Evolutionary Optimization of Robust and Chattering-Free Mamdani Type Fuzzy Controller

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ABSTRACT

In fuzzy control area, the evolutionary algorithm is one of the most common design tools for fuzzy knowledge base generation. In this paper, we present the application of an integer evolutionary algorithm (IEA) for simultaneous optimization of fuzzy rule base and fuzzy data base of Mamdani-type fuzzy controller. The motivation behind this work is to design a robust and accurate controller without chattering phenomenon in the control input. More specifically, we consider the minimization of the variance of the control input in the same time as root mean square tracking error during the optimization. This fact leads the IEA to search for accurate fuzzy controller that provides just enough control input for smooth behavior. To assess the design technique, simulations were conducted with direct-drive DC motor. The simulation results show the effectiveness of the proposed IEA in designing a robust and chattering-free Mamdani fuzzy controller with high accuracy as compared to a conventional PD controller.

KEYWORDS: Mamdani fuzzy controller; Evolutionary algorithm; Chattering phenomenon; Direct-drive DC motor

1 INTRODUCTION

In the two last decades, evolutionary algorithms (EAs) have been widely used in automatic generation of fuzzy knowledge base for different types of fuzzy logic controllers (FLCs) [1-5]. Nevertheless, the designed FLCs are not involved directly in the control process and their remarkable potentials are far from being fully exploited. This is due in large part to the chattering phenomenon that can damage the controlled plants. This problem can be avoided by a suitable FLC design that consists mainly in determining the fuzzy rule base (FRB) and the fuzzy data base (FDB). The FRB is a set of fuzzy IF-THEN rules that express linguistic knowledge about actions or conclusions (THEN part) in given circumstances (IF part). The FDB is a collection of concepts related to definition of the fuzzy variables of the FLC, such as the boundaries of the universes of discourse, the number of fuzzy partitions within these universes, the shape of membership functions (e.g., triangular, trapezoidal or gaussian) and its descriptive parameters (e.g., the width and the center if the shape is symmetric triangular).

In this paper, we investigate the use of integer evolutionary algorithm (IEA) for simultaneous optimization of the FRB and the FDB of Mamdani type fuzzy controller, also known as linguistic FLC. The choice of integer coding is done because it has the advantage in reducing the Hamming Cliff effects [6] associated with binary coding and reduces the convergence time since the length of the chromosome is further reduced compared to the binary one [7]. In the FDB, we fixed the number of fuzzy partitions within each universe of discourse and the shape of the membership functions which is symmetric and triangular. The descriptive parameters of the membership functions associated to both input and output linguistic variables of the SFLC and the overlaps are automatically generated by the proposed IEA. The design problem is considered as the FKB optimization where we seek to minimize the tracking error and alleviate the chattering in the control signal that leads to high stress of the actuator to be controlled. The basic idea of taking into account the chattering phenomenon during the optimization process is the introduction of the sum of variance of the control signal as optimization criterion. Doing so will ensure that the designed FLC provides just enough voltage to get the control job accomplished.

The remainder of this paper is organized as follows. The model of the DC motor used in the simulations is described in section 2. Brief descriptions of the techniques used in this paper are given in section 3. In section 4, the structure and the components of the Mamdani-type FLC in question are described. Their parameters to be optimized are presented in section 5. The application of the proposed IEA to FLC design is detailed in section 6. Simulation results and discussions are given in section 7.

2 DIRECT-DRIVE DC MOTOR

The system to be controlled is a direct-drive DC motor. The main characteristic of this type of motors is that the load is directly driven without motion transfer mechanism such as belt, chain, ball screw or gearbox. In fact, the motion transfer mechanisms are known to be the source of some undesirable nonlinear effects such as vibration, friction, backlash, and elasticity. Direct drive motor, however, need a more precise controller. This is due to its significant sensitivity to any low variation in load parameters or external disturbances since they are directly reflected on the motor dynamic. The dynamic equations of the used direct-drive DC motor are given by:

$$E_a = R_a . I_a + L_a . \frac{dI_a}{dt} + K_e . \dot{q} \quad (1)$$

$$T_m = K_T . I_a \quad (2)$$

$$I_n . \ddot{q} = T_m - D . \dot{q} - T_l \quad (3)$$

Where q , $\dot{q}$, and $\ddot{q}$ denotes the angular position, angular velocity and angular acceleration of the motor shaft. E_a the input voltage, I_a the rotor current, T_m the generated torque, and T_l the load torque. The other parameters and their numerical values are given on Table 1.

Parameter	Notation	Value	Unit
Rated input voltage	E_{ar}	24	V
Rated output power	P_r	17	W
Rated output torque	T_{mr}	5.29	N.m
Viscous friction constant	D	1.74	N.m.s/rad
Motor inertia moment	I_n	0.0974	N.m.s^2/rad
Torque constant	K_T	0.54	N. m/A
Voltage constant	K_e	5.44	V/rad/sec
Stator resistance	R_a	2.8	Ω
Stator inductance	L_a	1.1	mH

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4 PRELIMINAIRIES

4.1 Evolutionary Algorithm

EA is a population-based optimization method inspired from the strategies of natural selection and genetics. It evolves a population of potential solutions of the problem to be solved to explore the search space. These potential solutions are called chromosomes, individuals, or genotypes. To determine how well each chromosome solves the problem, EA calculates a "fitness" function (objective function or cost function) which measures the profit, the utility or the quality to be optimized. Along the generations, the EA tends to improve the fitness of the population by selecting chromosomes (parents) according to the basic criteria of "survival of the fittest", and creating new chromosomes (children) by recombining parts of the selected parents in a random

manner. Thus, EAs are able to use historical information as a guide through the search space. The new chromosomes are again evaluated and transformed using such probabilistic operators. The process continues until a convergence is achieved or a suitable solution is found.

