An Innovative Fuzzy Decision Making Based Genetic Algorithm

M. A. Sharbafi, M. Shakiba Herfeh, Caro Lucas, A. Mohammadi Nejad

***Abstract*—**Several researchers have proposed methods about combination of Genetic Algorithm (GA) and Fuzzy Logic (the use of GA to obtain fuzzy rules and application of fuzzy logic in optimization of GA). In this paper, we suggest a new method in which fuzzy decision making is used to improve the performance of genetic algorithm. In the suggested method, we determine the alleles that enhance the fitness of chromosomes and try to insert them to the next generation.

In this algorithm we try to present an innovative vaccination in the process of reproduction in genetic algorithm, with considering the trade off between exploration and exploitation.

***Keywords*—** Genetic Algorithm, Fuzzy Decision Making.

I. Introduction

ONE of the most important concepts in control theory is optimization which is the problem of finding the minimum (or maximum) of a function. Steepest descent, Quasi-Newton, Genetic Algorithm and Ant Colony are some of usual methods which have been used to solve optimization problem. From 70s, genetic algorithm is widely deployed to such problems. A genetic algorithm (GA), based on the genetic evolution of a species was proposed by Holland [1]. The detailed genetic algorithm and implementation were given by Goldberg [2]. This algorithm provides a robust procedure not only to explore broad and promising regions of solutions but also to avoid being trapped at the local optimization. However, the computational amount is very large. Many researchers try to improve this drawback of genetic algorithm [3]-[5]

In this paper we propose a new method for reducing the convergence time of GA. We use Fuzzy Decision Making to detect some chromosomes with special characteristics that speed up the algorithm. The trade off between exploration and exploitation is considered too.

The main purpose of this paper is to use heuristic decision making to improve the performance of the genetic algorithm. Although the computation amount in the suggested algorithm is more than ordinary algorithm in one generation, the simulation results show that this algorithm reaches the global optimum in fewer generations, and the total time of convergence is better.

The remainder of this paper is organized as follows: section II explains a summary of genetic algorithm. A brief description of decision making theory is presented in section III. In section IV we propose our new algorithm. Simulation results and evaluation of the algorithm are given in section V. Finally, we conclude our paper in section VI.

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II. Genetic Algorithm

Genetic Algorithms are computing algorithms to solve optimization problems by making use of evolutionary principles as known from biology. In nature the fitness of individuals depends on their genes. According to Darwin’s principle, individuals superior to their competitors, are more likely to promote their genes to the next generations.

According to this concept, in Genetic Algorithms, we encode a set of parameters mapped into a potential solution, named chromosome, to the optimization problem. The quality of solution is defined by fitness function.

GA is an optimization method by using multiple alternatives, where “crossover”, “mutation”, and “selection” are the fundamental genetic operators [2].

In crossover, two chromosomes are selected from the population and split in two or more parts, and replace the parts between selected points. After applying the crossover operator, two new chromosomes will be produced. With this operator, we can search the space which generate by the initial population’s genes and can not explore the whole solution space. So by imitating the nature, mutation is used to explore globally and not trapping in local minima. In mutation one or more genes are selected randomly in a chromosome and they are replaced with new random genes.

Selection is a process for choosing a pair of chromosomes to reproduce. The higher probability is devoted to the chromosomes with higher fitness function. Some usual methods exist in literature like Rolette Wheel, Tournament Selection, and etc. These methods are also used to select the next generation, from the parents and the offspring.

The main problems of Genetic Algorithm are its long convergence time and the right trade off between exploration and exploitation. Several strategies, improving these problems are proposed.

III. Multi Criteria Decision Making

Selecting or prioritizing alternative(s) from a set of available alternatives with respect to multiple criteria, is often refer to Multi-Criteria Decision Making (MCDM). Considerable efforts and advances have been performed towards the development of numerous MCDM methodologies for solving different types of problems [6]-[8].

In practical applications, alternative ratings and criteria weights can not always be assessed precisely. Unquantifiable, incomplete, unobtainable information, and partial ignorance may cause subjectiveness and vagueness in decision preference. Classical MCDM methods can not effectively handle with such imprecise information [9]. The application of fuzzy set theory to MCDM models provides an effective way of dealing with the subjectiveness and vagueness.

An important issue in multiple optimization is the handling of human preferences. One way of illustrating the preferences is “Utility Values” [10], in which a scaled real number is assigned to each alternative to indicate its relative importance. In its fuzzy approach each alternative has a linguistic utility such as very poor, poor, fair, good, very good. Similarly, the weighting vector which evaluates criteria of decision making can be given in fuzzy linguistic terms.

One way to show these linguistic terms is considering the three numbers which express the fuzzy membership function e.g. in fig. 1, (3,5,7) can define the “fair” term. In [11] the algorithm begins with the generation of a performance matrix (Z), by multiplying the weighting vector by the decision matrix.

