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FUZZY MODEL IDENTIFICATION: A NEW PARALLEL BB-BC OPTIMIZATION BASED APPROACH

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ABSTRACT

Evolving a performance evaluation model for universities and institutes of higher learning is very desirable, but is a tedious and time consuming task due to their inherent higher degree of complexity and nonlinearity. Soft Computing based approaches have gained significant popularity towards evolving high dimensional fuzzy logic based models. This paper proposes the application of simple and parallel Big Bang and Big Crunch (BB-BC) based optimization [1 2] approaches to the identification of fuzzy logic based system from the available numerical data. This system identification problem for overall rating and evaluation of institutions of higher learning was formulated as a minimization problem. Simple BB-BC and parallel BB-BC algorithms are applied to identify TSK type zero fuzzy models. Simple BB-BC is a single population approach whereas parallel BB-BC is a multiple population approach. The paper compares performances of both of these algorithms. Parallel BB-BC approach was observed to be computationally more efficient and has much better accuracy.

KEYWORDS: Fuzzy Logic Based System Identification, Membership Functions, Optimization, Parallel Big Bang, Big Crunch Algorithm, Simple Big Bang, Big Crunch Algorithm

INTRODUCTION

The 21st century is the century of knowledge driven industry. This requires a larger knowledge force to be developed. It is widely believed that the nations with good knowledge force will lead rest of the world. In order to develop the excellent knowledge force, institutions of higher learning like universities or professional colleges are required to be created and nurtured. Increased number of these institutes will have a negative impact on the development if these miss the target of quality education and research. It is imperative that to improve the performance of such institutes the performance of these institutions need to be assessed and evaluated. Performance evaluation of universities and the institutes of higher learning is essential to identify and analyze the weak areas and performance bottlenecks. Once the performance bottlenecks are identified and removed academic excellence follows.

Designing performance evaluation systems of universities and institutes of higher learning involves a large number of inputs. Further in addition to being large these systems are quite nonlinear as well. The classical techniques and the exact reasoning based approaches make the design of performance evaluation system a very tough task. Such problems turn out to be NP Hard problems. Hence, one has to adopt approximate reasoning/ soft computing based approaches to design and implement such systems. Fuzzy logic based systems are one of the important class of knowledge based systems which simplify the design of such type of complex systems. Though using fuzzy logic based approach simplifies the design problem to certain extent yet design of system for evaluation of institutes of higher learning is a quite tedious and time consuming task; as it needs large number of parameters to be considered which are difficult to measure. Further designing such system by eliciting knowledge from the domain experts is very difficult and complicates system design process. Discussions and interviews with the experts and design engineers is boring, cumbersome, time consuming and adds to the cost of the project. Thus designing of fuzzy systems directly from the available training data is highly desirable. Wang and Mendel, in their paper [4] and Mendel et. al. [5] provided the rulebase generation and formulation of complete fuzzy system as two different problems. Many fuzzy logic based and artificial neural network based approaches for the identification of such systems can be found in the literature. Nural network based approaches[6]-[14],GAs [15]-[24], ACO [25]-[31], BBO [32],[33]- and PSO based approaches [34]-[35],for generation of rulebase and identification of fuzzy logic based system can be found in literature.BB-BC optimization based approach [3], [36]-[39] has also been applied to fuzzy model identification. This paper presents a data driven model identification approach to performance evaluation system modeling for the universities and institutes of higher learning. We formulate fuzzy logic based model identification problem as a minimization problem in this paper. Simple as well as parallel BB-BC optimization approaches are applied to enumerate desirable solutions.

This paper consists of 5 sections. Section 2 of this paper introduces BB-BC theory of evolution of universe, section 3 and section 4 presents BB-BC based performance system identification methodology and proposed model for the system, Section 5 discusses the applications, simulation, observations, and results of the system identification by these two approaches. Section 6, concludes the paper.