4.2 Fuzzy Logic Control

Fuzzy logic theory was proposed by L. Zadeh in 1965 and applied for the first time in control application by Mamdani in 1973. Since then, i.e., over forty years, much work and progress have been done in the field of fuzzy control. The most important characteristics of FLC are the use of linguistic variables instead or in addition to numerical variables, and the description of the relationship between input and output variables by conditional fuzzy statements (fuzzy rules). Figure 1 depicts the basic structure of a simple FLC. In fuzzification process, the crisp inputs are converted into fuzzy input sets so the fuzzy inference engine can operate on. Based on all these fuzzy input sets and the fuzzy implication rule, the fuzzy inference engine derives fuzzy output set from each fuzzy rule of the FRB. The resulting fuzzy output sets are then aggregated and converted in the defuzzification process into crisp value representing the control action.

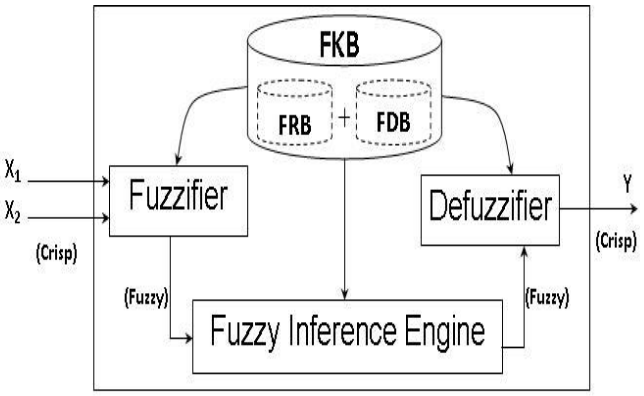

Figure 1: Structure of the fuzzy logic control.

5 MAMDANI FUZZY CONTROLLER TO BE EVOLVED

As almost all FLCs set to work nowadays, we have chosen the inputs of our FLCs to be the error x_1 and the change error x_2 on the angular position of the motor shaft. At the output, the FLC provides the input voltage E_a that excites the DC motor and brings it in the desired angular position. This choice makes the FLC to be evolved by the proposed IEA a PD-like fuzzy controller, which is the most suitable in direct-drive DC motor. This is due to its fast response and its ability to predict the future error of the actuator response.

The FLC used in our application can be viewed as a mapping from crisp inputs $\underline{x} = (x_1,x_2)^T \in U \subset IR^2$ to crisp

Output $y \in V \subset IR$, and this mapping can be expressed quantitatively as $y=f(\underline{x})$ where f is non-linear. Let the universe of discourse be $U=U_1 \times U_2$, where $U_1=U_2=[U_{min}, U_{max}]= [-0.05, 0.05]$, and $V=[-24, 24]$.

The FLC consists of the following components:

A ***singleton fuzzifier*** that converts a crisp value $\underline{x} \in U$ into a fuzzy singleton Ax within U such that:

$$\mu Ax\,(x`) = 1 \quad \text{if} \quad x`=x \tag{4}$$

$$\mu Ax\,(x`) = 0 \quad \text{if} \quad x` \neq x \tag{5}$$

The ***fuzzy data base***: The space of x_1 is partitioned into three triangular and symmetric membership functions associated to the following labels: negative (N), zero (Z) and positive (P). The space of the second input x_2 and the output y are partitioned into seven membership functions associated to the following labels: negative big (NB), negative medium (NM), negative small (NS), zero (Z), positive big (PB), positive medium (PM), and positive small (PS).

The ***fuzzy rule base*** consists of a collection of fuzzy IF-THEN rules expressed as:

$$R^{(l)}: \text{ IF } (u_1 \text{ is } A_1^l \text{ and } u_2 \text{ is } A_2^l) \text{ THEN } (v \text{ is } Cl) \tag{6}$$

Where, u_i and v are linguistic variables; A_i^l and C^l are terms associated to the fuzzy sets F_i^l and G^l defined in Ui and V, respectively, with $l = 1,2,.....,M$. M is the number of rules in the FRB. Here we have chosen M = 3x7 = 21 to account for every possible combination of input fuzzy sets.

Each fuzzy IF-THEN rule defines a fuzzy implication:

$$Rl = F1l \times F2l \rightarrow Gl \tag{7}$$

$$= \{ ((\underline{u},v), \mu_{R^l}(\underline{u},v)) \mid \underline{u} \in U, v \in V \} \tag{8}$$

Where $\mu_{R^l}(\underline{u},v)$ is defined by the following Larsen's fuzzy implication rule:

$$\mu_{R^l}(\underline{u},v) = \mu_{F_1^l \times F_2^l}(\underline{u}) \,.\, \mu_{G^l}(v) \tag{9}$$

$$= (\mu_{F_1^l}(u_1) \,.\, \mu_{F_2^l}(u_2)) \,.\, \mu_{G^l}(v) \tag{10}$$

The ***fuzzy inference engine*** derives from each fuzzy rule of the FRB an output fuzzy set, in the following way:

Each fuzzy rule of (6), described by a fuzzy implication R^l, determines a fuzzy set $B^l = Ax \text{ o } R^l$ in V such that:

$$\mu_{B^l}(v) = \mu_{Ax \text{ o } R^l}(v) \tag{11}$$

$$= \sup_{\underline{u} \in U} \{ \mu_{Ax}(\underline{u}) \,.\, \mu_{R^l}(\underline{u},v) \} \tag{12}$$

The ***defuzzifier*** used in our fuzzy controller is the modified height defuzzifier.