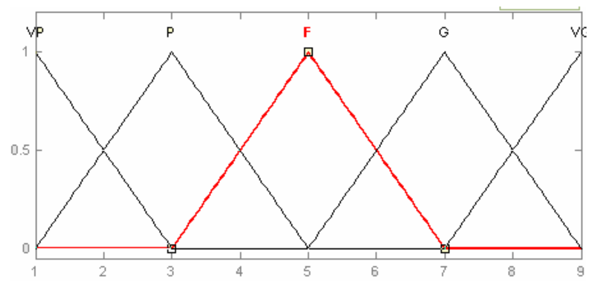

Fig. 1 Linguistic terms used by decision matrix

By using an α-cut on the performance matrix, an interval performance matrix is derived as by (1), where $\alpha \in [0,1]$. The value of α represents the DM’s degree of confidence in the fuzzy assessments.

$$Z_\alpha = \begin{bmatrix} [z^\alpha_{11l}, z^\alpha_{11r}] & [z^\alpha_{12l}, z^\alpha_{12r}] & \cdots & [z^\alpha_{1ml}, z^\alpha_{1mr}] \\ [z^\alpha_{21l}, z^\alpha_{21r}] & [z^\alpha_{22l}, z^\alpha_{22r}] & \cdots & [z^\alpha_{2ml}, z^\alpha_{2mr}] \\ \cdots & \cdots & \cdots & \cdots \\ [z^\alpha_{n1l}, z^\alpha_{n1r}] & [z^\alpha_{n2l}, z^\alpha_{n2r}] & \cdots & [z^\alpha_{nml}, z^\alpha_{nmr}] \end{bmatrix} \quad (1)$$

Incorporated with the DM’s attitude towards risk using an optimism index λ, an overall crisp performance matrix is calculated as in (2).

$$Z^{\lambda'}_\alpha = \begin{bmatrix} z^{\lambda'}_{11\alpha} & z^{\lambda'}_{12\alpha} & \cdots & z^{\lambda'}_{1m\alpha} \\ z^{\lambda'}_{21\alpha} & z^{\lambda'}_{22\alpha} & \cdots & z^{\lambda'}_{2m\alpha} \\ \cdots & \cdots & \cdots & \cdots \\ z^{\lambda'}_{n1\alpha} & z^{\lambda'}_{n2\alpha} & \cdots & z^{\lambda'}_{nm\alpha} \end{bmatrix} \quad (2)$$

where:

$$z^{\lambda'}_{ij\alpha} = \lambda z^\alpha_{ijr} + (1-\lambda) z^\alpha_{ijl} \quad , \quad \lambda \in [0,1] \quad (3)$$

The positive and negative ideal solutions can be determined from (2) by selecting the maximum and minimum values across all alternatives. By applying the vector matching technique, the degree of similarity between each alternative and the positive and negative ideal solutions can be illustrated respectively by $S^{\lambda+}_{i\alpha}$ and $S^{\lambda-}_{i\alpha}$.

An overall preference index for each alternative is determined by (4). The larger the index value, the more preferred the alternative.

$$P_{\alpha i} = \frac{S^{\lambda+}_{i\alpha}}{S^{\lambda+}_{i\alpha} + S^{\lambda-}_{i\alpha}} \quad (4)$$

IV. The Decision based Genetic Algorithm (DBGA)

In this section we will describe our algorithm, genetic algorithm based on decision making. In finding the best fuzzy controller with GA, if we know a correct rule we can determine its value from the beginning. For example in stabilizing the inverted pendulum, we know that if the angel and the angular velocity are equal to zero the control effort should be set to zero. Thus in optimizing the rules of fuzzy controller with GA, this rule can be considered zero during running the algorithm.

Usually our knowledge is not crisp, and there is some uncertainty in our information. In this situation, we can vaccinate these genes, including our uncertain knowledge, to the considerable chromosomes. If the result of fitness function of each generation could be observed, then maybe we could detect the genes which are in chromosomes with higher fitness. Similarly, for obtaining the exploration, we can find and insert the genes that are rare in the population. We propose a new method to extract such results with decision making algorithm described in section II, during the reproduction process.

We define the preference matrix with respect to fitness of chromosomes and the number of appearance of genes in every k iterations. In our simulations k=3. We name it k-generation.

After each m*k generation, an $n \times m$ preference matrix is created. n is the number of possible values that genes can get. For example in binary coded genetic algorithm, n=2.

We suppose any k-generation a criterion for decision making problem. The weighting matrix, can be defined by assuming the first criterion, with the least weight. So the later the criterion, the higher the weight.

