9 Parameters Estimation of an Extended Induction Machine Model Using Genetic Algorithms

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Abstract

Industries are innovating, developing and optimizing production line to improve productivity, quality and robustness of the production in order to be competitive. The different existing goals of optimization, such as the computation of closed-loop drive-fed motors, the reduction of energy consumption or the detection of motor faults, lead to the necessity to identify the induction machine parameters (resistance, inductances, …). To these ends, researchers and companies are investigating efficient methods to identify these parameters. In this paper, we propose for the first time an effective identification of 9 parameters of the extended induction machine model based on the θ-NSGA III. In addition, a comparison between a classic genetic algorithm, the well-known NSGA II and the θ-NSGA III is performed. Results show that the θ-NSGA III provides a better estimation of parameters than the two other genetic algorithms.

1. Introduction

Over the past decades, computer processing power has been improved allowing industries to increase their competitiveness and productivity by optimizing their automation systems [1]. These systems are generally composed of conveyors, electrical machines and sensors. This paper focuses on the induction machine, which is the main element in automation systems. Indeed, this machine is considered as the most used motors in industry because of its ease of implementation and sturdiness [2]. Thus, the optimization of the asynchronous motor exploitation leads an improvement of the automation systems.

In general, the optimization of the induction machine is based on an accurate knowledge of its parameters such as resistances and inductances on the stator and the rotor. This approach is very useful for computing the closed-loop drive-fed motor (e.g. speed optimization), managing the power consumption (e.g. saving 5% of power consumption), designing electrical installation and predicting of the induction machine failures (e.g. predictive maintenance optimization). Moreover, these parameters could be changed with the aging of the electrical machine and the substantial resources deployed by industries to optimize these systems for the first time could be useful/wasted. Therefore, they have to re-estimate the parameters in order to define a new optimization.

The prediction of the induction machine behavior responds partially to this expectation. In order to predict the asynchronous machine behavior, the induction motor parameters have to be extracted. There are two possible approaches to obtain these parameters. The first one is the measurement method, which consists of blocking the rotor and applying no resistance load [3]. In the second approach, signals are acquired and compared with a mathematic model of the induction motor (concept of black-box). This one uses optimization algorithms such as traditional gradient method optimization (e.g.: Newton-Raphson) [4] and Evolutionary Algorithms (EAs) [5]. In addition, this method has the advantage of being almost automatic compared to the first approach.

The most common estimation method is EAs which is based on a criterion named the objective function (or fitness function). Indeed, the derivative of this function is not always possible with traditional optimization algorithms. Accordingly, EAs and, in particular, Genetic Algorithms (GAs) are very popular for identification processes.

EAs and, more specifically, GAs, Multi-Objective GAs and Particle Swarm Optimization (PSO) are broadly applied and the most popular algorithms in order to estimate parameters of the induction motors [6-11]. Several works [12-14] assert that PSO algorithms give the best results to identify parameters but the difference between GAs and PSO could be negligible. Nevertheless, in order to perform an effective control of the motor, the machine parameters have to be known precisely. In addition, the induction motor for the closed-loop drive fed requires the identification of 5 parameters that constitute the model in the Park's frame [15]. In this work, the three-phase asynchronous machine model is used allowing to simulate and work in the failures detection domain. This model has 9 parameters that have to be estimated. This number of parameters leads to an increase in the search solutions space. Consequently, utilizing the GAs for the 5 parameters model may not be effective anymore. Furthermore, all works identified for the estimation of induction machine parameters used restrictive bounds for the search of solution. Finally, in most cases, the identification problem is defined by a single objective function leading to the loss of population diversity.

In this paper, we propose an effective identification of an extended induction machines model with 9 parameters using GAs. As mentioned above, this model is also used to simulate stator faults as describe in [16] and the accuracy of the identification is essential in order to perform an effective faults detection. Moreover, a comparison is done between a classic GA and several well-known multi-objective GAs. In addition, the new θ-NSGA III algorithm is used for the first time in order to estimate the induction machine parameters efficiently. The results of this comparison show that the new θ-NSGA III algorithm gives a better identification than the two other. Finally, the multi-objective approach allows to identify the segment with the biggest error between the reference signal and the model signal.

