Determining the parameters of induction motors by Genetic Algorithms

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Abstract. The paper presents an approach for determining the equivalent circuit parameters of two widely used induction motors types by Genetic Algorithms. The T-shaped equivalent circuit without considering the steel losses is utilized. Genetic Algorithms are applied and the results are compared by using one, two and three data sets. The accuracy of the proposed approach is analyzed by determining the relative error in the parameters, obtained by Genetic Algorithms, with regard to analytical values. The different computation times for one, two and three data sets are discussed. The results indicate that to obtain low relative error, the proposed approach using the conventional parameters settings and fitness function needs three points from the motors load curves.

1. Introduction

Induction motors are the most widely used in domestic, commercial and various industrial applications. Particularly, the squirrel cage type is characterized by its simplicity, robustness and low cost and for these reasons took the leading place in industrial sectors.

Two types of induction motors are analysed in this paper - the T80B4 type and the АО-90S-4 type. The former is manufactured by Elmatech Shareholders Company and the latter - by the M&C Electric Power CO. These motors are widely used in various industrial and household applications such as cooling fans and blowers, machine tools, die stamping, crushers, conveyors and compressors.

The necessity of knowing the equivalent circuit parameters of IM is constantly growing due to the following reasons:

- students should get deeper, up-to-date and accurate knowledge in the physical processes occurring in IM;
- increasingly adequate models of IM are needed for their research and improvement.

The conventional method for estimation of IM equivalent circuit parameters is based on the no-load and blocked rotor tests which are a time-consuming task, especially if the motor is already coupled to driving equipment.

This paper presents a more sophisticated approach for determining the equivalent circuit parameters of induction motors. The approach is based on only a few sets of measured or analytically obtained data such as stator voltage, current, power factor and slip. A genetic algorithm model for determining the parameters is synthesized that enables the simultaneous satisfaction of steady-state stator current and power factor for various operating points by defining an objective function. The
results obtained by the synthesized model are compared with analytical data. An analysis is performed that proves the validity and adequacy of the proposed approach.

2. Methods for IM equivalent circuit parameters estimation

The methods for IM equivalent circuit parameters estimation can be classified in two main groups - experimental and computational.

The classical experimental methods are a good alternative to the methods using nameplate data. They are performed by two tests – no-load test, blocked rotor test and measurement of the stator winding resistance [1]. The no-load test is used to determine the core loss resistance. The blocked rotor test enables to calculate the rotor resistance, the magnetizing reactance and the sum of the stator and rotor leakage reactances. By this approach, however, it is not possible to know how the leakage reactances are shared between the rotor and stator. This deteriorates the accuracy when predicting the dynamic performance of the motor. Moreover, in order to perform these tests in practice, several difficulties are faced. First, it is difficult to block the rotor when the motor is incorporated in a drive system. Second, the no-load test is often hard to perform since IM usually rotate with load such as fan or gear. Third, IEEE Standard 112 requires performing the motor tests with a voltage unbalance not exceeding 0.5% [1]. Field conditions, however, may exceed this limit significantly. Thus when evaluating motor performance in the field a more accurate and reliable approach is needed.

The modern experimental methods include all methods using tests different from the classical no-load and blocked rotor tests. Such methods include the use of transients in the motor equivalent circuit when supplied from direct voltage and/or direct current [2]. These methods have the following advantages - they are of short duration (only a few seconds) and the motor is not separated from the driving mechanism. Their disadvantage is the necessity of converter to have additional functions in order to perform the tests and to be provided with software to analyze the motor response to these tests. These functions are comparatively easy to realize. Recently electric drives appeared that perform auto adjustment by no-load and standstill tests.

An efficient modern experimental method is proposed in [3]. It determines the equivalent circuit parameters based on the recorded time variations of voltage, current, power and speed from start-up till no-load. The method is accurate but has several disadvantages. It needs expensive equipment to record the time variations of the above electrical and mechanical quantities. The method is intrusive since all loads should be decoupled from the motor during the test. Finally, it is applicable only to high-voltage induction machines rated 1 MW and above.

Some of the computational methods are based on the motor nameplate and catalog data. Three methods for determining the equivalent circuit parameters when taking into account the steel losses are described in [4]. The methods are based on several assumptions such as:
- equal leakage inductances of stator and rotor windings;
- zero value of the referred leakage inductance of rotor winding when determining copper losses;
- zero value of the referred leakage inductance of stator winding when determining steel losses, etc.

All three methods require knowing the rated supply voltage, stator current, rated power, power factor, rated speed and efficiency. It is also necessary to know the stator resistance which is easy to measure. The errors of the different parameters vary from \((4\% \div 60\%)\) [4].

