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Constructing Fuzzy Membership Function Subjected to GA based Constrained Optimization of Fuzzy Entropy Function

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Abstract

This paper presents a Genetic Algorithm based optimization algorithm for fuzzy logic system. The proposed algorithm employs fuzzy entropy function as optimization bound(s) parameter. Membership function formation plays a key role in performance of a fuzzy system, as an improperly designed MF may lead to an inefficient system. Majority of literature focuses on optimization of shape of a MF and not the support. Proposed optimization method focuses on optimizing support of MF and not on its shape. For this optimization process predefined membership functions are used, the support of these membership functions these predefined sets are varied using standard deviation of the system data obtained by simulation or real-time analysis of the system. The support of these membership functions these predefined sets are varied using standard deviation of the system data obtained by simulation or real-time analysis of the system. Entropy for each displaced Fuzzy Set is maximized subjective to constraint optimization and thus optimized value of support is obtained. The proposed algorithm optimizes the support of Fuzzy Sets and hence can be combined with any other optimization tool for obtaining even better results.

Keywords: Fuzzy Entropy, Genetic Algorithms, Support Optimization

1. Introduction

In[1] proposed Fuzzy Set theory in the 1960s to deal with uncertain, imprecise or ambiguous data. Applicability of a Fuzzy Logic System (FLS) depends on a number of factors which include although not limited to: Membership Function (MF), rule base, inference engine. MF (MF) has a vital role as an improper designed MF may lead to below average performance of the system even if all other factors are chosen wisely. Fuzzy deals with uncertainty and hence the idea of an accurate empirical formula to calculate MF will not suffice the generalized applicability of FLSs. In view of these numerous techniques have been proposed for constructing MF. In[2] proposed a technique to estimate MFs of Fuzzy Sets (FS) using statistical data. The method utilized probability density function (pdf) obtained from the statistical data. In[3] introduced the concept of normalized spline MFs along with normalized basis spline MF. Utilizing the advantage of spline functions to determine a class of piecewise polynomial functions; satisfying continuity properties while passing through a set of points. In[4] used the concept of fuzzy event and finding the event that has maximum fuzzy entropy corresponding to it and using s-function for MFs. Algorithm developed

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was applied to image processing applications; however according to author the same can be extended to other applications as well. In[5] proposed a learning method to automatically determine rules and MFs from a preexisting set of training examples. The developed fuzzy expert system was tested to classify Fisher's Iris data[6] with an accuracy of about 92%. In[7] provided an extension to[5] work by building an appropriate number of initial MFs based on selection of relevant attributes as compared to the large set of MFs corresponding to available attributes. This not only reduced the complexity but also reduced the computational time. The developed algorithm was tested to classify Fisher's Iris data with an improved accuracy of about 94%. In[8] proposed a method to optimize MF using extended Kalman filter and is compared with gradient descent optimization technique. The advantage of the method is reduction in computational time with the use of a pseudo-steady-state Kalman filter. The proposed technique is applied to automotive cruise control system and results have been compared. In[9] presented a brief review of various types of fuzzy information measures: Entropy. Classical Shannon entropy and fuzzy entropy were compared and various representations of fuzzy entropy were discussed. In[10] introduced a method to fit MF through given data points with the help of Bezier curve: which were developed by[11]. This method was peculiar as it has the feature of a control point with the placement of which shape of obtained MF could be altered. In[12] used the application of nonlinear filtering for parameter optimization of MF. Constrained H_∞ state estimation filters was used and the results were compared with Kalman filter[8] for the application of automotive cruise control system. In[13] proposed neural network based self-organizing feature maps to optimize FLS using unsupervised learning technique. The robustness of the developed system was tested on Fisher's Iris data. In[14] developed Genetic Algorithms (GAs) based method to optimize the MF parameters and rule base for Takagi-Sugeno (T-S) fuzzy model. The optimized system has been applied to identify inverse and forward dynamic behavior of a Magneto-Rheological (MR) damper which possesses hysteresis and highly nonlinear dynamics. In[15] proposed a hybrid model which uses Type-1 Fuzzy Logic System (T1FLS) or Type-2 Fuzzy Logic System (T2FLS) and GA is used for optimization of MF parameters in FLS. The proposed system is used to solve the output regulation problem of a nonlinear backlash exhibiting servomechanism. Results for both T1FLS and T2FLS were compared and found to be satisfactory. In[16] proposed an optimization method to integrate given pdf and fuzzy Shannon entropy extending the statistical theory to heuristic method centered on human cognitive behavior. The method was compared to modified S-curve based mf optimization and the results were compared. But due to complexity of optimization indices the proposed method was computationally intensive as found out by author. In[17] proposed an algorithm to integrate fuzzy Shannon entropy with piecewise linear function by using heuristic method based on cognitive behavior of humans and subjectivity. The proposed algorithm defines a nonlinear mathematical programming problem objective which is subjected to constrained optimization based on Lagrange function and KKT condition.

