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Performance Analysis of Cuckoo Search Algorithm for Automatic Fuzzy Rule Base Generation

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Abstract: It is a proven fact now that fuzzy logic is a powerful problem-solving methodology with wide range of applications in industrial control, consumer electronics, management, medicine, expert systems and information technology. It provides a simple way to draw definite conclusions from vague, ambiguous or imprecise and incomplete information. It is a natural way of making a decision and is very close to the way the human beings think and make decisions even under highly uncertain environments. Fuzzy Classifiers are powerful class of fuzzy systems. Evolving fuzzy classifiers from numerical data has assumed lot of remarks in the recent past. This paper proposes a method of evolving fuzzy classifiers using a three-step technique. In the first step, a modified Fuzzy C–Means Clustering technique is applied to generate membership functions. In the next step, rule base is generated using cuckoo search algorithm. The third step was used to reduce the size of the generated rule base. By this method rule explosion issue was successfully tackled. The proposed method was applied using MATLAB. The approach was tested on a very well-known multi-dimensional classification data sets i.e. Iris Data. The performance of the proposed method was very encouraging. Further the algorithm is implemented on a Mamdani type control model for a battery charger data set. This integrated approach was able to evolve model quickly.

Keywords: Fuzzy Rules, Mamdani Control Model, Cuckoo Algorithm.

I. INTRODUCTION

The theory of fuzzy sets and fuzzy logic was introduced by Lotfi A. Zadeh through his seminal paper in 1965 [1]. Both these, fuzzy set theory and fuzzy logic is a powerful method for dealing with imprecision and nonlinearity in an efficient way [2], [3]. As the need of fuzzy set theory is concerned, there are numerous situations in which classical set theory of 0 and 1 is not sufficient to describe human reasoning. Thus, for such situations we need a more appropriate theory that can also define membership grades in between 0 and 1 thereby providing better results in terms of human reasoning. Fuzzy set theory helps in solving this problem.

Fuzzy set theory leads to the development of fuzzy logic-based systems. These systems are capable of making a decision on the basis of intelligence or knowledge provided to the system through rule bases. As a proper combination of input is given to the system, system on the basis of knowledge embedded into it in the form of rules makes a decision and processes those inputs. As the intelligence of these systems depends upon rule base, these systems are also called as Fuzzy Rule Based Systems. These systems have been successfully applied to a huge range of problems from different areas presenting uncertainty in different ways. These FRBS„s can be categorized as data driven systems and knowledge-based systems. There are two ways of providing knowledge to the systems. In first type of systems called data driven systems to automatically generate the rule base, a number of classical approaches like Hong and Lee, s Algorithm [9], Wang and Mendel Algorithm [4], Online Learning Algorithm [13], Multiphase Clustering Approach [14] and soft computing techniques like Artificial Neural Networks Genetic Algorithm Swarm Intelligence based techniques, Ant Colony Optimization, Particle Swarm Optimization, Biogeography based Optimization, Big Bang – Big Crunch Optimization technique are available in the literature.

In knowledge driven modeling, the rule base is provided by an expert who has the complete knowledge of the domain while in second type of models called data driven models, this rule base is generated from available numerical data.

This paper is based on an integrated approach that makes use of a modified Fuzzy C–Means Clustering approach (FCM) and Cuckoo Search Algorithms. The approach was implemented in MATLAB for fuzzy classification problems of Iris data, and Battery Charger data (control problem). A system was evolved using set of training examples and systems performance was then evaluated using test data set for the given system. The system performances were evaluated in terms of Average Classification Rate (for classification problems) and Mean Square Error (for control problem). The paper is arranged in a following way: Section I contains introduction of paper. Section II introduces Fuzzy Logic Based Systems. Section III discusses the proposed integrated approach and CS method for rule base generation. In section IV the result analysis along with the comparative study for above mentioned standard data sets are shown and section V includes conclusions.

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II. FUZZY MODEL

A zero-order TSK fuzzy system. It is clear from the figure that such system consists of 4 major modules i.e. fuzzifier, rule composition module (fuzzy t-norm/s-norm), implication module (multipliers in this case), and defuzzification module.

