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Application of a hybrid evolutionary technique for efficiency determination of a submersible induction motor

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Abstract

Electric motors are the largest consumers of electricity in plants and induction motors constitute nearly two-thirds of them. The replacement of in-service induction motors with more efficient ones is a very important strategy for energy savings and consequently nearly 30 different methods have been used to determine the efficiency of induction motors in the last 2 decades. This paper aims to develop the efficiency determination of a 20 Hp submersible induction motor. Due to getting perfect efficiency of the submersible induction motor, a robust hybrid evolutionary optimization technique, which consists of a genetic algorithm and simulated annealing, is used. The obtained results are compared with genetic algorithm and torque gauge result values and dramatically significant results of our proposed algorithm are observed.

Key Words: *Submersible induction motor, efficiency determination, hybrid evolutionary method*

1. Introduction

The phenomenon of emphasis on energy savings has increased rapidly in the last 2 decades. Nowadays, about 60% or more of the total electricity is used by electric motors including induction motors (IMs), which constitute the majority of the electric motors. Therefore, replacing in-service IMs with more efficient ones has significant effects on energy savings [1].

Studies of energy savings have encouraged researchers to investigate efficiency determination of IMs for many years, so nearly 30 methods with different features, (e.g., accuracy, simplicity, safety, low price, and practicality) have been used to determine IM efficiency [2], [5]. The mentioned studies may briefly be classified into 6 groups according to their striking features:

- Direct efficiency method, namely measuring the ratio of output torque of IMs to input torque by dynamometer, is the most accurate. However, it is very expensive, complex, and not practical in field studies.

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- Another method that needs the computed average air-gap torque and power values is the air-gap torque method. To calculate the air-gap torque and the power of an IM, the values of the IM's instant input line voltage and currents are required and subsequently the stray load, friction, and windage losses are calculated. Due to the necessity of a no-load test, this method is not useful to determine IM efficiency in an industrial plant.

- Using the slip method for efficiency determination is very simple. According to this method, the efficiency of an IM is determined by calculating the output power of the working motor in the different slip values. However, error values of slip method are high, around 20%.

- The motor current method uses the value of the IM current for calculating the efficiency, but the relationship between the current and the output power of an IM is not linear for a wide range of loads. Hence, this method has low accuracy.

- Efficiency determination of an IM using the segregated loss method is known as the E method in IEEE 112 [4], so it should, in principle, give more accurate results. However, the segregated loss method is not a suitable field test method of efficiency since it includes removing the rotor or reverse-rotation tests for direct measurement of stray load losses.

- The equivalent circuit method, which requires a no-load test and a locked-rotor test of an IM, is similar to the F method in IEEE 112. In addition to the difficulty of in-situ field-testing, this method is not safe and requires expert staff to administer it. However, the equivalent circuit method has been carried out in order to inspire the researchers for the efficiency determination of IM by stochastic methods [8], [9].

All in all, because many of the latest empirical methods of efficiency calculation require a no-load test, which is not possible during in-situ determination, evaluation of IM efficiency often depends on the motor's nameplate or on manufacturer's data. Therefore, beyond these traditional methods, the above-mentioned different evolutionary optimization methods have been used for efficiency determination of in-service IMs [7], [11], [16]. The techniques with flexible structure employed to determine the IMs efficiency are based on randomness and natural selection.

For efficiency determination of in-situ IMs, Pillay et al. [11] suggested the use of a genetic algorithm (GA), which may be the most familiar evolutionary optimization method. In the mentioned study, 2 methods with stator current, input power, power factor, and nameplate output power as the input parameters were used to estimate the motor efficiency. The objective function's effect on accuracy of efficiency determination was strictly observed, and the accuracy of the method was based on a single load point at a period. Since then, either genetic algorithms or other optimization studies have been used in the determination of IM efficiency [9], [10]. Even though GA is the most popular and applicable optimization method, it has disadvantages like easily falling into a trap and hence, GA could be improved by inserting another evolutionary technique [13]. In this optimization study, a hybrid evolutionary technique, combining GA and simulated annealing (SA) methods, is used to determine the efficiency of a submersible IM.

The use of submersible IMs has increased quickly and also the amount of energy consumed by submersible IMs has accelerated, due to global warming and particularly dryness levels in the field. Therefore, replacement of working submersible IMs with more efficient ones provides considerable energy savings and demand side management as for the other IMs in industrial plants.

The traditional determination techniques of IM efficiency, namely, using the manufacturer's data or the motor's nameplate, cannot be carried out on an in-service submersible induction motor because of great errors [1], [6]. This paper aims to introduce a hybrid evolutionary optimization technique for the determination of submersible IM efficiency. The proposed technique is composed of both GA and SA optimization procedures.