When catalog data for motors is available, it is easy to develop procedures for changing one type of equivalent circuit with another, as well as to relate the obtained results with synchronous speed, rated power, rated, breakdown and starting torque. One of the main disadvantages of the methods based on the motor nameplate and catalog data is the fact that the three most frequently used standards (NEMA, JEC, IEC) are not in agreement which may results in different efficiencies for a given motor. Secondly, the motor may have been rewound and the nameplate or catalog data may no longer be valid. On the other hand, the field voltage unbalance and harmonics content may be different from that for which the nameplate or catalog data is derived. In this way when estimating the equivalent circuit parameters a great percentage of statistical error may be introduced. Another problem is the fact that due to various reasons, most manufacturers usually do not publish detailed data about their production.
Other computational methods for equivalent circuit parameters estimation are the analytical methods using analytical expressions, developed decades ago [5]. They aim to obtain the steady-state performance of a motor for a given set of dimensions. The solutions by these methods are obtained very quickly, typically in seconds, on modern computers. The analytical methods, however, make quite a number of approximations, as IM operation involves 3D phenomena, saturation, eddy currents, etc. Some important details of geometry are also overlooked. These approximations deteriorate the accuracy of analytical methods.

The fast improvement of computer performance, combined with the development of the finite element method (FEM), lead to another important class of computational methods – the numerical methods. The numerical methods predict IM parameters using the magnetic field numerical solutions [6]. A number of professional software packages using FEM are now available that provide two or three dimensional magnetic field solutions. The 3D solutions are accurate but need long preprocessing and solution times. Therefore mostly 2D models of IM are analyzed. The 2D FEM analysis of IM yields reliable results, but has several disadvantages. First, the good software packages are commercial and expensive. Second, the finite element method requires detailed information about the stator and rotor geometry, number of turns, wire diameter, reluctivity curve of steel, etc. Third, it is necessary to compute analytically the stator end turn leakage reactance, the rotor end ring reactance and resistance [7].

The last class of computational methods are the methods based on genetic algorithms, applied in the present paper.

The survey of the methods for equivalent circuit parameters estimation shows that intrusiveness, cost and accuracy are the major considerations when selecting a method for determining IM parameters. Users prefer a cheap and low intrusive method providing a good accuracy.

3. Main operators of Genetic Algorithms
The performance of GA depends on three main operators [8]:

**Selection** - the process of choosing individuals in the population that will create fitter offspring. This is a method that randomly chooses chromosomes from the population according to their evaluation function. The higher the fitness, the bigger chance an individual has to be selected.

The selection process must balance the selection pressure and population diversity. The degree to which the better individuals are preferred is called selection pressure. It is one of the main factors affecting the improvement of population fitness over successive generations.

The most common types of selection are roulette wheel and tournament selection. The roulette wheel selection only guarantees that fitter individuals have greater opportunity to be selected. Their selection, however, is not guaranteed. The opportunity of selection is proportional to the individual's fitness. The roulette wheel is easy to implement but inconsistent in terms of promoted individual's fitness.

For this reason in the present analysis the tournament selection is used. Selective pressure is applied by holding a tournament competition among the individuals of the population. The winner of that tournament competition is the individual with the highest fitness thus consequently to be introduced to the mating pool. The tournament is repeated until the mating pool is filled. Since the mating pool is comprised of tournament winners, it has higher average fitness.

The tournament selection is very efficient and usually leads to an optimal solution.

**Crossover** - the process of taking two parent solutions and producing a child. Selection reproduces the fit individuals but does not create new ones. The crossover operator is applied to the mating pool. It aims at creating a better offspring through recombination of the best characteristics (genes) of the individuals in the population. Thus crossover actively supports the population diversity.

In the present work scattered crossover is preferred. A random binary vector called a mask is utilized. It selects the genes where the vector is 1 from the first parent and the genes where the vector is 0 from the other parent and introduces them into the offspring. A recombination of the characteristics of the parent individuals generates the child.
Mutation - it prevents the algorithm from being trapped in a local minimum. Mutation introduces new genetic structures in the population through random modification of some of its building blocks. GA is allowed to explore wider search space and genetic diversity is instituted in the future offspring.

Genetic algorithms have several advantages over the other optimization methods. They find the global minimum, instead of a local minimum. GA do not require the use of the derivative of the function, which is not easily obtained or may not even exist.

4. Implementation of the GA model and objective function definition

In order the natural selection to be used for estimating the parameters of induction motor equivalent circuit, an objective function should be defined. This function is based on the equations of the T-shaped equivalent circuit without considering the steel losses (figure 1).

