Optimization Iteration Min-Max Cross Over Genetic Algorithm To Generate Fuzzy membership Function Automatically

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Abstract. Generating membership function fuzzy for Fuzzy system is important to representative of the problem. Some research generating a membership function automatic had done and still have a problem to generate procces in max iterasi, so that this research will generating membership function fuzzy otomatic used genetic algorithm by analysing the cross over point. Keyword : membership function fuzzy, cross over, Genetic Algorithm

1. Introduction
The development of times that are increasingly rapid in this century requires rapid changes in determining each decision, so that every decision maker is required to use a computerized system as a decision support. One computerized decision system is a fuzzy system. The purpose of using a computerized system is to get an accurate decision support system. So that the results can be used as an appropriate reference in determining the final decision.
Fuzzy system is a system that represents a problem that contains uncertainty into one linguistic language by using fuzzy logic which is then linked to a function that states the membership value at intervals [0,1] (Zadeh, 1965). The fuzzy set and function are called membership functions while the value is called the membership degree.
There are several membership functions, namely trapezoidal, sigmoid, triangle and other membership functions. To generate a fuzzy system membership function, classification or clustering methods are used. While this method still relies on an expert in determining the classification of datasets, so that the next problem with these conditions is that if the experts are not available it will cause difficulties in generating membership functions and can even cause the developed fuzzy system to not function properly (Hong, et al 2006).
Several previous studies related to the generation of membership functions include research conducted by (Pernama & Hashim 2010), conducting research on the use of PSO (Particle Swarm Optimization) algorithms as an optimization algorithm that is added to fuzzy system performance. The PSO
algorithm can generate optimal fuzzy sets by adjusting the membership function automatically; (Hong, et al. 2006) conducted research using the training examples method as a framework for automatically generating membership functions and fuzzy if-then rules; (Ketata, 2007) in his research introduced a new approach which is managing membership functions, generating and reducing fuzzy rule base against data at the same time; (Yang & Bose 2005) in his research automatically generated fuzzy membership functions using self-organizing feature map (SOFM); (Yunizar, 2012) conducted a study with the aim of getting a fuzzy membership function that is more appropriate in accordance with the data provided by using a neural backpropagation algorithm.

Genetic Algorithms are systems that perform searches by mimicking the mechanisms of natural selection and natural genetics, (Goldberg, 1989). In its application, genetic algorithms are computer programs that simulate the evolutionary process, by generating chromosomes from each population randomly and allowing the chromosome to multiply according to the evolutionary laws which are expected to produce prime chromosomes.

2. Methodology

This system consists of 4 variables, namely Productivity, Social Relations and Accessibility variables which each of these variables will be classified first in the pre-process so as to produce 4 ranges namely Low (L), Medium (M), High (H) and Very Height (VH) of each range is represented in the graph of the triangle function.

2.1. Data Training

In this study used input data consisting of 4 variables and each consisting of a certain range. The data used in this process are as follows:

1. Productivity variable, with a range of 20-70
2. Social Relations Variables, with ranges from 30 – 90
3. Accessibility variables, with a range of 45 – 85
4. Isolation Variables, with a range of 12 – 80

2.2. Problem Solving Process:

The work procedure for generating fuzzy membership functions using Genetic Algorithms is seen as a whole as follows:

- **Input:**
  - Productivity (20-70)
  - Social Relations (30-90)
  - Accessibility (45-85)
  - Isolation (12-80)

- **Process:**
  - Initial Chromosom
  - Fitness Value
  - Sekksi
  - Crossover
  - Mutasi

- **Output:**
  - Membership Function fuzzy Graphic

Figure 1. Problem Solving Process Flow
2.3 Designing Genetic Algorithms

Genetic Algorithms are an iterative process. Each iteration is called generation. Usually the number of generations for a Genetic Simple algorithm is between the range of 50 to 500. All sets of generations are called rounds. And at the end of the round it is expected to find one or more of the most appropriate chromosomes.

Here is an example of representing a chromosome into a triangular membership function. A productivity variable with a range 20-70

Productivity Variabel : 23, 29, 26, 50, 53, 33, 60, 62, 67, 73, 43, 70, 43, 44, 55, 56, 60,61, 33 , 34, 47,48, 50, 53, 35, 38, 37, 55, 56, 67

From the series of productivity variables, 9 values were taken randomly, namely 20, 30, 38, 45, 47, 59, 62, 64, 70. 9 of these numbers will form 3 triangles on the triangle graph as shown in Figure 3.6. 3 numbers represent a triangle, where the number is 1 = the value of the left foot, the number 2 = the middle value of the triangle and the number 3 = the value of the right foot of the triangle. Likewise for 6 other words representing the value of the left foot, middle value and right foot value for the second third and the third triangle.

![Figure 2 Membership function triangle Variabel Productivity](image)

Based on figure 3.6 Graph the membership function is represented on a chromosome, as follows:

| K1  | 20  | 30  | 45  | 38  | 47  | 62  |
|-----|-----|-----|-----|-----|-----|-----|
| 59  | 64  | 70  |

R1

![Figure 3 Representative chromosome variable productivity](image)

2.4 Min Max Aritmatic Cross over and mutation operations in the population

In the cross over process methods are done, namely min-max cross over. The crossover process that occurs is as follows:

In the crossover process with the Min max arithmetic method the crossover will produce 4 new chromosomes. Using equation 9 and the marriage between 2 chromosomes with d = 0.3.

