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By Mohammad Jalali Varnamkhasti
University Putra Malaysia

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ANFISGA -ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM GENETIC ALGORITHM

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ANFISGA -Adaptive Neuro-Fuzzy Inference System Genetic Algorithm

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Abstract: In optimization, when the genetic algorithm fails to find the global optimum, the problem is often credited to premature convergence. Premature convergence is influenced by different parameters. One of the important parameters is diversity population. In this study, we use a novel method to keep diversity in population. A new technique for choosing the female chromosome during sexual selection in a genetic algorithm is proposed. A bi-linear allocation lifetime approach is used to label the chromosomes based on their fitness value. The label will then be used to characterize the diversity of the population. During the sexual selection, the male chromosome is selected randomly. The label of the selected male chromosome and the population diversity of the previous generation are then applied within a set of fuzzy rules and Adaptive Neuro-Fuzzy Inference System Genetic Algorithm to select a suitable female chromosome for recombination. Extensive computational experiments are conducted to assess the performance of the proposed technique with some commonly used sexual selection mechanisms found in a standard GA for solving some numerical functions from the literature. The computational results show that the proposed technique produces higher solutions quality compared to others.

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I. Introduction

Genetic algorithm (GA) is an optimization algorithm that incorporates the process of evolution. Problems by inspiring an evolutionary process including selection, crossover and mutation are solved. GA uses a population of chromosomes, each representing a solution to the problem that has been solved. In a traditional (GA), chromosomes reproduce asexually: any two chromosomes may be parents in crossover. Gender division and sexual selection here inspire a model of gendered GA in which crossover takes place only between chromosomes of opposite sex. The Sex of chromosomes is not only accountable for preserving diversity in population and maintaining a victorious genetic pool by means of selection, crossover and mutation, but also are accountable for the optimization of the different tasks which are very important to survival. We know that female choice is an important factor in both species recognition and sexual selection. In this study, an obvious characteristic Between the two gender groups, with the possibility of embedding different tasks for each one is considered such as the determination of what partners are suitable for mating and recombination. We suppose a relation between age, effectiveness and fitness as in biological systems affecting the selection procedure. A bi-linear allocation lifetime approach is used to label the chromosomes based on their fitness value. In this paper lifetime is utilized just to label the chromosomes, and here lifetime doesn't mean, the number of iteration that chromosome is remained for generation. The obtained chromosomes labels are used to characterize the diversity of the population. Then the population is divided into two categories, male and female, so that male and female are selected in an alternate way. In each generation the layout of selection for male and female are changed. In optimization, when the genetic algorithm cannot to find the global optimum, the problem is often accredited to premature convergence. Premature convergence is influenced by different parameters. One of the significant parameters is diversity population. To sum up, the aim of this paper is keeping the diversity of population by female choice. Female selection is donethrough a set of fuzzy rules and a new Adaptive Neuro-Fuzzy Inference System (ANFIS) combined with genetic algorithm called Adaptive Neuro-Fuzzy Inference System Genetic Algorithm (ANFISGA). The paper is set up as follows: in section 2, literature review is given. In section 3 fuzzy rules system is considered, in section 4 is reviewed adaptive neuro-fuzzy inference system. Adaptive neuro-fuzzy inference systems genetic algorithm in section 5 is introduced. The experiments and test set are presented in section 6. Algorithms and numerical results are given in section 7 and the conclusion is drawn in section 8.

