Parameter Estimation for Electric Motor Condition Monitoring

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ABSTRACT

This paper presents parameter identification technique to quantify the faults in motor condition monitoring. Genetic Algorithm (GA) has been used as a key technique to estimate the motor parameters. The zero-sequence voltage equation for the stator has been used as a model to estimate motor stator parameters – the stator resistance and the stator leakage inductance. The comparison of the parameter estimation by the earlier Rrecursive Least Square (RLS) method and the proposed GA technique has been discussed. The GA technique shows better accuracy in the estimation. The estimation has been tested on both simulations and a real test motor.

KEYWORDS

Condition Monitoring, Parameter Identification, Induction Motor, Genetic Algorithm, Stator Fault

1. INTRODUCTION

The induction motors are the most widely used motors among different electric motors because of their high level of reliability, efficiency and safety. However, these motors are often exposed to hostile environments during operation which may leads to early deterioration of motors i.e., development of faults. If the fault is not detected at the early stage, the problem may become serious such as secondary damages to downstream equipments, and often leads to the unexpected breakdown. To reduce such negative impacts from the motor fault, the number of the condition monitoring techniques has been suggested in the literature for the early fault detection and diagnosis so that the remedial action can be done in much planned way to reduce the machine downtime and to maintain the overall plant safety. Heng *et al.* [1] and Jardine *et al.* [2] gave the review on the condition based maintenance (CBM) of the rotating machines. The general and/or accepted practice to use the vibration diagnosis to identify the faults in the motor [3], however the limitation of this approach is that it can quantify the extent of the fault in terms of the motor related parameters. On the other hand, the Motor Current Signature Analysis (MCSA) is one of the most spread procedures for health monitoring of the motor since decades. One of the main reasons for using this method is that the other methods require invasive access to the motor and they also need extra equipment/sensors for measuring the required signals. The research has been progressed in mainly two directions using the stator phase current and voltage signals – the detection of faults [4-16] and the quantification of the faults by the motor parameters estimation [17-27]. First one is important for the quick health assessment on routine basis, however the later one useful to know the extent of the faults so that remedial action can be done quickly. Hence the present study is related to the motor parameter estimation.

It has also been observed that 30-40% of all the recorded faults are generally related to the stator of the motor [4], hence the estimation of parameters related to the stator has been considered using the motor phase current in the present study. Several methods have been suggested to estimate the motor related parameters with their relative advantages and limitations [17-27]. Recursive Least-Square (RLS) has been applied to estimate motor parameters [17-19]. Treetrong *et al.* [17] have also used the RLS method to estimate the stator related parameters. Horga *et al.* [18] have used the RLS method to estimate the squirrel-cage induction motor related parameters. They used algorithm of the continuous parametric model of the induction motor for this purpose. The model was based on a technique that used the Poisson moment functional theory. The RLS method was also applied to determine the rotor resistance, self-inductance of the rotor winding, and the stator leakage inductance of a three-phase induction machine [19]. Extended Kalman Filter (EKF) is another optimization technique that has been proposed earlier to determine the motor parameters [20-21]. Velazquez *et al.* [20] have used the EKF method to identify the speed of an induction motor and rotor flux based on the measured quantities such as stator currents and DC link voltage. In another study [21], the EKF method has been used to estimate the speed of induction motor from speed-sensorless field-oriented control and direct-torque control of induction motors.

Genetic Algorithm (GA) is one of intelligent search technique to find optimized solution. It has also been used to determine the motor parameters. It is because the GA method efficiently handles both linear and non-linear equations and the estimation shows generally high accuracy [23-27], compared with the conventional recursive method. In fact, in absence of the actual values of the rotor and stator related parameters in healthy condition, one can estimate these parameters using the motor specifications generally listed in the nameplate by the earlier studies based on the GA method [23-24]. Huang *et al*. [25-26] have proposed a GA based method to estimate both the rotor and stator parameters using a motor model in the Park'd-q reference frame. The estimation method uses fewer measurements but was just validated on simulation and it requires data during machine transient operation which restrict the practical use of this method. Abdelhad *et al*. [27] have used a model based on the single-phase equivalent of Park'model to estimate the motor parameters. But, the model requires data from off-line tests to estimate parameters. Hence, the proposed GA method for the stator parameters estimation is different from the earlier studies [23-27]. The present study has used a new scheme on the parameter estimation using 3-phase current and voltage signals and rotor speed during normal motor operation. It is practically more viable for any condition monitoring method as there is no requirement of the machine transient operation and the off-line tests. The zero-sequence motor model derived from the unbalance stator voltage for the induction motor has been used to identify stator parameters – the stator resistance R_s and leakage inductance L_{ls}. The method has initially been validated on number of simulations and then tested on the experimental motor with the stator faults only. The advantage of the proposed GA method over the RLS method in the stator parameters estimation has also been brought out.