2. Genetic algorithm

A genetic algorithm consisting of chromosomes (strings) is a powerful stochastic and evolutionary optimization technique [3]. GA does not require knowledge of initial estimates and does not use derivative functions, unlike numerical methods. Furthermore, each string of a GA is one of the solutions of the optimization problems; in other words, GA is a global search method for system determination. Each string in a genetic algorithm is coded binary codes and real codes. A conventional GA consists of 3 operators: reproduction, crossover, and mutation.

Reproduction, the first GA operator, is a process in which every string is selected to produce a new generation. Each string's fitness value is calculated by objective functions accordingly and then the individuals with high fitness value are sorted by a selection criterion into a mating pool. At this stage, the assigned objective functions and the selection criterion influence the robustness and performance of the genetic algorithm.

The crossover operator is used in every iteration. Chosen parents from the mating pool are intercrossed such that all digits of the 1st string and 2nd string are swapped by means of a random point or points. Two new strings are thus reproduced from the parents. The last operator of GA is mutation. It protects the population against the loss of useful genetic information, but excessive use of the mutation operator decreases the GA's convergence speed. The operator works by selecting one bit location in a string and randomly changing the bit from a 1 to a 0 or vice versa.

3. Simulated annealing

Simulated annealing was developed from the simulation of thermal annealing of critically heated solids to deal with highly nonlinear problems. A slow and controlled cooling of a heated solid ensures proper solidification with a highly ordered crystalline state that corresponds to the lowest internal energy. The SA method approaches the global solutions similarly to GA [14].

The SA method is based on comparison of 2 neighbouring strings according to fitness values. First of all, a high temperature (T) and 1 string are randomly selected. Then a 2nd string is selected in the vicinity of the initial string and the difference in the function values (ΔE) is calculated. If the 2nd point has a smaller function value, the point is accepted; otherwise, the point is accepted with a probability $\exp\left(-\Delta E/T\right)$. This process completes the only iteration of the SA procedure.

In the next generation, another point is created randomly in the neighbourhood of the current point and the metropolis algorithm is used to accept or reject the point. That is, the probability of the next point being a minimum value depends on the difference in function values at these 2 points, or on $\Delta E = E\left(t+1\right) - E\left(t\right)$, and is calculated using the Boltzmann probability distribution, $P\left(E\left(t+1\right)\right) = \min\left[1, \exp\left(-\Delta E/kT\right)\right]$.

4. The process of efficiency determination of submersible IMs

The proposed hybrid method, which consists of GA and SA, enables avoidance of no-load measurements while keeping the high accuracy of the IEEE E1 and F1 methods as well as GA [1]. All of these methods include the basic ideas of the loss segregation method and the equivalent circuit method, and so the procedure of measurements is the same as in the segregated loss method. To obtain input parameters and objective functions of the methods, some tests were made as follows [11].

Stator line resistance is measured after shutting down the motor. For a star-connected submersible IM,

$$r_1 = 0.5 \times r_{1line} \tag{1}$$

where r_{1line} is the stator line resistance and r_1 is the stator phase resistance.

$$power\ factor\ (pf) = \frac{P_{in}}{\sqrt{3}V_1 I_1} \tag{2}$$

where V_1 is the stator voltage, I_1 is the stator current, P_{in} is the input power and the speed at different load points are taken simultaneously.

Stray load loss affects the determination of IM efficiency, and so 2 different equivalent circuits of the submersible IM including stray load losses have been used for comparison purposes (Figures 1a and 1b).

$$r'_m = \frac{r_m x_m^2}{r_m^2 + x_m^2} \text{ and } x'_m = \frac{r_m^2 x_m}{r_m^2 + x_m^2} \tag{3}$$

where, in Figures 1a and Figure 1b, x_m and x'_m represent mutual reactance while r_m and r'_m represents equivalent resistance. The parallel connections of r_m and x_m are transformed into a series connection for making scalar compatibility of r_m and x_m parameters with the other parameters of equivalent circuits in the hybrid method. In addition, resistances r_2, $r_2(1-s)/s$, and r_{st} represent the rotor phase resistance, the output power of the motor, and the stray load loss respectively. The stray load loss related to the square of the rotor current can be symbolized as a resistance in the rotor branch of the equivalent circuits.

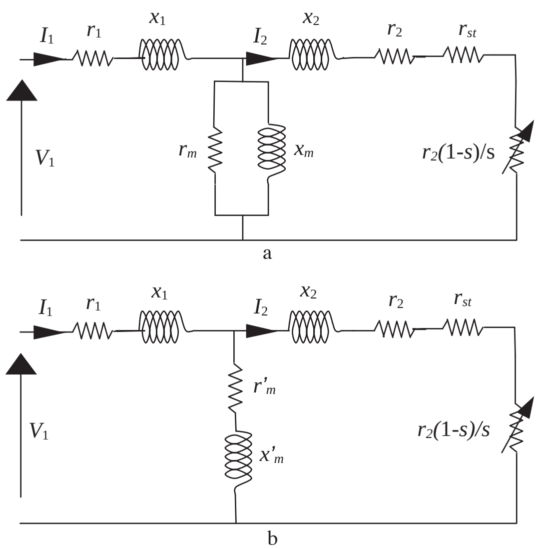

Figure 1. Equivalent circuits of a submersible IM.

