The Use of the Genetic Algorithm for in-situ Efficiency Measurement of an Induction Motor

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Abstract: In-situ efficiency determination of working motors in an industrial plant, if done non-intrusively, is less expensive than laboratory tests, which need disconnection of the motors from the loads. This paper presents a new approach to non-intrusive in-situ efficiency determination of an induction motor. By monitoring the input voltages, the input currents, the input power and the motor speed, an equivalent circuit based optimization process using the Genetic Algorithm calculates the motor efficiency. The convergence and the precision have been improved by taking into account several load points in the objective function, as well as the temperature dependency of the stator and rotor resistances. A sensitivity analysis of the method to parameter changes is also presented. Experimental results confirm the validity of this method.

Keywords: Induction motor, Efficiency, In situ measurement

I. INTRODUCTION

The interest in improving the efficiency of electric motors stems from the fact that they represent 60 to 70% of the total industrial and commercial load. A knowledge of the efficiency of motors operating in an industrial plant is necessary when deciding whether standard motors should be advantageously replaced with more efficient motors. However the real efficiency of a motor is usually different from its nameplate value, as it can decrease significantly due to aging or following a repair. A measurement of the efficiency in the laboratory, which can be precise, is too expensive to be considered as a systematic procedure for the evaluation of industrial motors without shutdown. On the other hand, the in-situ measurement of the motor efficiency is difficult and may perturb the process. To increase the attraction of in-situ measurement, it is necessary to reduce as much as possible, the perturbation to the process and to minimize the labor cost.

There are numerous efficiency determination methods [1]. They differ by their precision, their implementation and their suitability for plant conditions. An analysis of these methods for in-situ efficiency determination is presented in [2]. In fact, in-situ measurement of motor output torque is very difficult to perform while the no load test or the blocked-rotor test is not acceptable in most cases. So these tests are excluded in the present study. Up to date, few works have achieved in-situ motor efficient determination in a non-intrusive way.

Many in-situ methods proposed in the past have not been widely accepted by the industry due to their high disturbance to the process. For example, Ontario Hydro has proposed a method using strain gauges on the motor shaft [3]. Although potentially precise, this method requires plant shutdown and considerable labor for preliminary set-up. Another method is proposed in [4], based on the measurement of air-gap torque and air-gap power. It gives accurate results but still requires the motor to be disconnected from the load to perform the no load test.

Ref. [2] is by far the most original work that meets the requirements of non-intrusive in-situ measurement. But its optimization process, based on a single load point at a time, usually converges to different values for successive trials and the average value has to be taken. Furthermore, it does not meet the required high accuracy for the purpose of energy savings management.

In the present study, the equivalent circuit based approach is adopted. Similar to [2], the Genetic Algorithm (GA) (GaLib from MIT) will be used as the optimization tool. The measurements needed are the input voltages, the input currents, the input power and the speed of the motor. By optimizing the input impedance of the equivalent circuit, the estimated values of each circuit element are updated after each evolution, until a convergence criterion has been reached. The efficiency of the motor is then computed from the model for any load point. Multiple load points are taken into account in the objective function, leading to a considerable improvement of the optimization process. In fact, unlike [2], repeated tests lead to more or less the same efficiency value. Therefore it represents a considerable improvement.

The paper organized as follows: Section II presents the equivalent circuit model of an induction motor and the GA used for the purpose of optimization. Section III presents the results obtained from synthetic data. Section IV gives an analysis of parameter sensitivity of the method. Section V shows some experimental results from laboratory tests for a 50 hp motor. Section VI gives the conclusions.

II. PARAMETER OPTIMIZATION USING GA

A. *Equivalent Circuit Model of Induction Motor*

Equivalent circuit methods for efficiency determination have the ability to provide the efficiency for an arbitrary load point. The conventional exact equivalent circuit of the induction motor is modified to account for mechanical and

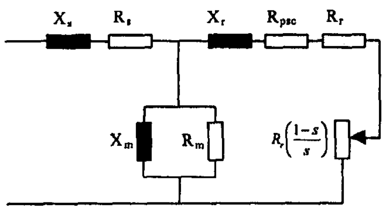

Fig. 1: Equivalent circuit model of the motor

stray losses as shown in Fig. 1. The resistance R_{st} in the rotor circuit stands for stray load losses while R_m account for both mechanical and core losses [2].