II. Literature Review

Genetic Algorithm was developed by J. Holland in 1975 [10]. The basic approaches for retarding premature convergence aim to maintain genetic diversity. Different publications are available presenting various ways to better maintain diversity population ([5], [7], [8]). Some researchers studying the occurrence of premature convergence ([10], [11]), or analyzing the interaction of

About: Laboratory of Applied and Computational Statistics, Institute for Mathematical Research,University Putra Malaysia, 43400 UPM Serdang, Selangor, MALAYSIA Department of Basic Science, Islamic Azad University, Dolatabad Branch, Esfahan, IRAN
Email: jalali@inspem.upm.edu.my

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different forces inside GAs (e.g. [19]).Work has been performed using mate choice in GA, with encouraging results. Ref. [16] shows how the use of a seduction function based upon a visual measure, such as unitation in the case of the royal road problem [13], where it has been shown that selection of the second parent can improve GA performance. Work in [12] discussed the various ways of sexual selection that can be used in evolutionary computation, and indicate that speciation behaviours may occur when sexual selection is used [15]. Good genes models of sexual selection rely on the idea that fitness is genetic, which contrasts stridently with the non-additive form of genetic quality associated with compatible gene models of sexual selection, which is not generally considered heritable([14], [15]). Theoretical developments have played a critical part in understanding the role of genetic ability in sexual selection by providing new hypotheses and predictions for empiricists to test. Several works in this issue explore new theoretical avenues with respect to genetic ability ([11], [15]). In another research showed that "incest prevention", the exclusion of crossover between identical or very similar strings, can prevent premature convergence [11]. Cavicchio [5] has extended the idea of incest prevention fairly by introducing the concept, of ancestry in other words, solution are prohibited from mating with, say, their grandparents, siblings. Ratford et al. [6] have shown the sexual selection appears to be a robust technique for improving GA performance over wide rang of test problems in the GA literature [15].

III. Fuzzy Rules Systems

Fuzzy knowledge -based systems are rules that built on fuzzy logic and fuzzy set theory. A rule system consisting of a number of rules with a condition part and an action part: IF "condition," THEN "action" The condition part is also known as the rule premise, or simply the IF part. The action part is also called the consequence or the THEN part. A fuzzy rule system is a rule system whose variables or part of its variables are linguistic variables. A linguistic variable is characterized by a quintuple {x, T(x),G,M,U} in which x is the name of the variable, T(x) is the term set of x, that is, a set of linguistic values of x, which are fuzzy sets on the universe (U), G is the syntactic rule for generating the names of values of x, and M is a semantic rule for associating each value with its meaning, that is, the membership function that defines the fuzzy set[18]. In this paper we use a linguistic variable, age, for chromosomes. Figure 1 describes a linguistic variable age: Infant, Teenager, Adult and Elderly are the linguistic values. The membership functions for the linguistic terms are called semantic rules.

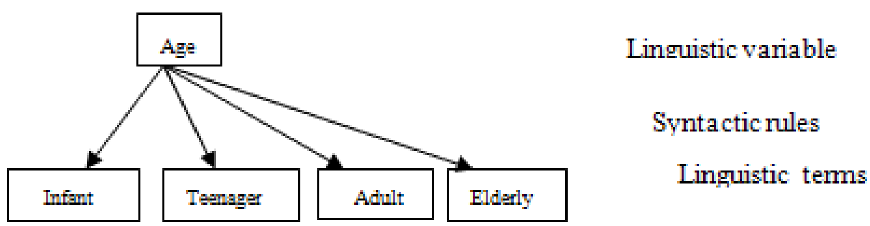

Figure 1. The linguistic variable "age".

In this study to find a membership function, we use fitness value of each chromosome and average of fitness functions in each generation. Each chromosome has its own label determined by membership function. Let

$$\varphi = \frac{f_i - f_{min}}{f_{avr} - f_{min}}, \phi = \frac{f_i - f_{avr}}{f_{max} - f_{avr}} \text{ and } \tau = f_{avr} - f_i$$

then membership function is:

$$\mu(c_i) = \begin{cases} \dfrac{L + \alpha\varphi}{n} & \tau \geq 0 \\ \dfrac{\beta + \alpha\phi}{n} & \tau < 0 \end{cases} \quad \text{.................. (1)}$$

$$\mu(c_i) = \begin{cases} \dfrac{U - (L + \alpha\varphi)}{n} & \tau \geq 0 \\ \dfrac{U - (\beta + \alpha\phi)}{n} & \tau < 0 \end{cases} \quad \text{................ (2)}$$