There are five unknowns in the circuit in figure 1, namely: stator resistance $R_1$, and stator leakage reactance $X_1$, rotor resistance $R_2$, and rotor leakage reactance $X_2$ (both referred to stator), and magnetizing reactance $mX$. The known quantities from measurement are the input voltage $V_1$, that equals the rated voltage, the input current $I_1$, the power factor $\cos \phi$, and slip $s$.

Based on the T-shaped induction motor equivalent circuit in figure 1, the stator current can be calculated:

$$I_1 = \frac{V_1}{Z_{eq}} = \frac{V_1}{R_{eq} + jX_{eq}}, \quad (1)$$

where $Z_{eq}$ is the equivalent circuit impedance.

![Figure 1. T-shaped equivalent circuit.](image)

Now the power factor can be calculated:

$$R_{eq} = R_1 + \frac{X_m^2 R_2}{s} \left( \frac{R_2}{s} \right)^2 + (X_2 + X_m)^2 \quad (2)$$

The equivalent circuit reactance $X_{eq}$ is computed as follows:

$$X_{eq} = X_1 + \frac{X_2^2}{\left( \frac{R_2}{s} \right)^2 + (X_2 + X_m)^2} \quad (3)$$

Now the power factor can be calculated:
\[
\cos \varphi = \cos \left( \tan^{-1} \frac{X_{eq}}{R_{eq}} \right).
\]  

Based on formulae (1) and (4), we shall develop the objective function [9]:

\[
F_{obj} = \sum_{i=1}^{n} \left( \cos \varphi_{c,i} - 1 \right)^2 + \sum_{i=1}^{n} \left( \frac{I_{c,i}}{I_{m,i}} - 1 \right)^2. 
\]  

In (5) \( I_{c,i} \) and \( \cos \varphi_{c,i} \) are the values computed by (1) and (4). \( I_{m,i} \) and \( \cos \varphi_{m,i} \) are the measured values [10]. The variable \( n \) varies from 1 to 3 in our case.

The analysis of (5) shows that the developed objective function reflects the error in the measured motor data and the results obtained with GA optimization. This means that the lower the error in the computed and the measured data, the smaller the values of the objective function. Thus, the fitness of the individuals rises because the objective function is reciprocal of the fitness function.

The aim of GA is to minimize the error of the objective function defined by (5). In the present work the value of \( F_{obj} \) is set to zero and in this way the global minimum of the objective function is found.

5. IM equivalent circuit parameters estimation

The equivalent circuit parameters of a T80B-4 and an AO-90S-4 type squirrel cage induction motors are estimated. The motors have 0.75 kW and 1.5 kW output power, respectively. The following nameplate data applies to both motors: 380 V phase-to-phase voltage, 50 Hz frequency and 2 poles.

The obtained GA results for the above mentioned motors are compared to the analytical data sets shown in Table 1 and Table 2.

| Table 1. Data sets used in GA for the AO-90S-4 motor. |
|-----------------------------------------------|
| Stator current [A] | Slip | Power factor |
| 2.58 | 0.06 | 0.63 |
| 3.36 | 0.10 | 0.72 |
| 4.09 | 0.14 | 0.74 |

| Table 2. Data sets used in GA for the T80B-4 motor. |
|-----------------------------------------------|
| Stator current [A] | Slip | Power factor |
| 2.06 | 0.06 | 0.59 |
| 2.56 | 0.10 | 0.70 |
| 3.07 | 0.14 | 0.74 |

The performance of the GA optimization greatly depends on the proper choice of the GA parameters such as selection, crossover, mutation, population size, generations, etc. According to the parameters setup, different results are obtained [11].

Their accuracy is measured by the relative error:

\[
\varepsilon = \left( X_{GA} - X_{an} \right) / X_{an}. 
\]  

In (6) \( X_{GA} \) is the value of the parameter computed by the GA optimization and \( X_{an} \) is the analytical value of the same parameter.

The population size value is significant for GA performance. If the population size is too small, accurate solutions may not be reached. A too large population size requires additional computation time and renders the configuration inefficient.

The default setting for population size is 20 to 100 individuals [11]. In order to guarantee good accuracy, however, population size higher than the default (500) is chosen, although it leads to slightly
higher computation time. Otherwise the population would lack diversity, the algorithm would explore only a small part of the search space and not find global optimal solutions.

The conventional configuration of the GA parameters is given in Table 3.