The paper is organized as follows: Section 2 describes the identification system with a brief presentation of the induction machine model and GAs used in this paper. Section 3 presents the GAs settings and results of the different estimation tests. Section 4 discusses and compares our results. Finally, Section 5 briefly concludes the paper and gives an overview of our future works.

2. The Identification System

We propose an effective parameters identification method of the extended induction machine model composed of 9 parameters using GAs. The process of identifying the parameters of an induction machine can be synthetized as illustrated in Fig. 1. This process has been implemented in MATLAB.

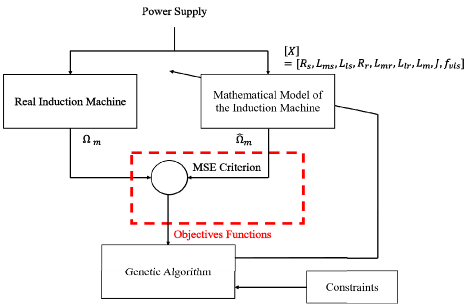

Fig. 1. Process of parameters Identification of the induction machine

As we can see in Fig. 1, we first have to know the power supply used for the real asynchronous machine. Indeed, this information is defined as an input in the mathematical model in order to simulate the behavior of the induction machine. Next, the real and predicted signal generated from the model of the machine are compared and the mean squared error (MSE), which is the most common criterion in identification processes, is computed. Then, by an iterative process, the GAs is used to minimize or maximize an (or several) objective function(s), which creates new vectors of the induction machine parameters, noted $[x]$, under constraints noted $g(x)$.

2.1. Genetic Algorithms

GAs are an heuristic (or metaheuristic) algorithms based on a stochastic search inspired by the natural biological evolution and developed for the first time as algorithm by John Holland [17]. Fig. 2 illustrates the natural process of solutions search of GAs. They belong to the class of EAs, which are used to find solutions optimizing complex problems such as the optimization of closed-loop drive-fed motors. Indeed, their uses to solve complex problems respond to the necessity to generate approximate solutions when the exact solution cannot be find with a classic optimization method (e.g. Newton-Raphson).

As we can see in Fig. 2, GAs create randomly an initial population of individuals under constraints. Then, the population is evaluated, and individuals are selected thanks to a probability score of reproduction. Finally, the offspring population are generated with the crossover and/or mutation operations on the selected individuals.

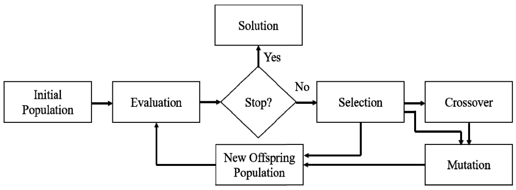

Fig. 2. Natural process of GAs

2.1.1 Single Objective Genetic Algorithms

The single objective GAs are defined by one fitness function. Thus, GAs give us only one best solution for the optimization problem. There are several GAs [18-20] that have been modified in order to be more efficient in particular optimization problems. Finally, the structure of GA is based on three stages, which are selection, crossover and mutation.

2.1.2. Multi-Objective Genetic Algorithms

The Multi-Objective Genetic Algorithms (MOGAs) are defined by a set of objective functions which must be minimized. As for the single objective GAs, MOGAs search the variables (parameters) that optimize the objective functions $f(x)$. Moreover, the set of parameters have to satisfy the constraint functions $g(x)$. We can describe objectives functions, which have to be optimized by the following expression:

$$f(x) = [f_1(x), f_2(x), \dots, f_m(x)], \qquad (1)$$

where $x = [x_1, x_2, \dots, x_n] \in X$ is the variables vector from the decision space $\Omega; f: F \to \Omega \subseteq \mathbb{R}^m$, n and m denote respectively the number of parameters and objectives.

