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INFLUENCE OF GENETIC ALGORITHM PARAMETERS ON THE INDUCTION MOTOR PARAMETERS ESTIMATION

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Abstract: *The genetic algorithms are used for many optimization problems, because they are stabile, do not require good initial values and are able to find the global minimum of the objective function. Because of that, they are very popular technique for complex multivariable problem solving, without taking care about continuality, differentiability etc of objective function Induction motors are used in electrical drives where simple reliable and robust machine is the first requirement. For the modern problem solving techniques which deal with induction motor drives, stator, rotor and mutual resistances and inductances of each motor must be known. The one of the possible ways for their estimation is usage of the known catalogue data. The basic idea for all techniques based on catalogue data is same: estimation of the equivalent circuit parameters that gives motor characteristics very close to known catalogue data. With the good motor model, genetic algorithms can be used for equivalent circuit parameter estimation using catalogue data. The accuracy of estimated resistances depends on motor model, accuracy of catalogue data and setup up of genetic algorithms. In this paper are presented developed algorithm for the equivalent circuit parameters estimation based on the genetic algorithms and the influence of genetic algorithm setup on the results.*

Key Words: ***Genetic algorithms Induction motor drives, Parameter estimation, Catalogue data,***

1. INTRODUCTION

Induction motors are used in electrical drives where simple reliable and robust machine is the first requirement. Therefore nowadays induction motors participate in over 85% of all installed AC drives, in power ranging from few watts to over 10 MW. As result of power electronics development and control systems improvement, in the last years induction motor has been replacing DC motor more frequently in adjustable speed drives (ASD).

In induction motor adjustable speed drives the accurate dynamic model of machine is necessary. For the induction motor drive model stator, rotor and mutual resistances and inductances must be known. They could be determined experimentally or estimated with a help of some motor model based on catalogue data.

The equivalent circuit parameters estimation is multi-variable optimization problem, where more input (catalogue data) and output values (equivalent circuit parameters) have to be estimated. The estimation of the motor parameters and their recurrence and accuracy depend on used motor model, the used estimation technique, number of used catalogue data in calculation and their accuracy.

In the catalogues manufacturers report steady state induction motor data, so the steady state induction motor equivalent circuit model is logical choice for almost all authors who work in this field. The equations for the current, power, torque, etc can be developed using the equivalent circuit. The differences between authors are in complexity of the used model and the number of used catalogue data. In the simplest model stator resistance is neglected and the basic name plate data are used. In the most complex models the influences of the saturation of the magnetic core and the skin effect are involved in the model so the all possible catalogue data are used for the parameter estimation. Which model have to be used depend on purposes of induction motor data.

The each equivalent circuit parameter has different influence on catalogue data calculation. Authors tried to solve this problem using different estimation algorithms. The most common used is mean square technique, but some authors used other alternative techniques, as sensitivity analysis, fuzzy logic, genetic algorithms etc. All authors are satisfied with the reached result and used algorithm.

The genetic algorithm can be used to solve analyzed problem, which can be expressed as a system of nonlinear equations. The genetic algorithm uses objective functions based on some performance criterion to calculate an error, does not require a good initial values and is able to find the global minimum, instead of a local minimum. The genetic algorithm abilities allow catalogue data inaccuracy influence analysis, without taking care about objective function characteristics, as continuality, differentiability etc.

2. INDUCTION MOTOR MODEL

Stator, rotor and mutual resistances and reactances could be obtained in the few different ways: experimentally, with model based on catalogue data and with the implementation of some identification techniques [8]. The catalogue data usage is the simplest and the cheapest method for this purpose [4]. Often, this is the only way to get needed motor data.

Usually, the following catalogue data is known: Nominal power; Nominal voltage; Nominal current; Nominal speed; Nominal slip; Nominal Breakdown torque; Locked rotor torque;power factor; Nominal efficiency; Locked rotor current; Number of pole pairs.

Depending of the parameter purposes various methods with different catalogue data are used for obtaining motor's resistances and reactances.

The idea of the used method is, by using of induction motor steady-state equivalent circuit, to estimate motor parameters, so that with calculated values of resistances and reactances, to be very close to known catalogue data. The usage of steady state equivalent circuit for the parameter estimation produces nonlinear multi variable functions.