There are seven unknowns in this circuit, namely: stator resistance R_s and stator leakage reactance X_s, rotor resistance R_r and rotor leakage reactance X_r, stray load losses resistance R_{psc}, magnetizing reactance X_m, core and mechanical losses resistance R_m. The known quantities from measurement are the input voltage, the input current, the phase angle between voltage and current and the slip. The measured active and reactive powers have been used to deduce the phase angle of the input current, so they are not used here as independent quantities. The number of unknowns is greater than the number of equations that we can write from the equivalent circuit using the measured quantities. So different sets of parameter values can be fitted to the same measured data to give different values of motor efficiency. An improvement in the convergence of the parameters is obtained by doing multiple measurements at different load points and accounting for them in the objective function of the optimization process. In this way, both R_s and R_r depend non-linearly on the load points because the resistances of the stator winding and the rotor squirrel cage vary with their respective temperatures. So two additional thermal resistances R_{ths} and R_{thr} have been introduced, increasing the number of unknowns to 9.

B. Application of the Genetic Algorithm

The genetic algorithm is an optimization method based on random number manipulation and natural selection. The optimization procedure for solving a problem is illustrated in Fig. 2. Initial solutions to a problem are encoded as binary strings (i.e., individuals). In the present case, the unknown parameters are encoded as shown in Fig. 3, where each parameter takes 16 bits. A number of initial individuals constitute the initial population.

The criterion to select the best individuals for reproduction is the objective function. Proceeding in this way, the next generation is usually closer to the real solution of the problem. The objective function used in the present study is the average error of the input impedance for different load points, i.e.:

$$value=\frac{1}{n}\sum_{j=1}^{n}\left(\sqrt{\left|\hat{R}_j-R_j\right|}\right)+\left(\sqrt{\left|\hat{X}_j-X_j\right|}\right) \tag{1}$$

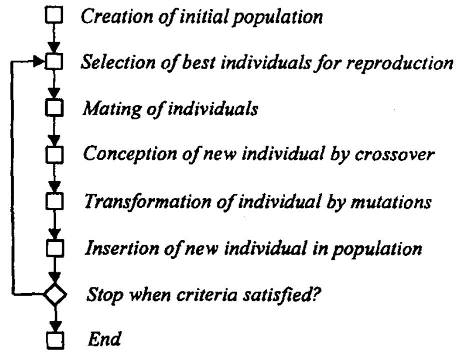

Fig. 2: Procedure to solve a problem

Fig. 3: Representation of one individual

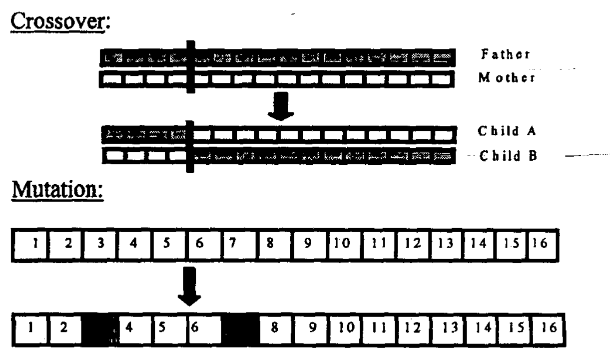

Fig. 4: Crossover and mutation manipulations

Another possibility that has been explored is to use the slip in the place of the input impedance with the following objective function:

$$value=\frac{200}{n}\cdot\sum_{j=1}^{n}\left|\hat{s}_{r_j}-\left|s_{r_j}\right|\right|+\left|s_{r_j}\right| \tag{2}$$

The results presented in sections III to V are computed with (1) but the results obtained from (2) are equivalent.

