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Estimation of induction motor parameters: an overview

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The parameters of induction motor depends on various factors such as: machine internal state, machine ageing, magnetic saturation, operating conditions, the coupling effect between the internal system and external system. The paper deals with an overview of parameter estimation of three phase induction motor using different soft computing techniques. The soft computing techniques which are considered in the paper are fuzzy system, artificial neural network (ANN), Neuro-Fuzzy, genetic algorithms (GA) and particle swarm optimization (PSO). It is observed that the estimated parameter using soft computing techniques were much closer to actual value.

Keywords: *Induction motor, parameter estimation, soft computing techniques, ANN, Neuro-Fuzzy, GA, PSO*

1.0 INTRODUCTION

The induction motor parameter estimation is the art and science of building mathematical models of dynamic systems from observed input-output data. It can be seen as the interface between the real world of applications and the mathematical world of control theory and model abstractions. The knowledge of all the machine parameters is very important to tune the controllers of a high performance motor drive system. The accurate knowledge of the induction motor parameters is critical for the sensor less drive strategies based on the stator flux estimation [1]. This fact has stimulated the development of specific techniques to determine the induction motor parameter [2]. There are various techniques to estimate the induction motor parameters, such as:

1. Conventional techniques
2. Soft computing techniques

a. Fuzzy system
b. Artificial neural network
c. Genetic Algorithms
d. PSO
e. Integration of above techniques

2.0 CONVENTIONAL METHODS

There are various conventional methods available with their merits and demerits [3, 4]. There are many ways to detect mechanical and electrical problems in induction motors, either directly or indirectly, such as motor current signature analysis, line neutral voltage signature, instantaneous reactive power signature, stator current and motor efficiency, electromagnetic field monitoring, chemical analysis, temperature measurement, infrared measurement, acoustic noise analysis, partial discharge measurement and

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vibration monitoring and fault detection based on parameter adaption [5]. The Knowledge of all the machine parameters is very important to tune the controllers of a high performance motor drive system [6, 7, 8]. For several decades, the Kalman filter has proved to be a powerful tool for state and parameter estimation of linear and nonlinear systems and has been applied in induction motor for estimation of flux [9, 10] and its parameters [11]. Induction motor parameters change with temperature, frequency and saturation. The consequence of any mismatch between the parameter values used in the controller and those in the motor is that the actual rotor flux position does not coincide with the position assumed by the controller. The parameters that may need to be identified offline or tracked online depend on the vector control scheme under consideration [12]. The most important offline identification and online parameter estimation techniques are reviewed.

3.0 OFF-LINE PARAMETER ESTIMATION TECHNIQUES

It is often the case in practice that one manufacturer supplies the inverter with a vector controller, while the machine comes from another manufacturer. It is then not possible to set the parameters of the controller in advance and these have to be set on site, once when the inverter is connected to the machine. Such a situation has led to the development of the so-called self-commissioning procedures for vector controlled induction machines. The main idea behind this concept is that the controller automatically determines all of the parameters of an induction machine, required for vector control. The automated procedure of testing and calculation is done following the first enabling of the controller. As the induction motor may already be coupled to a load, the tests aimed at self-commissioning have to identify the required parameters at standstill. The identification is therefore performed with single-phase supply to the machine. In principle, two types of excitation may be applied dc or ac. The one ideal for true self-commissioning is dc. From applied dc voltage and resulting dc steady state current, one finds the value of the stator resistance. Determination of the remaining parameters is then based most frequently on transient current response that follows application of the dc voltage. Self-commissioning schemes that rely on this approach are those described in [13]. The methods regarded as suitable for commissioning but inappropriate for self-commissioning are those that either require some special conditions to be satisfied during the commissioning (for example, the machine is allowed to rotate) or they require substantially more complicated mathematical processing of the measurement results, when compared to the self-commissioning methods. For example, procedures described in [14] are all based on some tests with single-phase supply to the machine. The maximum likelihood estimation method described in [15], which requires application of the recursive least squares algorithm, this being the same as for the procedure of (16). The second possible excitation for parameter identification at standstill is single-phase ac. Standstill frequency response for the parameter identification [17]. A method based on trial- error and essentially does not require any computations. Some of the offline identification procedures surveyed so far enables identification of the machine's magnetizing curve in addition to other rated parameter values [18].