BIG BANG-BIG CRUNCH THEORY

The Big Bang Big Crunch (BB-BC) theory is a well known optimization technique for finding out the solutions to the complex problems involving functions with nonlinear behavior, where traditional mathematical programming methods prove to be of little use. This method is based upon the theory of the evolution of the universe called Big Bang-Big Crunch theory [1]. In the Big Bang phase, energy dissipation produces disorder and randomness is the main feature of this phase; whereas, in the Big Crunch phase, randomly distributed particles are drawn into an order. Inspired by this theory, an optimization algorithm was proposed, which was called the Big Bang-Big Crunch optimization algorithm [36][37].

Parallel BB-BC Algorithm

Parallel BB-BC algorithm is a multi-population algorithm, was first proposed by Shakti et. al. [2]. The pseudo code for parallel BB-BC is given in figure 1.

Begin

/* Big Bang Phase */

Generate N populations each of size *NC* candidates randomly;

/* End of Big Bang Phase */

While not *TC* /* *TC* is a termination criterion */

/* Big Crunch Phase */

For i = 1: N

Compute the fitness value (center of mass using Equation 1) of all the candidate solutions of i^{th} population;

$$x_c = \frac{\sum_{i=1}^{NC} \frac{1}{f^i} x_i}{\sum_{i=1}^{NC} \frac{1}{f^i}} \quad (1)$$

Best fit individual can be chosen as the center of mass instead of using Eq. 1;

Sort the population from best to worst based on fitness (cost) value;

Select local best candidates $l_{best}(i)$ for i^{th} population;

End

From amongst "N" l_{best} candidates select the globally best g_{best} candidate;

For i =1: N

With a given probability replace a gene of $l_{best}(i)$ with the corresponding gene of global best g_{best} candidate

End

/* End of Big Crunch Phase */

/* Big Bang Phase */

Calculate new candidates around the center of mass by adding or subtracting a normal random number whose value decreases as the iterations elapse using Equation 2;

$$x^{new} = x^{c} + l(rand)/k \tag{2}$$

/* End of Big Bang Phase */

End while

End

Figure 1: Pseudocode for the Proposed Parallel BB-BC Algorithm

FUZZY MODEL IDENTIFICATION FOR TSK TYPE-0 FUZZY

Fuzzy model identification is a process of designing the complete system from a given set of data. This fuzzy model identification can be divided into three sub-processes namely structure specifications, parameters estimations and model validations [42]. Structure Specifications deals with input variable selections, partitioning of input spaces, membership function specifications and deciding the rule base of the system. In order to model a fuzzy model from a given training data set we proceed to formulate the problem as given below:

- Construct a fuzzy model with arbitrary selection of membership functions of given shapes for each input and output variable.
- Deciding the rule base for the fuzzy model.
- For entire training data set:
  - Evaluate output of the model for each training example.
  - Calculate error between the computed output and given output of the training example.
  - Compute mean square error for the identified model.
- Minimize the objective function i.e. MSE using some efficient techniques.

Thus this problem of fuzzy model identification from the given data is formulated as search and minimization problem. The optimization algorithm used must simultaneously adjust membership function parameters and consequents in such a way so as to minimize the objective function i.e. MSE:

Minimize Objective Function (MSE)

$$MSE = \frac{1}{N}\sum_{k=1}^{N}[O_A - O_C]^2 \tag{3}$$

Subject to the Constraint that

- $R_k C \in$ {universe of discourse of output variable}; (4)
- $X_{n\min} < E_{n1} < E_{n2} < \ldots < E_{nm_n} < X_{n\max}$ (5)

Where O_A is the actual output, O_C is the computed output, N is number of data points taken for model validation and $R_k C$ represent consequent of k^{th} rule.

In this paper we have applied BB-BC based optimization approaches to develop a suitable fuzzy model based upon the available training data set**.** Values of all the parameters of input and output variables such as membership functions and their shapes, along with consequent for the each rule was identified for the designing of complete fuzzy logic based system.

PROPOSED FUZZY LOGIC BASED MODEL FOR INSTITUTE RATING

In this section a fuzzy based system for the evaluation of institutions of higher learning is designed using simple and parallel BB-BC approaches. For designing such system all input and output variable parameters such as membership functions and their shapes, along with consequent for the each rule are identified.