2. ZERO-SEQUENCE MOTOR MODEL

The purpose is to estimate the stator parameters, hence the stator zero-sequence voltage model for the induction motor has been used. The model can be presented as

$$v_{s0} = R_s i_{s0} + L_{ls}\frac{di_{s0}}{dt} \qquad (1)$$

where v_{s0} is homopolar voltage of stator

i_{s0} is homopolar current of stator

R_s is stator resistance

L_{ls} is stator leakage inductance

The homopolar current and voltage can then be calculated by

$$i_{s0} = \frac{1}{\sqrt{3}}(i_{s1} + i_{s2} + i_{s3}) \qquad (2)$$

$$v_{s0} = \frac{1}{\sqrt{3}}(v_{s1} + v_{s2} + v_{s3}) \qquad (3)$$

where i_{s1}, i_{s2}, i_{s3} are the terminal current of an induction motor

$v_{s1}\ v_{s2}\ v_{s3}$ are the terminal voltage of the induction motor

The parameters - stator resistance (R_s) and stator leakage inductance (L_{ls})- have been estimated from this model. The equation can be arranged into following form for the GA method.

$$\bar{i}_{s0} = (v_{s0} - L_{ls}\frac{di_{s0}}{dt}) / R_s \qquad (4)$$

where $\bar{i}_{s0}$ is estimated zero-sequence current. The input data of the model is stator voltage. The GA technique is now applied to search the best parameters by comparing the estimated and measured zero-sequence current.

3. PARAMETER ESTMATION GA METHOD

A Genetic Algorithm (GA) is a search technique used in computing to find solution in optimization problems [28]. It applies the principles of evolution found in nature to the problem of finding an optimal solution. In a "genetic algorithm," the problem is usually encoded in a series of bit strings that are manipulated by the algorithm. Based on principle of GA optimisation, a parameter scheme for electrical motors can be conducted based on the process shown in Figure 1 and are summarized in 5 steps.

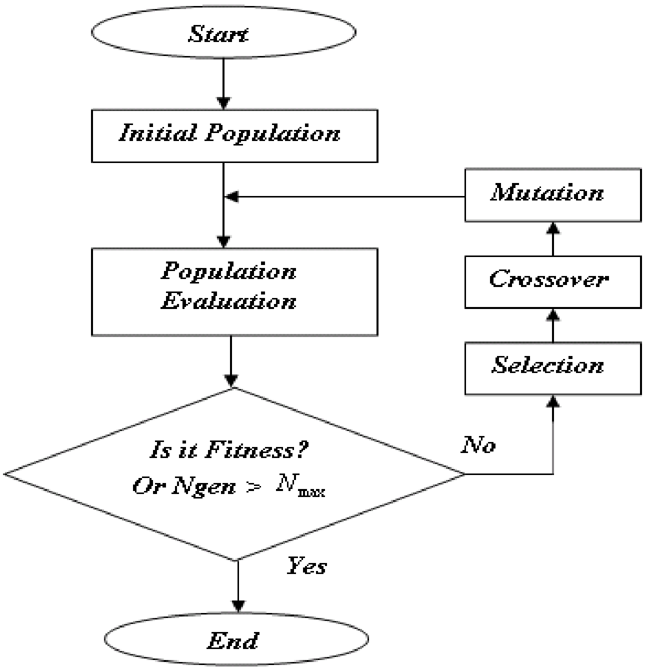

Figure 1 GA based scheme for the motor parameter estimation

3.1 The Creation of an Initial Population of Parameters (P_{00})

The initial generation P_{00} has been generated with randomly selected individuals. Each individual parameter has been constrained by the following condition

$$P_{\min} \le P_{ij} \ge P_{\max} \qquad i = 1,2,...,n \text{ and } j = 1,2,...,m$$

where $P_{\min}$ and $P_{\max}$ are the limits of the parameter vector value. n I is maximum number of generation and m is number of parameters or variables. When computation starts, the initial parameters (decimal number) translated into binary number for the purpose of generating new population of the parameters.

