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APPLICATION OF GENETIC ALGORITHMS FOR DETERMINING THE PARAMETERS OF INDUCTION MOTORS

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Preliminary notes

An approach is presented for determining the equivalent circuit parameters of squirrel cage induction motors by genetic algorithms. An equivalent circuit without considering the steel losses is analyzed. The sensitivity of the approach is discussed by using one, two and three sets of data. 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.

Key words: *equivalent circuit parameters, genetic algorithms, induction motor*

Primjena genetskih algoritama za utvrđivanje parametara asinkronog motora

Prethodno priopćenje

Predstavljen je pristup za utvrđivanje nadomjesnih parametara strujnog kruga kaveznog asinkronog motora pomoću genetskih algoritama. Analizirano je nadomjesno strujno kolo bez razmatranja gubitaka u čeliku. Razmotrena je osjetljivost pristupa uporabom jednog, dva i tri niza podataka. Točnost predloženog pristupa je analizirana pomoću određivanja relativne pogreške u parametrima, dobivene genetskim algoritmima, u odnosu na analitičke vrijednosti.

Ključne riječi: *asinkroni motor, nadomjesni parametri strujnog kruga, genetski algoritmi*

1 Introduction
Uvod

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 set 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.

2 Survey of the methods for equivalent circuit parameters estimation
Pregled metoda za procjenu parametara nadomjesnog strujnog luka

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]. The analytical methods 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 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 good accuracy.

3
Genetic algorithms – description, parameter definition and selection
Genetski algoritmi – opis, definicija i izbor parametara

Genetic algorithms (GA) belong to optimization methods for solving sets of non-linear equations. They use objective functions based on some criterion which is most often the calculated error. Sometimes the reciprocal value of this criterion, called fitness function, is used. GA are based on natural selection and natural genetics. Using random numbers, they do not need a good initial guess for unknowns. The mechanisms of the most elementary GA consist of the following steps [12]:

! create an initial population;
! evaluate the fitness of each population member;
! invoke natural selection;
! select population members for mating;
! generate offspring;
! mutate selected members of the population;
! terminate or go to step 2.

GA use the following operators – reproduction, crossover and mutation. Reproduction is the process in which members of the population are selected according to their fitness. Fitness is determined by calculating how well each member fits an objective function. The fit members are assigned the highest probability of being selected for mating. The two most common ways for choosing mates are roulette wheel and tournament selection. Roulette wheel selection is easy to implement but unstable. For this reason the present study uses the tournament selection. The tournament selection randomly selects two small groups of individuals (solutions) and the individual with the lowest cost in each group becomes a parent. Such tournaments are held till the required number of parents is generated.

Crossover is step in GA in which each pair mutually interchanges a randomly selected portion of bits to produce variety. Thus, new strings are generated in the new population. If there is no crossover, offspring is exact copy of parents. If there is crossover, offspring is made from parts of both parents. Crossover is carried out in hope of creating a better offspring.

After crossover the entire population passes through another step in GA called mutation. Mutation prevents the algorithm from being trapped in a local minimum. During mutation randomly selected bits of a randomly selected string are changed from 1 to 0 and vice versa to prevent the GA from losing useful information. If crossover is supposed to exploit the current solution to find better individuals, mutation is supposed to help for the exploration of the whole search space.

The substantial advantages of genetic algorithms over other optimization methods are:

! GA are able to find the fitness function's global minimum instead of a local minimum. This is due to the fact that GA simultaneously explores many points in the search space. Covering the whole search space, they are less likely to stop at a local minimum;
! GA do not require problem-specific auxiliary knowledge such as derivatives of the function;

- initial guesses for estimated parameters do not need to be close to the actual values;
- GA perform very well for large-scale optimization problems.
- The limitations of GA include:
- problems of identifying the fitness function;
- occurrence of premature convergence;
- problems when choosing the various parameters like the size of population, mutation rate, crossover rate and the selection method;
- GA require large number of fitness function evaluations.