According to the calculation procedure for stray load loss, the loss under full load can be approximated to 1.8% of the output power for a 1-90 kW rated induction motor and, moreover, the stray load loss at any load point should be calculated as follows [4]:

$$P_{st} = P_{stfl} I_2^2 / I_{2fl}^2 \tag{4}$$

where P_{st} and P_{stfl} are stray load losses at any load point and at full load, respectively. I_2 and I_{2fl} are the corresponding rotor phase currents. Hence, the resistance of stray load loss should be equal to $r_{st} = 0.18 \times r_2(1 - s_{fl})/s_{fl}$ where s_{fl} is slip of the motor under full load.

All variables relating to equivalent circuits are estimated but only the stator resistance is calculated from the stator resistance test. For the sample submersible motor, the ratio between stator and rotor reactance is assumed to be 0.67 because x_1/x_2 is 0.67 for the design B motors [4]. Therefore, the remaining variables in the parallel or series equivalent circuits, viz., x_1, r_2, x_m (or x'_m), and r_m (or r'_m) are to be determined.

The stator and rotor winding temperatures of working submersible IMs are accepted to be the same value and calculated by using the following formula for any load currents and data of the motors at different loads as shown in Table 1.

$$T_t = \left(\frac{I_1 - I_0}{I_{fl} - I_0} \right) \times (T_r - T_s) + T_s \tag{5}$$

where I_1, I_{fl}, and I_0 are the measured stator current, nameplate stator current, and stator current under a no-load dc test respectively. $T_r = 55°C$ is the assumed reference temperature in underground water, and $T_s = 25°C$ is the ambient temperature. The stator and rotor resistances are verified to the test temperature conditions in the following way:

$$r_{1c} = r_1 \frac{T_t + K_c}{T_s + K_c} \text{ and } r_{2c} = r_2 \frac{T_t + K_c}{T_s + K_c} \tag{6}$$

where $K_c = 234.5$ is the correction factor for copper, and the rotor bars are copper.

Table 1. Measured and calculated data for efficiency determination of the tested induction motor.

% load	Stator phase voltage V_1 (V)	Stator line current I_1 (A)	Power input P_{in} (kW)	Input power factor (cosϕ)	Speed (rpm)	Power output P_{out} (kW)	Efficiency (%)
22.52	381.28	16.40	4.53	0.418	2972	3.312	73.08
50.05	381.78	20.67	9.24	0.672	2935	7.360	79.65
73.92	381.00	25.79	13.47	0.781	2888	10.871	80.71
100.00	382.46	32.64	18.13	0.841	2846	14.705	81.10

The complex admittances of the branches of the equivalent circuit of Figure 1a and Figure 1b are calculated as follows:

$$\overline{Y}_1 = \frac{1}{r_{1c} + jx_1} \tag{7}$$

$$\overline{Y}_2 = \frac{1}{r_{2c}/s + r_{st} + jx_2} \tag{8}$$

For the equivalent circuit of Figure 1a,

$$\overline{Y}_m = \frac{-j}{x_m} + \frac{1}{r_m} \tag{9}$$

For the equivalent circuit of Figure 1b,

$$\overline{Y}_m = \frac{1}{r'_m + jx'_m} \tag{10}$$

The stator current equals

$$I_{1est} = \left|\left(\overline{I}_{1est}\right)\right| = \left|\left(\frac{\overline{V}_1\overline{Y}_1\left(\overline{Y}_2 + \overline{Y}_m\right)}{\overline{Y}_1 + \overline{Y}_2 + \overline{Y}_m}\right)\right| \tag{11}$$

where $V_1 = V_1/\sqrt{3} + j0$ and I_{1est} is the stator line current.

The power factor is calculated as

$$pf_{est} = \frac{Real\,(I_1)}{I_{1est}} \tag{12}$$

The rotor current is calculated as

$$I_2 = \left|\frac{\overline{V}_1\overline{Y}_1\overline{Y}_2}{\overline{Y}_1 + \overline{Y}_2 + \overline{Y}_m}\right| \tag{13}$$

The current through the resistance r_m for the circuit of Figure 1a is

$$I_m = \left|\frac{\overline{V}_1\overline{Y}_1}{r_m\left(\overline{Y}_1 + \overline{Y}_2 + \overline{Y}_m\right)}\right| \tag{14}$$

The current through the resistance r'_m for the circuit of Figure 1b is

$$I_m = \left|\frac{\overline{V}_1\overline{Y}_1\overline{Y}_m}{\overline{Y}_1 + \overline{Y}_2 + \overline{Y}_m}\right| \tag{15}$$