Where i c=chromosome i ,L=minimum age,U= maximum age,i f=fitness value of chromosome i,avr f =average fitness values, min f =minimum fitness values, max f =maximum fitness values in k th generation, n is population size α =(U-L)/2 and β(U+L)/2.Formula (1) is based on a better lifetime for higher fitness value and formula (2) is based on a better lifetime for lower fitness value. This idea is inspired by the idea of lifetime [14]. The fuzzification interface defines for each chromosome the possibilities of being

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{Infant, Teenager, Adult, Elderly}.These values determine the degree of truth for each rule premise. This computation takes into account all chromosomes in each generation, and relies on the triangular membership functions shown in Figure 2 (Here we consider L=2 and U=10).

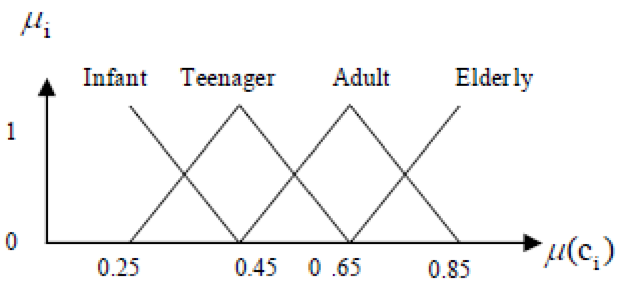

Figure 2: The membership function for Age of chromosomes

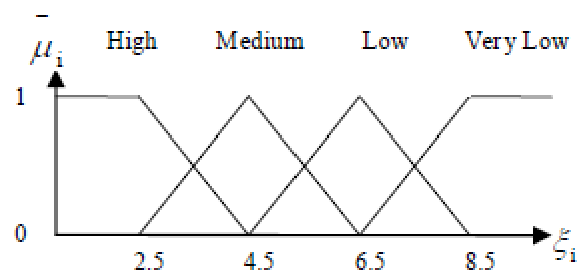

Figure 3: The membership function for Diversity

On the other hand we can consider linguistic rules and membership function for each rule as follow:

$$\text{Linguistic rules and membership function for Age chromosomes} = \begin{cases} \text{Infant} & \mu_1 = \begin{cases} 1 & x < 0.25 \\ -5x + \frac{9}{4} & 0.25 \le x < 0.45 \end{cases} \\ \text{Teenager} & \mu_2 = \begin{cases} 5x - \frac{5}{4} & 0.25 \le x < 0.45 \\ -5x + \frac{13}{4} & 0.45 \le x < 0.65 \end{cases} \\ \text{Adult} & \mu_3 = \begin{cases} 5x - \frac{9}{4} & 0.45 \le x < 0.65 \\ -5x + \frac{17}{4} & 0.65 \le x < 0.85 \end{cases} \\ \text{Elderly} & \mu_4 = \begin{cases} 5x - \frac{13}{4} & 0.65 \le x < 0.85 \\ 1 & x \ge 0.85 \end{cases} \end{cases}$$

………………… (3)

With these labels, population can be divided into four levels, Very Low, Low, Medium and High diversity, and relies on the triangular membership functions shown in Figure 3. Where $\xi_i \,(i = 1,2,3,4)$ is, average of lifetimes that calculated as follow:

$$\text{lifetime}\,(c_i) = \begin{cases} L + \theta \dfrac{f_i - f_{min}}{f_{avr} - f_{min}} & f_{avr} \ge f_i \\ \dfrac{1}{2}(U + L) + \theta \dfrac{f_i - f_{avr}}{f_{max} - f_{avr}} & f_{avr} < f_i \end{cases}$$

………………… (4)

