High Performances of an Advanced Approach for Self Tuning Levenberg Marquardt Relaxation Parameter

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Majed Jabri[1], Houssem Jerbi[2], Naceur Benhadj Braiek[3]

Abstract

In this paper we develop an algorithm for on-line identification of a Moving Horizon Estimation (MHE) based on advanced techniques. The aim of this work is the implementation of an advanced MHE strategy essentially characterized by a reduced converging time of the estimates. This is obtained by combining a Fuzzy Logic System (FLS) and Genetic Algorithm (GA) in order to adjust the Levenberg Marquardt (LM) parameter. By using this method to the electrical systems, the estimation of the field and the armature resistances for series DC motor is proposed. Simulation results show that the proposed method is quite efficient.

Keywords

Fuzzy Logic; Genetic Algorithm; Moving Horizon; Parameter Estimation, Electrical Machine.

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[1,2,3]Laboratoire d'Etude et de Commande Automatique des Processus LECAP, University of Tunis, Polytechnic School, Department of Electrical Engineering, Tunisia.

Corresponding author:
Email: majed.jabri@gmail.com

Introduction

In most practical cases, the process parameters are partially or totally unknown. They can be determined with parameter estimation method by measuring input and output signals if the model structure is known. In fact, the use of sensor for measurements has a number of inconveniences such as higher operating costs, less immunity to noise and greater cost of maintenance (Sira-Ramirez 1990)[1]. Due to these limitations, two approaches for parameter estimation can be mentioned: approaches using the output error and approaches using the equation error. Generally the equation error is linear in the parameters which allow direct estimation (Bemporad (2002)). These approaches need nonlinear optimization methods and an iterative procedure, such as, Extended Kalman filter (Shi 2002), Unscented Kalman filter (Akin 2004), Marquardt-Levenberg (Mendis 2006) and Gauss-Newton algorithm[2].

The convergence of the last two algorithms is related to the adjustment of the LM parameter λ. A lot of research has been carried on the adjustment of λ, by making this parameter equals to the absolute value in the Jacobian matrix. Another technique is equating λ to the norm of Jacobian matrix. Both techniques have the same performance. It is clear that the dynamics of the estimator depends mainly on the choice of the parameter λ. Yamashita and Fukushima (Akin 2004) chose the LM parameter λ equal to the quadratic of two norm error between the measurements and the model output. Fan and Yuan (Mayne 1990) considered the choice of λ equal to two norm error of the function to be minimizing.

The main contribution of the development given in this work is the implementation of a different approach: the use of Fuzzy Logic System (FLS) and Genetic Algorithm (GA) in order to adjust the LM parameter λ of the Levenberg-Marquardt algorithm on-line through moving horizon window[3].

This work is structured as follows: Section 2 presents the parameter estimation algorithm introducing the fuzzy logic system and genetic algorithm. In Section 3 the model of the series DC motor is reviewed. Section 4 considers the application of this method on the estimation of the field and the armature resistances of the series DC motor. Finally some concluding remarks are given in Section 5[4].

Design of the on-Line Parameter Estimation Algorithm

First, some basic concepts about the moving horizon method will be presented. We assume that a system we are studying is modelled by parameterized first-order ordinary differential equations described by as follows:

$$\frac{dy}{dt} = f(t, y, \theta). \tag{1}$$

where $\theta = (\theta_1, \theta_2, \ldots, \theta_n)^T \in R^n$ denotes the vector of estimated parameters, $y = (y_1, y_2, \ldots, y_m)^T \in R^m$ is state vector, and $t \in R$ is the time. Fig. 1 illustrates the framework to estimate parameters of a general nonlinear dynamical system. The trajectories of the real system are compared to the trajectories of the mathematical model. Based on the mismatch and the trajectory sensitivities information, the fitting algorithm updates the model parameters[5].