The input power for the circuit in Figure 1a is

$$P_{inest} = 3\left(I_1^2 r_{1c} + I_2^2\left(r_{2c}/s + r_{st}\right) + I_m^2 r_m\right) \tag{16}$$

The input power for the circuit in Figure 1b is

$$P_{inest} = 3\left(I_1^2 r_{1c} + I_2^2\left(r_{2c}/s + r_{st}\right) + I_m^2 r'_m\right) \tag{17}$$

The output power is

$$P_{outest} = 3I_2^2 r_{2c}\frac{1-s}{s} \tag{18}$$

The efficiency is

$$eff = \frac{P_{outest}}{P_{inest}} \times 100 \tag{19}$$

5. Implementation of the proposed hybrid evolutionary techniques for the efficiency determination of a submersible IM

Genetic algorithms and simulated annealing with high convergence speed, simple operators, and superior accuracy are well-known optimization methods. Therefore the proposed hybrid evolutionary optimization method consists of combining the GA and SA methods; moreover, the basis of the hybrid optimization method is the GA. The hybrid genetic algorithm converges straight to an optimum solution with the local search assistance.

There are 2 main hybrid GA forms used for engineering applications, the Lamarckian hybrid GA and the Baldwinian hybrid GA. The Lamarckian method updates the strings after the local search, but the Baldwinian method does not update, so the local optimization is only used as a fitness evaluation. Therefore, the Lamarckian hybrid GA has been more widely accepted compared to the Baldwinian algorithms [12]. The Lamarckian hybrid optimization procedure is used in this paper.

The proposed algorithm is exhaustively explained below:

a) Initial population – Firstly, the strings that symbolizes a possible solution to the problem are randomly generated by the optimization algorithm as binary codes. Because the beginning values influence the accuracy and speed of the hybrid GA, prior to running the algorithm, the population size and bit count of each chromosome must be determined forcefully (respectively, population number is 50, iteration number is 100, and each chromosome has 50 bits).

b) Local search – The disadvantage of a local search algorithm, in our case the simulated annealing method, is that it requires many function calls and a longer computational time. Moreover, excessive use of local optimization can degrade the diversity of the population. Therefore, the local search algorithm is not applied to every iteration of the process. After the local search subroutine runs, the worst chromosomes in the original population are replaced with newly generated ones. More detailed explanation about the local search subroutine is given in the following "**Local Search Procedure**" section.

c) Selection strategy – In the hybrid GA, the selection of parents plays an important role in producing successful generations. The aim is to allow the fittest individuals to be selected in the reproduction process. While the initial population can randomly be generated, the next generation is chosen from the previous generation members by using a probabilistic selection process. A roulette wheel selection method is used so that each string's survival ratio can be random.

d) Crossover operation – The crossover operator combines genetic material from the selected parents. A variety within the population is finally obtained and good features of the old population are transmitted to the new population. In this study, a 0.8 crossover rate and scattered crossovers are used to achieve mixing superiority. The scattered crossover generates a random binary vector and also 2 distinct individuals from the population are randomly selected. The chosen members are crossed over in such a way that the bits are selected if the vector bit is a 1 from the 1st parent and if not from the 2nd parent and subsequently the selected genes are combined to form the offspring as indicated in Figure 2.

Random vector:	10011011010101101101			
Parent-1:	11011100011010110010	⟶	Offspring-1:	111110000 11010100010
Parent-2:	01100010001111001010	⟶	Offspring-2:	0100011000111101101 0

Figure 2. Usage of the scattered crossover operator in a GA.

e) Mutation operation – It is a common genetic manipulation operator and involves the random alteration of genes during the process of copying chromosomes from one generation to the next. Raising the ratio of mutations increases the algorithm's freedom to search outside of the current region of parameter space. So the mutation ratio number 0.05 was selected and varied in inverse proportion to the iteration number. How the mutation works is displayed in Figure 3.

Mutation point

↓

String A: 1101110**0**011010110010

String A : 1101110**1**011010110010

Figure 3. Presentation of the mutation operator in a GA.

f) Fitness function – The individual fitness is a decimal value used to assess the performance of population members. The fitness of each individual in this situation is calculated by the fitness function given in Table 2. Where I_{1est}, P_{inest}, pf_{est}, and P_{outest} are estimated stator current, input power, power factor, and output power, and also I_1, P_{in}, pf, and P_{out} are measured stator current, input power, power factor, and output power, respectively.

g) Reinsert offspring – At this point a new offspring population is achieved as follows: all individuals are evaluated as described in step "f" and the following steps starting from step "b" are repeated. The procedure is completed when an assigned number of iterations are reached.

Table 2. Fitness and objective functions used in the hybrid evolutionary method.