Table 3. Conventional Genetic Algorithm parameters.

| Parameter          | Value |
|--------------------|-------|
| Population size    | 500   |
| Selection function | Tournament |
| Tournament size    | 4     |
| Elite count        | 2     |
| Mutation function  | Adaptive Feasible |
| Crossover function | Scattered |
| Crossover fraction | 0.8   |

It must be noted that an elite count is set up. Elitism guarantees that the first best chromosome or the few best chromosomes (two in our case as evident from the elite count) are copied to the new population.

These settings are chosen by analogy, namely using past experience that has proved successful for similar problems [11, 12].

Tables 4 and 5 show the equivalent circuit parameters estimated by the genetic algorithm as well as the relative error in the estimated parameters with regard to the analytical values.

Table 4. Equivalent circuit parameters and relative error for the AO-90S-4 motor.

| Parameter | R₁ [Ω] | R₂ [Ω] | X₁ [Ω] | X₂ [Ω] | Xₘ [Ω] |
|-----------|--------|--------|--------|--------|--------|
| Analytical value | 8,12 | 5,26 | 22,42 | 1,05 | 91,95 |
| 1 data set  | GA [Ω] | 42,17 | 6,11 | 51,64 | 31,97 | 45,13 |
| ε [%]       | 419,33 | 16,16 | 130,33 | 294,47 | -50,91 |
| 2 data sets | GA [Ω] | 8,38 | 5,30 | 22,50 | 1,054 | 91,51 |
| ε [%]       | 3,1 | 0,76 | 0,39 | 0,38 | -0,47 |
| 3 data sets | GA [Ω] | 8,21 | 5,24 | 22,37 | 1,048 | 91,76 |
| ε [%]       | 1,01 | -0,35 | -0,21 | -0,22 | -0,21 |

Due to the random nature of GA, every computed parameter value in Tables 4 and 5 is an average of the best values from GA obtained in 10 runs. The results in Tables 4 and 5 show that the proposed GA approach is very sensitive to the number of the data sets used.

Table 5. Equivalent circuit parameters and relative error for the T80B-4 motor.

| Parameter | R₁ [Ω] | R₂ [Ω] | X₁ [Ω] | X₂ [Ω] | Xₘ [Ω] |
|-----------|--------|--------|--------|--------|--------|
| Analytical value | 12,20 | 7,33 | 26,37 | 1,46 | 103,53 |
| 1 data set  | GA [Ω] | 63,11 | 8,23 | 51,79 | 8,13 | 52,76 |
| ε [%]       | 417,29 | 12,28 | 96,40 | 456,84 | -49,04 |
| 2 data sets | GA [Ω] | 12,60 | 7,29 | 29,61 | 1,47 | 102,78 |
| ε [%]       | 3,24 | -0,51 | 0,89 | 0,89 | -0,72 |
| 3 data sets | GA [Ω] | 12,36 | 7,31 | 26,49 | 1,47 | 103,27 |
| ε [%]       | 1,3 | -0,23 | 0,45 | 0,45 | -0,25 |
When one data set is used, there is a great discrepancy between analytical and estimated values. In this case the maximum error exceeds 400%, because one single point can not define the nonlinear IM current-slip curve accurately.

The use of two data sets greatly improves the accuracy, the maximum relative error being slightly more than 3%.

With three data sets the maximum relative error is within 1%. Thus, it can be concluded that when more data sets are used, the accuracy of the results is enhanced.

The average computation (CPU) time for one data set is 11 minutes, for 2 data sets - 8 and for three sets - 5 minutes. The computations are performed on a quad core Intel Pentium Processor N3710, 1.6 GHz and 4GB RAM.

The greater the number of points from the motor load curves we use for the GA, the lower the CPU time. This is due to the fact that the GA has more reference points on which to base probable solutions.

The settings of the GA have a strong effect on the computation time. One of the main factors, impacting the CPU time in GA, is the population size. The greater the population size, however, the more CPU time is required.

The choice of the fitness function also greatly impacts the computation time and accuracy. This choice will be discussed in another paper.

6. Conclusion
A genetic algorithm approach for estimating the equivalent circuit parameters of two types of induction motors is proposed. The approach is based on a widely used fitness function and the conventional parameter settings of genetic algorithms.

When one data set is used, there is a great discrepancy between analytical and estimated values, because one single point can not uniquely define the nonlinear IM current-slip curve.

The increase in the number of data sets used improves the accuracy and decreases the CPU time. To obtain relative error within 1%, three sets of electrical input data (voltage, current, power factor and slip) of the motor are needed.

The proposed approach has several advantages over the similar methods for estimating the equivalent circuit parameters of induction motors. The approach is simple, accurate, faster, cheaper and less intrusive than the other experimental or computational methods.

In our future work we shall propose ways for reducing the number of required data sets while preserving the accuracy of the proposed approach.

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