Induction motor equivalent circuit must correspond to reality [3] [4], but effects of saturation, hysteresis, eddy current, deep rotor bars and etc have no significant influence on the nominal working conditions. The usually suggested equivalent circuit of induction motor for each phase is shown in *Fig. 1*.

In *Fig. 1* are presented: X_m is magnetic field reactance. R_1, X_1, R_2 and X_2 are stator and rotor resistances and reactances respectively and s is rotor slip.

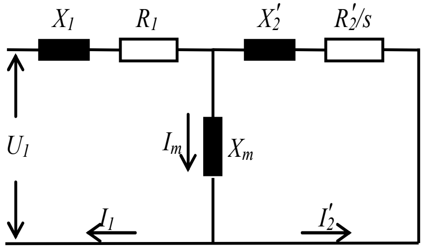


Fig. 1 *Equivalent circuit of induction motor for parameter estimation based on catalogue data*

In the *Fig. 1* model resistance R_m, which represents power losses in magnetic core, is missing. Its influence on the motor characteristics is very small and usually is neglected, but when motor losses and temperature are calculated it has respectable influence on the results, and must be involved into the model.

The equivalent circuit shown in *Fig. 1* and the induction motor relations allow to be set all needed equations. For the genetic algorithm testing purposes the calculated nominal induction motor data are used instead of manufacturer's catalogue data. For faster calculation purposes, parameter estimation is done in two steps:

1. With nominal data and equations based on the experience, the initial values for the reactances and resistances are estimated and
2. Involving genetic algorithms the final values are calculated [5], [8].

The accuracy of catalogue data and its influence on the final data are analyzed in [1], [2].

3. GENETIC ALGORITHMS

Genetic algorithms maintain and manipulate a family or population of solutions and implement a "survival of the fittest" strategy in their search for better solutions. This provides an implicit as well as explicit parallelism that allows exploitation of several promising solution space areas at the same time. Genetic algorithms search the solution space of a function through the usage of simulated the survival of the fittest evolution strategy. In general, the fittest individuals of any population tend to reproduce and survive to the next generation.

Initially, the binary string manipulation techniques were developed and latter the real number and string techniques were established. The real numbers are more native and suitable for this problem, so the real number genetic algorithms are used.

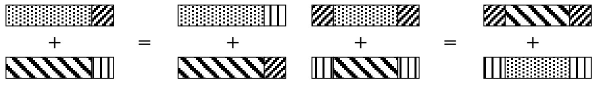
3.1. Selection

Selection algorithm works on the entire population to determine the number of copies that each individual would have in the next generation. The selection of individuals which would pass in the next generation is based on individual average fitness, so individuals with higher fitness have more chances to reproduce themselves in the next generation. Mainly used selection techniques are: Roulette Wheel, Rank selection, Steady state and Elitism. In this case the normalized geometric selection is used. There are no needs for steady state and elitism techniques. More information about this selection method will be given in the result presentation chapter.

3.2. Crossover

The crossover operator deals with the selected individuals - takes two random individuals and creates new, mating and swapping parts of their strings. The result of the crossover is two new strings (solutions) which are candidates for the best solution in the next generation. For the binary strings, simple crossover in one or multiple points is used. The schematic of the binary crossover process is shown in *Fig. 2*.

For the real valued representation, simple, arithmetic and heuristic crossover, developed by Michalewicz, are used.



a. b.

Fig. 2 *Crossover process in one point (a) and in two points (b)*

All three real value crossover techniques are combined in the genetic algorithm implementation.

3.3. Mutation

Mutation involves the random number change in some individuals producing single new solution. In this way variation into population is being introduced. Binary mutation flips a random bit with predefined probability.

$$[00010101\mathbf{1}001011001]\ \mathbf{mutation} \rightarrow [00010101\mathbf{0}001011001]$$

$$[00\mathbf{0}10101100101100\mathbf{1}]\ \mathbf{mutation} \rightarrow [00\mathbf{1}10101000101100\mathbf{0}]$$

Fig. 3 *Binary mutation in one and two point*

The process of mutation is shown in the *Fig. 3*. The random selected bits (shown bold) change their values. In the real valued representation, mutation is implemented in similar way, but the selected number is changed with the randomly generated number between 0 and 9. There are differences in the way of how the number is selected and therefore the combination of the uniform, non-uniform, multi-non-uniform and boundary mutation is used.