Fitness functions	Objective functions
$ff_1 = 1 / \left(f_1^2 + f_2^2\right)$	$f_1 = 100 \times (I_{1est} - I_1)/I_1$
$ff_2 = 1 / \left(f_1^2 + f_2^2 + f_3^2\right)$	$f_2 = 100 \times (P_{inest} - P_{in})/P_{in}$
$ff_3 = 1 / \left(f_1^2 + f_2^2 + f_4^2\right)$	$f_3 = 100 \times (pf_{est} - pf)/pf$
$ff_4 = 1 / \left(f_1^2 + f_2^2 + f_3^2 + f_4^2\right)$	$f_4 = 100 \times (P_{outest} - P_{out})/P_{out}$

Local Search Procedure: The proposed local search algorithm is explained in the following section [15]:

i) A new iteration number and neighbourhood random number u for each equivalent circuit parameters are selected. Also a string of the current population is selected for the local search. Subsequently, a temperature $(T_{initial})$, which is an average of the fitness values of the population, is selected and then the local search procedure is applied.

ii) A new string neighbouring the gene of the population is produced as follows:

$$\begin{aligned}
&Smax = Max\ boundary\ value \\
&Smin = Min\ boundary\ value \\
&String_{neighbour} = S_{min} + u \times (S_{max} - S_{min})
\end{aligned} \tag{20}$$

iii) Fitness values (i.e. energy) of the 2 strings are calculated. If $\Delta E = E\left(String_{random}\right) - E\left(String_{neighbour}\right) < 0$, $String_{random}$ is replaced with $String_{neighbour}$, or a random number (r) in the range $0 < r < 1$ is produced and then if $r < exp\left(-\Delta E/T\right)$, $String_{random}$ is replaced with $String_{neighbour}$.

iv) If $\Delta E > 0$ and $r > exp\left(-\Delta E/T\right)$, go to step "b" (start a new iteration) until the total iteration number has been reached.

v) Temperature $(T_{initial})$ is reduced by means of cooling factor c.

$$T_{new} = c \times T_{initial} \tag{21}$$

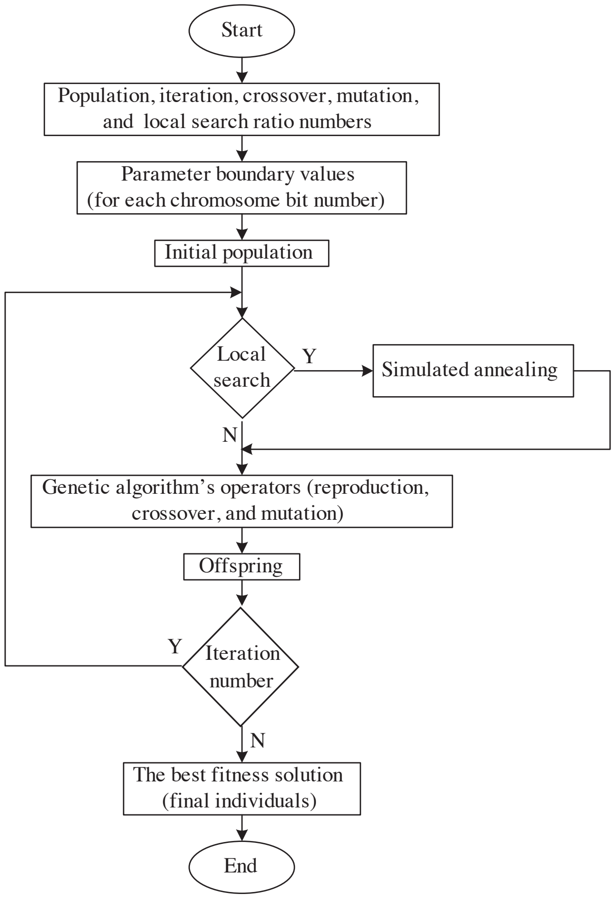

Figure 4. Flowchart of the hybrid evolutionary optimization method.

The efficiency determination of a submersible IM, like the determination of an equivalent circuit parameter of the motor, is a problem that uses nonlinear algebraic equations. Hence, the hybrid technique is used to solve this problem by minimizing the difference between measured and calculated efficiency values at different loads. The developed technique's implementation is shown in the flowchart in Figure 4.

The range of equivalent circuit parameters is x_1, r_2, x_m, and r_m in the case of a parallel equivalent circuit and x_1, r_2, x'_m, and r'_m in the case of a series equivalent circuit. The efficiency of the submersible IM is calculated by using the method described in previous sections and the randomly generated equivalent circuit parameter values. Moreover, the adopted algorithm has different objective functions that are used for calculating efficiency of the motor; namely stator current, input power, power factor, and output power. The set of fitness and objective functions is defined in Table 2.

6. Results and comments

To determine the efficiency of a submersible IM and to test the performance of the proposed hybrid evolutionary technique, 2 different methods ,method 1 and method 2, are employed.