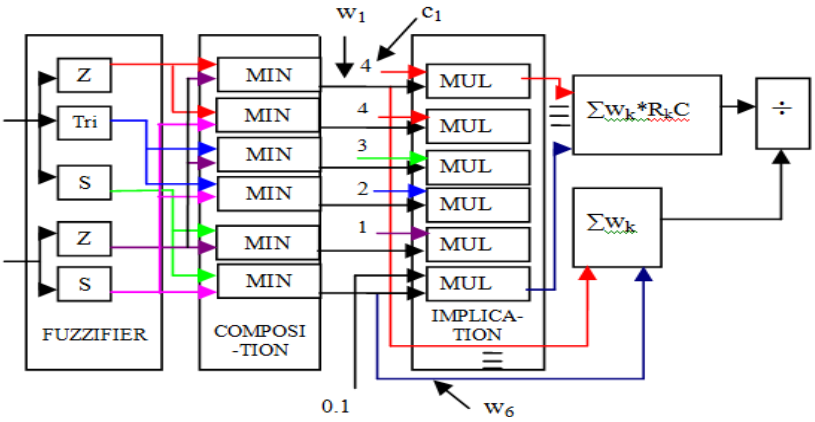

Figure 1: A zero-order TSK fuzzy system

In data driven modeling we first cluster the input data for all the input variables. The number of clusters represents membership functions for each input variables. Various techniques have been suggested in literature to partition universes of discourse of input and output variables. We use modified FCM [7] to partition the given data. The next step is to extract rule base from data.

In zero-order TSK model a rule is of the following form [1]:
R_k: If x_1 is A_{k1} and x_2 is A_{k2} and … and x_n is A_{kn}
Then y is R_kC, k = 1, 2, …,R
Where R_kC are the consequent of k^{th} rule. $x_1, x_2, \ldots, x_n$ and y are input and output variables respectively and $A_{k1}, \ldots, A_{kn}$ are linguistic labels, each one of them having associated a fuzzy set defining its meaning.
The maximum number of fuzzy rules can be computed as follows:

$$R=\prod_{i=1}^{n} m_i$$

where m_i represents the number of membership functions for i^{th} input variable and n is the number of input variables. But these R rules are due to combinations of membership functions of input variables and these are incomplete as we could have knowledge only about antecedent part and consequents are yet unknown.
The total output of the zero-order TSK model (Sugeno model) [2] is computed by

$$\text{Computed output } (O_C) = \frac{\sum_{k=1}^{R} w_k (R_k C)}{\sum_{k=1}^{R} w_k}$$

where w_k is the matching degree (i.e., the firing strength) of the k^{th} rule. Therefore, the degree the input $x_1 = a_1$, $x_2 = a_2$, …, $x_n = a_n$ matches k^{th} rule is computed using the min operator:

$$w_k=\min\left(\mu_{A_{k1}}(a_1), \mu_{A_{k2}}(a_2), \ldots, \mu_{A_{kn}}(a_n)\right)$$

In our problem we are using min operator as composition operator or we can use product operator instead of min. Because for any set of inputs, w_k are easily computed by fuzzifier and rule composing modules, the right hand side of output expression can be evaluated if we could choose the proper values for R_kC. Our problem is to find the optimal values of R_kC such that the difference between the computed output and the actual output as given in input data set is minimal.
Let the error be defined as follows:
Error = Actual output (as given in training data set) – Computed output
For each training example we compute error . For the complete data set mean square error (MSE) is computed. This MSE is used as the fitness function to evaluate the quality of fuzzy model.
With this pre-amble the whole problem of rule base generation boils down to minimization problem as stated below:
Minimize objective function (MSE)

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$$\text{MSE} = \frac{1}{N}\sum_{k=1}^{N}\left[O_A - O_C\right]^2$$

Subject to the constraint that

$R_kC \in$ {specified set of consequents};

where, O_A= Actual output as given in data set

O_C= Computed output of model R_kC = Consequent of k^{th} rule.