3.4. Termination and evaluation functions

The genetic algorithm moves from one to another generation selecting and reproducing parent until termination criterion is met. The most used termination criterion is the maximum number of generations. The next strategy is population convergence criterion. This means than when the sum of the deviations among individuals becomes smaller, then predefined values algorithm stops. The algorithm, also, can be terminated when lack of improvements, in the best solution, in the predefined number of generations. Also, other criteria can be used depend on implementation of algorithm. Different criteria can be used in the same algorithm, and the process stops when one criterion is met.

4. THE GENETIC ALGORITHM INFLUENCE ON THE ESTIMATED VALUES OD INDUCTION MOTOR EQUIVALENT CIRCUIT

When genetic algorithms are used, the setup and tuning of the population and operators may have high impact on the estimated values and needed time for results obtaining. When genetic algorithms are used usually, population, number of generations, the selection function and its parameters, crossover and mutation parameter have influence on results.

Problem of setup and genetic algorithms tuning are analyzed on the five induction motors with different power rates, speed and purposes. For each motor catalogue data and manufacturer's equivalent circuit parameters are known. The basic information about used motors are given in Table 1.

Table 1 The basic data for the used motors

	Type	Power [kW]	Voltage [V]	Speed [RPM]	Purpose
1	WRIM	736	4000	1773	General
2	SCIM	400	400	742	CSI
3	SCIM	250	400	989	VSI
4	SCIM	18.5	380	1465	General
5	SCIM	2.2	220	700	General

Because of catalogue data inaccuracy, for each motor with the known equivalent circuit parameters, the nominal catalogue data were calculated. The calculated catalogue data were used as an input values in the implemented genetic algorithms. In this paper only influence of the genetic algorithms on the results and calculation speed is analyzed.

The genetic algorithms influence analysis was made for each parameter and each motor. The final result errors, the mean error of the population and calculation time for the best solution were criteria for the parameters setup. For each parameter analysis, the other parameters are kept with average values, usually used in the different applications. The calculations were repeated 10 times for statistical relevant informations.

4.1. The population

The number of individuals in the population has influence on the obtained results and estimation time. The small population can produce high error and long estimation time. When the population is too big, the estimation time is very long without improvement in results. The population analysis was done for 30, 60, 90, 120 and 150 individuals. In the Table 2 are given average results for all motors. The typical genetic algorithm diagram is given in Table 2.

Table 2 Average values for all motors for the different population

Indivi-duals	Calcul-ation time for 200 gen	Best solution			Average error in last gen
		Average Error	Generation	Estimation time [s]	
30	2,9091	0,0332	88,68	1,2866	0,0436
60	2,7378	0,0330	87,22	1,1929	0,0370
90	2,7269	0,0330	88,66	1,2084	0,0352
120	2,7231	0,0328	81,24	1,1025	0,0349
150	2,7878	0,0345	97,04	1,3498	0,0360

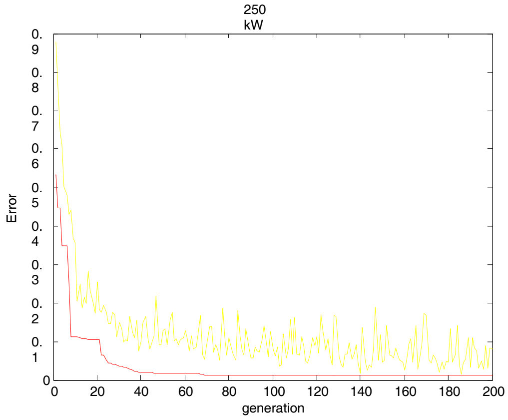


Fig. 4 *Error of best solution (red) and average error (yellow) vs. genetic algorithm generations for 250 kW motor and 60 individuals*

The results shows that there are no significant error in the obtained best solution and its time, but population with 30 individuals has longer estimation time and higher average error in last generation. That means that 60 individuals will be enough for reliable results.