In doing so first the shapes of Membership functions were fixed to be either triangular, trapezoidal or variation of these leading to sigmoidal or Z-type membership functions. Here, modified fuzzy C-Means clustering (FCM) [40] has been used to derive these membership functions. In the following sections, we use modified FCM [41] for the initial parameter settings of membership functions and further tuning of both the parameters of membership functions as well as rule base is done simultaneously to evolve an optimal fuzzy model.

In this paper, system under design consists of 14 input variables and one output variable named “overall rating”. Input variable used are given in the table: 1 below:

Table 1: Input Variables

1	Laboratories And Workshops (ILW)
2	Class Room And Tutorials, Discussion Rooms (ICT)
3	Library (Book, Journals) (ILB)
4	Academic Facilities (IF)
5	Teaching-Learning Process (TLP)
6	Student/Teacher Ratio (TSR)
7	Teacher Training/Updation (TU)
8	A/V Aids Used /Teaching Techniques (TT)
9	Research Orientation (RO)
10	Research Publications (RP)
11	Research Projects/Conferences/Seminars (RC)
12	Student Placements (SP)
13	Students Merit (Pass Percentage) (SM)
14	Admission Preference (SA)

Shown in figure 2 is block diagram of the desired multi input single output fuzzy system with “n” number of input variables. These have been labeled as $x_1, x_2, \ldots, x_n$ and the number of membership functions for each of the input variables are $m_1, m_2, \ldots, m_n$ respectively. Here number of inputs n =14.

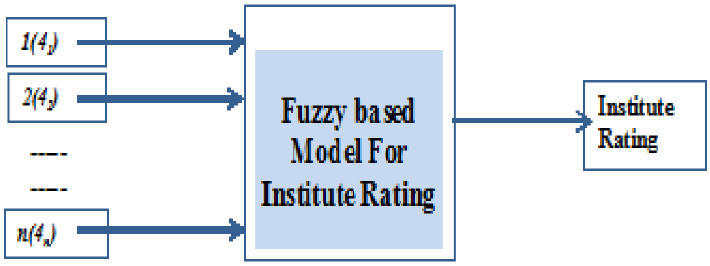

Figure 2: Block Diagram of the Required Fuzzy System

This fuzzy model has been identified using simple and parallel BB-BC algorithms. These algorithms are implemented in MATLAB. Each individual in the population represents a fuzzy system which consists of two parts. First part represents membership functions of antecedents and the second part represents rule-base. To obtain solution, the membership functions and rule base are modified simultaneously, since, these are codependent in a fuzzy system.

For each of these inputs number of membership functions are taken as 4(m=4) and the consequents are selected from a range of 0.1 - 10. The shapes of membership functions are fixed as triangular, sigmoidal and z-type membership functions for both input and output variables and are placed symmetrically over the universes of discourse. First and last membership functions of each input and output variable are represented with z-type and S-type membership functions respectively and all others are considered to be as triangular membership functions. Shape of the four membership functions of the first input variable “Laboratories and Workshops (ILW)” is shown in figure (3).

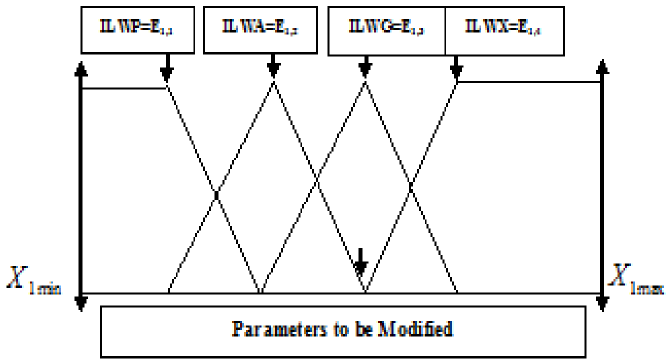

Figure 3: Membership Functions of Input Variable

The vertices of these fuzzy membership functions of the inputs are denoted as $E_{1,1}$ $E_{1,2}$ ----$E_{1,4}$,---$E_{14,4}$. $E_{1,1}$ means first input, first membership function and $E_{n,m}$ means n^{th} input, m^{th} membership function. Membership parameters for the first variable n=1 are fixed such that: $X_{1,min} < E_{1,1} < E_{1,2} < E_{1,3} < E_{1,4} < X_{1,max}$. For a better design, overlapping of adjacent membership functions is ensured.

