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Fuzzy Rulebase Generation: Three New Soft Computing Based Approaches

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Abstract: This paper proposes three new approaches of rule base generation for a Fuzzy system from numerical data and compares their performance with the approaches that have been used in literature for either rulebase generation or fuzzy model identification. A total of nine optimization algorithms are implemented for the rulebase generation problem including the new approaches GWO, CSO and DE along with the existing methods based on GA, BBBC, PB3C, MA, FA and PSO. All the approaches are implemented in MATLAB and their performance is compared over a representative example. We compare these approaches on two parameters namely accuracy in terms of MSE and convergence time for that given MSE parameter. We observe that BBBC, PB3C and GWO algorithm gave same best MSE performance followed by MA, GA, CSO, PSO, DE and FA in that order. As far as convergence time for the problem of rapid fuzzy battery charger is concerned, we found that BBBC is the fastest followed by PB3C and GWO.
Keywords: GA, DE, BBBC, PB3C, FA, MA, CSO, GWO, PSO, MSE, Rulebase Generation, Fuzzy Model Identification, Convergence time.

I Introduction

Rulebase generation is an important step in designing rule based fuzzy models. Extracting knowledge or rulebase from a given numerical data is a complex problem that has drawn the attention of research community in the recent past.

Many classical as well as soft-computing methods have been applied to generate rulebase for specific systems. As each system has different number of inputs, outputs and their membership functions, the rulebase generation is generally an application specific problem. In a multi-input single-output (MISO) system the maximum number of rules includes every combination of input membership functions in antecedent part. As the number of inputs and their membership functions increases the complexity in finding the appropriate set of consequents also increases. There are many rulebase minimization techniques which reduce the number of rules by eliminating redundant rules and by merging the rulebase [1,2]. The rulebase generation problem can be combined with the problem of parameter estimation and both the problems can be solved simultaneously or separately [3].

Fuzzy Model Identification (FMI) is a well established field and there are many methods available in literature based on clustering [4], Fuzzy C Means Clustering (FCM) [5,6], Fuzzy C Regression Models (FCRM) [7], Modified FCRM [8], subtractive clustering [9-12], Modified Gath-Geva algorithm [13], Neural Networks [14-16], Genetic Algorithms (GA) [18- 25], Particle Swarm Optimization (PSO) [26-29], Ant Colony Optimization (ACO) [30-31], Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture [32,33], Firefly Optimization (FA) [34], Big Bang Big Crunch (BBBC) [35,36] and Parallel Big Bang Big Crunch [37], Extended Kalman Filter [38], Gravitational Search algorithm (GSA) based Hyperplane Clustering algorithm (GSHPC) [39] and Root mean square error minimization [40] techniques. Hodashinsky et al. [41] proposed Monkey Algorithm for rule base extraction for a set of classification problems.

Many a times these algorithms are used jointly to solve the FMI problem eg. Hybrid of gradient descent and least means squares [42], FCRM and PSO [43,44], Hough Transform and Clustering [45], Evolutionary Programming and Least Squares estimate [46], FCM and GA [47], FCRM and Gradient Descent Algorithm [48], FCM and Least Squares estimate [5,49], Fuzzy Discretization Technique and Orthogonal Estimator [50] based approaches have been proposed in literature. Hybrid techniques are usually hierarchical where two algorithms are used at different levels of hierarchy or coarse tuning of parameters is performed with one method and fine tuning with the other.

A rulebase generation problem can be framed as a minimization (or maximization problem) and can be effectively solved by using biologically / nature inspired techniques. This paper proposes three new soft computing based approaches to rulebase generation from given numerical training data of Ni-Cd rapid battery charger. These new approaches are Grey Wolf Optimization (GWO) [51], Chicken Swarm Optimization (CSO) [52] and Differential Evolution (DE) [53,54] based approaches. In addition to these, for comparison purpose the following optimization algorithms i.e. Genetic Algorithms (GA), Big Bang Big Crunch (BBBC) [55,56], Parallel Big Bang Big Crunch (PB3C) [57], Firefly Algorithm (FA) [58,59], Monkey Algorithm (MA) [60] and Particle Swarm Optimization (PSO) [61] are also applied to identify the rule consequent of each fuzzy rule. All these approaches are implemented in MATLAB and their performance over a rapid battery charger example is evaluated. In these algorithms, initially a random population/ multi population of solutions is generated and as iterations progress the population is modified to improve the value of objective function. Generally in minimization algorithms the objective function is the performance error and it gets reduced with increase in iteration steps. We have considered the algorithm accuracy as well as the convergence time as the performance parameters.