Randomly, we select some of these prominent genes, and combine them with randomly selected genes from the population. We define this chromosome the "manual chromosome". We compose some manual chromosomes and reproduce new offspring by mating the population with them.

To prevent premature convergence, we define a new mutation method. We define the genes which are rare in the population as "rare genes". After each m*k generations, we detect the rare genes with similar decision making algorithm. In our manual mutation selected genes will be replaced with the rare genes instead of random genes. The advantage of this manual mutation is giving opportunity to the genes which didn't appear. Note that in ordinary genetic algorithm, the probability of appearance of such rare genes is much less than our algorithm.

In Real Coded Genetic Algorithm (RCGA), that n is infinity; we can consider some Probability Density Functions (PDF), which cover the whole range. The rare PDF can be defined as the PDF with least sum of the probabilities of genes in each PDF. In the rare PDF a gene can be selected by its probability.

V. Simulations and Results

To evaluate the suggested method, the ordinary genetic algorithm and DBGA are applied to a benchmark optimization problem, Bohachevski problem. This function is depicted in (5). Fig. 2 shows the function has abundant local minima in [-1,1].

$$f(x,y) = \frac{(x^2 + y^2)}{2} - 2\cos(20\pi x)\cos(20\pi y) + 2 \qquad (5)$$

In the ordinary genetic algorithm the probability of crossover and mutation is set to 40% and 10% respectively. (Because of rough behavior of the problem the percentage of mutation should be more than usual problems)

In 69%, the ordinary genetic algorithm can't find the global minimum till the 10000th generation. It is also observed that the average convergence time is long (7351 generation) and from generation near 100th, a few responses are qualified. This shows that they trapped in local minima most of the time. But in the DBGA 99% simulation in 1000th generation, reach the global optimum and the convergence time is much less than the ordinary GA (1383 generation).

Fig. 3 and Fig. 4 illustrate the average of output of the function during 100 simulations with different initial conditions, for the ordinary GA and DBGA respectively.

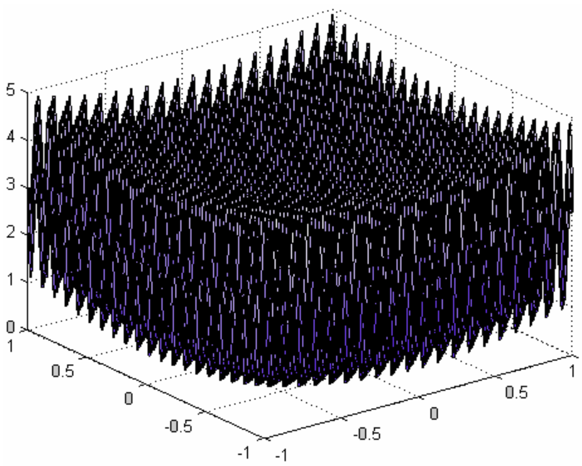

Fig. 2 The Bohachevski function in [-1,1]

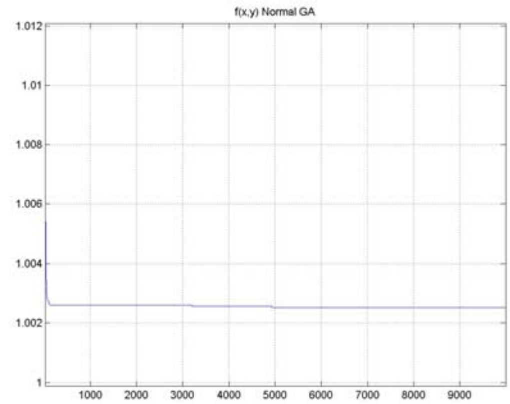

Fig. 3 The average output of the Bohachevski function of 100 simulations in ordinary genetic algorithm

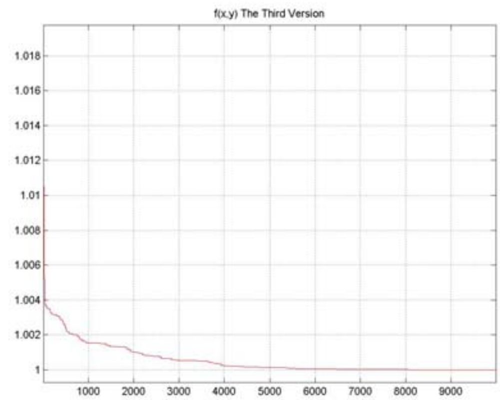

Fig. 4 The average output of the Bohajowski function of 100 simulations in DBGA

VI. Conclusion

Simulations show that, our method, Decision Based Genetic Algorithm, is faster and more reliable than ordinary Genetic

Algorithm, and it is a powerful way for problems with many local minimum. The cost is that our algorithm is a little more complicated algorithm. And it seems that it is a good method for optimizing fuzzy controllers.

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