In all iterations of each algorithm the x_1, r_2, x_m, and r_m parameters for the parallel equivalent circuit and x_1, r_2, x'_m, and r'_m parameters for the series equivalent circuit are estimated and then the stator current, input power, power factor, and output power input parameters are calculated using estimated equivalent circuit parameters. Each run of the evolutionary optimization technique gives different values for the submersible induction motor equivalent circuit parameters and efficiency. Therefore, every algorithm is run 5 times and the average efficiency values, which are calculated by means of motor parameters, are compared with the torque gauge results and the errors are obtained. In addition, the efficiency results are tabulated (Tables 3-5), and Figures 5-8 show the error values.

Table 3. Efficiency values of the SA for methods 1 and 2.

	Fitness function / % load	% average efficiency in Figure 1a				% average efficiency in Figure 1b			
		22.52	50.05	73.92	100.00	22.52	50.05	73.92	100.00
Method 1	ff1	71.73	80.87	81.74	80.24	72.74	81.03	81.28	79.39
	ff2	70.36	79.93	80.99	79.55	69.65	79.25	80.19	78.61
	ff3	73.33	81.13	81.77	80.15	70.72	80.01	80.82	79.20
	ff4	72.37	79.97	80.92	79.40	70.68	80.26	81.37	79.97
Method 2	ff1	70.67	80.39	81.23	79.53	70.61	82.13	81.27	78.67
	ff2	69.42	80.07	81.84	79.92	71.35	80.60	81.01	78.83
	ff3	70.08	80.66	81.38	79.23	69.58	80.67	80.99	79.27
	ff4	69.57	79.76	81.34	79.85	70.08	80.97	81.90	80.41

Table 4. Efficiency values of the GA for methods 1 and 2.

	Fitness function / % load	% average efficiency in Figure 1a				% average efficiency in Figure 1b			
		22.52	50.05	73.92	100.00	22.52	50.05	73.92	100.00
Method 1	ff1	74.06	81.36	80.93	78.64	74.51	81.63	81.09	78.74
	ff2	71.93	80.28	80.47	78.48	75.33	81.97	81.14	78.64
	ff3	76.49	82.72	81.78	79.26	75.38	82.16	81.54	79.18
	ff4	77.43	83.10	81.83	79.15	75.31	82.03	81.29	78.85
Method 2	ff1	71.08	80.95	81.34	78.50	72.84	81.42	81.60	78.66
	ff2	69.05	80.49	80.37	78.35	71.21	80.52	80.55	78.33
	ff3	72.83	80.52	81.12	79.18	72.22	80.60	81.09	79.23
	ff4	73.40	80.63	80.54	78.37	73.74	80.53	81.12	78.85

Table 5. Efficiency values of the HGA for methods 1 and 2.

	Fitness function / % load	% average efficiency in Figure 1a				% average efficiency in Figure 1b			
		22.52	50.05	73.92	100.00	22.52	50.05	73.92	100.00
Method 1	ff1	75.35	82.02	81.25	78.80	70.91	79.74	80.22	78.38
	ff2	72.67	80.63	80.55	78.42	75.10	81.75	80.90	78.38
	ff3	73.48	81.19	81.01	78.85	74.02	81.53	81.27	79.08
	ff4	75.24	82.09	81.43	79.04	73.61	81.25	81.03	78.85
Method 2	ff1	71.37	80.73	81.24	78.33	72.46	81.04	80.86	78.46
	ff2	71.91	80.78	80.57	78.83	72.11	81.07	80.92	78.48
	ff3	72.54	80.25	80.92	79.31	72.94	80.24	81.16	79.35
	ff4	73.05	80.32	81.03	78.92	72.59	80.77	80.80	79.06

The 2 different implementation methods, method 1 and method 2, have different input values for each algorithm and are implemented separately. Method 1 only makes use of the submersible IM's full load data. The motor parameters of series or parallel equivalent circuits which are obtained by use of full load data of submersible IMs are used to determine efficiency values in the other loads. Unlike method 1, method 2 uses all the measured actual values of a submersible IM to determine the efficiency values. Subsequently, the effects of the objective and fitness functions and every input parameter, viz. Figure 1a and 1b, from using method 1 and method 2 are investigated separately.

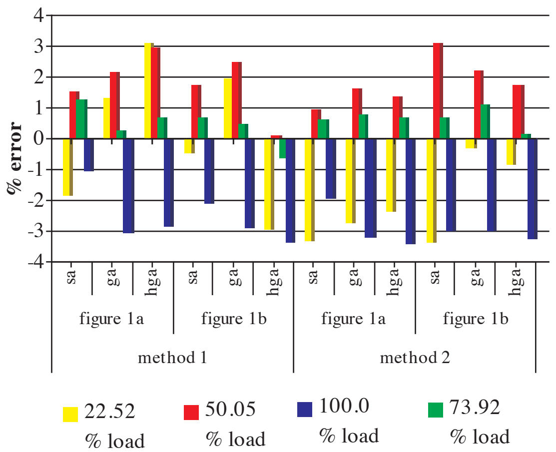

Figure 5. Error values for stator current and input power parameters.