The paper is organized as follows. Section I of the paper presents introduction. Section II and III briefs the implemented algorithms and problem formulation respectively. Simulation, results and comparison is given in section IV and section V concludes the paper.

II Implemented Algorithms

It is evident from the literature on Fuzzy Model Identification that there is a good scope of applying soft computing algorithms to the rulebase generation. In this work we have applied nine soft computing techniques to extract rulebase from a Ni-Cd Battery Charger dataset. The selected algorithms for this research are meta-heuristics based on evolution, physics and swarm intelligence. The evolutionary techniques used here are Genetic Algorithms and Differential Evolution which are based on the natural concept of reproduction. These are population based heuristics where next generation is generally but not always better than the parent population and has an improved value of objective function. The child population is created by selection, crossover and mutation of individuals in parent population.

The physics based methods employed here are Big Bang Big Crunch (BBBC) and Parallel BBBC (PB3C). In these methods a random population of search agents communicates and moves throughout the search space according to some set of physical rules. BBBC is inspired by the evolution of the universe and mainly consists of two phases i.e. Big bang phase and Big Crunch phase. In the Big Bang phase, a population of random solutions is generated whereas, in the Big Crunch phase, randomly distributed particles are all contracted towards the centre of mass. In contrast with BBBC, PB3C is a multi-population optimization technique that performs local as well as global search in a set of populations.

Swarm Intelligence mimics the social behavior of swarms such as search of food by ants in Ant Colony Optimization (ACO) [62], hunting process of wolfs in Grey Wolf Optimizer (GWO) [51], flocking of birds in Particle Swarm Optimization (PSO) [61], hierarchy of chicken swarms in Chicken Swarm Optimization (CSO) [52] and mountain climbing of monkeys in Monkey Algorithm (MA) [60]. Monkey Algorithm proposed by Zhao et al. [60] is based on the simulation of mountain climbing process of monkeys and mainly consists of climb, watch-jump and somersault processes which are repeated for iterations to find the highest mountaintop. PSO, developed by Eberhart and Kennedy in 1995 [61], refers birds or fish as particles and is a population based stochastic technique inspired by the behavior of flocking birds during migration to an unknown destination or fish schooling. Sayedali Mirjalili et al. in 2014 [51] proposed a new meta-heuristic named Grey Wolf Optimizer, which mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. CSO proposed by Xian-bing Meng et al. in 2014 [52] is a bio-inspired optimization technique and mimics the hierarchy of chicken swarms and their behavior. Each chicken swarm group consists of a rooster, many hens and chicks. Chickens in these swarms follow different laws of motion and hence there exist competitions between different chickens. Few soft computing methods like ACO, FA, MA, PSO, BBBC, PB3C have already been used in fuzzy system identification and in the present work out of three newly proposed approaches two (GWO and CSO) belong to the swarm intelligence based category.

III Problem Formulation

The rulebase of rapid Nickel-Cadmium (Ni-Cd) battery charger [63] is generated by using various soft computing algorithms with an objective to find an optimal amount of charging current to charge the 2AA Ni-Cd batteries in quickest possible duration with no harm to these. Each row of data contains the values of two inputs (Temperature and Temperature gradient) and an output (Charging Current) combination. A small training and testing data can be extracted from a database of 561 input output combinations. The input membership functions are determined by applying modified Fuzzy C means Clustering technique [64]. The universe of discourse of Temperature (T = 0°C to 50°C) is covered by 3 fuzzy sets i.e. Low, Medium and High and Temperature Gradient (dT/dt) is partitioned into two fuzzy sets i.e. Low and High. The membership functions of Temperature and Temperature Gradient are shown in Fig. 1 and 2 respectively. The number of rules formed in this case is 6 and are given below.