In this paper, we aim to minimize the objective functions. In order to reach this goal, the notion of Pareto front is used to determine solutions which are dominant. The concept of dominance is given by Definitions 1 to 4.

Definition 1: *Given two decision vectors x, y ∈ Ω, x is said to Pareto dominate y, denoted by* $x \prec y$, *if* $f_i(x) \leq f_i(y)$, *for every* $i \in \{1,2,\dots,m\}$ *and* $f_j(x) < f_j(y)$, *for at least one index* $j \in \{1,2,\dots,m\}$.

Definition 2: *A decision vector* $x* \in \Omega$ *is Pareto optimal if there is no* $x \in \Omega$ *such that* $x \prec x*$.

Definition 3*. The Pareto set, PS, is defined as:*

$$PS = \{x \in \Omega | x \text{ is Pareto optimal}\}. \qquad (2)$$

Definition 4. *The Pareto front,PF, is defined as:*

$$PF = \{f(x) \in \mathbb{R}^m, | x \in PS\}. \qquad (3)$$

In the following subsections, MOGAs used in this paper are briefly presented.

2.1.2.1. NSGA II

The NSGA II (Non-dominated Sorting Genetic Algorithm II) proposed by Deb *et al* [21] is a MOGA which uses non-dominated sorting and integrates elitism. This algorithm has a better solutions spread than the previous version (NSGA) developed by Srinivas. Actually, NSGA uses the sharing function approach and depends on the chosen σ_{share} value. This parameter is related to the distance computation between two individuals of the population. In the proposed NSGA II, the sharing function is replaced by a crowded-comparison approach. No setting is required by the user to maintain the diversity among individuals of the population. The structure between these two versions is based on the Pareto-optimal front.

2.1.2.2. θ-NSGA III

The θ-NSGA III proposed by Yuan *et al* [22] is an improved version of the NSGA III. In point of fact, the method used to generate reference points of the hyper plan, the normalization and clustering procedures are the main improvements. To complete the description of differences between NSGA III and θ-NSGA III, the improved algorithm uses the new θ-dominance notion for the Pareto dominance. The main objective of all these changes is to converge to the best solutions and increase the diversity of the population.

Finally, changes cited above increase the diversity among individuals of the population and manage easily many-objective.

2.2. Extended Model of the Asynchronous Machine

Usually, the mathematical model of the induction machine for an identification of parameters is the (d, q) synchronously rotating reference frame [11, 12]. This model has only 5 parameters to identify. In this work, we decided to identify the 9 parameters of the (a, b, c) model of the induction machine. This one has been chosen because simulations of stator failures are available and the features can be extracted for faults detection.

Finally, the different variables involved in the mathematical model are the 9 parameters to identify. There are shown in the following vector, noted $[x]$:

$$[x] = [R_s, L_{ms}, L_{ls}, R_r, L_{mr}, L_{lr}, L_m, J, f_{vis}]. \tag{4}$$

where R_s is the resistance of the stator, L_{ms} is the magnetization inductance of the stator, L_{ls} denotes the leakage inductance of the stator, R_r is the resistance of the rotor, L_{mr} is the magnetization inductance of the rotor, L_{lr} denotes the leakage inductance of the rotor, L_m represents is the maximum coefficient of the mutual inductance between one stator and rotor phase, J holds for the rotor and shaft inertia and f_{vis} is the viscous friction coefficient.

3. Application of EAs in Estimating Parameters of the Induction Machine

In this section, the tests conditions, the fitness function, the constraints functions and the settings of GAs used for the 9 parameters estimation are presented.

3.1. Tests conditions

For each EAs, we have tested different settings to determine one of the best algorithm conditions to realize, with efficiency, the parameters identification of asynchronous machines.

