Indian Journal of Science and Technology, *Vol 8(S8), 600-606, April 2015*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645
DOI: 10.17485/ijst/2015/v8iS8/71713

Fuzzy Position Control of PMBLDC Motor using Adaptive Genetic Algorithm

B. S. Sathish[1*] and P. Thirusakthimurugan[2]

[1]Sathyabama University, Chennai, Tamilnadu, India; sathish.enc@sathyabamauniversity.ac.in
[2]Department of EIE, Pondicherry Engineering College, Pondicherry-14, India; thirusakthimurugan@gmail.com

Abstract

In this paper, an identification of position controller design for Permanent Magnet Brushless DC Motor (PMBLDCM) using Fuzzy Adaptive Genetic Algorithm (FAGA) is presented. For optimal searching of the scaling factors of the antecedent and consequent parameters of the T-S fuzzy model is identified to minimize the Integral square error (ISE) between the closed-loop outputs of the motor system and the Fuzzy T-S model. An interesting alternative that could be investigated the use of fuzzy logic control methods.The mechanism of designing and implementation of transfer system (T.S).model FLC based on AGA is described and the simulation results are obtained using the proposed technique in comparison with the conventional PI controller is prescribed. The simulation result shows that the identification using the Adaptive genetic Algorithm based Fuzzy transfer system (T.S) model has smaller error when compared to the transfer function (T.F) model.

Keywords: Adaptive Genetic Algorithm, Fuzzy Adaptive Genetic Algorithm, Integral Square Error, Permanent Magnet Brushless DC Motor, Position Controller

1. Introduction

In latest years, brushless dc machines have expanded extensive use in electric drives. These machines are model for use in clean explosive environments such as aeronautics, robotics, electric vehicles, food industries, chemical industries and dynamic actuation. Actually using these machines in high-performance drives requires progress and physically powerful control methods[1]. Conventional control techniques require a perfect mathematical model that describes the dynamics of system under study. These techniques results in tracking error when the load varies rapid and overshoot during transients[2]. In requirements for forceful control design, they also lack consistent performance when changes occur in the system. An exciting alternative that could be investigated the exercise of fuzzy logic control methods. In most modern decade fuzzy logic controller has concerned significant attention as a tool for a work of fiction control approach because of the selection of compensation that it offers over the classical control techniques. Unlike other conventional control schemes in that fuzzy logic controller is a model free controller that does not need an exact mathematical model of the controlled system and therefore it is less sensitive to system parameter changes[3-9]. The estimated values of the design parameters of the fuzzy logic controller (FLC) could be determined intuitively based on human operator experience. Therefore more intelligent method to achieve the optimal or at least near optimal values of design parameters is necessary. One of the foremost of these methods is the adaptive genetic algorithms optimization[10-11]. The mechanism of designing and implementation of T.S.model fuzzy logic controller (FLC) based on Adaptive genetic algorithm (AGA) is described and the simulation results are obtained using the proposed technique in comparison with the conventional PI controller is prescribed.

2. System Identification

**Author for correspondence*

Traditional identification methods include least-squares procedure, maximum likelihood method and other methods based on impulse response. Though these classical methods have already been developed for many years, they gradually begin to expose the side of limitation with the system model more and more complicated. In order to identify a real system, the input signal must meet certain terms. First, in process of identifying, input signal can't influence the normal running; second, the signal must fully excite all modes of the system; third, to obtain higher precision identification result, how to design input signal should also be considered. For example, white noise signal and pseudo-random signal are often used. Error criterion is used to describe how close between the model and the real system. It is often express as a functionally of error as formula (1):

$$J(\theta) = \sum_{k=1}^{t} f[e(k)] \tag{1}$$

where, is the error function of modeling and is the function of e(k). Among the criterions, square function is the most frequently used as formula (2):

$$f[e(k)] = e^2(k) \tag{2}$$

The schematic diagram of model identification with Adaptive genetic algorithm is shown in (Figure 1).

