysis is as follows: the value of the excitation capacitance at both windings '*abc*' and '*xyz*' is maintained constant $C_{e1} = C_{e2} = 45$ µF while the rotor speed is varied within a given range. For each speed value, the impedance of the load to which the machine delivers power varies from a minimum value to a value that makes machine unloaded, the variation of performance parameters is recorded. Fig. 9 and Fig. 10 show respectively the variation of X_m and F for different values of load and speed using the three optimization algorithms. Fig. 11 depicts the variation of terminal voltage with respect to real power variation for different speeds.

As it can be seen from the results shown in Figs. 9 and 10, the induction generator cannot operate when the magnetizing reactance provided by the three algorithms is greater than the unsaturated value X_o. From Fig. 9, when the rotor speed is $v = 1\,pu$ and the load impedance Z_L is less than $1\,pu$, the magnetizing reactance is greater than X_o which results in failure of self-excitation. The points in the graph of X_m which are located in the curve's bended region defines the unstable region for the generator's operation. In Fig. 11, the unstable region is illustrated by the part of the graph where it has positive slope, since at normal operation it has a negative slope (the terminal voltage collapses as the generated active power increases).

4.2.2. Variation of excitation capacitance and load impedance

By setting now the speed to $v = 1.0\,pu$ and varying the values of the excitation capacitance in the same manner as in the rotor speed. The results in terms of X_m and F provided by the three optimization algorithms are shown in Fig. 12 and Fig. 13 respectively.

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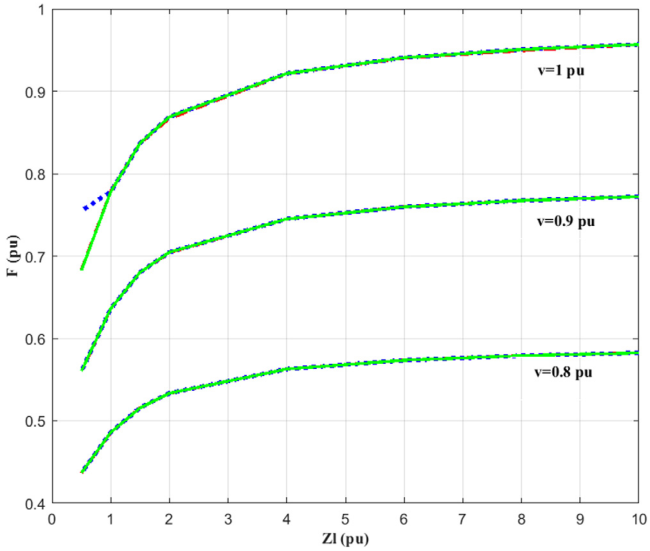

Fig. 10. Frequency F versus load for different speeds and $C_{e1} = C_{e2} = 45$ μF.

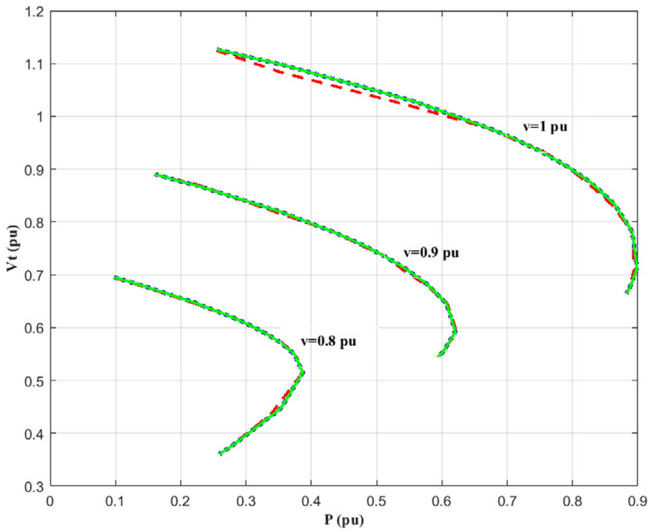

Fig. 11. Terminal voltage versus real power for different speeds and $C_{e1} = C_{e2} = 45$ μF.