It should be noted that accuracy of parameter determination in all offline identification techniques depends on the sample rate selection, quantization errors, resolution and accuracy of sensors [19]. Identified parameter values will therefore always be characterized with certain error margin. The major problem encountered in offline parameter identification at standstill is undoubtedly the inverter lock-out time and nonlinearity, which make the accurate parameter determination on the basis of reconstructed voltages very difficult without prior knowledge of the inverter voltage drop characteristics. A technique for overcoming this problem has recently been proposed based on recursive least squares [20].

4.0 ON-LINE ROTOR TIME CONSTANT ESTIMATION TECHNIQUES

The major effort has been put into development of rotor time constant (rotor resistance) on-line estimation methods. Due to a huge number of proposed solutions of very different nature, these are further classified into four subgroups.

A. Spectral Analysis Techniques

This group of methods encompasses all of the cases where online identification is based on the measured response to a deliberately injected test signal or an existing characteristic harmonic in the voltage/current spectrum [21]. Stator currents and/or voltages of the motor are sampled and the parameters are derived from the spectral analysis of these samples. In spectral analysis, a perturbation signal is used because under no-load conditions of the induction motor, the rotor induced currents and voltages become zero, so slip frequency becomes zero, and hence, the rotor parameters cannot be estimated. In [21] the disturbance to the system is provided by injecting negative sequence components. An online technique for determining value of the rotor resistance was used by detecting the negative sequence voltage. The main drawback of this method is that the strong second harmonic torque pulsation is induced due to the interaction of positive and negative rotating components of MMF.

B. Observer-Based Techniques

Loron and Laliberté [22] describe the motor model and the development and tuning of an extended Kalman filter (EKF) for parameter estimation during normal operating conditions without introducing any test signals. The proposed method requires terminal and rotor speed measurements and is useful for auto-tuning an indirect field-oriented controller or an adaptive direct field-oriented controller. Zai, De Marco, and Lipo [23] proposed a method for detection of the inverse rotor time constant using the EKF by treating the rotor time constant as the state variable along with the stator and rotor currents. This is similar to a previously mentioned method that injected perturbation in the system, except that in this case, the perturbation is not provided externally. Instead, the wide-band harmonics contained in a PWM inverter output voltage serve as an excitation. This method works on the assumption that when the motor speed changes, the machine model becomes a two-input/two output time-varying system with superimposed noise input. The drawbacks are that this method assumes that all other parameters are known and the variation in the magnetizing inductance can introduce large errors into the rotor time constant estimation. The application of the EKF for slip calculation for tuning an indirect field oriented drive is proposed in [24, 25]. Using the property that in the steady state the Kalman gains are asymptotically constant for constant speeds, the Riccati difference equation is replaced by a look-up table that makes the system much simpler. The disadvantage is that, although the complexity of the Riccati equation is reduced, the full-order EKF is computationally very intensive as compared to the reduced order-based systems.

C. Model Reference Adaptive System-Based Techniques

The third major group of online rotor resistance adaptation methods is based on principles of model reference adaptive control. This is the approach that has attracted most of the attention due to its relatively simple implementation requirements. The basic idea is that one quantity can be calculated in two different ways. The first value is calculated from references inside the control system. The second value is calculated from measured signals. One of the two values is independent of the rotor resistance (rotor time constant). The difference between the two is an error signal, whose existence is assigned entirely to the error in rotor resistance used in the control system. The error signal is used to drive an adaptive mechanism (PI controller) which provides correction of the rotor resistance. Any method that belongs to this group is based on utilization of the machine's model and its accuracy is therefore heavily dependent on the accuracy of the applied model [26].