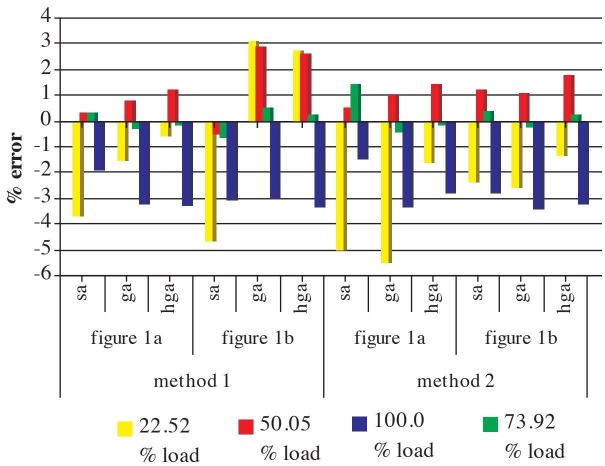

Figure 6. Error values for stator current, input power, and power factor parameters.

First of all, the error values for both method 1 using the full load values and method 2 using the different load values are mostly around 2%. Additionally, the best results are obtained at 73.92% load.

Using the output power and the power factor as an objective function improves the robustness and reliability of the algorithms; furthermore the output power is better. Because of using x'_m and r'_m, all figures except Figure 5 demonstrate that the equivalent circuit of the submersible induction motor in Figure 1b is more appropriate for evolutionary algorithms than the circuit in Figure 1a, particularly Figure 7 which uses the output power.

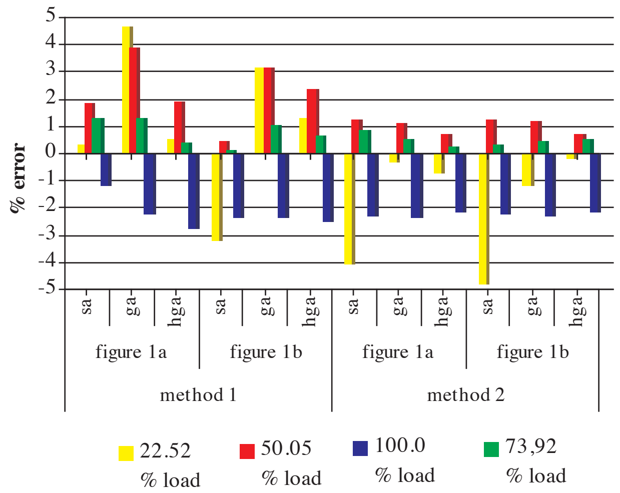

Figure 7. Error values for stator current, input power, and output power parameters.

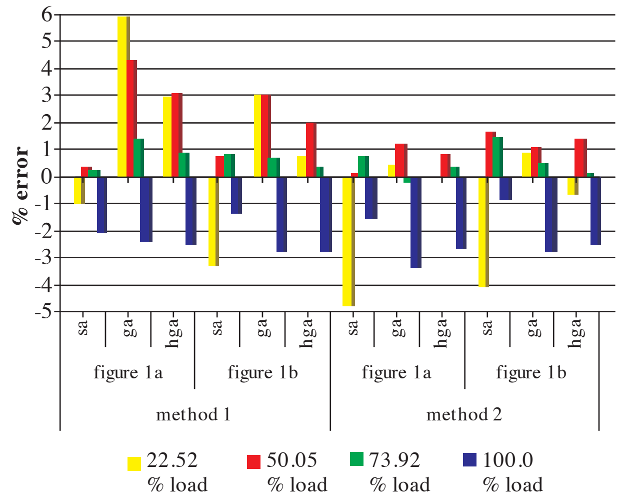

Figure 8. Error values for stator current, input power, power factor, and output power parameters.

The simulated annealing, the genetic algorithm, and the proposed hybrid evolutionary optimization techniques that are used in this study have similar efficiency values. However, the investigated hybrid method is more reliable due to the local search. In order to understand this fact, all efficiency values that were obtained by the genetic algorithm and the proposed hybrid method have been examined (Figure 9).