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$$\text{Avrage of labels} = \begin{cases} \xi_r & \psi \le L+t & r=1 \\ \xi_r & L+t<\psi \le L+t+1 & r=2 \\ \xi_r & L+t+1<\psi \le L+t+2 & r=3 \\ \xi_r & \psi > L+t+2 & r=4 \end{cases}$$

$$\eta = [n/10] \;,\; \xi_r = \frac{\sum_{j=1}^{\psi} \text{lifetime}(c_j)}{\psi} \quad (r=1,2,3,4), \qquad \text{.....................} (5)$$

Where, $\theta = (U- L) / 2$, ψ = the label of half of the population,

$$t = \left[\eta \times \frac{L+U}{n}\right]$$

is a parameter that has correlation with domain of labels in problem,

Lifetime is lifetime of chromosomejc in condition r (r =1 2, 3, 4), nis the population size and ([x] means, nearest integer number tox, for example [2.3] = 2 and [2.8] = 3).

$$\begin{matrix}\text{Linguistic rules and} \\ \text{membership function} \\ \text{for Diversity population}\end{matrix} = \begin{cases} \text{High} & \bar{\mu}_1 = \begin{cases} 1 & x<2.5 \\ -\frac{1}{2}x+\frac{9}{4} & 2.5\le x<4.5 \end{cases} \\ \text{Medium} & \bar{\mu}_2 = \begin{cases} \frac{1}{2}x-\frac{5}{4} & 2.5\le x<4.5 \\ -\frac{1}{2}x+\frac{13}{4} & 4.5\le x<6.5 \end{cases} \\ \text{Low} & \bar{\mu}_3 = \begin{cases} \frac{1}{2}x-\frac{9}{4} & 4.5\le x<6.5 \\ -\frac{1}{2}x+\frac{17}{4} & 6.5\le x<8.5 \end{cases} \\ \text{Very Low} & \bar{\mu}_4 = \begin{cases} \frac{1}{2}x-\frac{13}{4} & 6.5\le x<8.5 \\ 1 & x\ge 8.5 \end{cases} \end{cases} \qquad \text{...................} (6)$$

Where $x = \xi_r$, r = 1 ,

IV. ANFIS: Adaptive Neuro-Fuzzy Inference System

The Sugeno fuzzy model was proposed for a systematic approach to generating fuzzy rules from a given input-output data set. A typical Sugeno fuzzy rule can be expressed in the following form:

IF x1 is A1 AND x2 is A2 …AND xm is Am THEN y=f(x1,x2,..., xm)

Where, x1, x2 ,...,xm are input variables; A1,A2,...,Am are fuzzy sets; and y is either a constant or linear function of the input variables, When y is a Constant or linear function of the input variables. When y is aconstant, we obtain a zero-order Sugeno fuzzy model in which the consequent of a rule is specified by singleton. When y is first-order polynomial, i.e. $y= k_0 + k_1x_1 + k_2x_2 + k_m x_m$ kmxm we obtain a first order Sugeno fuzzy model.Figure 4 shows the ANFIS architecture that corresponds to the first order Sugeno fuzzy model. For simplicity, we assume that the ANFIS has two inputs x1 and x2 and one output y [17].