Let v^l denote the center of gravity of the fuzzy set B^l, which is associated with the activation of the l^{th} fuzzy rule. This defuzzifier evaluates $\mu_{B^l}(v^l)$ at v^l, and then computes the output of the FLC as:

$$y = \frac{\sum_{l=1}^{M} v^l \frac{\mu_{B^l}(v^l)}{\delta^l}}{\sum_{l=1}^{M} \frac{\mu_{B^l}(v^l)}{\delta^l}} \tag{13}$$

Where δ^l is the support's length of the triangular membership function of the consequent for the l^{th} fuzzy rule.

With this components, the FLC is called "*fuzzy system as expansion of FBF: Fuzzy Basis Function*" [8].

6 MAMDANI FLC PARAMETERS TO BE EVOLVED

To use the IEA, we must define first the parameters to be optimized and then code it as some finite-length strings or chromosomes "Ch". Two elements are to be optimized for the fuzzy controller: the FRB and the FDB. The FRB part of the chromosome involves the consequent labels (linguistic terms) of the fuzzy rules. The FDB part of the chromosome contains the descriptive parameter set of the I/O MFs. The shape of the MFs is assumed to be triangular and symmetric; hence we need only two parameters for its description. These parameters are elements of (center (C), width (W), overlap (O). It is obvious that the MFs located at the extremes are defined by the center and the deviation; while the others, their parameters are the center and the overlap.

In our application, we have the following implicit knowledge about the motor FLC design:

1. The fuzzy partitions along the universe of discourse for the input and output variables are symmetric;
2. If the inputs are zero, the output should be zero too;
3. If the inputs of the two fuzzy rules are symmetric, the outputs of these rules should also be symmetric.

We propose to make use of them in reducing the chromosome size and so the convergence time. Using the first piece of knowledge about the symmetrical aspect of the fuzzy partitions, just the MFs located in either the positive or negative part of the universe of discourse and the MF centered at zero need to be coded in the chromosome, figure 2. Furthermore, it is obvious that the MF associated to the zero term for each variable must have the center fixed at zero. The second knowledge gives already one fuzzy rule -if x1 is Z and x2 is Z then y is Z- which must be discarded from evolution. So there's no need to encode it in the chromosome

The last fact implies that we have to search only the half of the FRB and then deduce the other half by symmetry, figure3.

To sum up, by taking into account the knowledge about the FLC specifications, the chromosome size is reduced to less than a half.