Firstly, the objective functions to minimize are expressed by equations (5) to (7), and the constraint functions in order to reduce the decision space are shown in (8).

$$MSE_{SO} = \frac{1}{n}\sum_{i=1}^{n}(|\Omega_{m_i}| - |\widehat{\Omega}_{m_i}|)^2, \tag{5}$$

$$\begin{cases} MSE_{TS} = \dfrac{1}{N_{95}-1}\displaystyle\sum_{i=1}^{N_{95}}\left(|\Omega_{m_i}| - |\widehat{\Omega}_{m_i}|\right)^2 \\ MSE_{SS} = \dfrac{1}{n-(N_{95}+1)}\displaystyle\sum_{i=N_{95}+1}^{n}\left(|\Omega_{m_i}| - |\widehat{\Omega}_{m_i}|\right)^2 \end{cases}, \tag{6}$$

and

$$\begin{cases} MSE_1 = \dfrac{1}{N_{20}-1}\displaystyle\sum_{i=1}^{N_{20}}(|\Omega_{m_i}| - |\widehat{\Omega}_{m_i}|)^2 \\ MSE_2 = \dfrac{1}{N_{40}-1}\displaystyle\sum_{i=N_{20}+1}^{N_{40}}(|\Omega_{m_i}| - |\widehat{\Omega}_{m_i}|)^2 \\ MSE_3 = \dfrac{1}{N_{60}-1}\displaystyle\sum_{i=N_{40}+1}^{N_{60}}(|\Omega_{m_i}| - |\widehat{\Omega}_{m_i}|)^2, \\ MSE_4 = \dfrac{1}{N_{80}-1}\displaystyle\sum_{i=N_{60}+1}^{N_{80}}(|\Omega_{m_i}| - |\widehat{\Omega}_{m_i}|)^2 \\ MSE_5 = \dfrac{1}{N_{100}-1}\displaystyle\sum_{i=N_{80}+1}^{N_{100}}(|\Omega_{m_i}| - |\widehat{\Omega}_{m_i}|)^2 \end{cases} \tag{7}$$

where MSE_{SO} (Mean Square Error) is the objective function of the classic GA, MSE_{TS} and MSE_{SS} are respectively the objective functions for the transition state and the steady state of the NSGA II, n denotes the number of sample of the speed signal, Ω_m and $\widehat{\Omega}_m$ represent the real and the estimated signal of the mechanical speed of the rotor, and N_{95} is the number of samples until the rise time to 95%. For the many-objective case (θ-NSGA III), N_j represents the number of samples of the signal with j the percentage of sample from the beginning of the signal vector.

$$g(x) = \begin{cases} g_1(x) \\ g_2(x) \\ g_3(x) \\ g_4(x) \\ g_5(x) \\ g_6(x) \\ g_7(x) \\ g_8(x) \\ g_9(x) \end{cases} = \begin{cases} 0.8 \le R_s \le 1.3 \\ 0.1 \le L_{ms} \le 0.3 \\ 0.0005 \le L_{ls} \le 0.05 \\ 0.7 \le R_r \le 1.3 \\ 0.0005 \le L_{mr} \le 0.2 \\ 0.0005 \le L_{lr} \le 0.05 \\ 0.0005 \le L_m \le 0.2 \\ 0.0005 \le J \le 0.1 \\ 0 \le f_{vis} \le 0.00001 \end{cases} \tag{8}$$

The main settings of the classic GA, NSGA II and θ-NSGA III are shown in Table 1. These parameters are defined from different trials and represent one of the best settings for estimation of induction machine parameters.

Table 1. Values of the classic GA, NSGA II and θ-NSGA III Parameters

Parameters of the classic GA, NSGA II and θ-NSGA III	
Parameters	Values
Population size N	200
Evaluation generation	100
Number of tournament	1

SBX Probability p_c	0.9
Polynomial Mutation Probability p_m	0.3
Distribution index on the SBX η_c	80
Distribution index on the Polynomial Mutation η_m	30
Value of θ parameters (for θ-NSGA III)	5