Crossover and mutation manipulations are illustrated in fig. 4. Crossover consists in randomly selecting a position along parent strings and swapping all binary digits following that position. Mutation follows crossover and works by randomly selecting one string and one bit location, changing that string's bit from 1 to 0 or vice versa. In this study, the probability for crossover and mutation are initially set to 0.95 and 0.30 respectively. Then the mutation probability is gradually reduced throughout the optimization process so as to reach 0 at the end of each evolution.

The three genetic operations: reproduction, crossover and mutation, provide an effective search technique, resulting eventually in the objective function being satisfied.

C. *Temperature Dependency of R_S and R_r*

The characteristics of the motor are assumed to be relatively stable except for the stator resistance and the rotor resistance, which are affected by their respective temperatures (for the rotor, to a certain extent by the slip). The assumption is that in thermal equilibrium the resistive components of the circuit are stabilized to new values, while the reactive components are not affected. A simple representation of the thermal behavior of the motor is used, as shown by (3) and (4). Note that the losses in the rotor also contribute to the increase of stator temperature because the heat is assumed to flow from the rotor to the stator.

$$\Delta Ts = Kths \times (StarorLoss + RotorLoss) \tag{3}$$

$$\Delta Tr = Kthr \times (RotorLoss) \tag{4}$$

Then the actual resistances are calculated using (5) and (6):

$$R_s = R_{sa} * k_s \tag{5}$$

$$R_r = R_{ra} * k_r \tag{6}$$

where:

$$k_s=(k+ambient+\Delta T_s)/(k+ambient) \tag{7}$$

$$k_r=(k+ambient+ \Delta T_s+\Delta T_r)/(k+ambient) \tag{8}$$

R_{sa} and R_{ra} represent the ambient values of stator and rotor resistances.

The equations for rotor resistance calculation are similar to that for stator resistance calculation except for the coefficient k giving the variation of resistance as a function of temperature which is 225 for aluminum and 234.5 for copper.

The non-linearity is exploited to obtain a higher accuracy of the calculated efficiency because more than one operating point has been optimized. The additional constraints introduced by multiple points should lead to a better optimization of the parameters over the full range of operation.

III. STUDY WITH SYNTHETIC DATA

To compute the synthetic data, the following parameters of a 50hp 4 pole 460V 3 phases TEFC induction motor have been identified using the test results from IEEE Std 112 method B combined with IEEE Std 112 method F.

- R_s = 0.0540 ohm
- R_r = 0.0531 ohm
- X_s = 0.5338 ohm
- X_r = 0.8007 ohm
- R_m = 0.3645 ohm
- X_m = 13.18 ohm
- R_{psc} = 0.06921 ohm
- Kth_s = 0.23 °C/W
- Kth_r = 0.10 °C/W

These parameters are used for the calculation of the input current, the input power and the slip for different load points, taking into account the variation of the rotor and stator resistances with their respective temperatures. Then the reference values of the input impedance of the motor for different load points are computed. Although none of the above parameters can be assumed to be known for the optimization process, it is used to investigate how the estimated parameters converge to the known data.

As stated in Section II, the probability of mutation is linearly reduced after each generation to reach 0 for the last generation. The reason to do so is to prevent the optimization process being trapped in a local minimum but to also let it converge at the end.

The solution process starts by randomly creating an initial population of *150* individuals. As each parameter is represented with 16 bits, numerical scaling is done using a set of reasonable lower and upper limits for each parameter. This can be done without difficulty because sufficient knowledge of the range of the values of the parameters to be estimated is available. After an evolution of *150* generations, the population has moved to a more restricted region with better fitness. Before starting the second and successive evolutions, the search space is redefined around the location of the best individual at that time. This procedure is illustrated in Fig. 5. The new search space is always smaller than the previous one but larger than the area where the last population is located. Then the population of the last evolution is discarded. Instead, a new population within the new search space is randomly created. Eight evolutions were run with *150* generations each. The error on the efficiency at the six load points computed for the best individuals are shown in Fig. 6 for 20 computations. The error of the calculated efficiency after eight evolutions, compared to the theoretical value obtained from the given parameters, is given in Table 1 for the computation giving the best value.