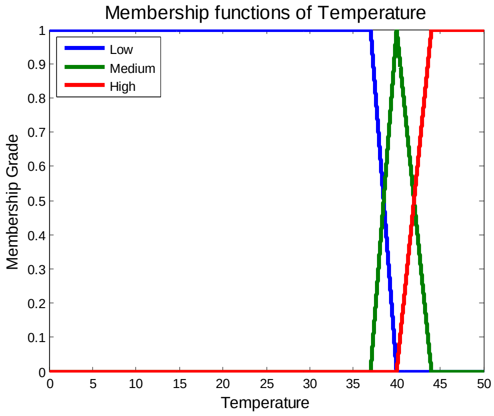

Fig. 1. Input 1: Fuzzy sets for low, medium and high temperature

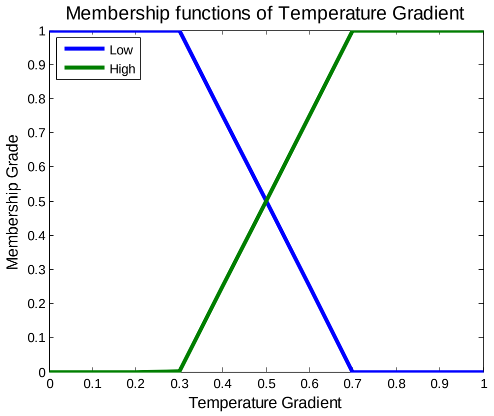

Fig. 2. Input 2: Fuzzy sets for normal and high temperature gradient.

Rule1: If Temperature is Low and Temperature_gradient is Low then Charging Current is C1

Rule2: If Temperature is Low and Temperature_gradient is High then Charging Current is C2

Rule3: If Temperature is Medium and Temperature_gradient is Low then Charging current is C3

Rule4: If Temperature is Medium and Temperature_gradient is High then Charging current is C4

Rule5: If Temperature is High and Temperature_gradient is Low then Charging current is C5

Rule6: If Temperature is High and Temperature_gradient is High then Charging current is C6

In order to identify the rulebase of above fuzzy system, we consider all outputs as singletons [65] and hence the problem of rulebase generation is encoded as the determination of constants C1 to C6 (with Lower bound = 0A and Upper bound = 4A) such that the Mean Squared Error (MSE) [32] of the system, implemented using the extracted rulebase, is minimum. MSE is considered as the performance index of the obtained fuzzy model and the objective of applying soft computing techniques is to minimize it. The mathematical expression for MSE is as given below in equation (1).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{y(i)} - \mathrm{y'(i)})^2 \qquad (1)$$

$$y'(i) = \frac{\sum_{i=1}^{N} w_i c_i}{\sum_{i=1}^{N} w_i} \qquad (2)$$

where y(i) is the desired output as provided in database, y'(i) is the computed output of model and N is the number of data points used for model validation. The output y'(i) is computed by using equation (2) where w_i and c_i are composed value and consequent value of i^{th} rule.

IV Simulation Results and Discussion

In order to evaluate the performance of these 9 algorithms, we implemented all these approaches in MATLAB. The training dataset used here is taken from [34] and is placed as Appendix A. The implemented

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software allows the user to select the optimization algorithm for rulebase generation of the battery charger by invoking the menu as shown in Fig. 3. After the generation of rulebase the rules with the extracted value of consequents are displayed in the figure window alongwith the convergence curve for the selected algorithm as shown in Fig. 4 and 5 respectively.