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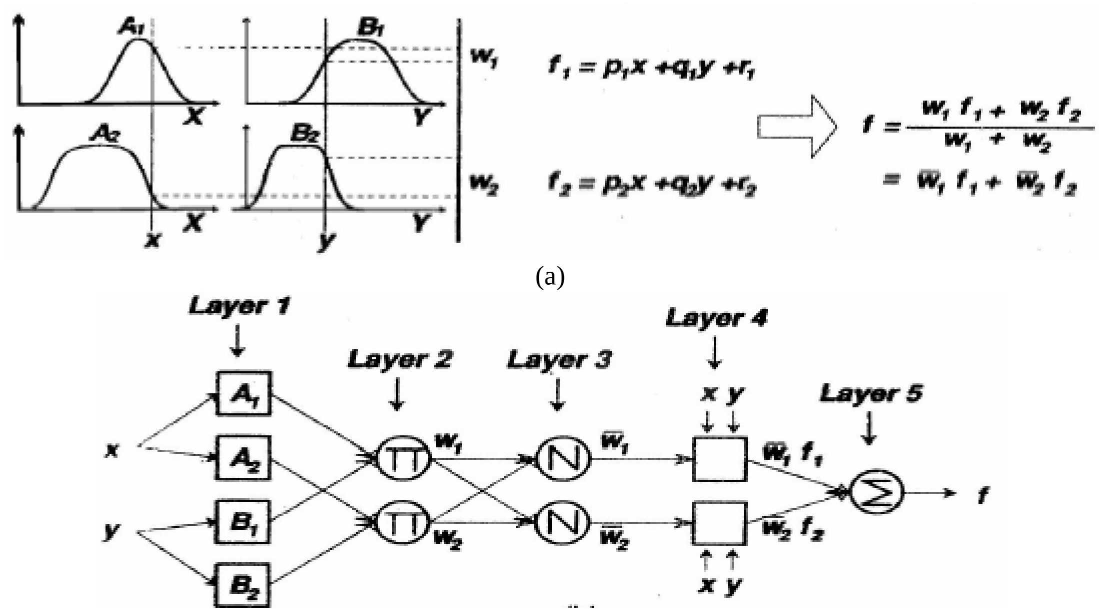

Figure 4: Adaptive neuro-fuzzy inference system

V. Adaptive Neuro-Fuzzy Inference Systems Genetic Algorithm (ANFISGA)

In this study we use Adaptive Neuro-Fuzzy Inference System Genetic Algorithm (ANFISGA). This method is based on Neuro-fuzzy inference system and genetic algorithm. In ANFISGA there are two inputs, x1 Male’s age and x2 Diversity of population, and one output y =Female’s age. InANFISGA we have five layers. Layer 1 is the input layer. Neurons in this layer simply pass external crisp signal to Layer 2. Layer 2 is the fuzzification layer. Neurons in this layer perform fuzzification.Layer 3 is the rule layer. Each neuron in this layer corresponds to signal Sugeno-type fuzzy rule.

Layer 4 is the normalization layer. Each neuron in this layer receives inputs from all neurons in the rule layer, and calculates the normalized firing strength of given rule. Layer 5 is the defuzification layer. Each neuron in this layer is connected to the respective normalization neuron, and also receives initial inputs, and . There are Two important difference between ANFISGA and ANFIS; firstly, normalization and secondly,adaptation. For adaptation of Neuro- fuzzy is used weights, but in our method weights are constant and for adaptation we use sexual selection based on female choice and diversity population. Figure 5 shows the ANFISGA architecture that corresponds to the first order Sugeno fuzzy model with genetic algorithm. We introduce rules for ANFISGA in Table1.