The key focus in this paper is to develop an algorithm to optimize support (the region of a FS with non-zero membership value[18] of MF. Generally optimization algorithms used in FLS can broadly be classified in following categories: (1. MF generation and optimization, 2. MF shape optimization, 3. Rule base optimization and 4. FLS optimization. This paper proposes an optimization algorithm based on entropy function using predefined MFs. First the Fuzzy Sets are obtained using equal distribution throughout the universe of discourse than these preformed MFs are displaced using standard deviation obtained from simulation/real-time analysis of process. The fuzzy entropy is than calculated and optimized subjected to constrained optimization parameters.

The paper is structured as follows. In Section 2 mathematical backgrounds required to design algorithm. Section 3 defines the objective function and Section 4 presents the optimization algorithm in detail. Here an example for a triangular MF optimization is discussed. Finally conclusions are drawn with future scope in Section 5.

2. Mathematical Background

In this Section we introduce mathematical definitions of: standard deviation, MFs and fuzzy entropy. As these parameters are required for optimization process of MF in the proposed algorithm standard mathematical representation are discussed which will be used in further sections.

2.1 Standard Deviation

One of the most effective and common tool to analyze data statistically is determination of: Standard Deviation (SD). This index is generally used in statistical quality control, the most popular being Six Sigma standard.SD for a population can be calculated using:

$$\sigma = \sqrt{\frac{\Sigma(x-\mu)^2}{N}} \quad (1)$$

Where σ represents SD, represents individual value in the population, μ represents mean of the population and is the number of data values (size) in the population.

SD gives information about variability of the data around the mean. In a properly designed FLS it can prove to be a vital factor in defining the MF. In[19] developed a technique for estimation of the MF using histograms obtained from the data set, the proposed technique exhibited satisfactory results for Fisher's Iris test.

2.2 Triangular MF

Being simplest triangular FSs are amongst most common used for designing FLS. A triangular MF is represented by the following equation:

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ (x-a)/(b-a), & a < x \leq b \\ (x-c)/(b-c), & b < x < c \\ 0, & x \geq c \end{cases} \quad (2)$$

Where "a" and "c" are the support of the MF and "b" is the value with membership value of 1. The MF considered for the algorithm is a normal convex (having maximum membership value of 1. Triangular membership functions as shown in Figure 1.

2.3 Fuzzy Entropy

In[20,21] founded the information theory and laid the mathematical base for communication systems; many of Shannon's findings have been applied to various fields like: FLS, clustering, decision making to name a few. Entropy gives the information about uncertainty associated with any variable due to randomness associated with it i.e. it gives a measure of the expected value of the information (or more precisely a bit) in a corresponding message. Fuzzy entropy is a measure of information (fuzzy) obtained from a FS. As Shannon entropy is based on the randomness uncertainty (probabilistic) and fuzzy entropy is based on vagueness and ambiguity uncertainties hence both the entropy measure deal with different concepts.

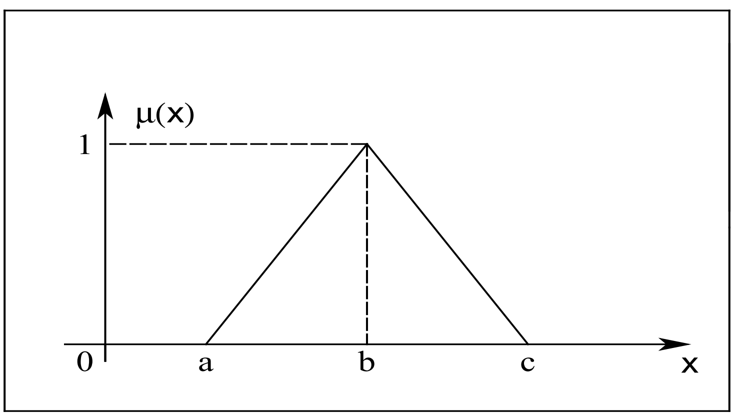

Figure 1. Normal triangular MF.

