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AN EFFICIENT APPROACH FOR DETERMINING INDUCTION MOTORS PARAMETERS

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Abstract: The paper presents an efficient approach for determining the equivalent circuit parameters of squirrel cage induction motors by genetic algorithms. A T80B4AB3 type squirrel cage induction motor is analyzed. The T-shaped equivalent circuit is utilized. There are five unknowns in the equivalent circuit, namely: stator resistance and stator leakage reactance, rotor resistance and rotor leakage reactance, and magnetizing reactance. The known quantities from measurement are the input voltage, input current, power factor and slip. Genetic algorithms are used for determining the induction motor parameters. The results are compared by using one, two and three sets of measured data. The accuracy of the proposed approach is verified by determining the relative error in the parameters, obtained by genetic algorithms with regard to analytical values. It is shown that the presented approach needs only two points from the induction motor load curve. In contrast, the standard approach requires at least three points from the motor load curve to obtain relative error less than 1%.

Keywords: genetic algorithms, induction motors, parameters of T-shaped equivalent circuit

INTRODUCTION

Electric drives using induction motors are one of the main fields of interest to the control systems and electrical engineering specialists. The quality and effective control of induction motors (IM) is based on their equivalent circuits [1].

The necessity of knowing the equivalent circuit parameters of IM is constantly growing due to the following reasons [2]:

- ✓ students should get deeper, up-to-date and accurate knowledge in the physical processes occurring in IM;
- ✓ designed power converters should possess better quality indices in static and dynamic modes;
- ✓ 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 series 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 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 such models in IM control systems.

SURVEY OF THE METHODS FOR EQUIVALENT CIRCUIT PARAMETERS ESTIMATION OF INDUCTION MOTORS

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 [3].

The no-load test is used to determine the core loss resistance. The blocked rotor test enables to determine 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% [3]. 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 [4]. 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 [5]. 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

large 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 [6]. 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 rated efficiency. It is also necessary to know the stator resistance which is easy to measure. The errors of the different parameters when using these methods vary from 4% to 60% [6].

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. Such approach is very attractive and several converter manufacturers use it [2, 7].

The methods based on the motor nameplate and catalog data are convenient and non-intrusive. They can be applied to various equivalent circuit modifications. Due to the assumption for constant efficiency the nameplate and catalogue data methods give good results for loads above 50%. When using these methods, however, three additional problems may occur. First, the nameplate efficiency may be given according to a standard other than IEEE Std. 112. The three most frequently used standards are the National Electrical Manufacturers Association (NEMA) that uses IEEE Std. 112, the Japanese Electrotechnical Committee (JEC) and the International Electrotechnical Commission (IEC). The three standards are not in agreement which may results in different efficiencies for a given motor [8]. Second, the motor may have been rewound and the nameplate or catalog data may no

longer be valid. Third, 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 [9]. They aim to obtain a 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 solution [10]. 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 [11].

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.

MECHANISM AND MAIN OPERATORS OF GENETIC ALGORITHMS

The genetic algorithms (GA) optimization is a stochastic search method that involves a random generation of potential solutions and then systematically evaluates the solutions until stopping criteria are met. Sets of non-linear equations are solved which are represented by objective functions based on some criterion (the calculated error). Also the reciprocal value of this criterion, called fitness function, is used. The mechanism of GA consists of the following steps [12]:

- ✓ Step 1: Create an initial population for mating;
- ✓ Step 2: Define the fitness (or objective) function of each member of the population;
- ✓ Step 3: Search for natural selection;
- ✓ Step 4: Select population members from the mating pool;
- ✓ Step 5: Generate offspring;
- ✓ Step 6: Mutate the members of the population;
- ✓ Step 7: Terminate the optimization or for continuing go to Step 2.

Genetic algorithms that find good results are composed of the following three operators:

- ✓ Selection – the process of choosing two parents from the population. The aim of this operator is to emphasize fitter individuals so that they can create offspring with higher fitness. Selection 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 most common types of selection are roulette wheel and tournament selection. The roulette wheel selection is easy to perform but it is unstable. For this reason in the present approach tournament selection is used. The best individual from the tournament is the one with the highest fitness and this one is the winner of the potential individuals. The tournament

selection is very efficient and leads to an optimal solution.