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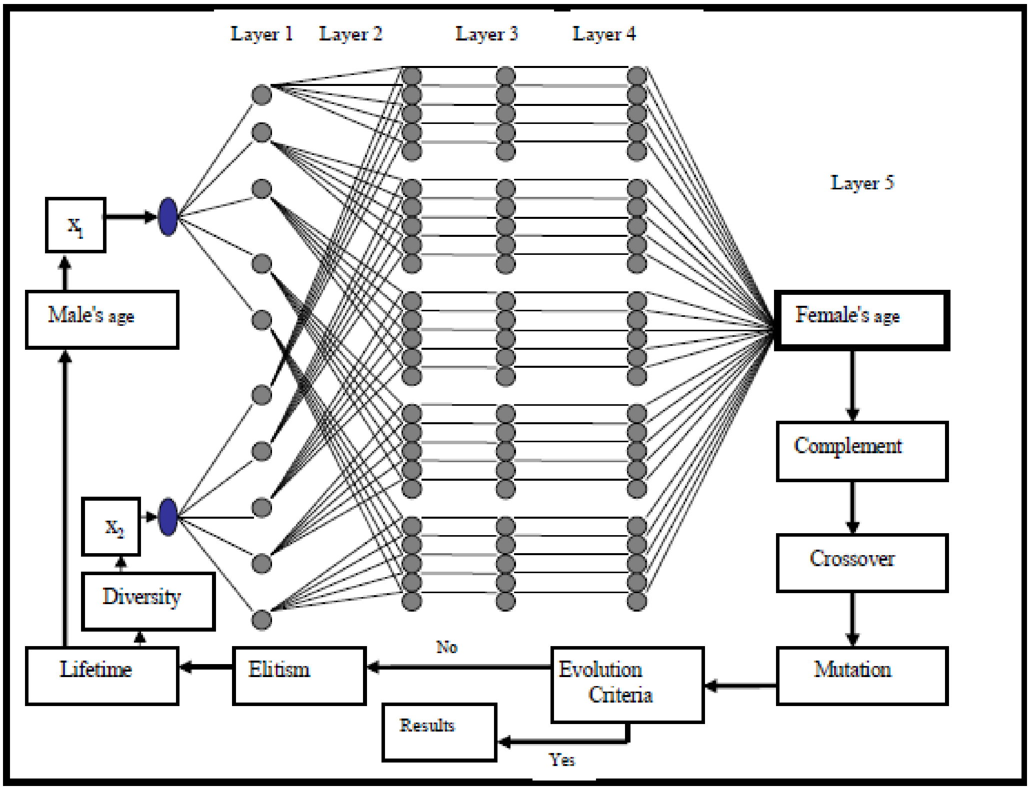

Figure 5: Adaptive Neuro-Fuzzy Inference System Genetic Algorithm (ANFISGA)

Table 1: Rules for ANFISGA

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Layer 3	Layer 5	Layer 3	Layer 5
$W_1 = w_1\mu_1 + w_2\bar{\mu}_1$	$D_1 = \bar{W}_1 + \beta$	$W_{13} = w_1\mu_2 + w_2\mu_3 + w_3\bar{\mu}_2 + w_4\bar{\mu}_3$	$D_{13} = \bar{W}_{13} + \beta/1.5$
$W_2 = w_1\mu_1 + w_2\bar{\mu}_1 + w_3\bar{\mu}_2$	$D_2 = \bar{W}_2 + \beta$	$W_{14} = w_1\mu_2 + w_2\mu_3 + w_3\bar{\mu}_3 + w_4\bar{\mu}_4$	$D_{14} = \bar{W}_{14} + \beta/1.5$
$W_3 = w_1\mu_1 + w_2\bar{\mu}_2 + w_3\bar{\mu}_3$	$D_3 = \bar{W}_3 + \beta$	$W_{15} = w_1\mu_2 + w_2\mu_3 + w_3\bar{\mu}_4$	$D_{15} = \bar{W}_{15} + \beta/1.5$
$W_4 = w_1\mu_1 + w_2\bar{\mu}_3 + w_3\bar{\mu}_4$	$D_4 = \bar{W}_4 + \beta$	$W_{16} = w_1\mu_3 + w_2\mu_4 + w_3\bar{\mu}_1$	$D_{16} = \bar{W}_{16} + \alpha/1.5$
$W_5 = w_1\mu_1 + w_2\bar{\mu}_4$	$D_5 = \bar{W}_5 + \alpha$	$W_{17} = w_1\mu_3 + w_2\mu_4 + w_3\bar{\mu}_1 + w_4\bar{\mu}_2$	$D_{17} = \bar{W}_{17} + \alpha/1.5$
$W_6 = w_1\mu_1 + w_2\mu_2 + w_3\bar{\mu}_1$	$D_6 = \bar{W}_6 + \beta/1.2$	$W_{18} = w_1\mu_3 + w_2\mu_4 + w_3\bar{\mu}_2 + w_4\bar{\mu}_3$	$D_{18} = \bar{W}_{18} + \alpha/1.5$
$W_7 = w_1\mu_1 + w_2\mu_2 + w_3\bar{\mu}_1 + w_4\bar{\mu}_2$	$D_7 = \bar{W}_7 + \beta/1.2$	$W_{19} = w_1\mu_3 + w_2\mu_4 + w_3\bar{\mu}_3 + w_4\bar{\mu}_4$	$D_{19} = \bar{W}_{19} + \alpha/1.5$
$W_8 = w_1\mu_1 + w_2\mu_2 + w_3\bar{\mu}_2 + w_4\bar{\mu}_3$	$D_8 = \bar{W}_8 + \beta/1.2$	$W_{20} = w_1\mu_3 + w_2\mu_4 + w_3\bar{\mu}_4$	$D_{20} = \bar{W}_{20} + \alpha/1.5$
$W_9 = w_1\mu_1 + w_2\mu_2 + w_3\bar{\mu}_3 + w_4\bar{\mu}_4$	$D_9 = \bar{W}_9 + \beta/1.2$	$W_{21} = w_1\mu_4 + w_2\bar{\mu}_1$	$D_{21} = \bar{W}_{21} + \alpha/2$
$W_{10} = w_1\mu_1 + w_2\mu_2 + w_3\bar{\mu}_4$	$D_{10} = \bar{W}_{10} + \beta/1.2$	$W_{22} = w_1\mu_4 + w_2\bar{\mu}_1 + w_3\bar{\mu}_2$	$D_{22} = \bar{W}_{22} + \alpha/2$
$W_{11} = w_1\mu_2 + w_2\mu_3 + w_3\bar{\mu}_1$	$D_{11} = \bar{W}_{11} + \beta/1.5$	$W_{23} = w_1\mu_4 + w_2\bar{\mu}_2 + w_3\bar{\mu}_3$	$D_{23} = \bar{W}_{23} + \alpha/2$
$W_{12} = w_1\mu_2 + w_2\mu_3 + w_3\bar{\mu}_1 + w_4\bar{\mu}_2$	$D_{12} = \bar{W}_{12} + \beta/1.5$	$W_{24} = w_1\mu_4 + w_2\bar{\mu}_3 + w_3\bar{\mu}_4$	$D_{24} = \bar{W}_{24} + \alpha/2$
		$W_{25} = w_1\mu_4 + w_2\bar{\mu}_4$	$D_{25} = \bar{W}_{25} + \alpha/2$