Probability measures for FS were defined by[22,23] formulated fuzzy entropy based on Shannon's function according to which the entropy for FSs can be written as:

$$H(A) = -\int_{-\infty}^{\infty} \{\mu_i \log \mu_i + (1-\mu_i)\log(1-\mu_i)\} \tag{3}$$

Where μ_i is the MF of A. This expression can also be written as:

$$H(A) = \int_{-\infty}^{\infty} f\big(\mu(x)\big)dx \tag{4}$$

Where

$$f(x) = -x ln x - (1-x)\ln(1-x)$$

Fuzzy entropy for a triangular membership can be evaluated using following:

$$H(A) = \int_{-\infty}^{a} f(0)dx + \int_{a}^{b} f\left(\frac{x-a}{b-a}\right)dx + \int_{b}^{c} f\left(\frac{x-c}{b-c}\right)dx + \int_{c}^{\infty} f(0)dx \tag{5}$$

This can be rewritten as:

$$H(A) = \int_{a}^{b} f\left(\frac{x-a}{b-a}\right)dx + \int_{b}^{c} f\left(\frac{x-c}{b-c}\right)dx \tag{6}$$

Substituting the MF in entropy function we get:

$$H(A) = -\left[\int_{a}^{b} \left(\frac{x-a}{b-a}\right) ln\left(\frac{x-a}{b-a}\right)dx + \int_{a}^{b}\left(1-\frac{x-a}{b-a}\right) ln\left(1-\frac{x-a}{b-a}\right)dx\right] - \left[\int_{b}^{c} \left(\frac{x-c}{b-c}\right) ln\left(\frac{x-c}{b-c}\right)dx + \int_{b}^{c}\left(1-\frac{x-c}{b-c}\right) ln\left(1-\frac{x-c}{b-c}\right)dx\right] \tag{7}$$

3. Objective Function and Algorithm

We propose the optimization algorithm in this section. This technique uses predefined set of MFs which are optimized for support around σ subjected to maximum entropy.

Generally FSs are named after linguistic variables and the FSs used in the text derive their names from there relevant position as compared to the error (ε). For any system the desired error is always 0, hence FS associated with 0 error is named as "z" (zero). FS associated with positive error are named as: "sp" (small positive), "mp" (medium positive) and "lp" (large positive). FSs associated with negative error are named as: "sn" (small negative), "mn" (medium negative) and "ln" (large negative) as depicted in Figure 2. For simplicity triangular FSs are considered as an example throughout the text.

The predefined sets are defined as:

- Fuzzy Set z: Triangular Fuzzy Set having support [−ε, ε] and μ = 1 at x = 0.
- Fuzzy Set sp: Triangular Fuzzy Set having support [0, 2ε] and μ = 1 at x = ε.
- Fuzzy Set mp: Triangular Fuzzy Set having support [ε, 3ε] and μ = 1 at x = 2ε.
- Fuzzy Set lp: Triangular Fuzzy Set having support [2ε, 4ε] and μ = 1 at x = 3ε.
- Fuzzy Set sn: Triangular Fuzzy Set having support [0,−2ε] and μ = 1 at x = −ε.
- Fuzzy Set mn: Triangular Fuzzy Set having support [−ε,−3ε] and μ = 1 at x = −2ε.
- Fuzzy Set ln: Triangular Fuzzy Set having support [−2ε,−4ε] and μ = 1 at x = −3ε.

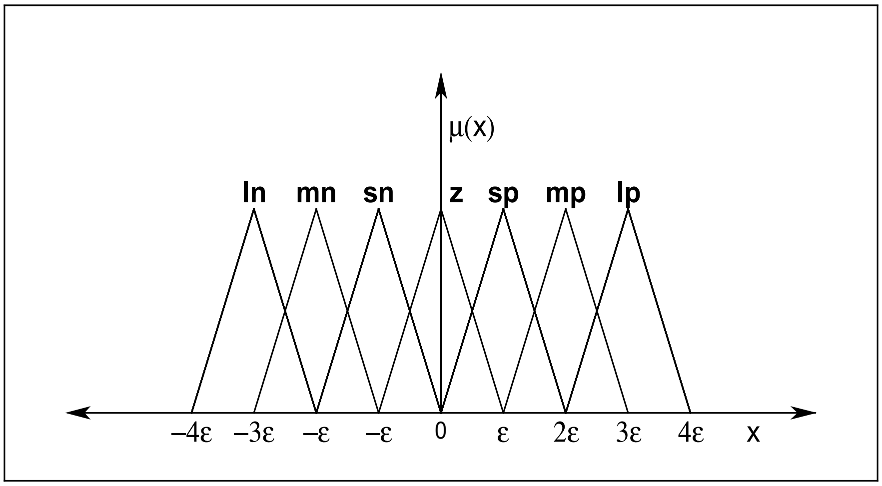

Figure 2. Predefined triangular MFs.