The Moving Horizon Estimation Concept

The basic idea of the Moving Horizon Estimation (MHE) approach is to maintain a constant length of the estimation window by discarding the oldest sample as a new measurement becomes available. Moving horizon concept control, commonly called model predictive control, has been studied extensively during

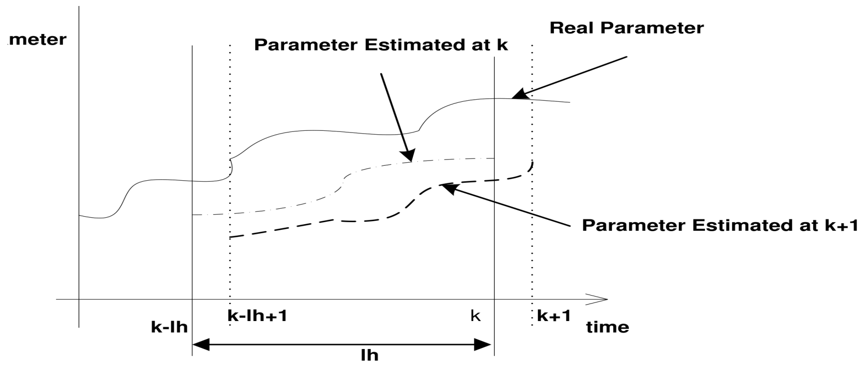

Figure 1. Moving Horizon Estimation Concept

the last decade (Bemporad 2003, Rao 2001). Recently the moving horizon strategy, also referred to as sliding window, has been applied to estimation problems (Rao 2003). Most of the work related to the moving horizon estimation uses a least-squares problem[6,7]. The goal of this strategy is to reformulate the estimation problem as a minimization of an output criterion described by the Eq.(1). The time horizon size lh moves forward each period at the sampling time in order to use the recently available measurement. This step seeks to the estimate parameters at the beginning of the time horizon by using an optimization algorithm called Levenberg-Marquardt (LM) (Mendis 2006). The algorithm starts after some data has been collected but necessary before the amount of data has reached the pre-defined size for the time horizon lh[8].

Levenberg-Marquardt (LM) Optimization

There are several algorithms which attempt to minimize the sum of squared error performance measure (Benchluch 1993).

The Levenberg-Marquardt approach is proposed to estimate initial conditions and parameters that will give the best fit between measurement and the model response[9,10].

Considering the quadratic function represented in Eq. (2) as the objective function to be minimized, for a multi-input multi-output system.

$$\min imize\ R(\theta) = \frac{1}{2}\sum_{k=1}^{n} e^2(\theta) \tag{2}$$

The LM algorithm can be also described as a blend of the steepest gradient descent and the Gauss-Newton method (Mendis 2006)[11].

The LM defines the next update $\theta(k+1)$ as following:

$$\theta(k+1) = \theta(k) - \left[J^T(\theta)J(\theta) + \lambda I\right]^{-1} J(\theta) \tag{3}$$

Note that $J(\theta) = \frac{\partial R(\theta)}{\partial \theta}$ is the Jacobian matrix of $R(\theta)$ (Benchluch 1993).

The LM algorithm uses the restricted step-size method to find the best solution of the new parameters. Such algorithm is used for calculating the next update $\theta(k+1)$ based on the trusts region $\delta(\theta)$ to achieve a good convergence (Ahmed 2004)[12,13].

The main idea of the LM algorithm can be reduced to the following steps:

1. Initialize the relaxation parameter λ, the trust region δ, and the initial parameter vector θ.
2. Recover the experimental data.
3. Solve the equation 3 using the original settings.
4. Compute the Jacobian vector J.
5. Update parameters.
6. According the error $R(\theta_{k+1})$, if $R(\theta_{k+1}) < R(\theta_k)$ then go to Step 7. Otherwise, go to Step 9.
7. Adjust $\lambda = \frac{\lambda}{2}$
8. Update parameters using Eq. (4)
9. Adjust. $\lambda = 2\lambda$
10. Update. $R(\theta_k) = R(\theta_{k+1})$
11. Compute δ, if $\delta <\in$ then go to Step 12. Otherwise, go to Step 4.
12. End

Steps (1), (2) and (3) are performed first and the items (4) to (11) are performed iteratively until the parameters have converged. The trust region calculation for above algorithm is given by:

$$\delta(\theta) = |R_{k+1}(\theta) - R_k(\theta)| \tag{4}$$

Initially, the algorithm starts by $\lambda = 1$ and arbitrary values for $\theta(1)$. The idea here is to replace step (6), (7) and (8) by a fuzzy adaptation mechanism or genetic algorithm which adjust automatically the LM parameter λ, in order to obtain a better value of the estimated parameter[14].