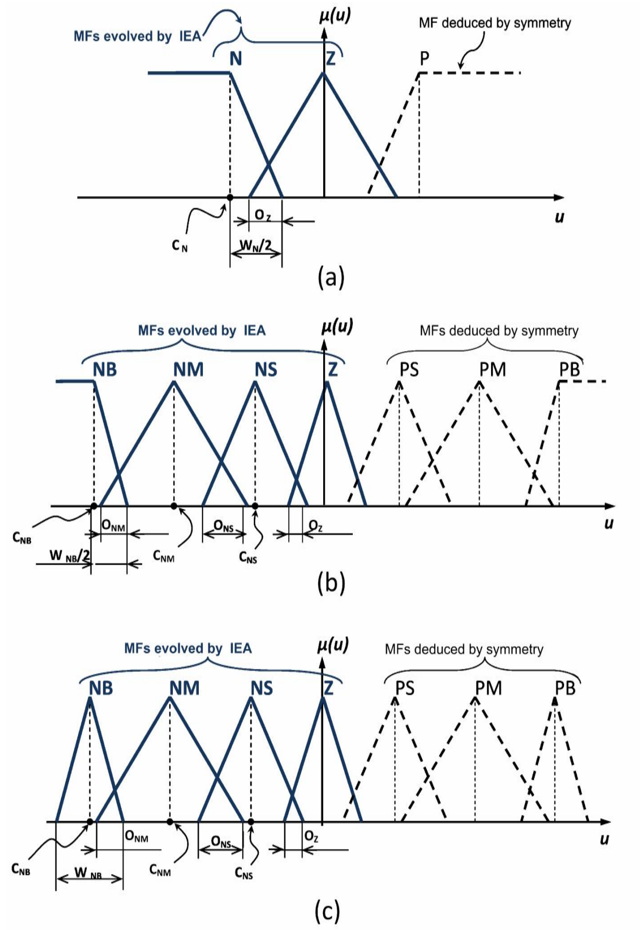

Figure 2: FDB parameters to be evolved by IEA

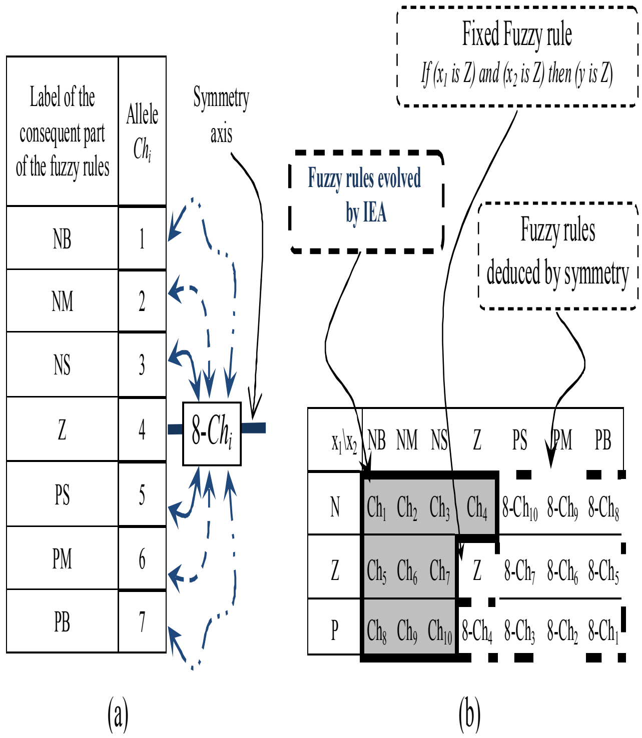

Figure 3: (a) Symmetry mechanism of labels in the consequent part of fuzzy rules, (b) FRB parameters to be evolved by IEA.

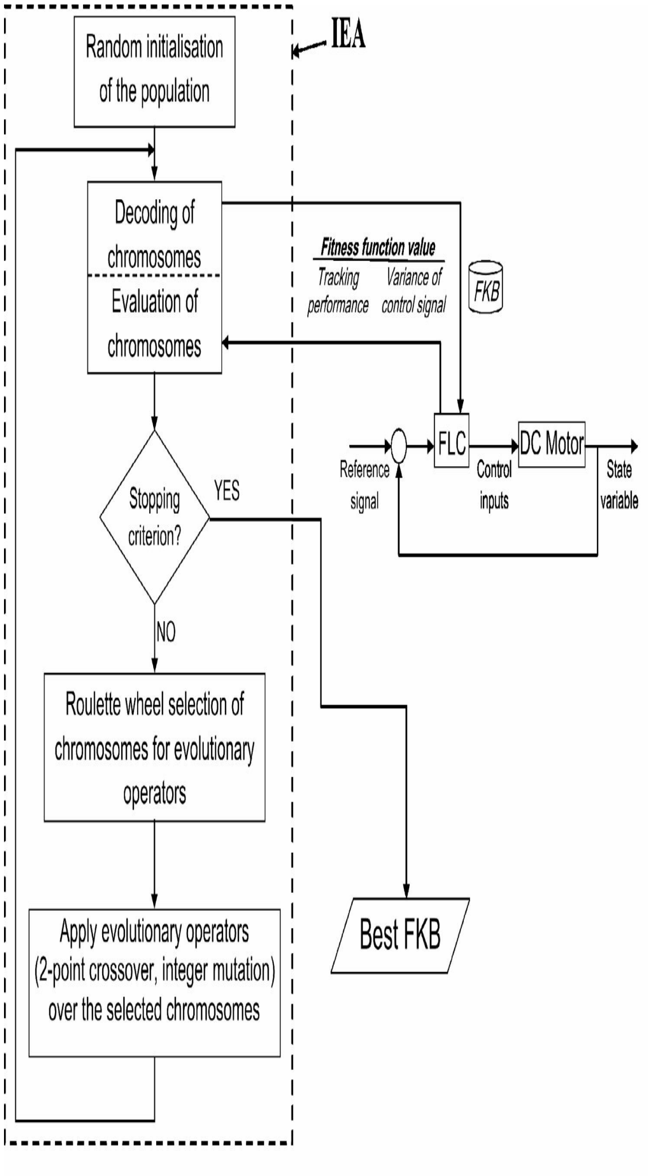

Figure 4: Integer evolutionary fuzzy control system configuration

7 IEA FOR CHATTERING-FREE MAMDANI FLC DESIGN

7.1 Method Principles

Figure 4 shows the overall structure of the integer evolutionary fuzzy control system used to automatically generate FKB for chattering-free Mamdani FLC. Starting from random initialization of the chromosome population, the IEA decode the chromosomes into potential FKBs. Mamdani FLC use each of these decoded FKBs to track the desired trajectory and in the same time to compute the fitness function value that measures the tracking performance end the variance of the control signal. Based on these fitness function values, chromosomes are selected by roulette wheel selection operator to be mutated or recombined by integer mutation operator and 2-point crossover operator, respectively. The new resulting chromosomes are evaluated and the evolutionary process repeat until the satisfaction of the stopping criterion.

7.2 Encoding Strategy

The genotype encoding the FKB parameters described in section 5 is defined as an array or chromosome (*Ch*) of 27 integer elements or genes. The first ten genes of the chromosome encode the FRB and take values from 1 to 7. The remaining 17 genes are used to compute the MF parameters which form the FDB. Their values vary between 0 and 9. Each MF parameter represents a percentage of a specific range. The general decoding relationship that calculates the numerical MF parameter (X) from its representative gene (ch_i) and the corresponding searching range length (I_X) is given by:

$$X = \frac{Ch_i + 1}{100} . I_X \tag{13}$$

The possible percentage values are 10%, 20%, …, 100%. As one can see, the proposed encoding strategy avoids zero percentage to ensure that all the MFs are overlapped and distinguished. The searching range lengths (I_X) of the MF parameters are given in Table 2.