Where

$$w_i = i\ ,\ \bar{W}_i = \frac{W_i}{\sum |w_i|},$$

α and β are introduced in (1), μ_i is given in (2), $\bar{\mu}_i$ is taken in (5) and output of Neuro-fuzzy inference system is

$D_i = F_{age}$ that is suggested for selection of female with at least this F_{age} of category females. After the finding F_{age}, we may not find a chromosome that has this F_{age} then we select a chromosome having the nearest fitness value to F_{age}, or may be we can find more than one chromosome which satisfies having F_{age} condition, therefore we choose a chromosome having the highest fitness value of them. This technique called complement method. In this paper we consider a weak method for crossover, two point

crossovers, because we want to show that our selection technique is robust.

VI. EXPERIMENTS

Minimization experiments on the test set, described in Subsection 6.1, have been carried out in order to study the behavior of the proposed ANIFSGA in the previous section, the algorithms built in order to do this are described, and finally, in section7, the results are shown and analyzed.

1) *Test Set*

For the experiments, we have considered three frequently used test functions of Benchmark problems:

- Sphere model (f_{Sph}) ([7]):

$$f_{Sph}(x) = \sum_{i=1}^{n} x_i^{\,2},\ \text{and} -5.12 \le x_i \le 5.12.$$

The fitness of the optimum is $f_{sph}(x^*) = 0$. This test function is continuous, strictly convex, and unimodal.

- Generalized Rosenbrock's function (f_{Ros})([7]):

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$$f_{Ros}(x) = \sum_{i=1}^{n-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2] \quad \text{and} \quad -5.12 \le x_i \le 5.12$$

The fitness of the optimum is $f_{Ros}(x^*) = 0$. f_{Ros} is a continuous and unimodal function, with the optimum located in a steep parabolic valley with a flat bottom. This feature will probably cause slow progress in many algorithms since they must continually change their search direction to reach the optimum.