By comparing the results depicted in Figs. 9 and 12, one can notice that the output frequency depends strongly on the prime mover speed but is less sensitive to the value of excitation capacitance. Whereas, from the results depicted in Fig. 14 it can be seen that increasing the capacitance value enlarges the normal operating region and increases the power delivering capability of the induction generator; yet, the generator will always have a maximum power which is the point where the graph bends.

4.2.3. Effects of power factor

A lower power factor is equivalent to a higher share of inductive loads. Fig. 15 shows the relation between the terminal voltage and the power output for different power factors of the total load connected. Fig. 16 shows the frequency variations for the same scenarios.

From these figures, it can be seen that the voltage and frequency collapse occurs at lower voltage levels for lower power factor. A higher share of inductive loads thus gives a smaller range of operation before collapse. This

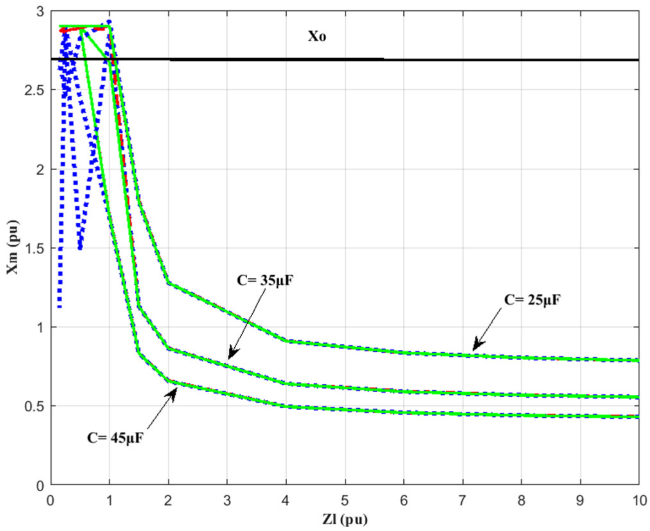

Fig. 12. Magnetizing reactance X_m versus load for different capacitance and $v = 1.0pu$.

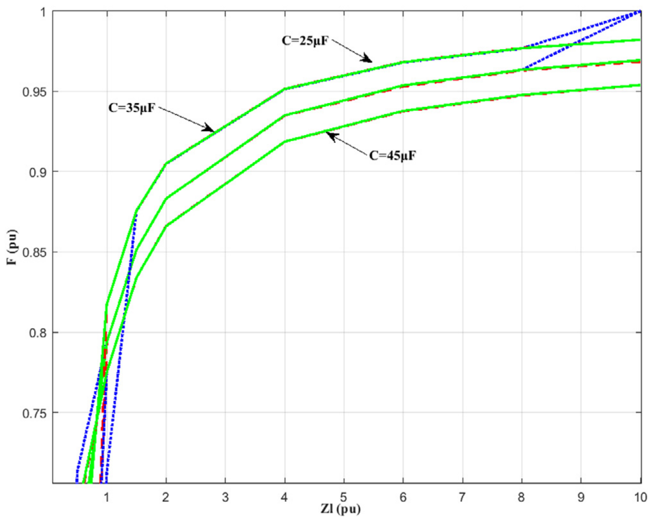

Fig. 13. Frequency F versus load for different capacitance and $v = 1.0pu$.

is due to the fact that, if an inductive load is connected to the generator, it will consume reactive power which means that some of the current from the capacitors will go to the load instead of the generator. This will reduce the reactive power supply to the generator, and the generator voltage will drop. An inductive load is influencing the total capacitance by decreasing the effective value. This is shown in Eq. (11), where the parallel connection of the excitation capacitor bank and the inductive load is represented as a new and reduced actual capacitance value. A reduction of C_{eff} will result in the reduction of the induction generators terminal voltage. If the resulting C_{eff} becomes smaller than the defined C_{min} for the system, the voltage will collapse.

$$C_{eff} = C_e - \frac{L}{{R_L}^2 + (\omega_n L)^2} \tag{11}$$

where R_L is the resistance corresponding to the resistive load and L is the inductance of the inductive load.