Self Tuning of the LM parameter λ using Fuzzy Logic

A fuzzy logic system is based on the knowledge of the process operator. This knowledge is represented as a collection of If-Then rules that specify the implication relationships between the input variables and output variables through linguistic variables (Berenji 1992, Takagi 1983)[15].

A basic configuration of a Fuzzy Logic System (FLS) is shown in Fig. 2.

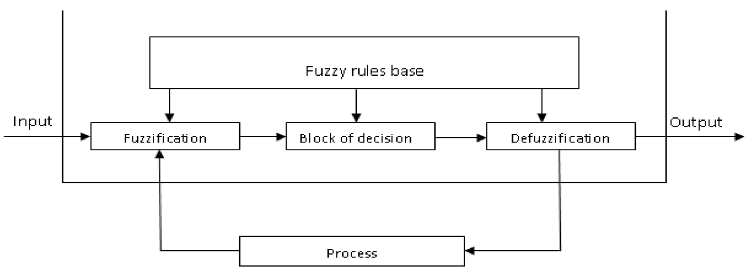

Figure 2. Basic Configuration of a Fuzzy Logic System

In this part we will carry out the estimation of LM parameter λ using FLS (Majed 2008). The design of FLS offers a high number of combinations and alternatives for the choice of this parameter.

The required objective is to generate values of the parameter λ which are more precise than those obtained by basic LM algorithm. Fig. 3 shows the proposed fuzzy logic of LM parameter estimation.

The inputs are obtained by standardizing the criterion and his derivative as follows:

$$R(k) = G_1 R(k) \tag{5}$$

$$dR(k) = G_2 \frac{(R(k) - R(k-1))}{T} \tag{6}$$

The exit of the fuzzy block is obtained as follows:

$$\lambda(k) = \lambda(k-1) + G_3 \Delta\lambda(k) \tag{7}$$

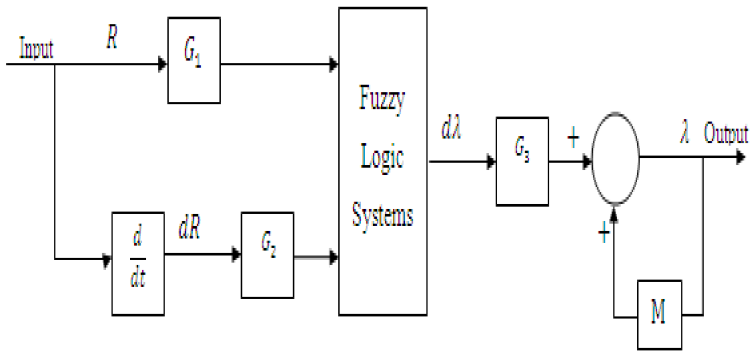

Figure 3. Configuration of the Implemented Fuzzy Logic System

The basic idea of fuzzy adaptation mechanism is to build an inference rules table for λ referred to the residual variation $R(\theta_k)$ and $R(\theta_{k+1})$ as shown in Table 1, in order to reduce the settling time of the parameter convergence even under severe variation of parameters[16].

Table 1. Rule Base for λ

R_{k+1} / R_k	ES	VS	S	M	L	VL	EL
ES	ES	P	L	M	VL	VL	EL
VS	ES	VS	L	M	VL	VL	EL
S	ES	VS	S	L	M	VL	EL
M	ES	TP	S	L	M	EL	EL
L	ES	TP	VS	VS	M	EL	EL
VL	ES	TP	VS	VS	M	EL	EL
TL	ES	ES	ES	ES	M	EL	EL

Seven overlapping triangular sets are defined: extremely small (ES), very small (VS), small (S), medium (M), large (L), very large (VL) and extremely large (EL). The controller, after defuzzification, produces four numerical effectors actions mentioned before. Internally, the four effectors actions are treated as linguistic variables too. Their linguistic values are output of the fuzzy inference engine.

The membership functions for the two inputs and the output are shown in Fig. 4.