Any minimization technique may not be applicable if the problem is very complex. Soft computing based optimization algorithms have the capability to find the optimal or near optimal solution in a given complex search space within a reasonable time

III. SIMULATION & RESULTS

The algorithm has been applied for identification of fuzzy model for the rapid Nickel-Cadmium (Ni-Cd) battery charger. The objective of this charger was to charge 2AA Ni-Cd batteries as quick as possible but without damaging these. For this charger, the two input variables used to control the charging rate (Ct) are absolute temperature of the batteries (T) and its temperature gradient (dT/dt). Charging rates are expressed as multiple of rated capacity of the battery, e.g. C/10 charging rate for a battery of C= 500mAh is 50 mA. The input and output variables identified for rapid Ni-Cd battery charger along with their universes of discourse are given in Table 4.1.

Table 1: Input and Output variables for rapid Ni-Cd battery charger along with their universes of discourse

INPUT VARIABLES	**MINIMUM VALUE**	**MAXIMUM VALUE**
Temperature (T)[°C]	0	50
Temperature Gradient (dT/dt)[°C/sec]	0	1
OUTPUT VARIABLE		
Charging Rate(Ct)[A]	0	8C

The block diagram for the system to be identified is given in Figure 4.1. Let us assume that the temperature with the universe of discourse ranging from 0-50 degree centigrade has been partitioned into 3 fuzzy sets namely temperature low, med (medium), and temperature high.

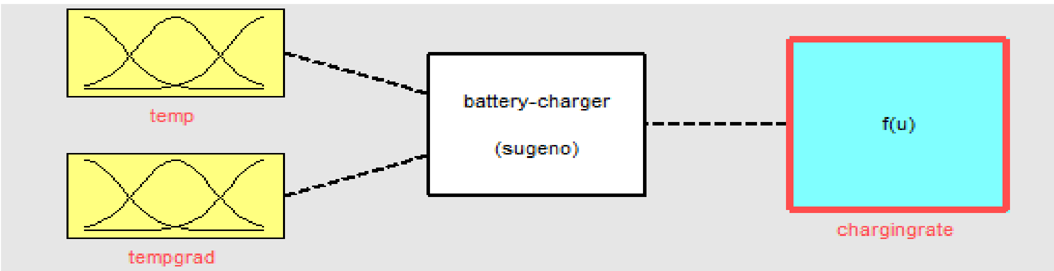

Figure 2: Stimulation parameter setting of Battery Charger (Control Problem)

The temperature gradient is partitioned into 2 fuzzy sets (membership functions) namely low and high. Intially we set the parameters of membership functions of input variables using modifed FCM clustering technique. Once fuzzification of the inputs is carried out, we get the 6 combination of input membership function (3*2 =6) representing 6 antecedents of the 6 rules. These 6 rules form the rule base for the system under identification. The rule base is yet incomplete as for each rule the consequent need to be found out. From the data set of Battery Charger, we find that there are only 5 consequents that form the set of consequents from where we have to choose one particular elements as the consequents for a particular rule. The specified set of consequents in this case are C1= Trickle=0.1 Amp, C2= Low= 1Amp, C3= Med= 2Amp, C4= High = 3 Amp and C5= Ultafast = 4Amp.

Parameter Settings for Cuckoo Search Algorithm

To obtain suitable parameters of cuckoo search algorithm which affect the performance in terms of solution quality and processing time, a large number of experiments were conducted with different parameter settings. We found that a population size of 50 and maximum number of iterations of 500 was adequate for cuckoo search algorithm. The other specific parameters of algorithm which came through experiments are listed in Table 2. All observations throughout the research work are made on Intel Core i3- 450 @ 2 GHz Dell Inspiron 15 (3000 series) with 4GB of RAM.

Table 2 Cuckoo Search Algorithm parameters for fuzzy model identification

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Parameter	Value
Population Size	30
No of iterations	500
Discovery rate of alien egg/solution	0.05

Simulation Results and Discussions

With the optimal parameters obtained, the large number of sets of trials was conducted . Each set consisted of 10 trials. The average performance of the set was compared with the output other algorithmsfor training purpose we selected 14 training examples out of 561 data points. The training data set was chosen based upon the mathematical relationship that exist in trapezoidal and triangular membership functions. Cuckoo search algorithm was executed for 500 iterations and the minimum, average and maximum MSE's were recorded.