The voltage drop caused by the inductive loads will cause an increase in speed, due to the fact that a reduction in voltage causes a reduction in the active power consumed by the loads. Hence, the power balance is disturbed,

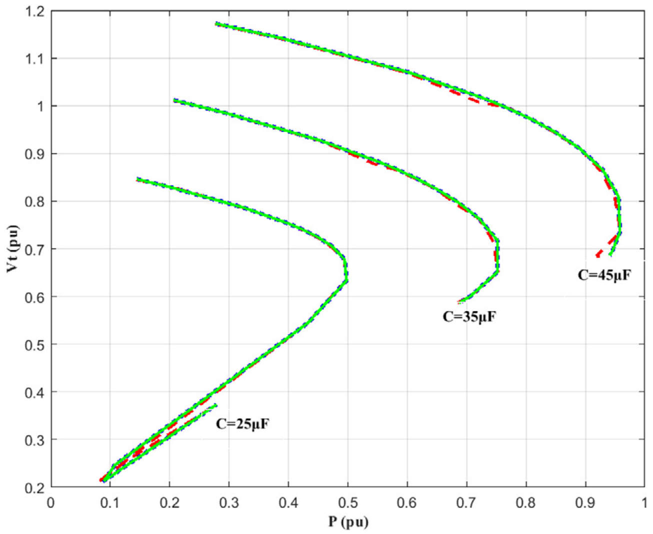

Fig. 14. Output voltage versus real power for different capacitance and $v = 1.0pu$.

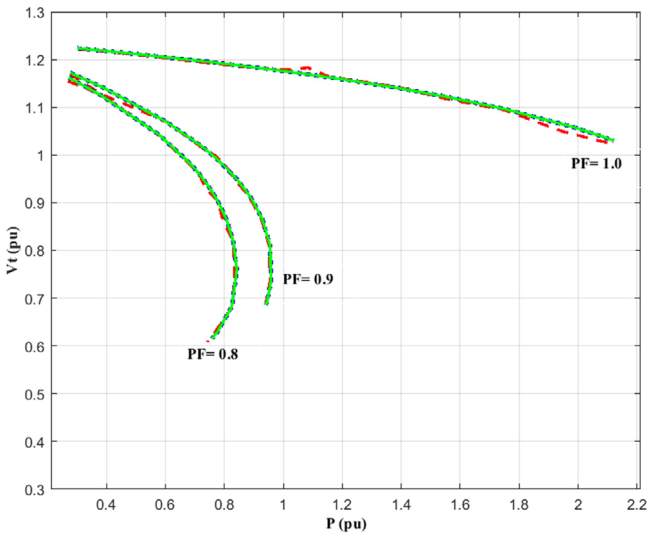

Fig. 15. Terminal voltage variation for different load power factors as a function of active power output.

and the speed increases. The increase in speed will increase the voltage, and the speed will increase until a level where power balance between the power consumed by the loads and the power delivered by the turbine is reached again. Hence, the inductive loads will also influence the frequency in the system as it is shown in Fig. 16.

5. Comparative analysis between GA, PSO and TM

To assess the performances of GA, PSO and TM in the analysis of the SEIG's steady state analysis, the three algorithms have been run on the same computer to minimize the determinant of the total admittance matrix. The various parameters used in the three different algorithms are given in Table 3 in the Appendix.

The comparison is made based on three aspects given as:

– The number of iterations the algorithm takes to achieve the minimum fitness value;
– Swiftness or the time the algorithm takes to finish the process;
– The minimum fitness value achieved.