3.2 Evaluation Operation

At this step, the new populations (binary numbers) translated back to decimal numbers for the estimation of the model parameters and the error in the objective function.The objective function is defined as

$$Err = \sum_{t=1}^{T\max} (i_{s0}(t) - \bar{i}_{s0}(t))^2 \qquad (5)$$

where $\bar{i}_{s0}$ is estimated zero-sequence current and i_{s0} is measured zero-sequence current. $T\max$ is the maximum time length of the data. The program terminates when Err becomes equal to or less than the set minimal level or when becomes equal to the maximum generation number ($Ngen$) set in the computational code developed for the study.

3.3 Selection Operation

The selection process is the next step in the computation that guides GA towards ever-better solutions. Nowadays, different algorithms are used to select the best individual value from the estimated population. They are Roulette wheel selection, Tournament selection, Remainder selection and Uniform selection. Tournament selection has been applied here to estimate the parameters because it is efficient and easy to implementation

3.4 Crossover Operation

It attempts to combine elements of existing solutions in order to create a new solution, with some of the features of each "parent". For example, the elements of the existing solutions that have been combined in a "crossover" operation as

Parent 1and 2

0	1	0	1	1	1	0	0	0	1	0	0
0	1	0	1	1	1	0	0	0	0	1	1

⇨

Child

0	1	0	1	1	1	0	0	0	1	1	1

The probability of the crossover (P_c) was assumed to be 0.85 in this study.

3.5 Mutation Operation

It periodically makes random changes or mutations in one or more members of the current population, yielding a new candidate solution (which may be better or worse then the existing population members).

Population 1	1	0	0	1	1	1	0	0	0	1	0	1
Population 2	0	0	0	1	1	1	0	0	0	1	1	1

The probability of Mutation (P_m) was 0.001 in this study. The computation will get terminated if the required minimal error in the objective function achieved or the maximum number of generation achieved.

4. SIMULATION STUDY

A computational code has been developed in the MatLab software code for the estimation of the stator parameters based on the theory and GA method discussed in Sections 2 and 3 and then applied to the simulated examples. Simulation tests were conducted for 3 different types of induction motors listed in Table 1. The actual values used in the simulations for Motor-1 to 3 for the parameters - stator resistance (R_s) and stator leakage inductance (L_{ls})- are listed in Table 2. To start the computation, the range ($P_{\min}$ and $P_{\max}$) for both parameters was set at 50% of real values, the maximum generation number 50 and the population size equal to 80. The results of the estimated stator parameters for the 3 simulations are shown in Table 2. The estimated values for the stator resistance (R_s) and stator leakage inductance (L_{ls}) are close to the actual values (within the error of 6%) of these parameters. Hence the proposed method seems to be estimating the parameters accurately.

Table 1 The specifications of 3 Induction Motors in simulations

Motor 1	3-phase	4 HP	230 Voltage	4 poles	50 Hertz
Motor 2	3-phase	1 HP	416 Voltage	4 poles	50 Hertz
Motor 3	3-phase	10 HP	220 Voltage	4 poles	50 Hertz

Table 2 The estimated of stator parameters for Motor 1-3

	Methods Parameters	Actual value	RLS	Error (%)	GA	Error (%)
Motor 1	R_s	2.2530	2.3200	2.97	2.6930	0.7235
	L_{ls}	3.1831e-4	3.1799e-4	0.10	3.1986e-4	0.4854
Motor 2	R_s	3.3500	3.4842	4.00	3.385	1.0448
	L_{ls}	0.0069	0.0051	26.07	0.06951	0.1614
Motor 3	R_s	0.0453	0.0344	24.13	0.0480	5.899
	L_{ls}	2.4669e-4	6.5979e-4	167.4	2.4335e-4	1.3560

Unit: R_s Ohm (Ω), L_{ls} Henry (H)

The results of the RLS method [17] are also listed in Table 2 for comparison with the actual values and the GA results. It can be seen that the parameter estimation by the GA show higher accuracy than the RLS. The estimation process by the proposed GA method has been further refined by a combination scheme. In this scheme, the values of the parameters estimated by the RLS method [17] have been used as the initial population for the present GA method. The results are shown in Table 3. It shows that the results are more accurate (error within 1%) compared to the earlier GA estimation in Table 2.