K1 =  5  5  10  5  15  5  20  5
K2 =  3  5  11  5  15  5  21  5

By using Min-max crossover, the crossing produced by 4 chromosomes is as follows:

K1 =  3.6  4.7  10.7  4.7  18  4.7  20.7  4.7
K2 =  4.4  4.7  10.3  4.7  18  4.7  20.3  4.7
K3 =  5  5  11  5  15  5  21  5
K4 =  3  5  10  5  15  5  20  5
Figure 4 Crossover chromosome method Min Max Aritmathic

From the four chromosomes that are formed, each chromosome value is calculated so that the highest chromosome value will be the next generation chromosome and then the mutation process is carried out. One-point mutation operators will form a new fuzzy membership function by randomly adding a value (between \( -w_{jk} \) and \( +w_{jk} \)) to the middle value or a linguistic area that is \( R_{jk} \). Where \( c \) is the middle value and \( w \) is the distance of half of a linguistic region. With the mutation operation, a new membership function value will be formed \( c + \varepsilon \) or \( w + \varepsilon \).

3. Result And Discussion

The generation of fuzzy membership functions using genetic algorithms at the completion stage consists of several stages and one of them is marriage, in this system consists of two marriage methods, two point crossover and min-max arithmetic crossover. The results of the trial will show the results of the membership function which is formed by using the two methods using the same data input which consists of 4 variables, productivity variables (20-70), social relations (30-90), accessibility (45-85) and isolation (12-80).

3.1. Variabel Input

The following is the value that is set in the initial stage application, namely the alpha value, \( E \) (mutation coefficient) while the variable input consists of randomly generated data:

\[ E = 6; \text{ Membership degree} = 0.1 - 0.9; \text{ Total Data} = 30 \]

Training Data :

- **Variabel Productivity** = 23, 29, 26, 50, 53, 33, 60, 62, 67, 73, 43, 70, 44, 55, 56, 60, 61, 33, 34, 47, 48, 50, 53, 35, 38, 37, 55, 67
- **Variabel Social Relationship** = 30, 34, 38, 43, 32, 89, 88, 56, 60, 90, 88, 87, 70, 76, 75, 74, 73, 60, 62, 63, 65, 78, 90, 56, 60, 56, 67, 78, 89, 80, 70
- **Variabel Accessibility** = 40, 55, 56, 76, 80, 78, 67, 76, 46, 83, 78, 68, 58, 48, 82, 65, 67, 68, 45, 48, 46, 56, 55, 54, 52, 53, 50, 60, 77, 78
- **Variabel Isolation** = 12, 20, 22, 21, 45, 56, 43, 44, 56, 67, 65, 78, 77, 75, 74, 34, 45, 33, 45, 55, 67, 34, 32, 35, 67, 46, 67, 43, 46, 47

Then each variable passes through the pre-process stage which is the formation of triangular graphs, which in the formation of triangular graphs pass through the stage of the formation of graphical intervals and the formation of boundary regions.

3.2 The Fuzzy Membership Function uses Min Max Arithmetic crossover.

Trials with the same input are carried out using the Min-Max Arithmetic crossover marriage method, using the same data and generated at the same number of generations, namely generation 50 and generation 100 with coefficients \( d = 0.3 \) and mutations = 6, the following are trial results,

Graph fuzzy membership function method of 100-generation min-max crossover.

For 100 generation min max arithmetic crossover, fitness is found to be the highest for productivity variable in the 90th generation with fitness value of 29.57, social relationship variable reaches the highest fitness value in the 90th generation with fitness value of 50, accessibility variables reach fitness value highest in the 95th generation with a fitness value of 25 and the isolation variable achieving the highest fitness value in the 84th generation with a fitness value of 66.67. The fuzzy membership function graph that is formed can be seen as shown in Figure 5 below.
Figure 5 Graphs of membership functions generated by 100 generations with crossover min max arithmetic

Figure 5 is a representation of the chromosome shape with the highest fitness value in 100 generations generated by using the crossover min-max arithmetic method, then the resulting graph of the fitness.

4. Conclusion and future Project

From the results of the study the authors get the following conclusions:

1. The number of generation generated will result in a high fitness value for the two-point crossover method as well as the cross-over min-max arithmetic method.

2. Both two-point and min-max arithmetic crossover methods will produce the best output fuzzy membership function in a particular generation randomly and not always in the highest generation.

3. The membership function formation process uses the same 4 input variables and the same output conditions are achieved but produces 2 output outputs in the form of different fuzzy membership functions for two point crossover and min max arithmetic crossover and each generated in 10 generations, 50 generation and 100 generations.

4. Fitness value for cross-arithmetic cross over min-max method tends to increase in each generation until the highest fitness value is achieved while the fitness value for the two point crossover method of fitness value tends to be random and more dynamic.

5. The two-point crossover method and min-max arithmetic will produce the highest fitness value and stable in the high generation.

Future Project:
As for the suggestions of the authors for the continuation of this research are:
1. In this study the maximum number of generation generated has not produced an expected fuzzy membership function, this research can be continued by using other algorithms that can accelerate the process so that maximum generation can be achieved so that a better form of membership function can be achieved.

2. This research can be continued by using the trapezoidal membership function approach, sigmoid to produce a better fuzzy membership function generator for a particular data trend.

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