3.2. Results

MATLAB have been used in order to compute the estimation of parameters of the induction machine. 5 runs have been performed for each GA presented in Section 2 with the best settings. The outcomes obtained with the previous information of fitness functions $f(x)$, constraint functions $g(x)$ and the GAs settings are shown in Tables 2, 3 and 4. In addition, variations in percentage which represents the relative difference between the values of the estimated parameters and the real parameters given by (9) of the asynchronous machine are also included in tables.

$$[x] = [1, 0.25, 0.018, 0.93, 0.1423, 0.01, 0.1215, 0.8, 0.000001]. \tag{9}$$

Table 2. Results from classic GA to estimate the induction machine parameters

	Parameters Estimation				
Parameters	1^{st} run	2^{nd} run	3^{rd} run	4^{th} run	5^{th} run
R_s	0,91330	0,89810	0,93527	1,23723	1,16696
L_{ms}	0,20006	0,16178	0,13577	0,28047	0,19209
L_{ls}	0,03399	0,01326	0,04822	0,04457	0,01524
R_r	0,79230	0,77461	0,89133	0,86703	0,81476
L_{mr}	0,12475	0,05828	0,03251	0,08831	0,03196
L_{lr}	0,01870	0,02195	0,00732	0,03478	0,00103
L_m	0,10175	0,06044	0,03821	0,09972	0,04574
J	0,09711	0,06454	0,03493	0,04949	0,02781
f_{vis}	9,90E-06	4,70E-06	7,10E-06	1,10E-06	2,70E-06
$\boldsymbol{MSE_{SO}}$	**0,01901**	**0.05310**	**0.13068**	**0.11993**	**0,15445**
Total variation in %	**1226,66**	**779,22**	**1102,35**	**597,79**	**563,73**

Table 3. Results from NSGA II to estimate the induction machine parameters

	Parameters Estimation				
Parameters	1^{st} run	2^{nd} run	3^{rd} run	4^{th} run	5^{th} run
R_s	0,98686	0,81635	1,01131	1,08328	1,12060
L_{ms}	0,17869	0,20339	0,13462	0,11503	0,14314
L_{ls}	0,00651	0,04430	0,03711	0,02110	0,04183
R_r	0,72874	1,02139	1,12006	1,18800	0,85258
L_{mr}	0,05395	0,05314	0,11592	0,04851	0,08437
L_{lr}	0,00517	0,03566	0,01048	0,02727	0,03771
L_m	0,06099	0,06363	0,07890	0,04423	0,06951
J	0,05593	0,04330	0,09171	0,05580	0,08979
f_{vis}	4,23E-06	5,19E-06	6,81E-07	3,19E-06	5,48E-06
$\boldsymbol{MSE_{TS}}$	**0,60966**	**0,77383**	**0,48098**	**4,85639**	**1,29298**
$\boldsymbol{MSE_{SS}}$	**0,10542**	**0,73430**	**0,09637**	**1,87856**	**0,04707**
Total	**0,71508**	**1,50813**	**0,57735**	**6,73496**	**1,34005**
Total variation in %	1089,08	1513,29	932,68	937,67	1618,92

Table 4. Results from θ-NSGA III to estimate the induction machine parameters

	Parameters Estimation				
Parameters	1^{st} run	2^{nd} run	3^{rd} run	4^{th} run	5^{th} run
R_s	1,10554	0,98647	0,96283	0,95116	1,06868
L_{ms}	0,18139	0,17617	0,16458	0,23235	0,21453
L_{ls}	0,01447	0,02027	0,03198	0,01834	0,02589
R_r	0,88766	0,83185	0,84974	0,93424	0,77534
L_{mr}	0,04230	0,07262	0,06813	0,08673	0,07997
L_{lr}	0,02646	0,00659	0,01099	0,00521	0,01591
L_m	0,05238	0,07095	0,06624	0,08956	0,08307
J	0,03560	0,06501	0,06837	0,05546	0,06653
f_{vis}	5,20E-06	2,70E-06	7,70E-06	5,00E-06	1,40E-06
$\boldsymbol{MSE_1}$	**0,20390**	**0,04063**	**0,14144**	**0,37256**	**0,02502**
$\boldsymbol{MSE_2}$	**0,04597**	**0,81686**	**0,34969**	**0,35055**	**0,33293**
$\boldsymbol{MSE_3}$	**0,04037**	**0,40258**	**0,03766**	**0,12672**	**0,14606**
$\boldsymbol{MSE_4}$	**0,11533**	**0,08211**	**0,07856**	**0,06698**	**0,04934**
$\boldsymbol{MSE_5}$	**0,13365**	**0,08238**	**0,08783**	**0,07120**	**0,05405**
Total	**0,53922**	**1,42456**	**0,69518**	**0,98801**	**0,60740**
Total variation in %	**829,14**	**367,45**	**916,22**	**558,22**	**272,92**