D. Other Methods

There exist a number of other possibilities for online rotor resistance (rotor time constant) adaptation, such as those described in [27]. It is based on a special switching technique of the current regulated PWM inverter, which allows measurement of the induced voltage across the disconnected stator phase. The rotor time constant is then identified directly from this measured voltage and measured stator currents. The technique provides up to six windows within one electric cycle to update the rotor time constant, which is sufficient for all practical purposes.

5.0 ONLINE ESTIMATION OF STATOR RESISTANCE

An accurate value of the stator resistance is of utmost importance in this case for correct operation of the speed estimator in the low speed region. If stator resistance is detuned, large speed estimation errors and even instability at very low speeds result. It is for this reason that online estimation of stator resistance has received considerable attention during the last decade [28, 29]. The other driving force behind the increased interest in online stator estimation was the introduction of direct torque control (DTC), which in its basic form relies on the estimation of stator flux from measured stator voltages and currents.

6.0 SOFT COMPUTING TECHNIQUES

The soft Computing Techniques have been employed to assist the fault-detection task to correctly interpret the fault data, such as expert systems, fuzzy logic, fuzzy NN, artificial neural network (ANN), wavelet transform technique and genetic algorithm.

A. Fuzzy system for parameter identification

A higher order fuzzy system (FS) identification method was drawn attention of many researchers for nonlinear dynamic system parameter identification [30]. To perform fault analysis on an induction motor using both experiments and simulation, and to study failure identification techniques applied for condition monitoring of the motor and finally to design an On-line condition monitoring system, fuzzy logic system using Lab View was suggested [31].

B. Artificial Neural Network technique

Artificial Neural Network (ANN) is a system based on the operation of biological neural networks; it is an abstract simulation of a real nervous system. ANN's have been applied with astonishing success in fields ranging from computer science to engineering to medicine.

The Induction motor is a nonlinear multi variable dynamic system with parameters that vary with temperature, frequency, saturation, and operating point. The rotor parameters are the most important parameters for the control of the induction motor drives. The rotor resistance can change up to 150% over the entire operation [32, 33]. The rotor parameter estimation is proposed by estimating the rotor temperature in [33]. This is based on the fact that the temperature influences the fundamental frequency component of the terminal voltage for a given input current.

In many papers, the use of ANN has been tried for estimating the rotor angular speed. Among the methods used, it is possible to note two types of ANN designs. One is based on the machine model and the other one uses stator currents and voltages for direct speed estimation.

C. Integration of ANN and FS

ANNs and fuzzy logic are widely used in the areas of modelling, identification, diagnostics and control of nonlinear systems. There are numbers of methods that can provide true on-line adaptation process of a fuzzy model. One of example is a Takagi–Sugeno–Kang fuzzy model, where the input space is automatically partitioned using a modified fuzzy adaptive resonance theory (ART) mechanism [34].

A simple fuzzy controller implemented in the motor drive speed control has a narrow speed operation and needs much manual adjusting by trial and error if high performance is required [35]. On the other hand, it is extremely tough to create a training data for ANN that can handle all the operating modes [36]. A neuro-fuzzy controller (NFC) for the induction motor drive has the advantages of both FLC and ANN. Over the last decade, researchers reported works on the application of NFC for variable speed drives [37]. However, the conventional NFCs utilized in earlier works have a large number of membership functions and rules.

D. Genetic algorithm (GA)

The basic procedure to develop a genetic algorithm was described and the examples of its application for parameter identification were introduced. In order to simplify the offline identification of induction motor parameters, a method based on optimization using a multi objective genetic algorithm was proposed [38].