Similarly all the 14 inputs are having 4 membership functions with similar shapes and values. Thus we have total number of 56 input parameters (vertices) constituting the first part of the individual. The number 56 results from equation 6 and is shown in the figure (4) below:

$$\text{Total number of membership functions} = \sum_{j=1}^{n} m_j \tag{6}$$

$E_{1,1}$	$E_{1,2}$	$E_{1,3}$	$E_{1,4}$	------- -------- -------------	$E_{14,4}$

Figure 4: Vertices of Membership Functions

These vertices are the input parameters whose values are to be modified to find the optimal solution. Right and left movement to these input parameters is governed by Eq 9.

The second part of the individual is set of consequents taken from a given of rule base as given by Eq 7. In this problem we considered 14 inputs each with 4 membership functions. With this a canonical fuzzy system will have maximum of 268435456(4*4*4*4*4*4*4*4*4*4*4*4*4*4=268435456) rules, which is a very large number and makes the system design very difficult.

Maximum number of rules (second constituent part of individual) $= \prod_{l=1}^{n} m_l$ (7)

In this model we have considered only 136 rules and hence 136 consequent values are to be identified for designing the system. It is observed that system with these many rules is giving the result to desired level of accuracy. The detail of these consequents is represented by figure (5) below:

R_1C	R_2C	R_3C	R_4C	------- -------- -------------	$R_{136}C$

Figure 5: Consequents

Thus the size of the individual in this problem is calculated by staying within the bounds as laid down by eq.(8)

Size of one individual (Sugeno model) = $\sum_{j=1}^{n} m_j + \prod_{l=1}^{n} m_l$ (8)

Here in this problem we have considered 136 consequents thus size of individual comes out to be:

Individual size = input parameters + consequents= 56+136= 192

Individual for this problem with 14 input each with 4 MFs and 136 rule consequents corresponding to a TSK type-0 model, is represented in figure (6) and figure (7)

$E_{1,1}$	$E_{1,2}$	----	$E_{n,m}$	----	$E_{14,4}$	R_{1C}	R_{2C}	R_{3C}	----	R_{136C}
1	2	3	---	---	56	57	58	----	----	192

Figure 6: Individual for the Fuzzy Model with 192 Genes

Columns 1-56 represent input parameters and 57- 192 represents the rule consequents.

Input Variable # 1	$E_{1,1}$	$E_{1,2}$	$E_{1,3}$	$E_{1,4}$
Input Variable # 2	$E_{2,1}$	$E_{2,2}$	$E_{2,3}$	$E_{2,4}$
----	---	---	---	---
----	---	---	---	---
Input Variable # 14	$E_{14,1}$	$E_{14,2}$	$E_{14,3}$	$E_{14,4}$

Rule Base (rule number)	R_1C	R_2C	R_3C	---	---	$R_{136}C$
R_1C: Consequent of Rule1; R_2C: Consequent of Rule2; and so on						

Figure 7: Representation of a TSK Type-0 Model by One Individual

The individual shown above in the figure (6) & (7) is a complete fuzzy system whose different parameter values are modified randomly to find out the best suited system with desired results. With this methodology system can be designed for any number of inputs with any number of membership functions. Movement of the membership functions is given as per the following.

For ensuring a movement of membership functions in the search space, we use the following equations:

new_population (i, j) = elite(i, j) ± (α+ (β- α)*ρ) (9) i= ith individual of population j = jth gene of ith individual

α = Lower movement limit β = upper movement limit

ρ= A randomly generated number with values between 0 to 1.