The minimum, maximum and average MSE was observed to be 0.0052,0.006 and 0.0054 respectively. For 500 iterations, Cuckoo Search took the minimum, maximum and average time of 20.3 sec,21.2 sec and 20.7 sec.

In table 3, M=MSE and C= CPU time in sec. BBO, FA, ACO, ABC, CA all are the algorithms applied on the battery charger problem. The number of iterations used for CA is 500 while all the other algorithms uses 5000 iterations with number of nests = 25 and population size = 30.

Table 3: Performance of five optimization algorithms in a set of 10 trials

Trails	**ALGORITHMS**									
	BBO		**FA**		**ACO**		**ABC**		**CA**	
	M	**C**	**M**	**C**	**M**	**C**	**M**	**C**	**M**	**C**
1	.004	204	.005	132	.005	241	.005	266	0.005	21.5
2	.010	205	.006	142	.006	257	.005	266	0.005	20.7
3	.007	207	.005	138	.007	254	.005	266	0.005	20.8
4	.009	211	.011	132	.009	254	.005	266	0.006	20.9
5	.007	206	.005	135	.020	262	.005	266	0.005	20.6
6	.005	203	.005	137	.009	259	.005	266	0.005	20.9
7	.009	206	.005	141	.006	266	.005	266	0.005	20.3
8	.002	205	.006	140	.005	253	.005	266	0.005	21.1
9	.003	203	.005	139	.006	252	.005	266	0.006	21.2
10	.005	207	.005	131	.007	249	.005	266	0.005	22.4

Table 4: Comparision of optimization algorithms in terms of MSE

Performance Measures	BBO	FA	ACO	ABC	CA
Min.MSE	0.002	0.005	0.005	0.005	0.005
Avg. MSE	0.006	0.006	0.008	0.005	0.005
Max. MSE	0.010	0.011	0.020	0.005	0.006

Further for training data as observed from Figure 3 one can see that Cuckoo Search will take some time to stabilize to minimum MSE(around 500 iterations)

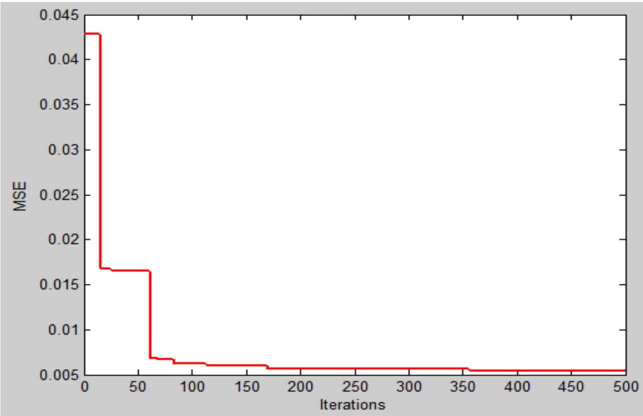

Figure 3. Iterations Vs MSE for Cuckoo search

IV. CONCLUSION

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The work undertaken in this research primarily discussed the rule base generation from numerical data for Mamdani type data driven fuzzy systems. No doubts, evolving fuzzy classifiers and fuzzy controllers from numerical data are a highly computationally complex problem. In this research work an integrated approach is applied to fuzzy model identification with the following conclusions:-

1. It is found that the proposed integrated approach is very effective for fuzzy classification as well as for fuzzy control system identification.
2. In first step of the proposed approach, modified Fuzzy C-Means clustering (FCM) is used for fuzzification of input and output domains.
3. In the second step, the classical cuckoo search algorithm is used for rule base generation.
4. In last step, a rule reduction technique is used to counter rule explosion issue i.e. to keep the size of rule base as minimum as possible.
5. Also, the proposed method was successfully validated on classification problems of Iris Data and control problem of Battery Charger Data Set.
6. The experimental results in terms of classification rates and Mean Square Error seem to be encouraging.
7. The method appears to be very efficient in evolving both fuzzy classification and control systems from given data sets.

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