- √ Crossover – the process of taking two parent solutions and producing a child. Thus, the population is enriched with better individuals. In the present work scattered crossover is used. It is created with the help of random binary vector called a mask. 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. That is how the child is produced by combining the genes of the two parents.
- √ Mutation – it prevents the algorithm to be trapped in a local minimum. Mutation makes small random changes in the individuals from the population, and thus it provides genetic diversity in the future offsprings and allows the GA to explore wider search space [13]. 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.

DEVELOPMENT OF THE GENETIC ALGORITHM 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).

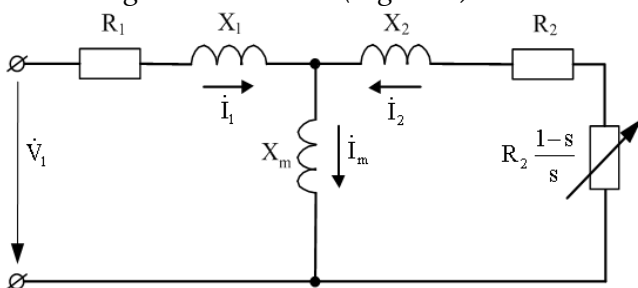


Figure 1. T-shaped equivalent circuit of the induction motor

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 X_m . The known quantities from measurement are the input voltage V_1 that

equals the rated voltage, the input current I_1 , power factor $\cos \varphi$ and slip s .

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

$$\dot{I}_1 = \frac{\dot{V}_1}{Z_{eq}} = \frac{\dot{V}_1}{R_{eq} + jX_{eq}} \tag{1}$$

where Z_{eq} is the equivalent circuit impedance.

The equivalent circuit resistance R_{eq} is equal to:

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

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

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

Now the power factor can be calculated:

$$\cos \varphi = \cos \left(\tan^{-1} \frac{X_{eq}}{R_{eq}} \right) \tag{4}$$

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

$$F_{obj} = \sum_{i=1}^n \left(\frac{\cos \varphi_{c,i}}{\cos \varphi_{m,i}} - 1 \right)^2 + \sum_{i=1}^n \left(\frac{I_{1c,i}}{I_{1m,i}} - 1 \right)^2 \tag{5}$$

In (5) $I_{1c,i}$ and $\cos \varphi_{c,i}$ are the values computed by (1) and (4). $I_{1m,i}$ and $\cos \varphi_{m,i}$ are the measured values. 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.

RESULTS AND DISCUSSION

The parameters of a T80B4AB3 type squirrel cage induction motor with the following nameplate data

are estimated: 0.75 kW output power, 380 V phase-to-phase voltage, 50 Hz frequency and 2 pairs of poles. The obtained GA results for the above mentioned motor are compared to the analytical data sets shown in Table 1.

Table 1. Analytical data sets used in GA

Stator current [A]	Slip	Power factor
1.86	0.06	0.62
2.39	0.10	0.74
3.07	0.15	0.78

One of the main difficulties when applying GA is how to choose an appropriate set of parameter values. Before running the algorithm, the user has to specify a number of parameters such as population size, selection rate, etc. According to the parameters setup, different results are obtained [14]. Their accuracy is measured by the relative error:

$$\varepsilon = (X_{GA} - X_{an}) / X_{an} \quad (6)$$

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

The population size value is very important for GA performance. If it is too small, accurate solutions may not be reached. On the other hand, if population size is too large, unnecessary computational time is spent. The standard setting for population size is 20 to 100 individuals [14]. In order to guarantee good accuracy, however, we chose population size higher than the standard (500), although it lead 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 standard configuration of the GA parameters is given in Table 2. These settings are chosen by analogy, namely using past experience that has proved successful for similar problems [14, 15].

Table 2. Genetic algorithm parameters

Population size	500
Selection function	tournament
Tournament size	4
Elite count	2
Mutation function	adaptive feasible
Crossover function	scattered
Crossover fraction	0.8

Table 3 shows 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. Due to the random nature of GA, each computed parameter value in Table 3 is an average of the best values from GA obtained in 10 runs.