Computing Output of Each Individual

For evaluating performance of such systems many performance measures such as Root Mean Square Error (RMSE), Mean Square Error (MSE) etc. found in literature. In this case we used MSE (as given in Equation 3) as performance parameter for the system. The ideal value of MSE would be zero. For computing the MSE, both the actual output and the computed output of each individual is observed for all the 136 training data points and error is calculated as per the following eq 10.

$$\text{Error} = O_A - O_C \tag{10}$$

Where O_C is

$$\text{Computed output } (O_C) = \frac{\sum_{k=1}^{R} w_k\,(R_k C)}{\sum_{k=1}^{R} w_k} \tag{11}$$

w_k is the firing strength of the k^{th} rule and R_kC is the consequent of k^{th} rule.

And O_A = Actual output as given in training data set

For entire training data set MSE is computed. This gives the MSE of each individual, which acts as the fitness function for rating the fuzzy model.

SIMULATION AND RESULTS

In order to validate our approach of system identification we conducted 10 sets each consisting of 10 trials for each of simple and parallel BB-BC approaches and recorded the MSE for each of the evolved system. The iterations versus MSE graph for one of the trials with simple BB-BC is given in figure (8). We executed the program for 200 iterations. This trial run produced MSE of 0.0761937 in 230.391967 seconds.

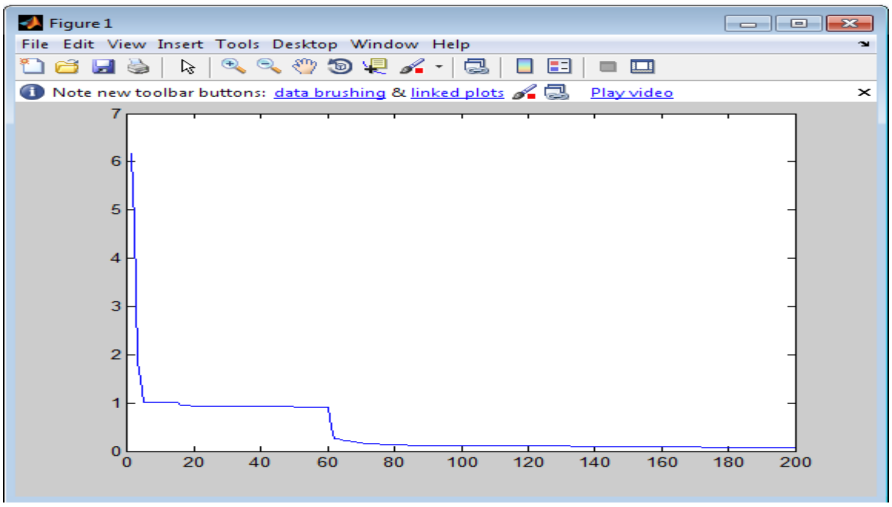

Figure 8: Iterations vs MSE for simple BB-BC Based Approach

Figure (9) presents the results for one of the trials for parallel BB-BC based approach. It shows a graph of number of Iterations Vs. MSE. In this trial we ran the program for 28 iterations and we recorded an MSE of 0.000 (zero) in 64.678327 seconds.