4 Development of the genetic algorithm model and objective function definition
Razvoj modela genetskog algoritma i definicija objektivne funkcija

The set of equations of the genetic algorithm model is based on the T-shaped induction motor equivalent circuit without considering the steel losses (Fig. 1).

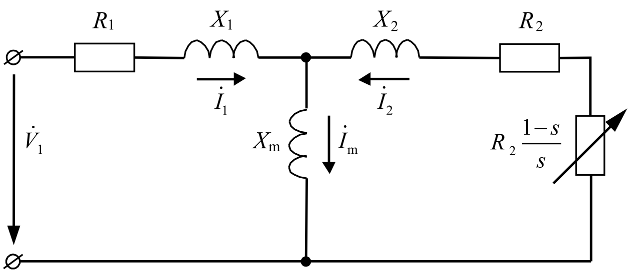

Figure 1 *T-shaped equivalent circuit*
Slika 1 *Nadomjesni strujni krug T-oblika*

There are five unknowns in this circuit, 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 the slip s.

Based on the circuit in Fig. 1, the stator current and power factor can be computed:

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

where Z_{eq} is the equivalent circuit impedance.

The equivalent circuit resistance R_{eq} and reactance X_{eq} in (1) are equal to:

$$R_{\mathrm{eq}} = R_1 + \frac{\dfrac{X_{\mathrm{m}}^2 R_2}{s}}{\left(\dfrac{R_2}{s}\right)^2 + \left(X_2 + X_{\mathrm{m}}\right)^2}; \tag{2}$$

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

Next the power factor can be computed:

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

The criterion for selecting the best individuals in the genetic algorithm is the objective function. An adequately-chosen objective function guarantees that the next generation is usually closer to the solution of the problem. The objective function F_{obj}, used in the present study, is the average error in the power factor and input current for various load points:

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

Here $I_{1c,i}$ and $\cos\varphi_{c,i}$ are the values computed by (1) and (4). $I_{1m,i}$ and $\cos\varphi_{m,i}$ are measured or analytical values. The variable n varies from 1 to 3 in our case.

The aim of GA is to minimize the error of the objective function defined by (5).

5 Estimation of equivalent circuit parameters
Procjena parametara nadomjesnog strujnog kruga

The approach described in the previous section is applied to a T80B4AB3 type three-phase induction motor with the following rated data: 0,75 kW output power, 380 V phase-to-phase voltage, 50 Hz frequency and 2 poles.

The sensitivity of the approach is investigated by using one, two and three sets of data shown in Tab. 1. In our study analytically obtained data is used.

Table 1 *Sets of data used in GA*
Tablica 1 *Komplet podataka korišten u genetskom algoritmu*

Stator current, A	Slip	Power factor
1,86	0,06	0,62
2,39	0,10	0,74
3,07	0,15	0,78

As stated in Section 3, 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.

There are two ways of parameters setting in GA – parameter tuning and parameter control [13]. In parameter tuning parameters are chosen in advance and remain fixed during the solution process. In contrast, in parameter control parameters are allowed to vary with time.

The GA parameters used in this paper are presented in Tab. 2. The values of parameters in Tab. 2 are chosen by means of parameter tuning by analogy, namely using past experience that has proved successful for similar problems [13, 14].

Table 2 *Genetic algorithm parameters*
Tablica 2 *Parametri genetskog algoritma*

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 *Analytical and estimated equivalent circuit parameters and relative error*
Tablica 3 *Analitički i procijenjeni parametric nadomjesnog strujnog kruga te relativna pogreška*

Para-meter	Analytical value, Ω	Estimated, one data set		Estimated, two data sets		Estimated, three data sets	
		GA, Ω	error, %	GA, Ω	error, %	GA, Ω	error, %
R_1	10,20	62,56	513,3	10,54	3,3	10,28	0,8
X_1	8,17	43,49	432,3	8,24	0,9	8,19	0,2
R_2	10,52	11,02	4,8	10,47	-0,5	10,48	-0,4
X_2	19,16	101,98	432,2	19,32	0,8	19,21	0,3
X_m	143,57	58,77	-59,1	142,73	-0,6	143,17	-0,3