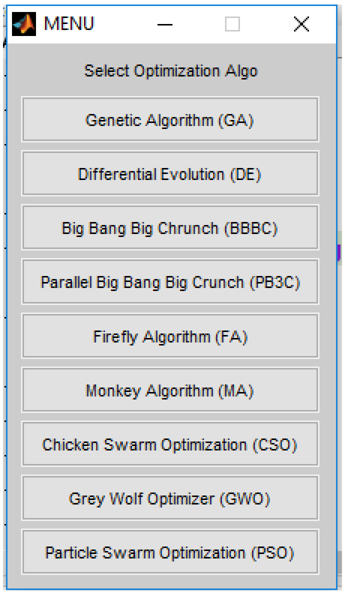

Fig. 3. Screenshot of menu to opt for choice of Optimization Algorithm

Rulebase generated for Battery Charger FLS using
Big Bang Big Chrunch (BBBC)

Rule1: If Temperature is Low and Temperature_gradient is Low then charging current is 4
Rule2: If Temperature is Low and Temperature_gradient is High then charging current is 4
Rule3: If Temperature is Medium and Temperature_gradient is Low then charging current is 3.0961
Rule4: If Temperature is Medium and Temperature_gradient is High then charging current is 2.0473
Rule5: If Temperature is High and Temperature_gradient is Low then charging current is 0.12721
Rule6: If Temperature is High and Temperature_gradient is High then charging current is 0.077932

MSE of the Battery Charger with the selected rulebase is 0.021575
Execution time = 2.9687sec

Fig. 4. Screenshot of generated rulebase

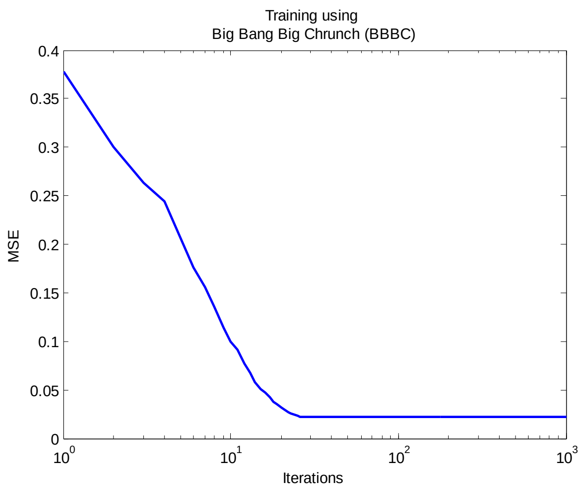

Fig. 5. Graph representing convergence of MSE as the iterations

Table 1 shows the parameters used for simulation of these approaches. We conducted 51 trials for each of the algorithms on a Dell laptop with Intel® Core i3-4005U CPU @ 1.70 GHz processor and 4GB of RAM.

Table 1
Selected values for algorithm specific desired parameters

Algorithm	Selected Parameter values
GA	Number of candidate solutions = 200 Number of generations = 600 Crossover probability = 0.8 Mutation probability = 0.2 Mutation interval = 20
DE	Number of candidate solutions = 10 Crossover Probability = 0.8
BBBC	Number of candidate solutions = 10 Update = (0.4 * rand * 4)/ generation id
PB3C	Number of parallel populations = 3 Number of candidate solutions = 4 Update = (0.4 * rand *4)/ generation id
FA	Number of candidate solutions = 50 alpha = 0.02 beta = 1 gamma = 0.8
MA	Number of candidate solutions = 10 Step length = 0.02 Eye sight = 0.5 Somersault Interval = [-1,1]
CSO	Number of candidate solutions = 20 Rooster percentage = 0.35 Hen percentage = 0.45 Mother percentage = 0.15
GWO	Number of candidate solutions = 10 'vector a' decreases from 0.2 to 0
PSO	Number of candidate solutions = 100 Maximum Velocity = 1 Update in velocity = [0.02, 0.1] phi1 = phi2 = 2

The MSE performance of each algorithm is listed in Table 2. In order to evaluate the convergence rate, we fixed the target accuracy of 0.021575 and evaluated the convergence time. It is found that except for BBBC, PB3C and GWO none of the other approaches could converge for the given accuracy of 0.021575. The time to converge to the minimum MSE by these three algorithms is presented in Table 3. Considering the performance of the other five approaches which could not converge consistently for the given accuracy we relaxed the accuracy target from 0.021575 to 0.02158. The MSE based performance for all approaches along with their convergence time and standard deviation is listed in Table 4. As shown in this table the standard deviation of MSE for 51 trials is nonzero for DE, CSO, FA and PSO which implies that these algorithms are not able to converge at the same value of MSE everytime. However the other 5 algorithms with standard deviation = 0 are consistent performers.