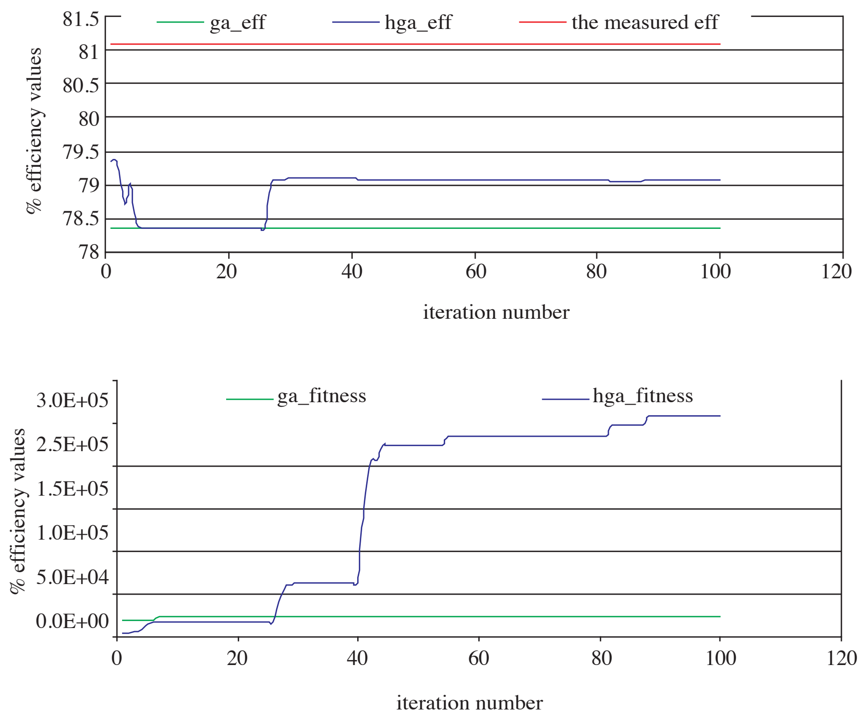

Figure 9. Changes of efficiency and fitness values during 1 iteration in the genetic algorithm and the proposed hybrid method.

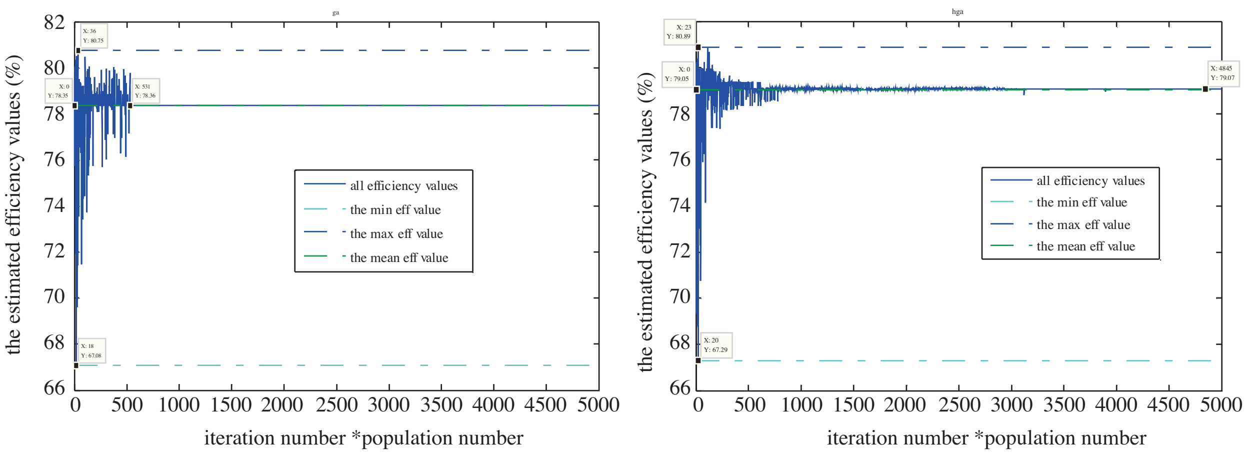

Figure 9. Continued.

At a rated load the algorithms are randomly run in method 1, which uses ff1 and Figure 1b as its fitness function and equivalent circuit, respectively. The figures show the genetic algorithm's maximum, minimum, mean, and last efficiency values of 80.75, 67.06, 78.35, and 78.36 and the proposed hybrid method's maximum, minimum, mean, and last efficiency values of 80.89, 67.29, 79.05, and 79.07 respectively. Due to fact that the local search subroutine is ignored until the 25th iteration number (1250th iteration $\times$ population number), maximum, minimum, and mean efficiency values are not considered. But Figure 9b shows that, despite the genetic algorithm falling into a trap on the 531st string number (11th iteration number), the proposed hybrid method continues the determination of efficiency of the submersible induction motor up to the 4845th string number (97th iteration number). Moreover, during the whole iteration the proposed hybrid method improves the fitness values as well as the efficiency values, because the solution space of the proposed hybrid method is richer than the genetic algorithm's by means of the local search subroutine (Figure 9a). Furthermore, according to the tuning of the local search algorithm frequency the hybrid method's sensitivity and convergence speed can be modified.

7. Conclusions

A new hybrid evolutionary technique composed of a genetic algorithm as the global search and simulated annealing as the local search is investigated for efficiency determination of a submersible induction motor. The obtained results have been observed and compared. Our proposed hybrid method is a highly sensitive evolutionary optimization technique for the determination of a submersible induction motor's efficiency. The hybrid method has both the evolutionary technique's advantages like robustness and, especially due to the local search, the richest solution space. Thus the hybrid method has the most sensitivity.

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