Table 2: Searching range length (I_X) for MF parameters

Variable	Parameter (X)	Searching range length(I_X)
Input (x_1)	C_N	U_{min}
	W_N	$- 2{*}C_N$
	O_Z	W_N
Input (x_2) and output (E_a)	C_{NB}	U_{min}
	C_{NM}	$C_{NB}/2$
	W_{NB}	$2{*}(C_{NM}- C_{NB})$
	O_{NM}	$W_{NB}/2$
	O_{NS}	W_{NM}
	C_{NS}	$(C_{NM}+W_{NM}-O_{NS})/2$
	O_Z	W_{NS}

7.3 Evolutionary Operators

Our algorithm uses roulette wheel selection with replacement to select parents for reproduction. The crossover operator is two-point crossover which refers to selecting randomly two sites on one of the chromosomes. Then, the fragment between the two sites is exchanged with the corresponding fragment of a second chromosome. As mentioned in the above section, the chromosome is integer based instead of binary based and each allele of this chromosome has an integer range according to the FLC parameter it represents. For example, alleles representing FRB have an integer range from 1 to 7, and those encoding the MF parameters have an integer range from 1 to 9. The mutation operator thus changes the allele randomly inside its range.

7.4 Fitness Function

The IEA requires that each chromosome of the population be assigned a fitness function value. This value reflects the extent to which the FKB represented in the chromosome produces the expected FLC behavior over the reference signal. In particular, we seek Mamdani FLC that has a good trajectory tracking and smooth behavior in control action. That is why the fitness function is chosen to have two components:

- Root of mean square error (*RMSE*) representing the accuracy objective defined as:
- $$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(q_i - q_{d_i})}{N}}$$
- Where q_i and q_{d_i} are the actual and the desired angular position, respectively, at the i^th sampling time. N is the sampling size.
- Sum of variance of the input voltage variable (*Sum*$|\Delta E_a|$) representing the smoothness objective defined as:
- $$Sum|\Delta E_a| = \sum_{i=1}^{N}|E_{a_i} - E_{a_{i-1}}|$$

Where E_{a_i} is the input voltage value at the i^{th} sampling time.

These measures are weighted and summed up so that they form a final quality value:

$$c_1.RMSE + c_2.Sum|\Delta E_a|$$

The parameters c_1 and c_2 are weights used to stress the relative importance of the different fitness function components. Currently, there is no systematic method available at the time for identifying these weights. Usually the empirical methods are used or optimized in the same time as the design parameters. Since our problem has only two objectives, it seems feasible to determine the weights by trial and error. The numerical values used are c_1=1 and c_2= 10^{-7}.

8 SIMULATION RESULTS

In this section, we investigate the proposed IEA in chattering-free Mamdani FLC design for tracking control of direct-drive DC motor described in section 2. The goals of the simulations are: (1) to reveal the influence of taking into account the objective of smoothness besides the accuracy objective; (2) to show that the proposed IEA can design chattering-free Mamdani FLC effectively; (3) to compare the tracking and robustness performances of the designed chattering-free Mamdani FLC with the conventional PD controller.
The objective of chattering-free Mamdani FLC design is to make the direct-drive DC motor position tarck a reference trajectory defined as:

$$q = 0.75(1 - cos(0.25.\pi.t))[rad] \quad (14)$$

The initial states are given by: $q = 0[rad]$, and $\dot{q} = 0\ [rad.s^{-1}]$.
The population size, the mutation rate and the crossover probability were set at 50, 0.1, and 0.8, respectively. Since IEA is stochastic algorithm, it is run ten times using different random number generator seeds producing in such a way different initial populations. The best FKB found by the IEA in each of the ten runs was recorded, and each of these runs was stopped after 100 fitness evaluations.

To investigate the impact of the introduction of the second objective in the design phase, we consider another evolutionary algorithm noted as IEA-1 for comparison. IEA-1 is similar to the proposed IEA except that the fitness function to be minimized is equal to only the RMSE.

Figure 5 and figure 6 show the evolution of RMSE and Sum$|\Delta E_a|$, respectively, for IEA and IEA-1 over the number of generations.

Figure 5 demonstrates clearly that the IEA succeeds to minimize the Sum$|\Delta E_a|$ greatly compared to IEA-1. On the contrary in figure 6, it is the IEA-1 that has less RMSE than IEA. This leads to note that the RMSE and Sum$|\Delta E_a|$ are two concurrently objectives, i.e. the amelioration of one objective implies the deterioration of the other one. The IEA thus tends to optimize the FKB over the generations by finding a tradeoff between the two objectives: MSRE and Sum$|\Delta E_a|$.

In order to highlight the effectiveness of the evolved fuzzy controller by IEA, we compare its performances to Mamdani FLC designed by IEA-1 and a conventional PD control. The gains of PD controller are given as: K_P = 400; K_D = 3. They are determined according to the Ziegler-Nichols tuning method based on the step response of the plant.

The performances of the different controllers are compared for two cases:

- Nominal case: It is a disturbance-free case where the nominal model of the DC motor described in section 2 is used without inducing any disturbances.
- Disturbed case: To perform a qualitative assessment of the robustness of the designed FLC, the motor is supposed to be affected by two types of disturbances: load disturbance, and measurement noise.