Estimation of parameters of three-phase induction motor in order to conduct on-site energy audits of existing motors was used to project a cost savings. This technique used only a few sets of data (voltage, current, speed, power factor or torque if possible) from the field test of motor (on-site), instead of the no load and blocked rotor tests, coupled with the genetic algorithm for evaluating the equivalent circuit parameters [39].

E. Particle swarm optimization (PSO)

Over the past few decades, with the indirect field-oriented control and non sinusoidal measurements, most of the methods can be roughly divided into three categories: signal injection-based method [40], model reference adaptive system-based technique, and optimization techniques. The signal injection-based method is to improve the estimation of low speed performance of sensor less schemes or to excite the machine to create various response signals. They often require extra hardware for signal injection. Applications of signal injection have been presented in dealing with the stator and rotor winding temperatures. The model reference adaptive system uses the error between the estimated and the reference signals to calculate the parameters. In optimization techniques, parameter estimation has been investigated by using the artificial intelligence including the particle swarm optimization (PSO) and the least squares strategy. These techniques have been reported to minimize the consequences of parameter sensitivity in vector controlled drives [41].

7.0 RESULT AND ANALYSIS

Flow Chart for the parameter estimation of I.M using soft computing Techniques is shown in Figure 1.

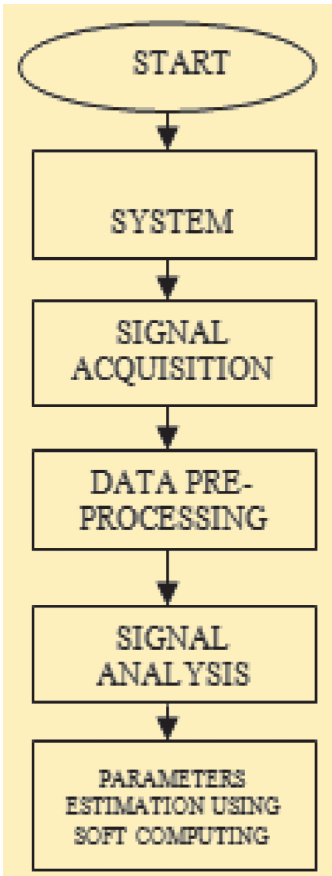

FIG. 1 FLOW CHART FOR PARAMETER ESTIMATION USING SOFT COMPUTING TECHNIQUE.

Current signature of the stator current at different load (no load, quarter load, half load) of the induction motor is shown below in Figure 2.

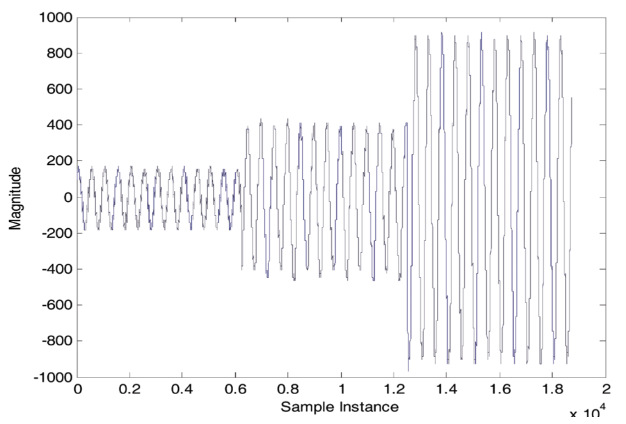

FIG. 2 CURRENT SIGNATURE OF I.M AT DIFFERENT LOAD

Analysis of the above current signature can be done by using Power spectral density is shown in Figure 3.