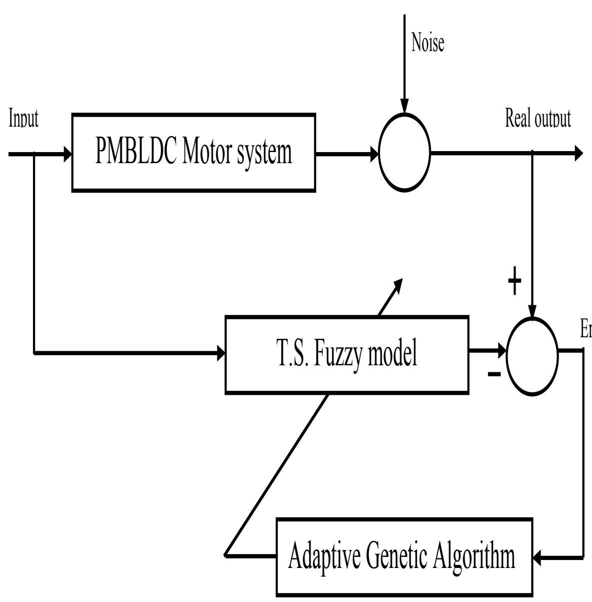

Figure 1. Schematic diagram of model identification

3. Adaptive Genetic Algorithm based Fuzzy Logic Controller

Both theoretic and practice have proved that how to select cross probability (P_c) and mutation probability (P_m) in genetic algorithm will influence its astringency directly. If P_c is oversize, the structure of high fitness individual will be destroyed quickly; if P_c is undersize, searching process will be so slow as to be stagnant. Similarly, if P_m is undersize, new individual cannot be generated easily; inversely, genetic algorithm will be a pure searching process. So how to set up the parameter in the algorithm is very important. However, either parameter select or improvement of genetic operator is determined on experience. The[11] has introduced variable P_m to majorisation calculation to improve precision of the result.

In this paper, adaptive genetic algorithm is introduced to optimize the antecedent and precedent values of the fuzzy transfer system (T.S) model. In the algorithm, both P_c and P_m have great relationship with fitness. When each individual in the colony is prone to be uniform, P_c and P_m should increase; inversely, they must decrease. Moreover, smaller P_c and are assigned to the higher fitness individuals, larger P_c and P_m to lower fitness individuals. The self-adaptive P_c and P_m is given in formula (3), (4):

$$P_c = \begin{cases} \dfrac{k_1(f_{\max} - f)}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ k_2, f < f_{avg} \end{cases} \tag{3}$$

Where:

f_{max}, the maximum fitness in colony;

$$P_c = \begin{cases} \dfrac{k_3(f_{\max} - f)}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ k_4, f < f_{avg} \end{cases} \tag{4}$$

Where

f_{avg}, the average fitness in colony;

f, individuals fitness going to cross or mutate;

The value of k_1, k_2, k_3, k_4 can be set in the span of (0 1). Then P_c and P_m can be self-adaptive.

Whether the fitness is more or less than the average, we can calculate its corresponding cross probability and mutation probability.

This will make the better individuals stagnant at an early stage in the evolution and drive the algorithm to local optimal solution. Therefore, we improve on the formula as given in (5) and (6):

$$P_c = \begin{cases} P_{c1} \dfrac{(P_{c1} - P_{c2})(f - f_{avg})}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ P_{c1}, f < f_{avg} \end{cases} \quad (5)$$

$$P_c = \begin{cases} P_{m1} \dfrac{(P_{m1} - P_{m2})(f - f_{avg})}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ P_{m1}, f < f_{avg} \end{cases} \quad (6)$$

In the formula, the improvement guarantees the colony multiplicity and the convergence and it also has a good application in real system identification.