The ***load disturbance*** models various external forces that affect the inertia during the interaction with the environment, e.g., forces due to material processing in tool machines or forces due to the impact, for example at spot welding. In the simulations the moment of inertia of the motor shaft is varied while the motor is in motion as:

- t < 2s, In=0.0974 N.m.s2/rad (nominal value);
- 2< t <5s, In=0.2922 N.m.s2/rad (three times of nominal value);

- 5< t < 6s, In=0.0974N.m.s2/rad (reduced inertia to
- nominal value);
- 6< t < 8s, In=0.5844N.m.s2/rad (six times of nominal inertia);
- 8< t <12s, In=0.0974 N.m.s2/rad (reduced inertia to initial value).

The ***measurement noise*** is introduced in the output signals of the system model to simulate noise-corrupted sensors. It is modeled as zero mean White Gaussian noise with 0.01 deg standard deviation.

The control task is to control the angular position of the motor shaft to track the following trajectory:

$$q = 0.75(1 - \cos(0.25.\pi.t))\,[rad] \quad (15)$$

The initial states are given by: $q = 0[rad]$, and $\dot{q} = 0\,[rad.s^{-1}]$.

The simulation results illustrating the tracking performance and control activities of the Mamdani FLC designed by IEA-1, the Mamdani FLC designed by IEA, and the conventional PD controller under the two cases are shown in figures 7-8, figures 9-10, figures 11-12, respectively.

According to figures 7(b), 9(b), and 11(b), the Mamdani FLC designed by IEA-1 yields the smallest tracking errors. After the disturbances are induced, Mamdani FLC designed by IEA shows the best tracking performance, while for Mamdani FLC designed by IEA-1 it is substantially deteriorated. The tracking errors for PD controller are still in acceptable tolerance.

As one can see in figure 8(a), 10(a), and 12(a), the effects of the added measurement noise are clearly evident in the input voltage signal for Mamdani FLC designed by IEA and PD controller, but there is no undesirable chattering phenomenon. Contrary to the Mamdani FLC designed by IEA-1 for which the chattering level is quite large.

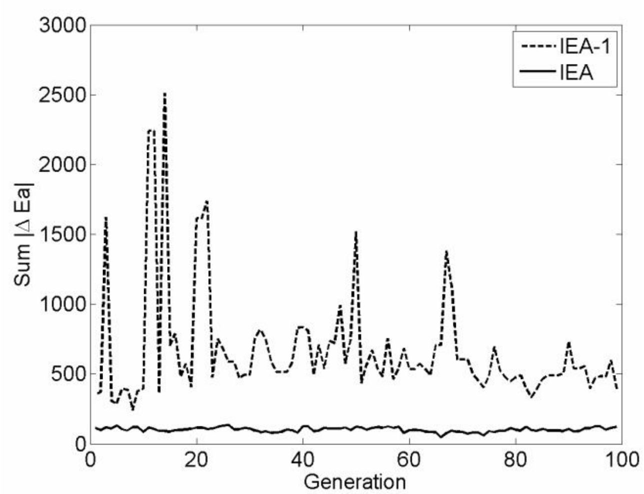

Figure 5: Evolution of the smoothness objective (Sum$|\Delta E_a|$) during the design phase for IEA and IEA-1

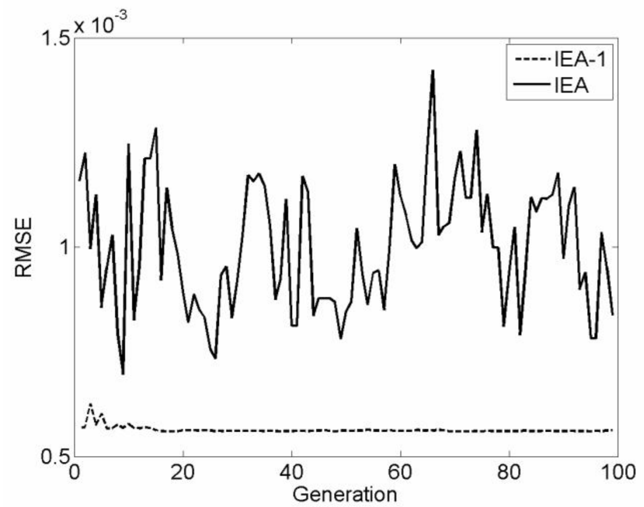

Figure 6: Evolution of the tracking accuracy objective (RMSE) during the design phase for IEA and IEA-1.

9 CONCLUSION

In this paper, we have proposed an integer evolutionary algorithm (IEA) for simultaneous optimization of FRB and FDB optimization of chattering-free Mamdani-type-1 fuzzy controller. By considering the variance of the control input as components of the fitness function, we get a robust and satisfactory smooth behavior at the evolved FLC output. The simulation results presented here, have demonstrated the effectiveness of the proposed IEA to design smooth and robust Mamdani fuzzy logic controllers capable of controlling direct-drive DC motor to track a desired trajectory. The evolved Mamdani type FLC was shown to be robust to measurement noise and load perturbations without significant chattering in the control input. Therefore, the proposed design technique constitutes a powerful tool to exploit the capabilities of fuzzy logic systems in actuators control.