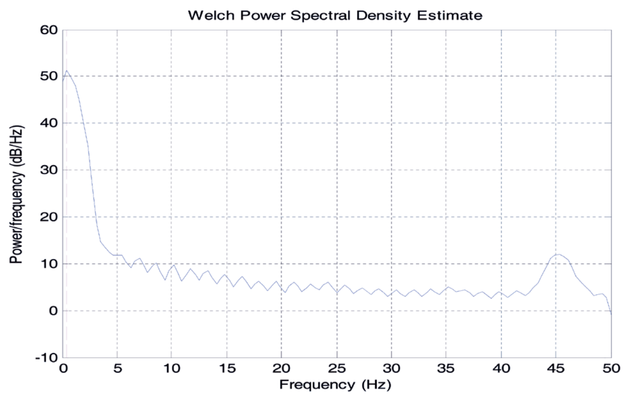

FIG. 3 PSD OF THE CURRENT SIGNATURE

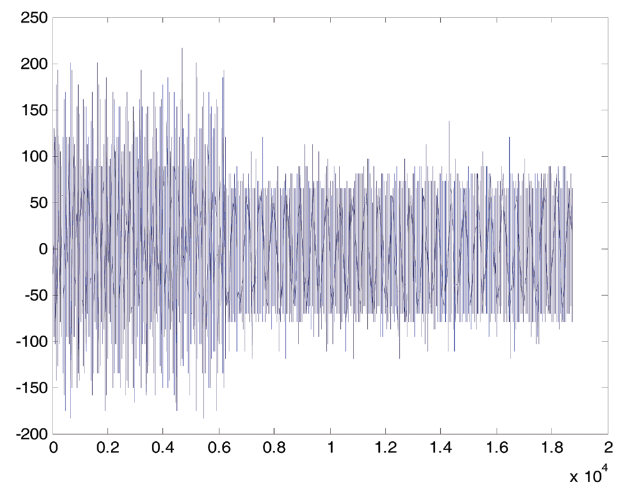

FIG. 4 VIBRATION SIGNATURE OF I.M AT DIFFERENT LOAD

Vibration signature of the induction motor at different load (no load, quarter load, half load) is shown in the Figure 4. It is observed that the vibration of the machine is reduced when the load is increased. That vibration signature can be analysed by the power spectral density (PSD) as shown in the Figure 5.

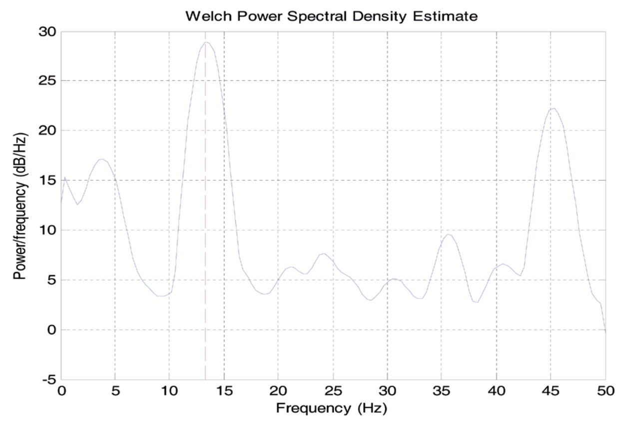

FIG. 5 PSD OF THE VIBRATION SIGNATURE

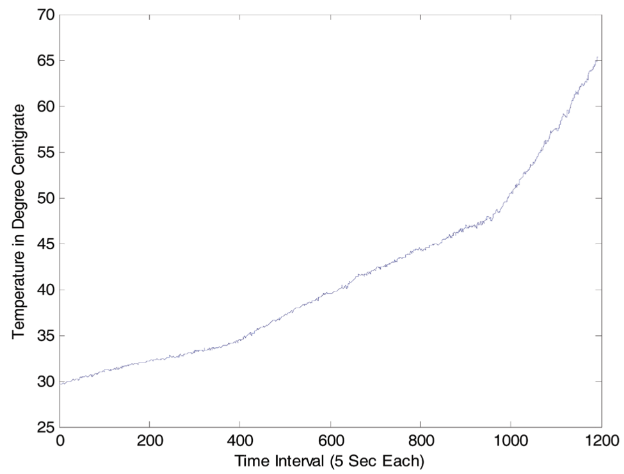

FIG. 6 TEMPERATURE RISE IN I.M AT DIFFERENT LOAD (NO LOAD, QUARTER LOAD, HALF LOAD) WITH FAULTY COOLING SYSTEM.