From above we write mathematical expression for FS z as:

$$\mu_A(x) = \begin{cases} 0, & x \le -\varepsilon \\ (x+\varepsilon)/\varepsilon, & -\Delta e < x \le 0 \\ (\varepsilon - x)/\varepsilon, & 0 < x < \varepsilon \\ 0, & x \ge \varepsilon \end{cases} \tag{8}$$

Where $a = -\Delta e$, $b = 0$, and $c = \Delta e$

Entropy for FS "z"; can be calculated as follows:

$$H(\mu_z) = \int_{-\varepsilon}^{0} f\left(\frac{x+\varepsilon}{\varepsilon}\right) dx + \int_{0}^{\varepsilon} f\left(\frac{\varepsilon - x}{\varepsilon}\right) dx \tag{9}$$

$$\begin{aligned} H(\mu_z) = &-\left[\int_{-\varepsilon}^{0} \left(\frac{x+\varepsilon}{\varepsilon}\right) ln\left(\frac{x+\varepsilon}{\varepsilon}\right) dx + \int_{-\varepsilon}^{0} \left(1 - \frac{x+\varepsilon}{\varepsilon}\right) ln\left(1 - \frac{x+\varepsilon}{\varepsilon}\right) dx\right] \\ &- \left[\int_{0}^{\varepsilon} \left(\frac{\varepsilon - x}{\varepsilon}\right) ln\left(\frac{\varepsilon - x}{\varepsilon}\right) dx + \int_{0}^{\varepsilon} \left(1 - \frac{\varepsilon - x}{\varepsilon}\right) ln\left(1 - \frac{\varepsilon - x}{\varepsilon}\right) dx\right] \end{aligned} \tag{10}$$

$$H(\mu_z) = -\left[\int_{-\varepsilon}^{0} \left(\frac{x+\varepsilon}{\varepsilon}\right) ln\left(\frac{x+\varepsilon}{\varepsilon}\right) dx + \int_{-\varepsilon}^{0} \left(-\frac{x}{\varepsilon}\right) ln\left(-\frac{x}{\varepsilon}\right) dx\right] - \left[\int_{0}^{\varepsilon} \left(\frac{\varepsilon - x}{\varepsilon}\right) ln\left(\frac{\varepsilon - x}{\varepsilon}\right) dx + \int_{0}^{\varepsilon} \left(\frac{x}{\varepsilon}\right) ln\left(\frac{x}{\varepsilon}\right) dx\right] \quad (11)$$

Assuming collective fuzzy entropy for FLS as sum of entropies of all the FSs in the FLS as:

$$H(\mu) = H(\mu_{\mathrm{ln}}) + H(\mu_{\mathrm{mn}}) + H(\mu_{\mathrm{sn}}) + H(\mu_z) + H(\mu_{\mathrm{sp}}) + H(\mu_{\mathrm{mp}}) + H(\mu_{\mathrm{lp}}) \quad (12)$$

or $$H(\mu) = \sum_{i=1}^{n} H(\mu_i) \quad (13)$$

Objective function for optimization:

Maximize

$$H(A) = \int_{a}^{b} f\left(\frac{x-a}{b-a}\right) dx + \int_{b}^{c} f\left(\frac{x-c}{b-c}\right) dx \quad (14)$$

Subject to maximum

$$H(\mu) = \sum_{i=1}^{n} H(\mu_i)$$

For example objective function for displaced Fuzzy Set "z" as depicted in Figure 3 can be written as:

Maximize

$$H(\mu_{z^*}) = -\left[\int_{-\varepsilon\mp\sigma}^{0} \left(\frac{x+\varepsilon\mp\sigma}{\varepsilon\mp\sigma}\right) ln\left(\frac{x+\varepsilon\mp\sigma}{\varepsilon\mp\sigma}\right) dx + \int_{-\varepsilon\mp\sigma}^{0} \left(-\frac{x}{\varepsilon\mp\sigma}\right) ln\left(-\frac{x}{\varepsilon\mp\sigma}\right) dx\right] - \left[\int_{0}^{\varepsilon\pm\sigma} \left(\frac{\varepsilon\pm\sigma - x}{\varepsilon\pm\sigma}\right) ln\left(\frac{\varepsilon\pm\sigma - x}{\varepsilon\pm\sigma}\right) dx + \int_{0}^{\varepsilon\pm\sigma} \left(\frac{x}{\varepsilon\pm\sigma}\right) ln\left(\frac{x}{\varepsilon\pm\sigma}\right) dx\right] \quad (15)$$

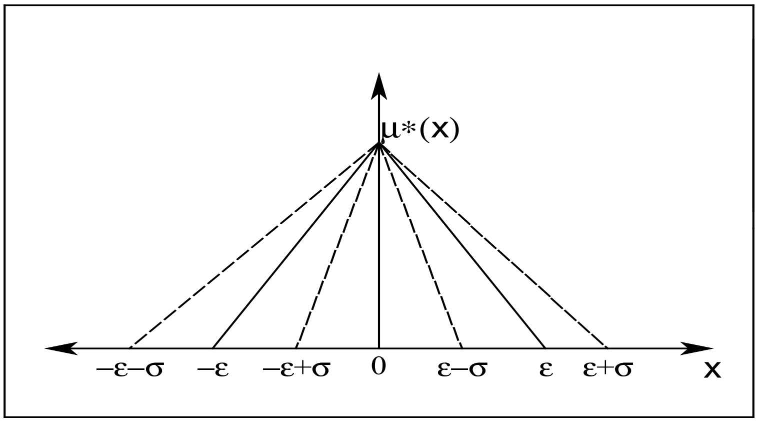

Figure 3. Displaced MF Z*.

Subject to maximum

$$H(\mu) = \sum_{i=1}^{n} H(\mu_i)$$

4. Genetic Algorithm based Optimization

In the proposed algorithm the optimization task includes: Determining the optimized value of displaced FS $\mu^*(x)$

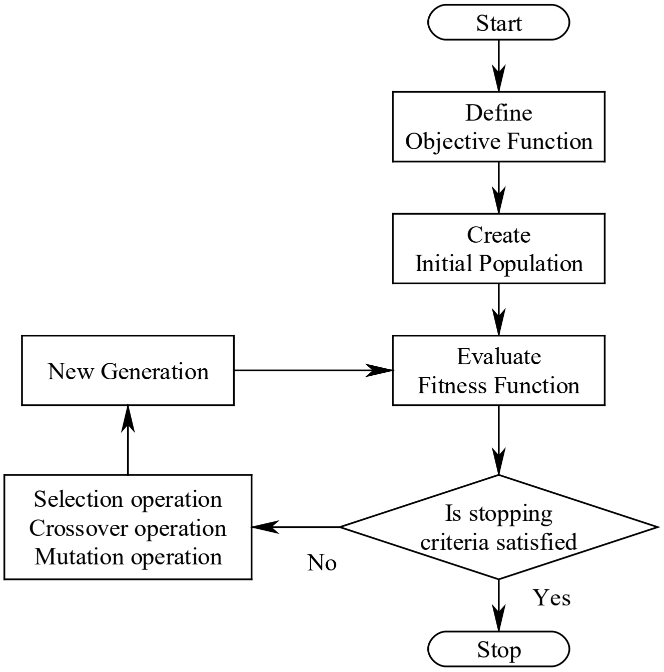

Figure 4. Flowchart for GA based optimization.

for each FS satisfying the constrained objective function as described in Equation (14).

GA based optimization methods[24] are used which are inspired from the process of natural evolution (survival of the fittest), it comprises of: Reproduction, crossover and mutation. A random population of size N is initially generated, where each entity may be a possible solution to the objective problem. Through genetic operations of reproduction, crossover and mutation a new generation is generated from the previous randomly generated population of N entities. Proficiency of GA technique is primarily affected by following two factors: 1. Crossover rate and 2. Mutation rate[25].