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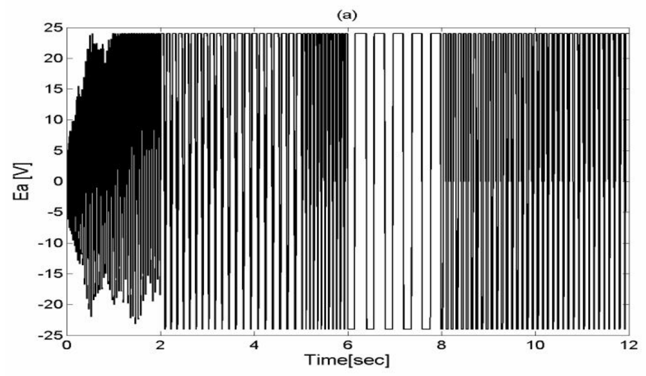


Figure 8: Tracking performances and control activities in disturbed case of Mamdani FLC evolved by IEA-1.

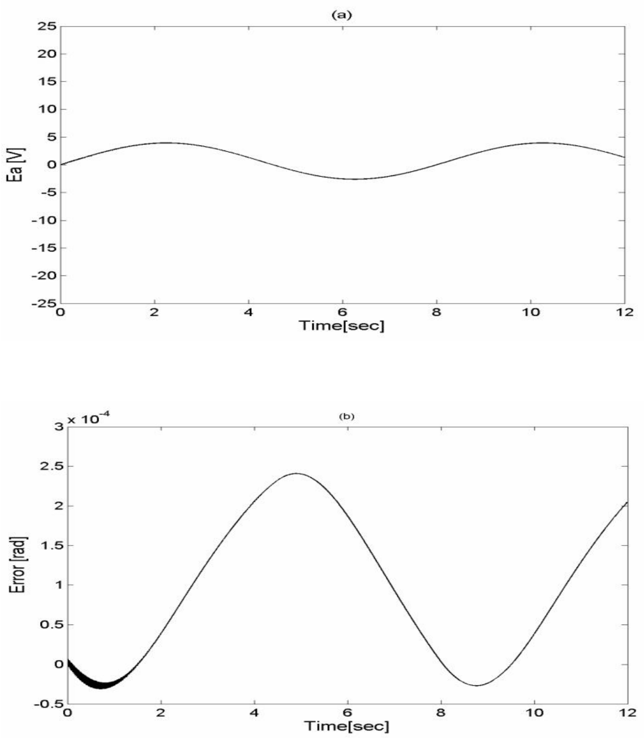


Figure 7: Tracking performances and control activities in nominal case of Mamdani FLC evolved by IEA-1.

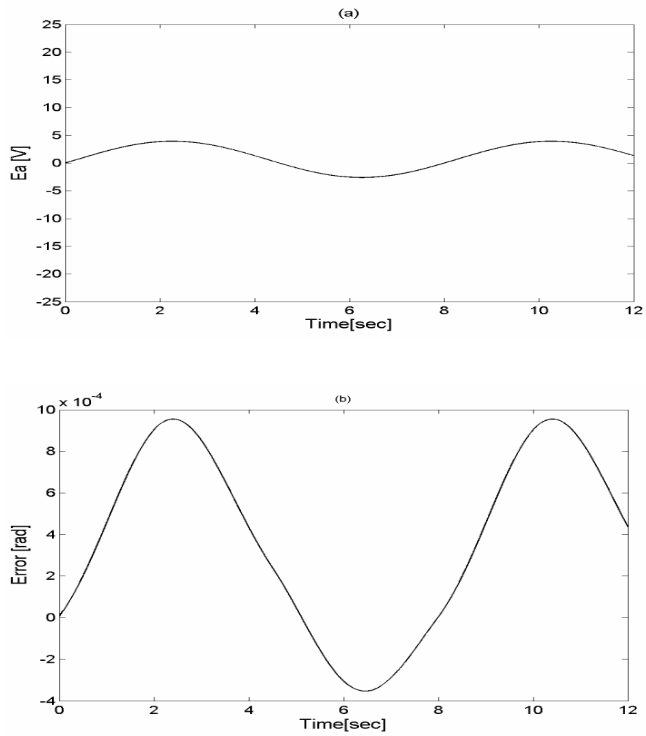
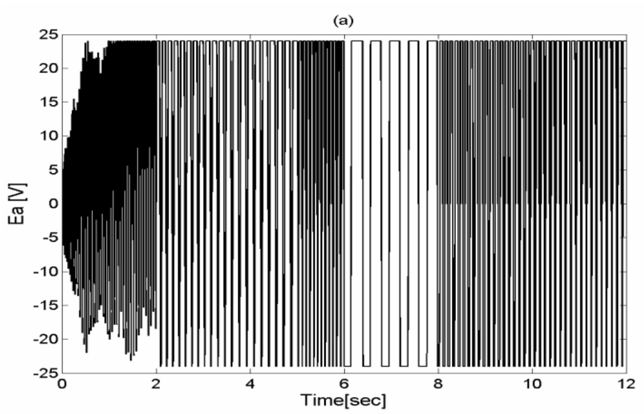
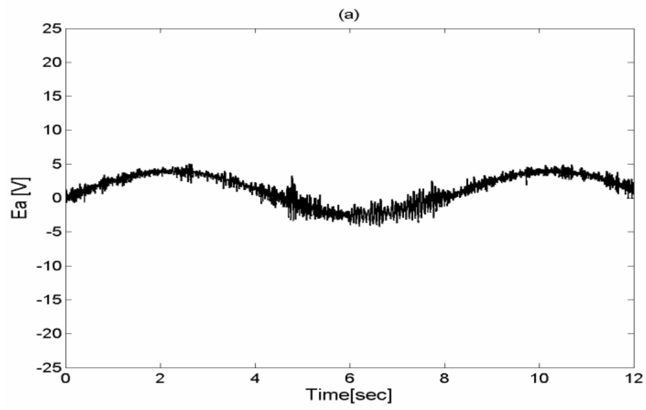


Figure 9: Tracking performances and control activities in nominal case of Mamdani FLC evolved by IEA.