Table 3 The estimated stator parameters for Motor 1-3 for the Combined Approach (RLS results used as the initial populations)

	Parameters	Actual value	GA	Error (%)
Motor 1	R_s	2.2530	2.2530	0.00
	L_{ls}	3.1831e-004	3.18e-004	0.09
Motor 2	R_s	3.3500	3.3510	0.03
	L_{ls}	0.0069	0.0067	0.03
Motor 3	R_s	0.0453	0.0457	0.88
	L_{ls}	2.4669e-004	2.4679e-004	0.04

Unit: R_s Ohm (Ω), L_{ls} Henry (H)

5. EXPERIMENTAL STUDY

Having validated the proposed GA method on the simulations, the method has now been tested on the experimental cases. The experimental setup is shown Figure 2. The setup consists of an induction motor with load cell with a facility to collect the 3-phase current - voltage signals and rotor speed decoder data directly to the PC at the user define sampling frequency. The technical specifications of the induction motor used in this experiment are listed in Table 4. The stator of the motor can be adjusted to 4 different conditions: open circuit (healthy condition), 5 turn shot circuit, 10 turn short circuit, 15 turn short circuit, which simulate different levels of the stator fault. Hence the experiments were conducted for these 4 different conditions at full load condition. The data were collected at the sampling frequency of 10240 samples/s.

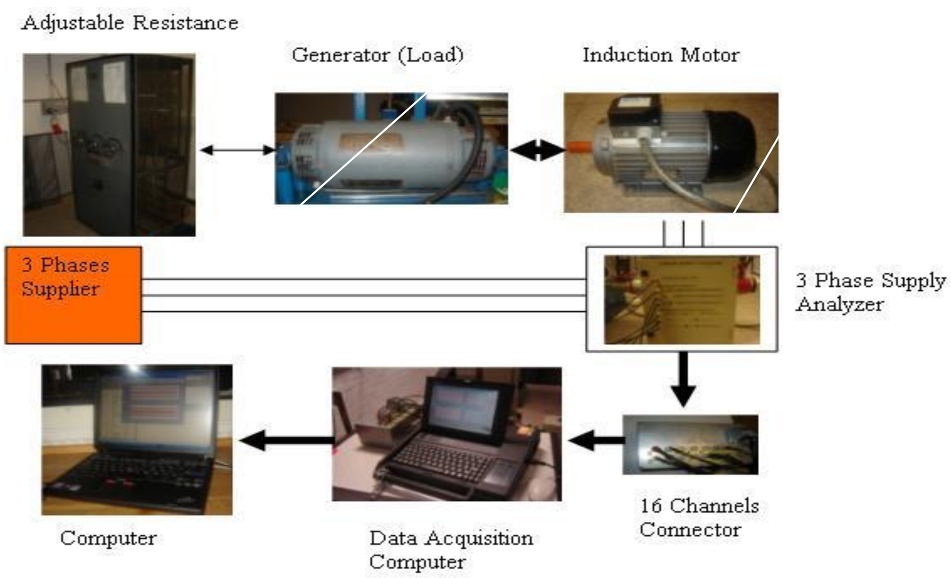

Figure 2 The experimental setup

Table 4 The specification of the Induction Motor used in the experiment

	Phase	Power	Voltages	Currents	Frequency	PF	RPM
Motor	3	4 kW	Δ230/Y400	12.3/7.1	50	0.75	1400

Table 5 The estimated stator parameters for the experimental Motor at different stator fault levels

Method	RLS Method		GA Method	
Parameter	R_s	L_{ls}	R_s	L_{ls}
Open Circuit (Healthy Condition)	1.5830	0.00623	1.5833	0.00621
5 Turns	0.8113	0.00641	0.8732	0.00630
10 Turns	0.5581	0.00631	0.5652	0.00640
15 Turns	0.3738	0.00567	0.3436	0.00530

Unit: R_s Ohm (Ω), L_{ls} Henry (H)

The experimental results are shown in Table 5 when the initial populations from the RLS method [17] were used. The decrease in the stator resistance, R_s, indicates extent of open fault in the stator from the condition 1 to 4 respectively. Typical stator parameters estimation process by the proposed GA method with generations for the healthy Motor is shown in Figures 3-4. Figure 5 shows the minimization process (i.e., Objective function, *Err*). It can be seen that no divergence has been occurred once the objective function finds its minima which indicates the robustness of the proposed algorithm.

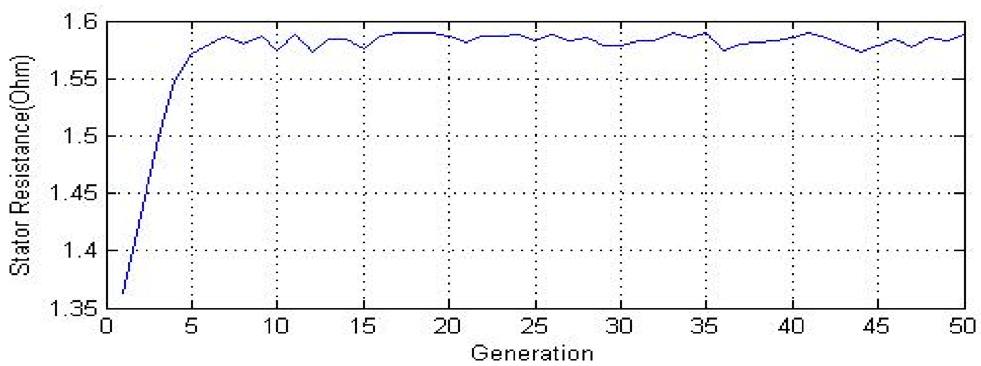

Figure 3 Stator resistance estimation with generation for the healthy experimental Motor