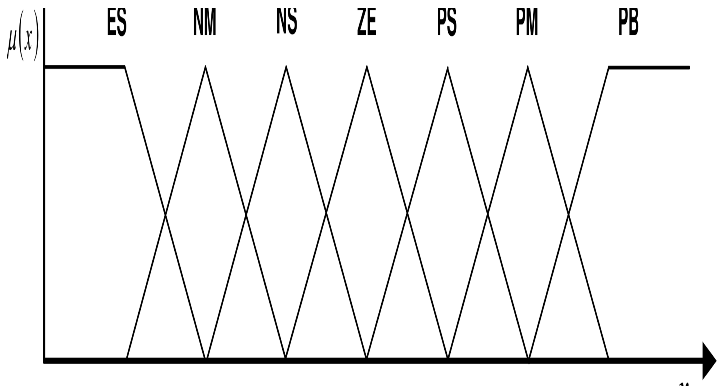

Figure 4. Functions for Error, Rate of Change of Error and Incremental Control Output

Fuzzy output can be calculated with the centre of area defuzzification area as:

$$z_i = \frac{\sum_{i=1}^{n} z_i \mu(z_i)}{\sum_{i=1}^{n} \mu(z_i)} \tag{8}$$

Where z_i is the abscissa at which the membership function reaches the maximum value $\mu(z_i)$ and n is the number of quantization levels of the output variable z.

Self Tuning of the LM parameter using Genetic Algorithms

The Genetic Algorithm (GA) is considered as an example of a global search optimization technique (Dréo 2003). At every generation, GA produces a new set of strings using the fragments of the fittest of the old. The main advantages of the GA are their robustness and their ability to provide a balance between efficiency and effectiveness in different environments which cover a variety of applications (Majed 2010).

In our application a gene is considered as a string of bits where the string is coded to represent some underlying parameter set. The initial population of genes which are called bit strings is created randomly and the length of the bit string depends on the problem which is to be solved. A fitness function which measures how good a solution string is must also be defined, based on the problem to be solved.

A GA is an iterative process that each iteration uses the information obtained from testing a current population of chromosomes to direct its search into promising areas of the search space. Thus, generating a suitable population of chromosomes is the key to the algorithm performance. In the simplest form, creating a new population of chromosomes to be tested involves three genetic operators: selection, crossover, and mutation. These genetic operators work on genotypes that encode phenotypes.

The role of the selection operator is to pick a population of chromosomes for further processing, called reproduction. Chromosomes are selected into a mating pool for reproduction with a probability proportional to their fitness.

The crossover operator randomly exchanges substrings between two-parent chromosomes to create two offspring. The simplest crossover operator is the one-point crossover, where a crossing site is randomly picked and the corresponding substrings are exchanged.

More complex crossover techniques exist in the form of Multi-point and Uniform Crossover Algorithms. The experienced boundary for crossover rate is from 0.6 to 0.9. The mutation operator randomly flips an arbitrary bit in a chromosome. For example, the chromosome 010101 might undergo a mutation in its third position to yield a new chromosome 011101.

In order to maintain diversity of the generation individuals, mutation rate is normally set with a small value from 0.1 to 0.3.

To estimate parameter with genetic algorithm, we must encode the vector of the parameters into binary code in order to let the manipulation with GA easier. The chromosome of the individual is given by:

$$\theta(n) \;\Big|\; \theta(n-1) \;\Big|\; \cdots\cdots\cdots \;\Big|\; \theta(2) \;\Big|\; \theta(1)$$

Figure 5. Vector of the Parameters

where $\theta(i)$ is the binary value.

The fitness to be minimized is given by Eq. (3). The GA settings used in this work are shown in Table 2.

Table 2. Genetic Characteristics

Parameters	Value
Pop-size	15
Crossover-rate	0.65
Mutation-rate	0.1
Max-generations	200

In order to adjust the LM parameter using GA, we have coding λ into 10 binary system code and put it into one chromosome as shown in the next figure.

$$\lambda = (\lambda_9, \lambda_8, \lambda_7, \lambda_6, \lambda_5, \lambda_4, \lambda_3, \lambda_2, \lambda_1, \lambda_0)$$

Figure 6. Binary code of the Relaxation Parameter λ

Mathematical Model of a Series DC Motor

Series DC motors are often used in applications requiring high torque/speed ratios. Such applications are found in traction drives, locomotives, cranes, hoists and in many other industries. In this kind of motor, the field circuit is connected in series with the armature circuit. The electromagnetic torque produced by the motor is proportional to the square of the current (Mehta 1998).

A schematic of the series DC motor is shown in Fig. 7.