Table 1: Results obtained with synthetic data

% load	25	50	75	100	110	115
error	*0.005*	*0.025*	*0.044*	*0.064*	*0.072*	*0.077*

Others search strategies have also been tried. For example, similar results have been obtained after only one evolution of 1000 generations for a population of 1000 individuals. In this case, the probability of mutation has been kept constant for the first 500 generations and then linearly decreased to zero for the second 500 generations.

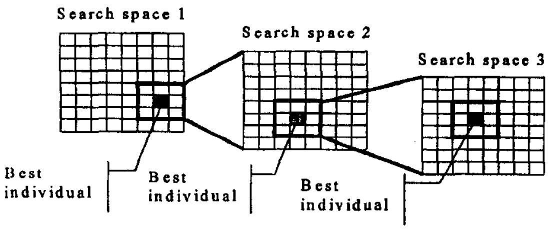

Fig. 5: New search space definition after an evolution

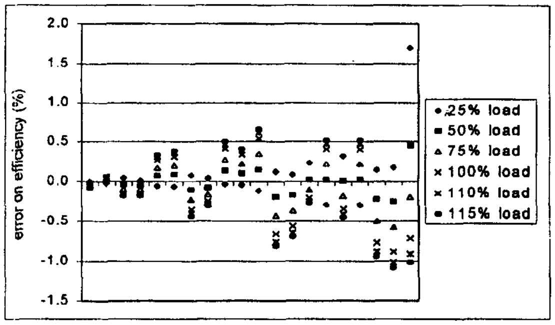

Fig. 6: Error on efficiency of best individual for 20 successive computations (sorted on value)

IV. SENSITIVITY STUDY

A sensitivity study on some parameters is included to investigate the robustness of the method.

A. Effect of the number of load points

It can be expected that more load points may result in better results. To verify this, the optimization process has been performed using 1, 3 and 6 load points, respectively. Although the trial that only uses only one load point has a low value, it converges to dispersed results for successive evolutions, as shown in Figs. 7 and 8. On the other hand, the trial with 6 load points gives a higher value than that with 3 load points but at the same time produced a more consistent value of efficiency. So, the optimization process using the GA should be designed to focus on finding the global minimum over the full power range rather than generating a set of well fitted parameters to a single load point.

B. Effect of the distance between load points

The difference between the load points can be expected to have an important effect on the quality of the result because more separated operating points may logically give more information about the motor. The computation has been done thrice with load points equally spaced between 40 and 57%, 25 and 115% as well as 5 and 125% of full load. Fig 9 shows

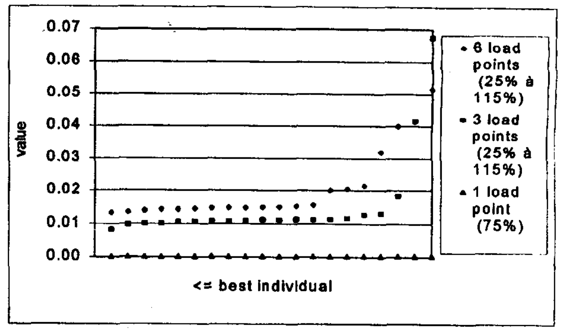

Fig. 7: Effect of the number of load points on the value of the best individual

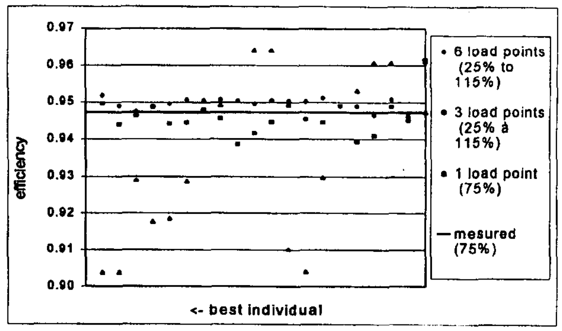

Fig. 8: Effect of the number of load points on the efficiency calculated using the best individual