3.1 T.S.Fuzzy Model

Japan Mu (Takagi) and Flowery field (Sugeno) presents a dynamic system Fuzzy identification method in 1985[3], this model generally referred to as TS model as shown in (Figure 2), based on this verbal description of the model rules presented as in (7).

$$R^i: \ if\ x_1\ is\ A_1^i,\ x_2\ is\ A_2^i, \ldots,\ x_m\ is\ A_m^i$$
$$then\ y^i = p_0^i + p_1^i x_1 + p_2^i x_2 + \ldots\ldots + p_m^i x_m$$

(7

i=1, 2, 3, .m: R^i said to be one of the first i fuzzy rules: is a fuzzy subset of its belonging function. The parameters were called before the department of parameters; x_j is the first j months before the pieces of input variables also known as the Department of variables; m is the number of input variables; y^i is the output of the fuzzy rules after the case, also known as

the department of variables; p_j^i is i first termination were fuzzy rules in paragraph j parameter called after pieces of the parameters. Assuming a given input vector

$$(x_1, x_2, x_3, \ldots\ldots x_k) = (x_1^0, x_2^0, x_3^0, \ldots\ldots x_k^0).$$

The output Y can be y_i rule of the weighted average seek what is called the "weight average method" launched the following steps:

Step 1: Calculation of each relations R^i after pieces of the value y^i, (8) - available.

$$y^i = p_0^i + p_1^i x_1 + p_2^i x_2 + \ldots\ldots + p_m^i x_m \quad (8)$$

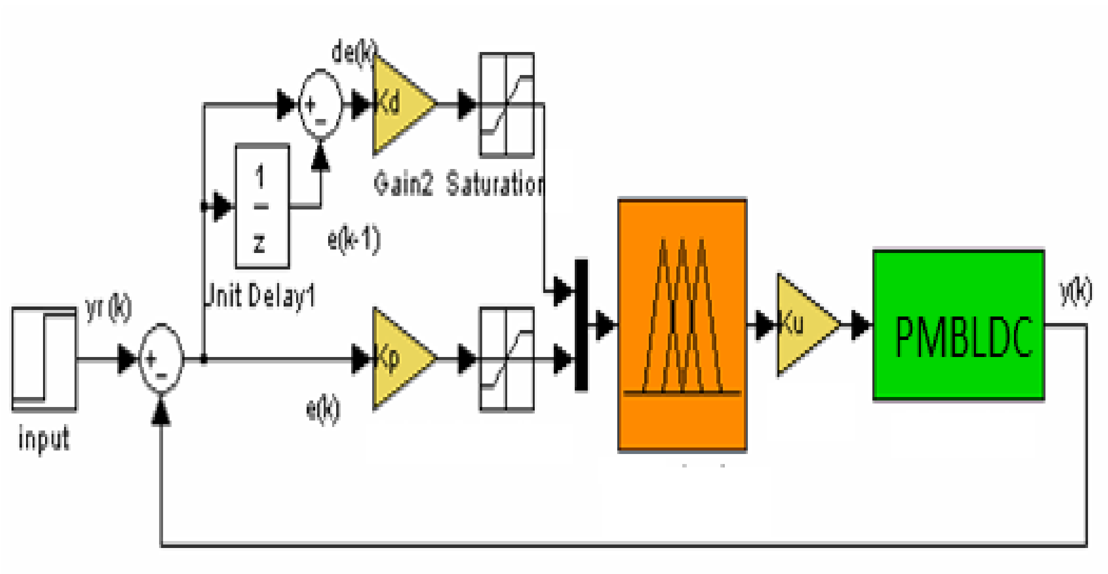

Figure 2. Conventional two-dimensional Fuzzy Control System

Step 2: Proposition $y=y^i$ calculated the true value, $y=y^i$ also said each of the so-called rules of the weights can be derived from (9)

$$\left|y = y^i\right| = \left|A_1^i(x_1^0) \wedge A_2^i(x_2^0) \wedge .... \wedge A_k^i(x_k^0)\right| \quad (9)$$

Step 3: the final output Y by all the rules y^i be the weighted average may be (10) Computing derived.

$$Y = \frac{\sum\left|y = y^i\right| \times y^i}{\sum\left|y = y^i\right|} \quad (10)$$

Here i=3, so the three rules R^1 to R^3 of the fuzzy inference is, and calculate the true value of each rule, and determined in accordance with the above steps for the final output value of Y.