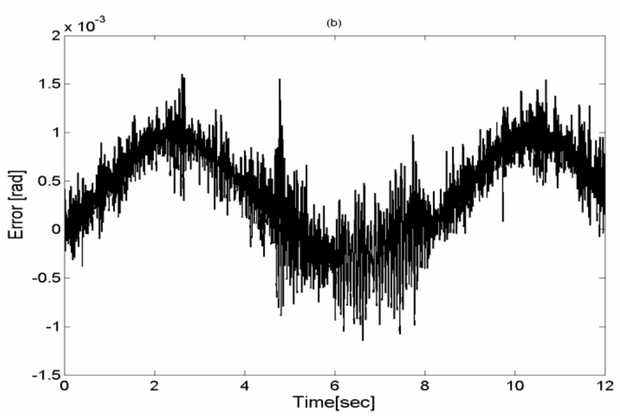


Figure 10: Tracking performances and control activities in disturbed case of Mamdani FLC evolved by IEA.

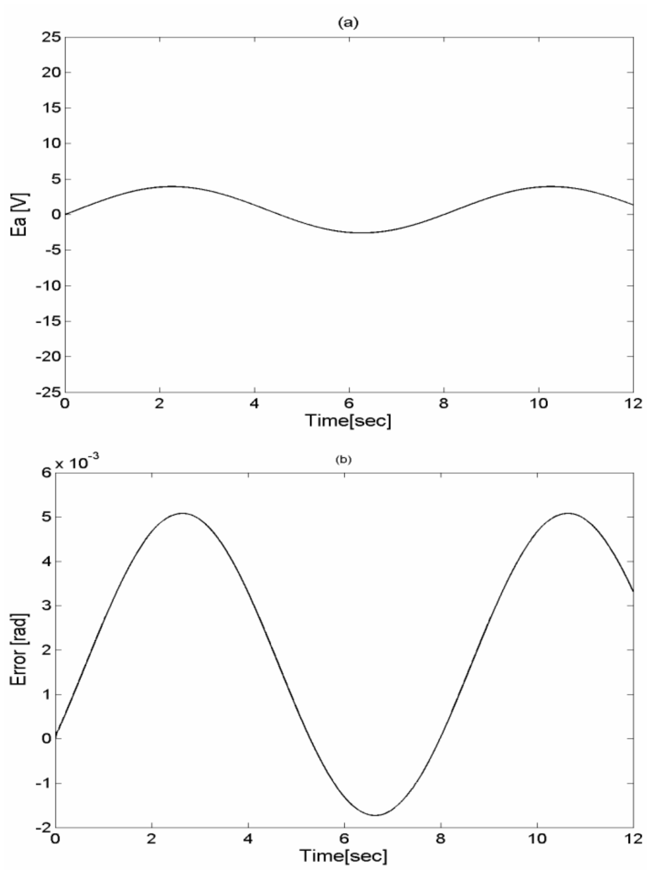


Figure 11: Tracking performances and control activities of PD controller in nominal case.

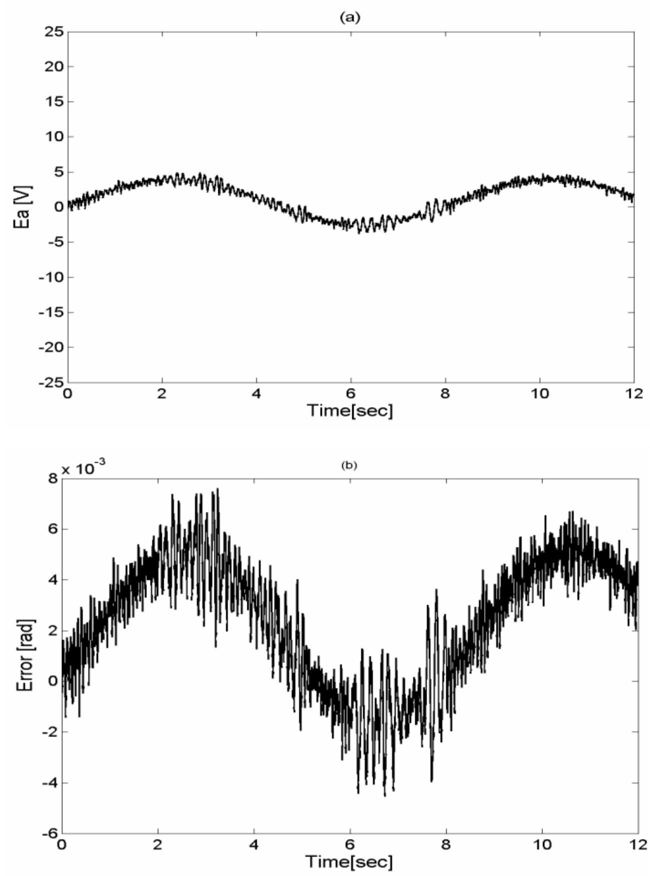


Figure 12: Tracking performances and control activities of PD controller in disturbed case.