Temperature rise in I.M at different Load (no load, quarter load, half load) with faulty cooling system is shown in Figure 6 and PSD of that signal is shown in Figure 7.

A. *Implementation of Genetic Algorithm and Simulation Result*

To verify genetic algorithm the Matlab/Simulink environment is used. The simulation model is used in this case instead of real induction motor because of checking algorithm. Sample time 0.25

ms is used for realization of simulation and space of solutions is used by the following intervals:

Rs ∈ (1; 10), *Rr* ∈ (1; 5), *Ls* ∈ (0.1; 1), *Lm* ∈ (0.1;1), *J* ∈ (0.0001; 0.1)

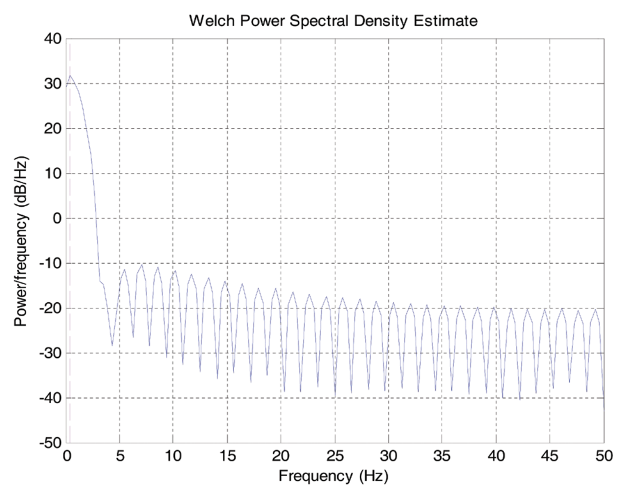

FIG. 7. PSD OF THE TEMPERATURE RISE IN I.M AT DIFFERENT LOAD WITH FAULTY COOLING SYSTEM.

Application of designed GA is tested for the different amplitudes and frequencies of the input voltages. The results of several identifications are presented in Table 1, where the percentage errors of this results and reference values are calculated. From the table, it is observed that the increase of the frequency decreases the accuracy of parameter identification.

The identification values of the system parameters approximate to their real values by the minimization of criterion. For the parameter identification, the integral criterion is used:

$$F = \int_0^T (y - y_m)^2 \, dt \quad ....(1)$$

Where y_m is output of the simulation model and y is output of the real system.

TABLE 1

RESULTS OF IDENTIFICATION FOR THE DIFFERENT AMPLITUDES AND FREQUENCIES OF THE INPUT VOLTAGES

		R_s	R_r	L_s	L_m	J
	Reference Value	7.607	3.71	0.6025	0.5797	0.0018
7.5 V, 5 Hz **Ts=2.5 ms** F=0.0013542	Identified Value	7.5975	3.6812	0.5992	0.5771	0.001695
15 V, 10 Hz **Ts=2 ms** F=0.0015665	Identified Value	7.5971	3.7074	0.6031	0.58215	0.0017028
30 V, 20 Hz **Ts=0.5 ms** F=0.0082013	Identified Value	7.627	3.6668	0.59843	0.57563	0.0016939
45 V, 30 Hz **Ts=0.2 ms** F=2.8285	Identified Value	7.8823	3.5949	0.59231	0.57027	0.0016335

8.0 CONCLUSION

The parameters of induction motor may vary due to several factors such as: machine internal temperature, machine ageing, magnetic saturation, the coupling effect between the internal system and an external system. In this paper, an overview of estimation of induction motor parameters has been presented using conventional and soft computing techniques. The soft computing techniques are better than conventional techniques in terms of adaptability and flexibility.

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