Table 3. Equivalent circuit parameters and relative error

Parameter	R_1	R_2	X_1	X_2	X_m
Analytical value [Ω]	10,2	10,52	8,17	19,16	143,57
1 data set					
GA [Ω]	63,32	11,11	44,74	104,92	56,84
ε [%]	520,80	5,55	447,61	447,61	-60,41
2 data sets					
GA [Ω]	10,44	10,48	8,21	19,25	142,85
ε [%]	2,39	-0,36	0,44	0,49	-0,56
3 data sets					
GA [Ω]	10,26	10,48	8,17	19,16	143,18
ε [%]	0,57	-0,36	-0,01	0,01	-0,27

The results in Table 3 show that the proposed GA approach is very sensitive to the number of the used data sets. When one data set is used, there is a great discrepancy between analytical and estimated values. In this case the maximum error exceeds 500%, 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 less than 3%. With 3 data sets the maximum ε is below 1%. Thus, it can be concluded that when more data sets are used, more accurate results are obtained.

Figure 2 shows the convergence versus the number of iterations when using 3 data sets. The total number of generations is 476 and the algorithm terminates at the value of 4.2026e-007. A zoomed picture for the 450th iteration is also shown in Figure 2.

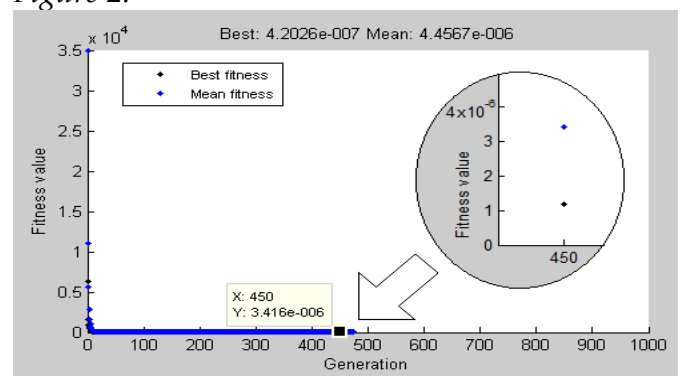


Figure 2. Convergence history with 3 data sets
Next a new improved setup for solving the GA model for estimating the IM parameters is proposed. Table 4 shows the GA parameters settings. The computed results are given in Table 5.

Table 4. Improved GA parameters

Population Size	500
Selection Function	Roulette Wheel
Elite Count	2
Mutation Function	Adaptive Feasible
Crossover Function	Intermediate
Crossover Ratio	1,0

Table 5. Results from the improved GA optimization

Parameter	R ₁	R ₂	X ₁	X ₂	X _m
Analytical value	10,2	10,52	8,17	19,16	143,57
1 data set					
GA [Ω]	66,19	19,11	44,71	104,85	51,92
ε [%]	548,88	81,63	447,21	447,25	-63,84
2 data sets					
GA [Ω]	10,25	10,49	8,14	19,09	143,13
ε [%]	0,52	-0,26	-0,32	-0,37	-0,30
3 data sets					
GA [Ω]	10,19	10,49	8,15	19,11	143,28
ε [%]	-0,06	-0,30	-0,24	-0,24	-0,21

The results from Table 5 confirm the fact that when one data set is used (i.e. one single point from the load curve), there is a great discrepancy between the analytical and estimated parameters. In this case the relative error exceeds 500% again.

When two data sets are used, however, the accuracy of the improved GA optimization is greatly increased. The maximum error is 0.52% as compared to the 2.39% from the standard approach.

Both the improved and standard GA optimization reach a relative error less than 1% when three points from the load curve are used.

Thus an adequate optimization process using GA should be designed to find the global minimum over a wider power range of the induction motor rather than using a single load point. This can be achieved by incorporating at least two (improved approach) or three (standard approach) load points in the objective function defined by (5).

CONCLUSION

An efficient genetic algorithms approach for estimating the equivalent circuit parameters of squirrel cage induction motors is proposed. It is less sensitive to the number of input data sets than the standard approach. The sensitivity and accuracy of the approach are analyzed. The results show that to obtain relative error less than 1%, the proposed approach needs only two sets of electrical input data (voltage, current, power factor) and slip of the motor. For comparison, the standard technique needs at least three points from the motor load curve to obtain error less than 1%. The proposed GA approach has several advantages over

the conventional methods for estimating the equivalent circuit parameters of induction motors. It is simple, less intrusive and yields practically the same results as when using the much more time-consuming and complicated conventional methods.

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