The results presented in Table 2, 3 and 4 illustrate that the θ-NSGA III is better than the classis GA and the NSGA II in order to research the real set of parameters in an extended space solutions of the asynchronous machines. Indeed, the classic GA gives solutions with an error (values of the fitness function) closer to the value zero (means that the signal from the induction machine model is almost superposed on the real signal) than the NSGA II and θ-NSGA III in 5 runs of parameters estimation. Nevertheless, the best estimation of the induction machine parameters in terms of percentage of variation (relative difference between the values of the real induction machine parameters and the estimated parameters provided by GAs) is given by θ-NSGA III with 272.9% of total variation as minimum. Furthermore, the mean of the variation in percentage are 588.8% for θ-NSGA III, 786.5% for NSGA II and 853.6% for the classic GA.

4. Discussion

This work shows the efficiency of the multi-objective optimization based on the new θ-NSGA III in order to identify the 9 parameters of extended induction machine model. Indeed, the parameters variation is less important with θ-NSGA III than the classic GA and NSGA II. This result can be explained by the fact that there are several solutions with a value of the objective function close to zero and an important parameters variation. Table 2 shows this phenomenon. Indeed, the fitness value for the classic GA are better than the NSGA II and the θ-NSGA III. Nevertheless, the parameters variation of the classic GA are higher than the two other algorithms. In reality, this outcome is due to the use of MOGAs. The advantage of NSGA II and θ-NSGA III is the sorting step because algorithms treat separately the different objectives allowing to maintain the diversity among individuals of the population. This is the main difference with the classic GA. In other words, an individual can be better than another individual which have a fitness function value close to zero with a significant variation on the estimated values. In NSGA II and θ-NSGA III, this solution has a chance of being in the next generation thanks to the multi-objective definition. Thus, related works [7, 8, 10, 12] that present a low parameters variation using a single objective function are only possible because they have extremely limited the search space. Furthermore, the θ-NSGA III presents another advantage which is the convergence to a limited solutions space. This convergence is faster for the θ-NSGA III than the NSGA II because of the θ-dominance [22].

5. Conclusion

In this paper, we proposed for the first time an effective computational method for identifying 9 parameters of the extended induction machines model using θ-NSGA III. This asynchronous machine model is also used in the failures detection domain and identification results presented in section 3 allow to use this MOGA for a generalized method of parameters estimation.

We implemented, in MATLAB, GAs and the model of the induction machine used for simulation of the stator failures in order to perform the parameters identification. Our results show the advantage to use MOGAs. Indeed, the classic GA gives a fitness function value close to zero but the parameters variation is higher than NSGA II and θ-NSGA III. These differences illustrated in section 4 are due to the sorting process, which maintains the diversity among individuals of the population thanks to the different fitness values. Therefore, the θ-NSGA III gives a better parameters estimation than the classic GA and the NSGA II because of the number of objectives and the convergence of this one.

Obviously, there is still much research to be done on the identification of induction machine parameters. In future works, we will introduce an adaptive function of GAs settings in order to change the selection, crossover and mutation parameters during the estimation, and to refine the identification. Secondly, the lower and upper bounds on the variables, in other word the decision space, will be extended to estimate parameters of a wide range of induction machines. Finally, we will parallelize GAs in order to reduce the time required for the identification.

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