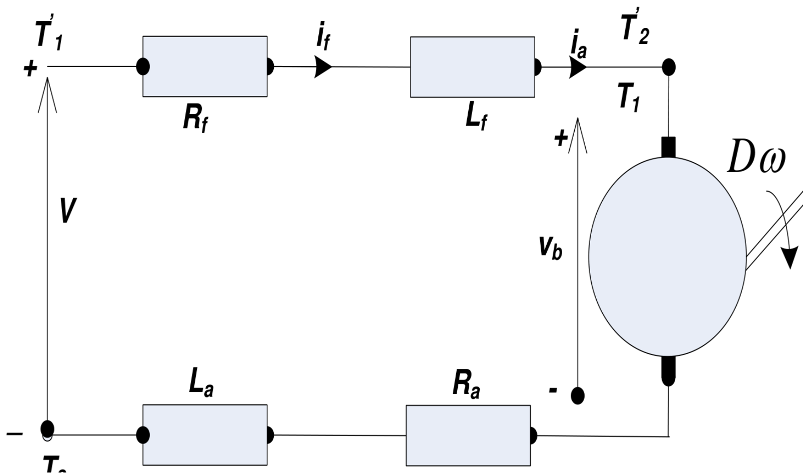

Figure 7. Equivalent Circuit of a Series DC Motor

In order to generate a load torque an external resistor R_L is connected to a permanent magnet DC motor, which is coupled with the series DC motor. We note that the dynamics of a series DC motor can be represented by the next two differential equations

$$\begin{cases} \dfrac{di}{dt} = \dfrac{-Ri - Kiw + V}{L} \\ \dfrac{dw}{dt} = \dfrac{Ki^2 - Dw - \tau_L}{J} \end{cases} \tag{9}$$

where: i is the armature current (or field current); V is the terminal control voltage; w is the rotational speed of the motor; L is the total armature and field circuit inductance; $R = R_a + R_f$ is the total armature and field circuit resistance; J is the moment of inertia associated with both motor and the load; K is the motor constant; D is the damping constant; τ_L is the load torque.

Simulation Results and Discussion

In order to investigate the efficiency of the proposed method, several tests were performed at different dynamic operating conditions, such as pseudo change sequence signal which is applied to the input system and for parameter variations. Fig. 8 shows the logical diagrams for the LM algorithm on-line estimation structure. The estimation results can be seen in Figs. 9, 10 and 11.

The motor data used in the simulation are depicted in Table 3.

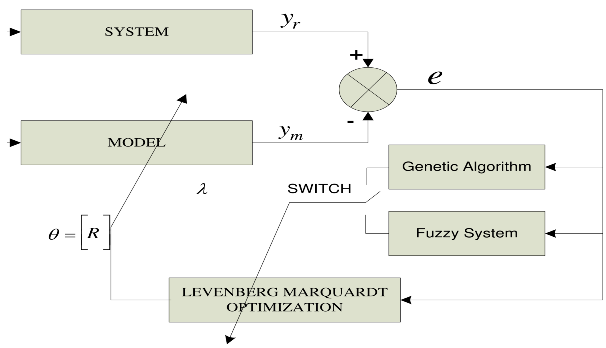

Figure 8. Block Diagram of the Estimation Variable

Table 3. Series DC Motor Parameters

Format symbol	Description
L	0.0917 H
R	7.2 Ω
D	0.0004 N.m/rad/s
K	0.1236 .m/Wb.A
J	0.0007046 Kg.m^2

In a first approach, the parameter estimation is investigated by using the basic LM algorithm. The results of this study are depicted in Fig.9. An important steady error is shown for an abrupt parameter variation which happens at t=0.24s. We have considered in this simulation that the field and the armature resistance is stepped up 50% from its nominal value. The dynamical behaviour of the field and the armature resistance estimate using FLS and GA adjustment of the LM parameter λ is shown in Fig. 10 and 11. It is assumed that the desired and the estimated value of the field and the armature resistance is stepped up 50% at $t = 0.24s$ from its nominal value. In the GA method, only a single value is represented with binary bit strings. Therefore, it is sufficient to choose a small population size (15 members) in order to implement the GA on line.