4. Simulation Results

The extensive simulation of PMBLDC motor perfor mancefor conventional and proposed method has been tested with step input. The identification of Transfer system (T.S) fuzzy model parameters are generated by the adaptive genetic algorithm as given in the table. To evaluate the performance of T.S. Model the importance performance index ISE is estimated from the outputs of the system. The performance index provides the improved result of T.S fuzzy model with selected fuzzy rule base in the process of evolution using adaptive genetic algorithm. As the results shown in figures, the algorithm yielded identification parameters that match the desired response of the system. (Figure 3) shows the conventional PID controller response of PMBLDC motor. (Table 1) depicts the identification results of Best controller parameters using TS model for step input. (Figure 4-6) shows the simulation of conventional Fuzzy controller. (Figure 7-12) shows the simulation of proposed scheme. (Table 2) depicts the identification results of Best controller parameters based on AGA. (Table 3) depicts the comparison between the transfer function model and Fuzzy T.S.model with respect to ISE and Identification time.

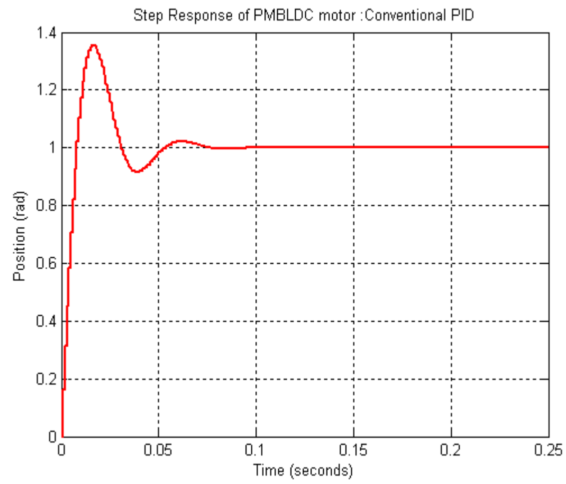

Figure 3. The conventional PMBLDC motor PID controller response

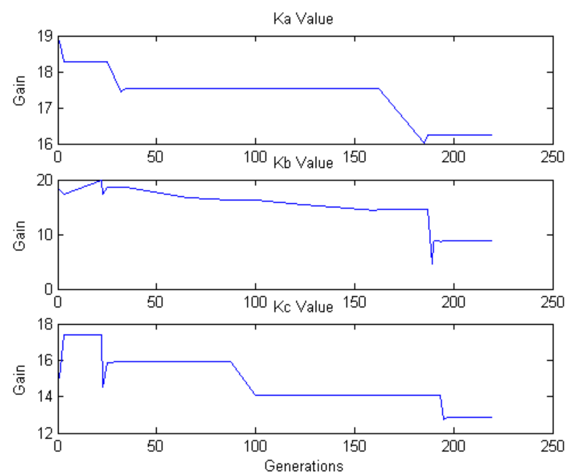

Figure 4. Transfer system (T-S) model identification to function evolution chart

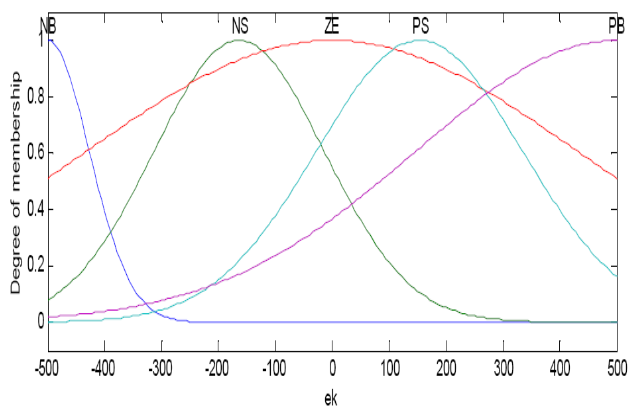

Figure 5. Transfer system (T-S) model identification results e(k)