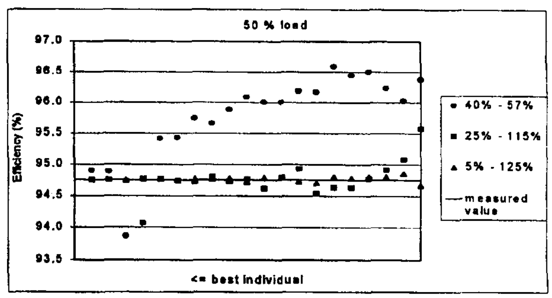

Fig. 9: Effect of distance between load points on efficiency

the calculated efficiency at 50% of the load. Note that the repeatability and the accuracy of the method are much higher if the data used are from measurements with well-spaced load points.

C. Effect of parameter error

By introducing a disturbance to one parameter at a time, its effect on the value of the best individual obtained is shown in

Fig. 10. The efficiency is affected more by errors in the resistive components while its sensitivity to errors in the reactive component is relatively low. Figs. 11 and 12 give further results that show the effect of the error in stator and rotor resistances on efficiency for different load points.

D. Effect of error on thermal coefficient

The effect of the parameter errors on the thermal coefficient of the rotor cage is examined by forcing the computation to use a wrong value, instead of the value from the genome. The error has been set to $\pm 10\%$ and $\pm 30\%$ where the good value is 0.1. Fig. 13 presents the value corresponding to different errors with 20 computations each. It can be expected that the true result may be found from these results because the lower values of all the computations coincide with the value obtained using the good coefficient. Fig. 14 gives the corresponding results for the efficiency.

V. EXPERIMENTAL RESULTS

The laboratory LTEE of Hydro-Quebec possesses a high quality test bench for motor efficiency measurement according to the 'IEEE Std 112 B' and 'CSA C390' test methods. Accuracies of 0.2% and a repeatability of 0.1% are attainable. Therefore test results using this facility are used to verify the results obtained from the proposed method. The test records variables such as voltages, currents, active power and reactive power, which are used to calculate the input impedance of the motor. The recorded speed is used to deduce the slip, which is also a parameter used in the objective function.

The proposed method has been applied to one motor of 50 HP. The population has 1000 individuals and each evolution has 1000 generations. The evolution process has been done 20 times to achieve the final estimation of the efficiency for the power range considered. Fig. 15 gives a comparison between the measured and estimated results. The results show the validity of the proposed method, as the error in efficiency determination is less than 1 percentage point for all load points.

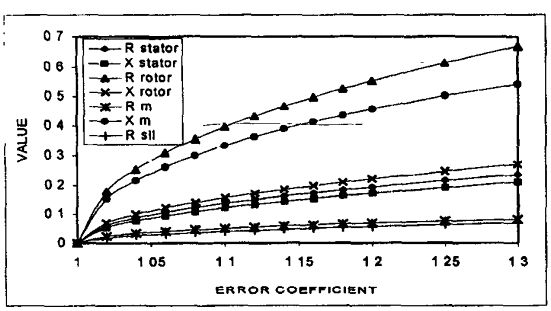

Fig. 10: Effect of error in different parameters on the value of the best individual