4.2. Selection Parameters

In 3.1 is mentioned that the normalized geometric selection is used. The normalized geometric selection is one of the ranking selection techniques. The probability of selection is determined by ranking and geometric normalization using:

$$p_i = \frac{q(1-q)^{r-1}}{1-(1-q)^P} \quad (1)$$

where: q – is probability for best individual selection, r – is individual rank (1 is best), P – population, p_i – probability for i-individual selection.

Considering (1), only q can be changed in the selection process. The value of q were changed in range 0,04-0,12 with the step of 0,02. The obtained results are given in Table 3.

Table 3 Average values for all motors for the different probability for best individual selection

q	Calculation time for 200 gen	Best solution			Average error in last gen
		Average Error	Generation	Estimation time [s]	
0,04	3,2113	0,0329	91,98	1,4584	0,0389
0,06	3,0694	0,0328	89,56	1,3585	0,0376
0,08	3,0287	0,0343	83,96	1,2591	0,0377
0,10	2,9435	0,0331	95,76	1,3936	0,0365
0,12	2,9016	0,0336	84,54	1,2126	0,0369

The results given in Table 3 show influence of the probability on the estimated results. The higher value of probability causes shorter time for the best result, but the result has higher error. The lower probability values have reversed influence. The mean value 0,08 is good compromise between fast and accurate solutions.

4.3. Crossover parameters

When real value genetic algorithms are used usually simple, arithmetic and heuristic crossover are combined.

The simple and arithmetic crossovers need only one parameter (number of crossovers as is shown in *Fig. 2*).

The heuristic crossover works in little different way than previous. Only heuristic crossover takes care about parent feasibility. When the random number r is generated in range [0,1] and the parent X is more feasible than Y, the (2) define final result.

$$X' = X + r\left(X - Y\right)$$
$$Y' = X \qquad (2)$$

If the X' is not feasible, the new random number r is generated and the process is repeated. But if child can not be created, after pre defined trials, the parents go to the next generation. That way the second parameter (number of trials) has to be determined. There are lot of combinations of crossover parameters, but for the analysis purposes three different combinations are used: [1;1 2;1], [2;2 3;2], [3;3 4;3]. Parameters in brackets are for simple, heuristic and arithmetic crossover respectively. In *Fig. 4* are given obtained results for different crossover parameters.

Table 4 Average values for all motors for the different probability for best individual selection

Crossover parameter	Calculation time for 200 gen	Best solution			Average error in last gen
		Average Error	Generation	Estimation time [s]	
[1;1 2;1]	2,8128	0,0330	100,38	1,4086	0,0378
[2;2 3;2]	3,1606	0,0356	96,90	1,5344	0,0393
[3;3 4;3]	3,5481	0,0343	86,34	1,5364	0,0380

The results shows that in this case higher values of crossover parameters cause higher error in same time with the longer calculation times for the whole generations and also for obtaining best solutions. The selection of the [1;1 2;1] combination is the native solution for the best and fast results.

4.4. Mutation parameters

The mutation in the genetic algorithm has role to involve unexpected and random changes in the generations, to avoid stall of the algorithm from the one side, and ovoid of the local extremes from the other side.

In the developed real number algorithm four different mutation techniques are used: boundary mutation, multi-non uniform mutation, multi non–uniform mutation and uniform mutation. Each of these techniques involves mutation in different way and with different influence on results.

Boundary Mutation changes one of the parameters of the parent and changes it randomly either to its upper or lower bound.

Multi-Non uniform mutation changes all of the parameters of the parent based on a non-uniform probability distribution. This Gaussian distribution starts wide, and narrows to a point distribution as the current generation approaches the maximum generation.

Non-uniform mutation changes one of the parameters of the parent based on a non-uniform probability distribution. This Gaussian distribution starts wide, and narrows to a point distribution as the current generation approaches the maximum generation.

Uniform mutation changes one of the parameters of the parent based on a uniform probability distribution.

Each of this mutation is randomly used during the calculations.

The boundary and uniform mutation need only one parameter which deals with crossover functions. The non uniform mutations need two more parameters: maximal generations and parameter for Gaussian distribution.