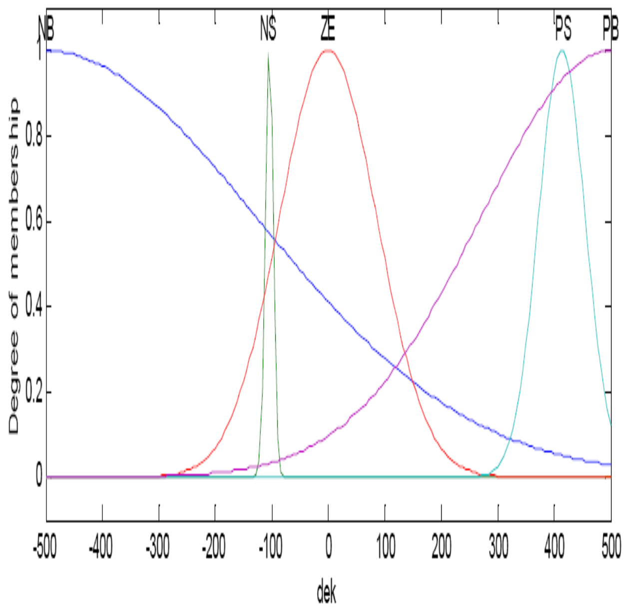

Figure 6. Transfer system (T-S) model identification results de(k)

Table 1. Best controller parameters using Transfer system (T.S) model for step input

	K_a	K_b	K_c
Identification results	1.05	0.562	0.320

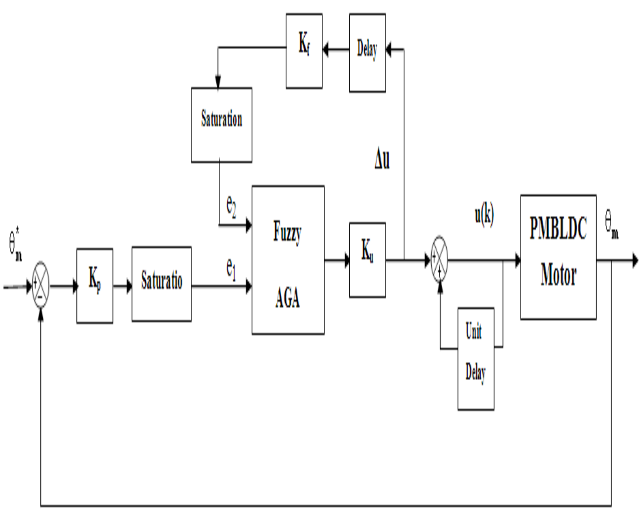

Figure 7. Proposed control system architecture

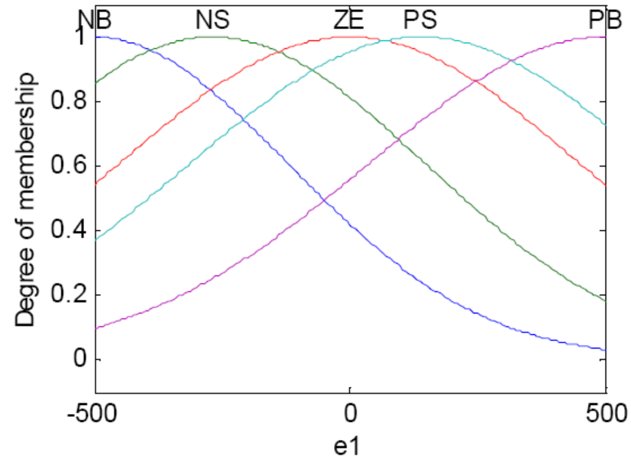

Figure 8. Step response by the Adaptive genetic algorithm (AGA) best input 1 membership functions