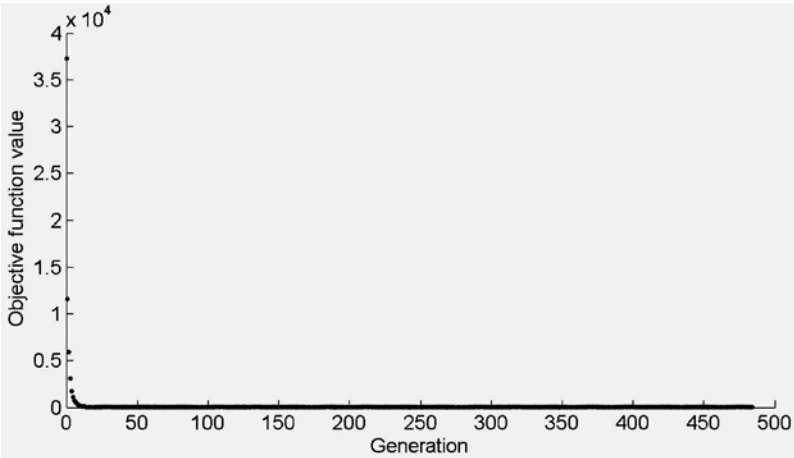

Figure 2 *Convergence history with three data sets*
Slika 2 *Konvergentna povijest s tri kompleta podataka*

The determination of an adequate population size is crucial for GA performance. If it is too small, GA may not be able to reach accurate solutions. If it is too large, unnecessary computational time is spent. The standard setting for population size is 20 to 100 individuals [13]. In order to guarantee good accuracy, however, we chose population size higher than the standard (500), although it leads to slightly higher computation time. Otherwise the population would lack diversity; the algorithm would explore a small part of the search space and not find global optimal solutions.

Tab. 3 shows the equivalent circuit parameters estimated by the genetic algorithm, as well as the relative error of the estimated parameters with regard to the analytical values. Due to the random nature of GA, each estimated parameter value in Table 3 is an average of the best values from GA obtained in 10 runs.

The analysis of the results in Table 3 shows that the proposed approach is sensitive to the number of data sets used. As expected, more data sets, i.e. more load points, lead to more accurate results. There is a great discrepancy between analytical and estimated parameters when only one set of data is used. In this case the error can exceed 500 %. This can be explained by the fact that one single load point does not represent the IM current-slip curve characteristic uniquely. The use of two data sets greatly improves the accuracy, the maximum relative error being less than 4 %. When three data sets are used, there is a very good agreement between analytical and estimated parameters. In this case the maximum relative error is less than 1 %.

Thus the 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 or three load points in the objective function defined by (5). Based on the results in Table 3, it can be concluded that this simple, fast and low-cost approach yields practically the same results as when using the much more time-consuming, complicated and expensive standard tests.

The convergence history of GA when using three data sets is given in Fig. 2. The objective function converges fast and smoothly. The objective function value at which the genetic algorithm terminates is 7.91E-7.

6 Conclusions
Zaključak

An efficient approach for determining the equivalent circuit parameters of squirrel cage induction motors is presented. Based on genetic algorithms, it needs only a few sets of electrical input data (voltage, current, power factor) and slip of the motor. The sensitivity and accuracy of the approach are analyzed. The results show that the approach is sensitive to the number of input data sets. In order to achieve acceptable accuracy, at least two sets of input data are required. When three sets of data are used, the approach yields excellent accuracy, the maximum relative error of the estimated parameters with regard to analytical values being less than 1 %. The proposed approach is more simple, faster, less intrusive and cheaper than the conventional experimental or computational methods for estimating the equivalent circuit parameters of induction motors.

6
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