The mutation influence on the obtained results is analyzed in five different parameter sets. One of the sets is with all values set to zero, which means that there is no mutation. Higher parameter values indicate that mutation is implemented more often. The results are given in Table 5. The mutation parameters are given in following order: boundary mutation, multi-non uniform mutation, multi non–uniform mutation and uniform mutation.

Table 5 Average values for all motors for the different probability for best individual selection

Mutation	Calculation time for 200 gen	Best solution			Average error in last gen
		Average Error	Generation	Estimation time [s]	
[0;0 0 0; 0 0 0; 0]	0,4066	0,3915	3,64	0,0073	0,3915
[2;3 50 1,5; 2 50 1,5;2]	1,4988	0,0474	103,88	0,7825	0,0476
[4;6 100 3; 4 100 3;4]	2,5300	0,0393	63,16	0,7969	0,0411
[6,9 150 4,5; 2 150 4,5;6]	3,5200	0,0344	57,82	1,0164	0,0438
[8; 12 200 6; 8 200 6;8]	4,4916	0,0329	50,34	1,1288	0,0586

The obtained results clearly show that the mutation is very important part of genetic algorithm and can not be neglected, or avoided. When there is no mutation the final “best” solution is calculated very fast, about 100 times than the next case, but the obtained result is 10 times worse than the other cases. Also if the mutation is used to frequently the calculation time became much longer without taking results. In *Fig. 5* and *Fig. 6* are shown tracks for different mutation parameters without and with mutation, respectively. In *Fig. 6* the influence of mutation is obvious, which is representing with the average generation error.

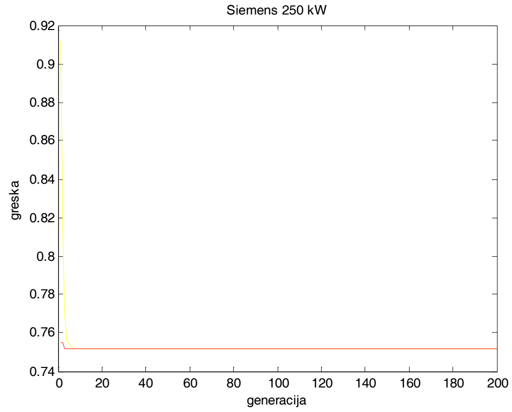


Fig. 5 *Error of best solution (red) and average error (yellow) vs. genetic algorithm generations for 250 kW motor without mutation*

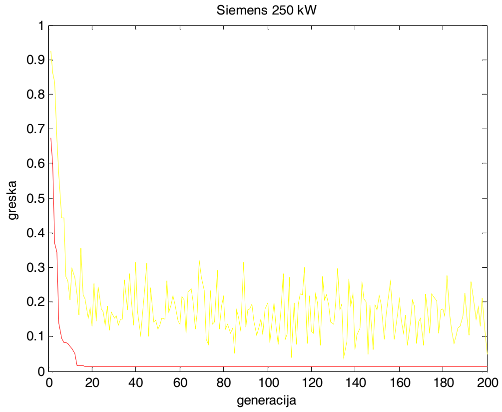


Fig. 6 *Error of best solution (red) and average error (yellow) vs. genetic algorithm generations for 250 kW motor with [8; 12 200 6; 8 200 6; 8] mutation*

The mutation parameter combination [4; 6 100 3; 4 100 3; 4] gives reasonable compromise between error and calculation time.

In this analysis the number of generation is assumed to be 200. All results shows that the best solution usually will be find in first 100 generation (average value). Some times the solution was found in more than 100 generations, so we think that the 200 generations always will be enough for the best results.

5. CONCLUSION

Genetic algorithms can be used to solve difficult problems with objective functions. With usage of genetic algorithms can be avoided complicated calculation of partial differentials, complicated equations etc.

In this paper is shown that the proper selection and tuning of genetic algorithm parameters is essential for accurate and fast calculation. Wrong parameter setup can cause worse results and longer calculation time.

In this paper only simple genetic algorithm setup process was described. The change of each operator’s parameter can cause better or worse results, so more complex analysis can be provided, e.g. simultaneous change of two or three parameters in same time.

The calculated values and estimation error also shows that genetic algorithm can be used for induction motor equivalent circuit parameters estimation using catalogue data.

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