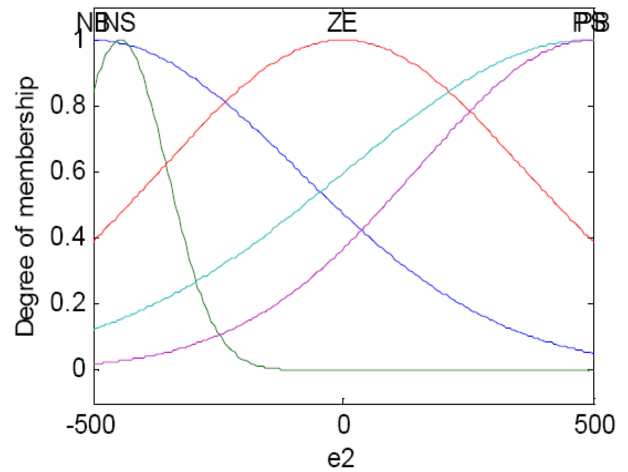

Figure 9. Step response by the Adaptive genetic algorithm (AGA) best input 2 membership functions

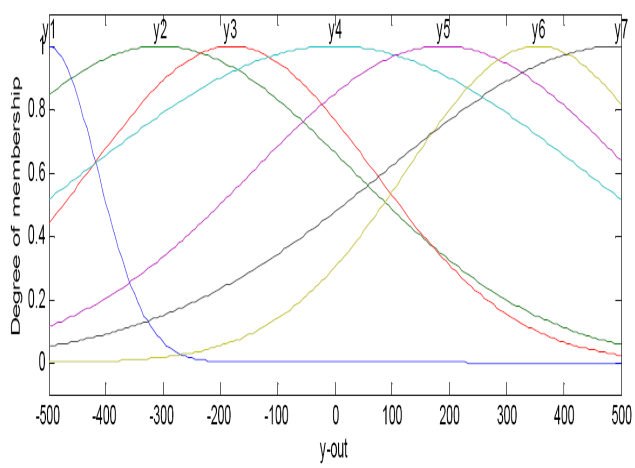

Figure 10. Step response by the Adaptive genetic algorithm (AGA) best output membership functions