The steps involved in GA based optimization[26,27] are summarized as follows:

- Step 1: Objective function is defined as given in Equation (14).
- Step 2: Create an initial random set of population. The size of population is selected so as to find a trade-off between: Convergence time and population diversity.
- Step 3: Fitness function evaluation: Fitness value for each randomly generated chromosome population in step 2 is calculated using objective function defined in step 1.
- Step 4: New population is generated using selection, crossover and mutation operations. These operations are carried on the current population to replace it by new population. For new population generation the chromosomes of preceding generation with superior fitness values are nominated and placed in a recombination pool using the roulette wheel selection technique. Genes linking two parent chromosomes are swapped over to acquire new offspring in order to get optimal solutions, the probability of creating new chromosomes in each pair is set to 0.7. Mutation is performed to alter the binary code with a probability of 0.06.
- Step 5: The steps described in step 3 and 4 are repeated until the population generation count reaches its predefined maximum value.

Flowchart[28] for the above process is depicted in Figure 4. Table 1 describes the parameters settings chosen for the optimization process:

Table 1. Typical parameters used for optimization using GA

Name	Value (Type)
No. of generations	250
Population size	150
Selection type	Uniform
Crossover type	Arithmetic
Mutation type	Uniform
Termination method	Maximum generation

Genetic Algorithm is an efficient optimization tool when the objective function to be optimized is non-linear. In[29] proposed an attribute selective based fuzzification technique for UCI benchmark datasets. Cluster elimination and classification for attribute selection has been optimized using reinstating GA by the authors. The optimization result exhibit good performance for various applications: Breast cancer, sensor and iris data. In[30] utilized GA for optimization of PID controller for room heating application. Experimental results exhibited an efficiency improvement by 12.11% as compared to classic control technique namely: ON-OFF and PID control. In[31] proposed GA optimized fuzzy logic control for permanent magnet BLDC motor. Being non-linear system adaptive GA based fuzzy control is proposed for control of PMBLDC motor. Performance of proposed controller is compared to PI controller and results indicate small error. In[32] proposed a hybrid classifier using GA and Decision Tree based evolutionary learning. The proposed algorithm was tested for clustering and results exhibited stable accuracy despite of implementing the system in error prone environments.

4.1 Optimization Algorithm

The optimization algorithm for one set is given below; same algorithm can be applied to obtain FSs for each of the variables associated with FLS.

Step 1: Obtain the data for the given system using simulation/real time analysis.
Step 2: Calculate σ from the obtained data using Equation (1).
Step 3: Determine Fuzzy Sets using predefined MF as discussed in Section 3.1.
Step 4: Find fuzzy entropy for Fuzzy Set using Equation (7).
Step 5: Displace the Fuzzy Set by standard deviation and replace a by $a^* = a \pm \sigma$ and c by $c^* = c \pm \sigma$.
Step 6: For each set in FLS optimize the objective function as explained in.
Step 7: Repeat step 4 to 6 for remaining sets of the FLS.
Step 8: The algorithm can be used to optimize all the variables of FLS.

The algorithm given above can be used to find optimized sets for all the variables involved in the FLS

5. Discussion

Fuzzy logic being a science of dealing with vague data, mimics human decision making capability. Hence implementation of a Fuzzy Logic System is typically application specific. In[33] carried out a comparative study of fuzzy FACTS controller for enhancement of power system stabilization. FLC exhibits improved damping characteristics as compared to classic control methods. In[34] proposed neuro-fuzzy algorithm for control of flexible robots. The optimization of the proposed controller was carried out using particle swarm optimization technique. The robot's claw with two independent arms was controlled and the proposed algorithm had an advantage of learning as compared to classic control techniques. Results indicate an improvement in performance characteristics in robot's dynamics.

The novelty of the proposed algorithm lies in the optimization philosophy utilized. In this paper, we proposed GA based entropy function optimization algorithm to obtain "Optimized Support" for FSs. An assumption of predefined FSs (by equal distribution across error) has been taken so as to generate a starting reference point for optimization process. The objective function comprises of maximizing entropy function of individual FSs subjected to maximum collective fuzzy entropy of the FSs. This vagueness in FS is obtained by displacing each set on X-axis by standard deviation obtained from system data. The proposed algorithm utilizes the ability of the statistical techniques: To analyze probabilistic/nondeterministic systems. Although the developed algorithm is applied on triangular MF, the same can be applied to other MFs (Gaussian, Biezer curves, s-functions etc.) as well. As the objective function used in the text in nonlinear GA optimization technique is used so as not to lose the general ability of objective function to cater a wide range of operating parameter variations.

However applicability of this method depends on the availability of data. For most practical systems data is available as reference or can be determined using simulation/experimental analysis methods. Therefore availability of reference data set will not limit the functionality of the proposed algorithm for majority of the systems.

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