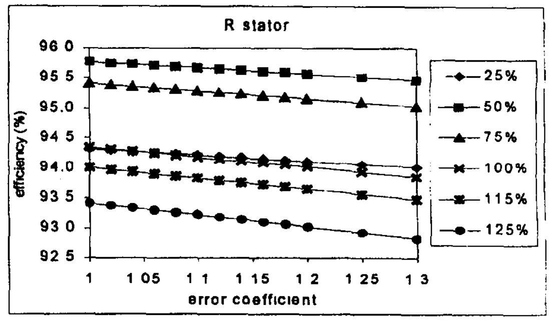

Fig. 11: Effect of error in stator resistance on the efficiency

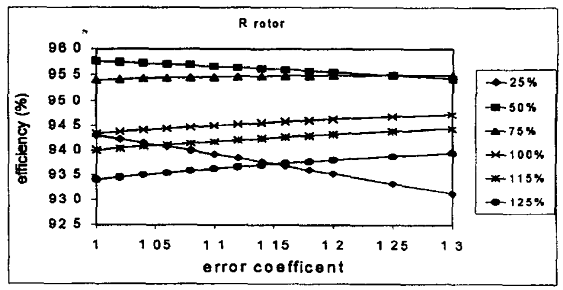

Fig. 12: Effect of error in rotor resistance on the efficiency

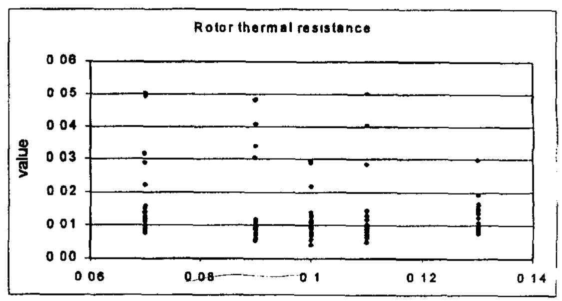

Fig. 13: Effect of error on rotor thermal coefficient on the best individual value

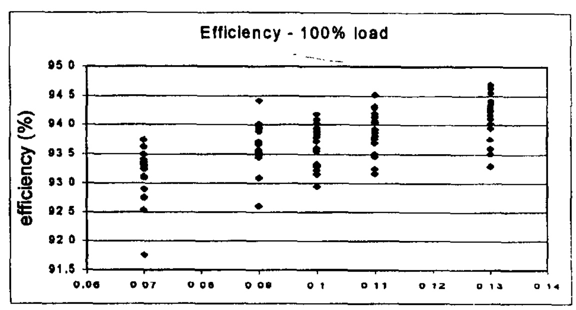

Fig. 14: Effect of error on rotor thermal coefficient on the efficiency

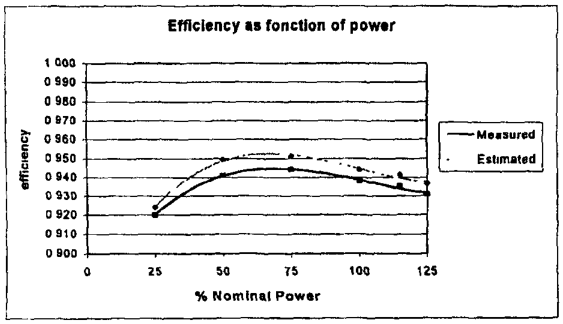

Fig. 15: In-situ estimated results vs laboratory test results

VI. CONCLUSION

This paper has extended previous work on the application of GAs to in-situ efficiency determination of induction motors to provide a noticeable improvement in accuracy and repeatability. This is accomplished by taking multiple load points into account in the objective function and by incorporating the non-linearity of the resistive components in the model. Besides the above improvements, the problem of convergence in the optimization process is also avoided. The proposed method is less intrusive than existing in-situ methods while still providing acceptable accuracy.

The study based on synthetic data shows that the method is sensitive to the number of load points and to their separation. Furthermore, thermal equilibrium has to be reached at each load point in order to obtain a good estimation of the resistive components.

Finally, results with experimental data give a good approximation of the efficiency for the full power range.

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The software for this work used the GAlib genetic algorithm package, written by Matthew Wall at the Massachusetts Institute of Technology."

LIST OF SYMBOLS

Value	performance of the individual
R_s	stator resistance
R_r	rotor resistance
X_s	stator leakage reactance
X_r	rotor leakage reactance
R_m	core and mechanical losses resistance
X_m	magnetizing reactance
R_{sll}	stray load losses resistance
Kth_s	stator thermal resistance
Kth_r	rotor thermal resistance
ΔT_s	increase in temperature of stator windings
k_s	temperature coefficient of stator resistance

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