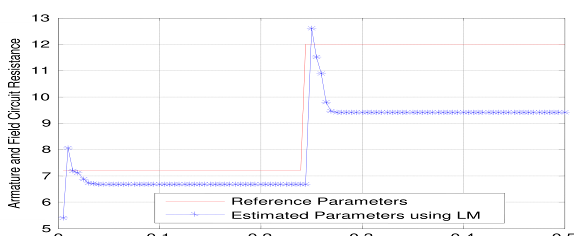

Figure 9. Actual and Estimated Field and Armature Resistance using LM

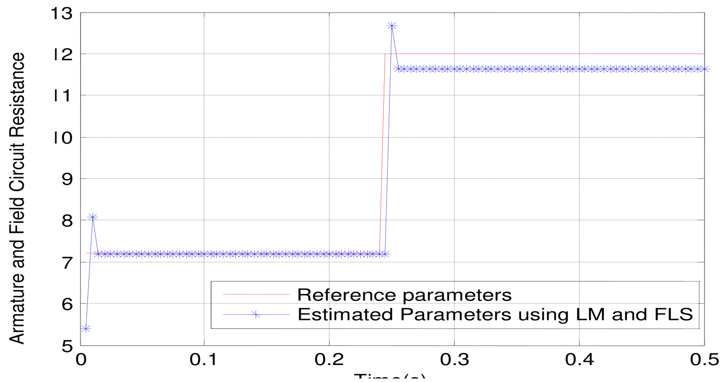

Figure 10. Actual and Estimated Field and Armature Resistance using LM and Fuzzy Variation of the LM Parameter λ

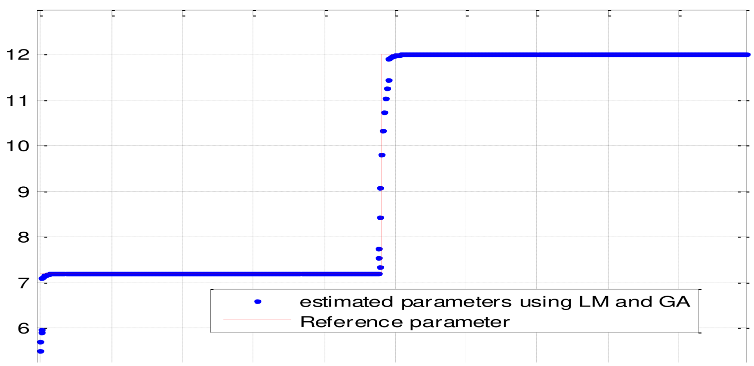

Figure 11. Actual and Estimated Field and Armature Resistance using LM and Genetic Variation of the LM Parameter

In Table 4 we summarize the main results for the relaxation parameter adjustment with the several methods under consideration. It is important to notice that for smooth assumptions the three investigated methods allows satisfactory performances. Nevertheless, for the considered abrupt variation of 50% of the estimated parameter with report to its nominal value, we can readily conclude about the superiority of LM combined GA technique.

Moreover, it is obvious that the initial value of the relaxation parameter affects straightforwardly the whole performance of the LM optimization algorithm. Indeed, an important initial value of diverge the estimator response. Equally important, we have noticed that to improve the performance of the LM combined with FLS we have to increase the number of fuzzy sets. However, this will disturb the on line implantation of the LM routine. Indeed the computing period will be increased versus the sampling and the horizon times. This issue will be categorically avoided with GA since we have to optimize only one parameter with small population size.

Table 4. Summary Results on the Relaxation Parameter Adjustment with Basic LM, FLS LM and GA LM methods

Time(s)	Initial Values	Optimal Values LM	LM and GA	LM and FLS	Convergence (%) LM	LM and GA	LM and FLS
0.01	7.2	8.2	7.1	8.2	86	99	86
0.1	7.2	6.8	7.2	7.2	94.5	100	100
0.25	12	12.5	12	12.5	96	100	96
0.3	12	9.5	12	11.7	79	100	97.5

Conclusion

In this paper we have presented advanced methods to improve of the MHSE performance. Mainly, we have proved that the evolutionary algorithm solves the problem of the relaxation LM parameter adjustment. In this way, and in order to track system parameters, we have proposed a new method combining the LM algorithm with GA and FLS to solve the proposed optimization problem. In order to improve the robustness of the method and the convergence property, sufficient rules on parameter variations and detailed algorithm are presented. A simulation study offers satisfactory results essentially characterized by a reduced tracking error and a much reduced convergence time, although the abrupt variation in time and in amplitude of the estimated parameter. As it is easily noticeable from the simulation study that the obtained performances permit to conclude about the efficiency and the advantage of the developed GA technique.

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