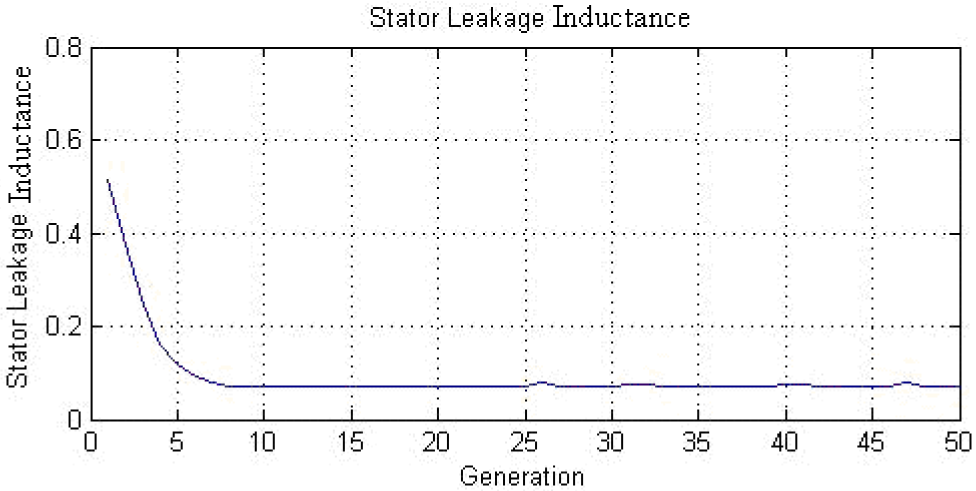

Figure 4 Stator leakage inductance estimation with generation for the healthy experimental Motor

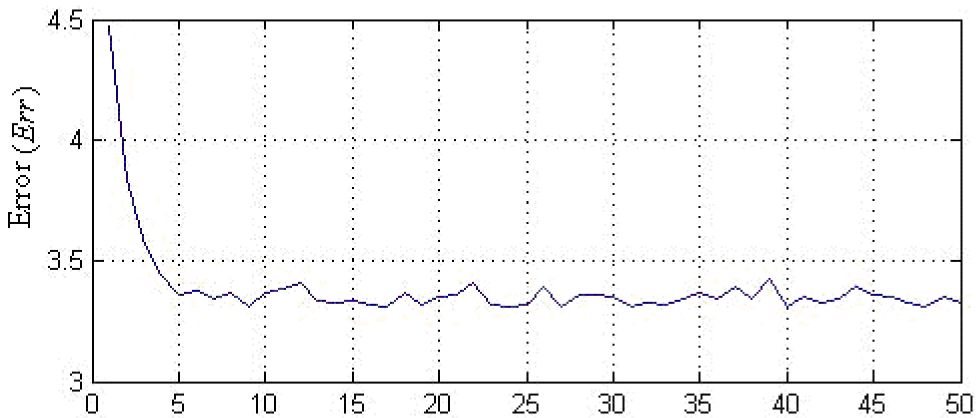

Figure 5 The Objective function with generation for the healthy experimental Motor

6. CONCLUSIONS

The GA method has been proposed to estimate the motor stator parameters using the Zero-Sequence Motor Model and the measured speed, 3-phase currents and voltages data. The parameter estimation by the GA shows better accuracy than RLS. The use of initial populations from the RLS method further improves the accuracy in the parameters estimation. The method has been successfully tested on the simulated examples and then applied to the experimental example of an induction motor with 4 levels of the stator fault. The experimental study indicates that both the stator parameters (Stator Resistance and Stator Leakage Inductance) decrease with increase in the stator fault. There are several common motor faults, e.g., loose electrical connections, short-circuits and imbalanced supply may also be detected by checking the change in stator resistance in a similar manner, but this needs further experiments. However the proposed method has shown a potential for more accurate and reliable condition monitoring of the induction motor. The extension of this method to the rotor related faults is underway.

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