- Generalized Rastling's function ((f_{Ras}) ([4]) :

$$f_{Ras}(x) = 10n + \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i)) \text{ and} - 5.$$

This function is a scalable, continuous, separable, and multimodal, which is produced from by f_{Sph} modulating it with

$k.\cos(wx_i.)$.

VII. Algorithms

We compare ANFISGA with some methods in GA that Herrera et al. used in [9]. They had been considered a generational GA model that applied a simple crossover operator and a mutation timepiece operator and selection probability calculation followed linear ranking ($_{n}$MIN = 0.5). The sampling algorithm was the stochastic universal sampling, and elitist strategy was considered. Also the overall qualities of the fuzzy logic control that they had been considered was the following: the minimum operator was used for conjunction of clauses in the IF part of a rule, the minimum operator was used to fire each rule and the center of gravity weighted by matching strategy as the defuzzification operator was considered. Table 2 shows these algorithms.

Table 2: Algorithms

Algorithms	Features
GA1	$p_m = 0.001$ and $p_c = 0.6$ fixed during the run.
GA2	$p_m = 0.005$ and $p_c = 0.6$ fixed during the run.
GA3	$p_m = 0.01$ and $p_c = 0.6$ fixed during the run.
GA-RAN	$p_m \in [0.001, 0.01]$ for each generation. $p_c = 0.6$.
GA-DET	Deterministic Control of the Mut. Prob. $p_c = 0.6$.
GA-AIL	Adaptive Control at Individual-level of the Mut. Prob $p_c = 0.6$.
GA-SELF	Self-Adaptive Control of the Mut. Prob ($\delta = 0.001$) $p_c = 0.6$.
GA-FLC	Adaptive Control of the Mut. Prob. by FLC (G = 50) $p_c = 0.6$.
ANFISGA	$p_m \in [0.001, 0.2]$ for each generation and $p_c = 0.6$.

Table 3: Population size is 60, and probability crossover is $p_c = 0.60$.

Algorithm	f_{Sph}	f_{Ros}	f_{Ras}
GA1	2.4e -10	1.1e -01	5.9e +00
GA2	7.7e -08	8.5e -03	5.1e -05
GA3	8.0e -06	1.2e -05	6.0e -02
GA-RAN	2.2e -07	6.9e -04	8.4e -05
GA-DET	2.8e -10	5.6e -05	3.3e -02
GA-AIL	2.4e -10	4.3e -02	1.2e +00
GA-SELF	2.4e -10	4.5e -02	1.7e +00
GA-FLC	2.4e -10	6.4e -04	6.1e -08
ANF ISGA	2.4e -10	1.3e -07	9.5e -09

With regards to the GA versions that we compared in Table 3, we can say that:

- For the easy test function, f_{Sph} result of ANFISGA technique is the same of the best result of other methods.

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- For the function with intermediate complexity, f_{Ras} and for the most complex function, f_{Ros} consequence of ANFISGA system is better of other methods .

Then ANFISGA technique, has the most robust behaviours, since for each function, it returns results that are very similar to the ones of the most successful GAs with intermediate complexity, or better than all them results for the function with intermediate complexity and for the most complex function.

VIII. Conclusions

We have proposed a method for controlling the diversity of population using fuzzy logic techniques and Adaptive Neuro-Fuzzy Inference System (ANFIS). However Weights in ANFIS is constant in our method we used sexual selection for adaptation. The principle conclusions derived from the results of experiments carried out are the following:

- The procedure presented is the most successful one for controlling diversity as compared with other methods proposed in the GA literature that have been considered for the experiments.
- The adaptation capability of this procedure allows suitable parent to be used for producing a robust operation for test function with different difficulties.

Therefore, we may conclude that the female choice by ANFISGA is a suitable way for improvement the results of GAs, and keep the diversity of the population.

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