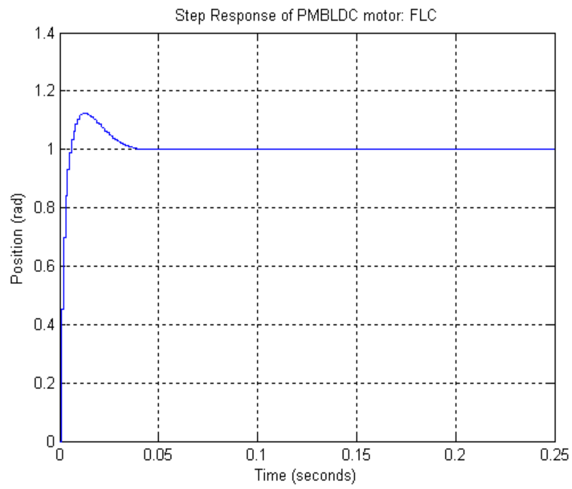

Figure 11. Step response of the PMBLDC motor using FLC

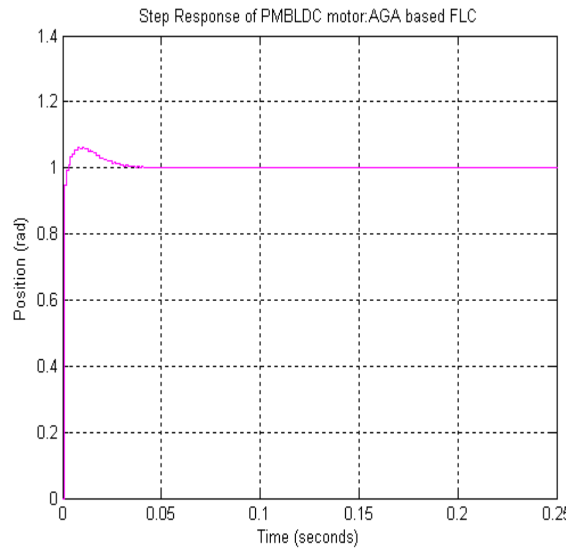

Figure 12. Step response of the PMBLDC motor using AGA based FLC

Table 2. Identification results based on Adaptive genetic algorithm (AGA)

	K_f	K_p	K_u
Identification results	8.89	1.680	4.760

Table 3. Comparison of the different models

	Transfer function (T.F) Model)	**Transfer system (T.S) Model**	**Adaptive genetic algorithm – Transfer system (AGA-TS) Model**
Integral square error (ISE)	511.5	132.4	85.6
Identification time (minutes)	11.31	298.36	15.69

5. Conclusion

This paper outlines the development of a new adaptive genetic algorithm based Identification of the T.S fuzzy model for PMBLDC motor system, whose structure allows it to be used on a wide variety of different controllers and control systems. The proposed method gives better transient response than the traditional FLC. The general fuzzy control structure are two-dimensional control system which are unable to meet control requirements, This proposed FLC design can be used in multi-dimensional to explore its feasibility.

6. Acknowledgement

The author is grateful and thanks to Col.Dr. Jeppiaar Founder & Chancellor of Sathyabama University Chennai, Tamil Nadu India for his encouragement and facilities provided.

7. References

1. Pillay P, Krishnan R. Application characteristics of Permanent Magnet Synchronous and Brushless DC motors for servo drives. IEEE transactions on Industry Applications. 1991; 27(5):986–96.
2. Pillay P, Krishnan R. Modeling, simulation, and analysis of permanent magnet motor drives-II. The brushless DC motor drive. IEEE Transactions on Industry Applications. 1989; 25:274–9.
3. Takagi T, Sugeno M. Fuzzy Identification of systems and its applications to modeling and control. IEEE Trans Systems ManCybernet. SMC-15. 1985 Jan/Feb; 116-132.
4. Li-Xin W. Design and analysis of fuzzy identifiers of nonlinear dynamic systems. IEEE Trans Automat Control. 1995 Jan; 40:11–23.

5. Rovatti R, Guerrieri R. Fuzzy sets of rules for system identification. IEEE Trans Fuzzy Systems. 1996 May; 4:89–102.
6. Xie WF, Rad AB. Fuzzy on-line identification of SISO nonlinear system. Fuzzy Sets and Systems. 1999; 107:323–334.
7. Chew KM, Rad AB. On-line fuzzy identification using genetic algorithms. Fuzzy Sets and Systems. 2002; 132:147–171.
8. Park M, Ji S, Kim E, Park M. A new approach to the identification of a fuzzy model. Fuzzy Sets and Systems. 1999; 104: 169–81.
9. Sagias DI, Sarafis EN, Siettos CI, Bafas GV. Design of a model identification fuzzy adaptive controller and stability analysis of nonlinear processes. Fuzzy Sets and Systems. 2001; 121:169–79.
10. Grefenstrtte JJ. Optimization of control parameters for genetic algorithms. IEEE Trans System Man Cybern. 1986; 16(1):122–8.
11. Srinivas M, Patnaik LM. Adaptive probabilities of crossover and mutation in genetic algorithms. IEEE Trans System Man Cybern. 1994 Apr; 24(4):656–67.