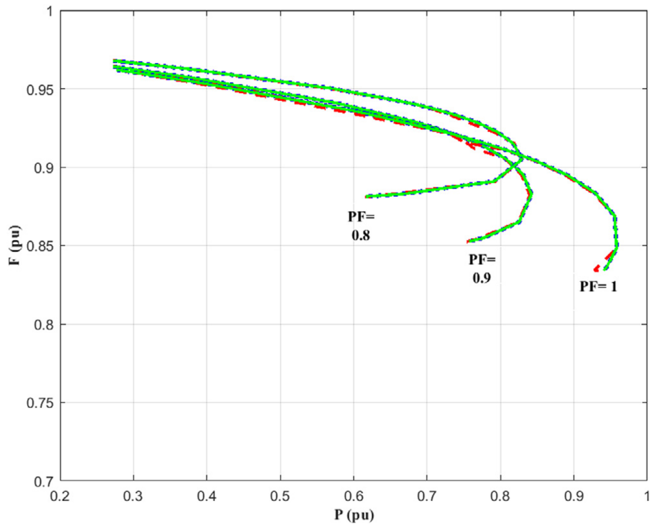

Fig. 16. Frequency variation for different load power factors as a function of active power output.

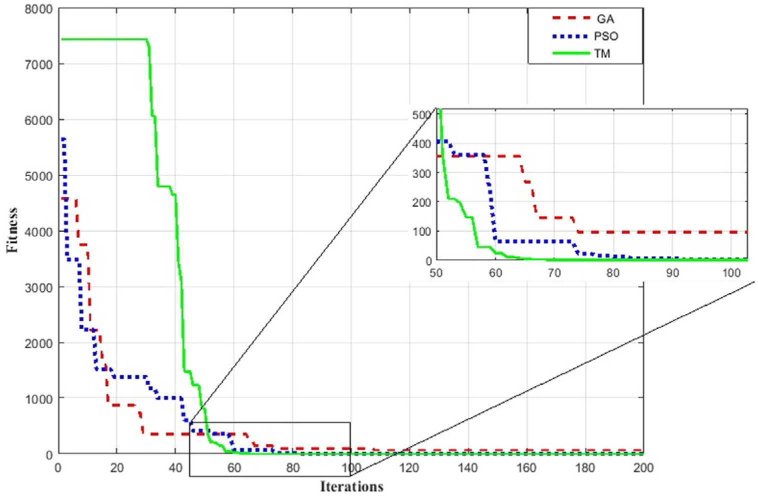

Fig. 17. Variation of fitness value versus number of iterations using GA, PSO and TM.

Table 2
Comparison of GA, PSO and TM.

Algorithm	$F(pu)$	$X_m(pu)$	Accuracy	Elapsed time (s)	Iterations
GA	0.9752	1.7941	1.0421×10^{-8}	1.5255	115
PSO	0.9752	1.7917	2.3838×10^{-11}	1.0417	95
TM	0.9752	1.7917	1.8501×10^{-11}	0.1803	65

Fig. 17 depicts the variation of fitness value versus the number of iterations to solve the objective function for F and X_m using the three algorithms.

From Fig. 17 we get the following table which summarizes some of the comparative parameters used in this analysis.

Table 2 indicates that the three algorithms lead the same solution for F and X_m, however from Fig. 17 it can be noticed that they converged with different accuracies and at different number of iterations. TM reaches minimum

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cost of 1.8501×10^{-11} at 65 iterations, while PSO reaches minimum cost of 2.3838×10^{-11} at 95 iterations. GA gets to a minimum cost of 1.0421×10^{-8} later at 115 iterations.

For the second aspects, Table 2 shows that the time taken by GA to cycle through all the 300 iterations is the longer, with 1.5255 s. PSO comes after with 1.0417 s. TM holds the record for the minimum time required, with only 0.1803 s, which is 555% faster than PSO and 844% faster than GA.