Table 2
MSE Performance (51 trials) of all Algorithms

Algorithm	Worst MSE	Mean MSE	Best MSE
GA	0.02170	0.021690	0.021689
DE	0.12114	0.024156	0.021575
BBBC	0.02158	0.021578	0.021575
PB3C	0.02158	0.021578	0.021575
FA	0.25416	0.047641	0.021587
MA	0.02163	0.021599	0.021585
CSO	0.02266	0.021878	0.021585
GWO	0.02158	0.021579	0.021576
PSO	0.02638	0.021979	0.021576

Table 3
Average convergence time to achieve Best MSE performance i.e. (0.02175)

Algorithm	Average Convergence Time (in sec)
BBBC	0.347
PB3C	0.475
GWO	3.13

Table 4
Performance of all algorithms for target MSE = 0.02158

Algorithm	Average MSE	Average Convergence Time (in sec)	Standard Deviation
GA	0.021690	6.988	0.000
DE	0.024156	7.94	0.014
BBBC	0.021578	0.347	0.000
PB3C	0.021578	0.475	0.000
FA	0.047641	3431.78	0.057
MA	0.021599	428.76	0.000
CSO	0.021878	153.65	0.003
GWO	0.021579	3.13	0.000
PSO	0.021979	54.375	0.001

Table 5
Convergence time of all algorithms for target MSE = 0.0242

Algorithm	Achieved MSE	Average Convergence Time (in sec)
BBBC	0.0234	0.0678
PB3C	0.0234	0.127
GWO	0.0241	0.493
MA	0.0234	1.188
GA	0.0241	7.357
CSO	0.0237	1.04
DE	0.0239	0.3039
PSO	0.0236	1.863
FA	0.0433	94.8

We further relaxed the desired accuracy target to 0.0242 and conducted 51 trials for each of the algorithms. The convergence performance is placed in Table 5. From the table we observe that BBBC converged in the shortest mean time of 0.0678 sec followed by PB3C with the mean convergence time of 0.127sec followed by GWO with 0.493 sec and MA 1.188 sec. It is also observed that out of 51 trials CSO did not converge for 2 trials, DE for 4 trials, PSO for 5 trials and FA for 6 trials.

From Tables 2 to 5 we observe that BBBC, PB3C, GWO and MA approaches outperformed other 5 approaches in accuracy as well as time complexity. A look at the convergence rates also indicates that as the problem complexity grows, the performance of PB3C is likely to outperform all other approaches.

V Conclusion

This paper presented three new algorithms namely GWO, CSO, and DE for rulebase generation from the numeric training examples. We implemented these proposed approaches alongwith GA, FA, BBBC, PB3C, MA and PSO in MATLAB. We evaluated the performance of all the nine algorithms on two performance parameters namely accuracy and convergence time. The approaches were validated on a Dell laptop with Intel® Core i3-4005U CPU @ 1.70 GHz processor and 4GB of RAM. We conducted 51 trials for every approach. From the simulation results we conclude that BBBC, PB3C, GWO and MA give the best performance in that order on both performance parameters. CSO, DE, PSO, GA and FA were observed to be inferior to the other four approaches on both MSE and convergence time performance parameters.

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APPENDIX A

Training Data			
Data Point	Temperature	Temperature Gradient	Charging Current
1	0	0	4
2	30	1	4
3	37	0.2	4
4	40	0	3
5	40	1	2
6	41	0.5	2
7	42	1	1
8	43	0.5	1
9	43	1	0.5
10	44	0	0.1
11	44	0.4	0.1
12	45	0.1	0.1
13	45	0.5	0.1
14	50	1	0.1