6. Conclusion

In this paper, genetic algorithm GA, particle swarm optimization technique PSO and Taguchi optimization method TM are used to evaluate the performance characteristic of SP-SEIG as optimization problem, instead of step by step analytical derivation of several equations as with the previous iterative techniques. The optimization goal is based mainly on minimizing the determinant of the nodal admittance matrix derived from the steady state equivalent circuit of the induction generator in order to obtain the two unknowns F and X_m, by which the other performance parameters can be computed. The solution is very sensitive to the input parameters of the wind driven self-excited induction generator in a way that their variations require an adequate choice of the initial guess for iterative and local search optimization techniques. This difficulty is eliminated by the proposed global optimization algorithms, namely GA, PSO and TM which are powerful and efficient algorithms that can solve the SEIG analysis problem without the need to carry out the tedious task of segregation the determinant of the total admittance matrix to its real and imaginary parts and the computation of the gradient matrix, and no prior knowledge of the initial guess is required. From the comparative study between these three algorithms, it is worth noting that PSO and TM yield on average the same effectiveness (solution quality) but TM was fastest to execute and to converge, since PSO took a big longer time to execute compared to TM. On the other hand, GA showed to be the slowest with the biggest minimum cost comparing to PSO and TM. Whereas, there some other remarks are made during the execution of these algorithms for different case studies of the induction generator: GA was more robust, and more stable, converging to the global minimum every time without significant tuning of its parameters, PSO in the other hand, is more prone to premature convergence, and tends to misbehave if the social and cognitive parameters are not set right, and thus many trials are required to get good results. The only inconvenient found concerning the TM algorithm is its difficulty to find the solution when it is close to the lower or upper boundaries which in our case, the solution for frequency are very close to the upper boundary, as a result, the algorithm kept getting stuck to other local solutions but the problem is overcome by increasing the initial level difference. It appears that TM outperforms GA and PSO in the SP-SEIG analysis problem considering its high accuracy and small convergence time besides its ease of implementation based on simple instructions and arithmetic operations.

Appendix

This appendix section provides the parameters of the model of the induction machine used for simulation in this paper.

The rating of the induction machine and its parameters given in pu are taken from [28] and given below:

- rated power: 696 W;
- rated and base voltage V_b: 240 V;
- rated and base phase current I_b: 2.9 A;
- rated frequency F_b: 50 Hz;
- rated speed N: $960 rpm$;
- base impedance $Z_b(Vb/Ib)$: 82.75.

The equivalent circuit parameters of the induction machine are given in pu as follows:

- $R_{s1} = R_{s2} = 0.05385$;
- $X_{s1} = X_{s2} = 0.0885$;
- $R_r = 0.11475$;
- $X_r = 0.1775$;
- $X_{lS} = 0.00973$;
- $X_o = 2.93$.

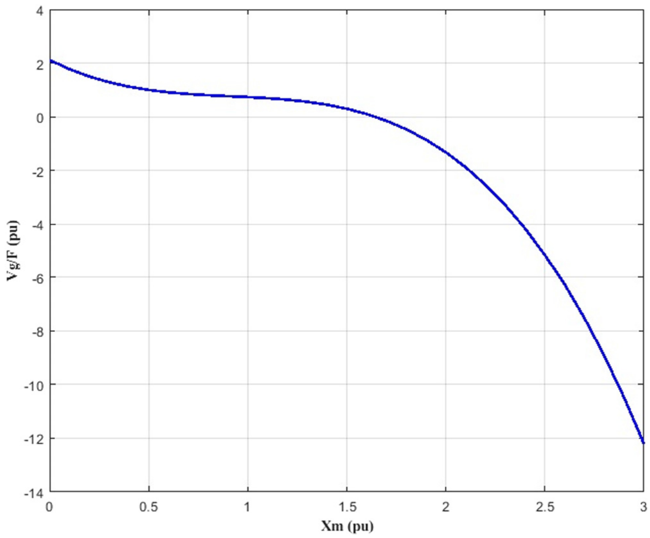

Fig. 18. Variation of air gap voltage with magnetizing reactance.

Table 3
Configuration parameters for GA, PSO and TM.

Algorithm	Parameters
GA	Population size = 80 Population kept = 50% Mutation rate = 40% Crossover type: single point Selection type: roulette wheel by rank
PSO	Population size = 80 Cognitive parameter = 2.5 Social parameter = 1.5
TM	Reduced function = 0.8 Orthogonal array OA = (9, 3, 3, 2)

As for the magnetizing characteristic, it is approximated by the following 3rd order polynomial equation [28]:

$$\frac{V_g}{F} = -1.358X_m^3 + 3.735X_m^2 - 3.757X_m + 2.113. \tag{12}$$

Fig. 18 and Table 3 provide, respectively, the variation of air gap voltage with magnetizing reactance, and the configuration parameters for the three algorithms GA, PSO, and TM.

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