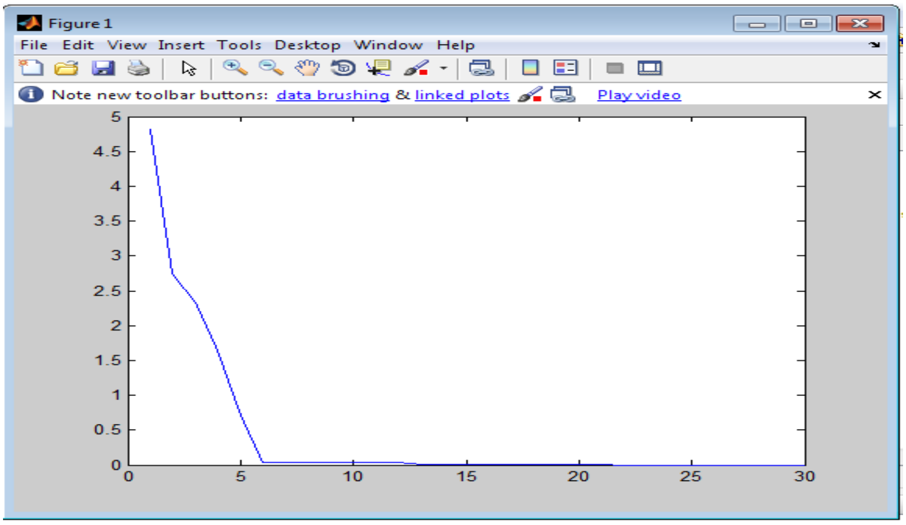

Figure 9: Iterations vs. MSE for Parallel BB-BC Based Approach

Comparison of the Performance of Simple BB-BC with Parallel BB-BC Algorithms

Table 2 and 3 given below present the performance comparison of two approaches. We conducted experiments with different combinations of number of individuals and iterations as shown in table 2. We observed that Simple BB-BC based modeling approach gave its best performance with a population size of 40 and 200 iterations. We conducted 10 sets each of 10 trials with these parameters and observed minimum, average and maximum MSE to be 00, 0.0505 and 0.1861 respectively. It is evident from the table 2 that minimum, average and maximum MSE with Parallel BB-BC was observed to be 0.0 in all the10 sets each consisting of 10 trials. We further conducted experiments to enumerate computing time.

As shown in table 3, for a given MSE goal of 0.00001 parallel BB-BC generated best, average and worst evaluation times of 51.49**,** 53 and 59.2 seconds respectively. With simple BB-BC the same were observed to be 124.98, 237 and 328 seconds respectively. It is amply clear from table 3 that as for as accuracy and computing time is concerned parallel BB-BC completely outperforms the simple BB-BC based fuzzy system modeling approach.

Table 2: Simple BB-BC V/S Proposed Parallel BB-BC Approach

Performance Measures MSE	Nind =15 Iterations =28	Nind =15 Iterations =150	Nind =15 Iterations =200	Nind =15 Iterations =250	Nind =20 Iterations =150	Nind =20 Iteration s=250	Nind =30 Iteration s=100	Nind =30 Iterations =200
Minimum	00	00	00	00	00	00	00	00
Average	00	0.7679	.4855	0.6360	0.407	0.4038	.3344	0.3305
Maximum	00	2.7316	2.120	2.7406	2.292	1.7749	1.6156	1.2483
Avg Time (sec)	64.7	70.31	92.83	115.78	128.09	154	99.005	182.79
	Simple BB-BC Approach							
	Nind=30 Iterations =250	**Nind =40 Iterations =20**	**Nind =40 Iterations =50**	**Nind =40 Iterations =100**	**Nind =40 Iterations =120**	**Nind =40 Iteration s=130**	**Nind =40 Iteration s=150**	**Nind =40 Iterations =200**
Minimum	00	0.1109	0.000	0.000	00	00	00	00
Average	0.3252	0.5096	0.3633	.2524	.2728	.2303	.2068	0.0505
Maximum	1.0077	1.366	1.267	1.720	1.247	1.435	1.7991	0.1861
Avg Time (sec)	234.61	26	63	126	151	165	190	237

Table 3: Comparison of Execution Time and MSE

Performance Measures	MSE			Execution Time for an MSE Goal of 0.00001		
	Minimum MSE	Average MSE	Maximum MSE	Worst Time (sec)	Average Time (sec)	Best Time (sec)
Simple BB-BC	00	0.0505	0.1861	328	236.18	**124.98**
Parallel BB-BC	00	00	00	59.2	53	**51.49**

CONCLUSIONS

This paper presented a new multi-population; BB-BC based model identification approach namely parallel BB-BC approach. We applied this approach to identify a 14 input, single output fuzzy system for evaluating the over-all rating of universities and institutes of higher learning. Each input variable consists of 4 membership functions. A canonical system could have consisted of 4^{14} = 268435456 rules. This rule explosion makes it difficult to identify a rating assignment system using knowledge driven approach. We used the available 136 point training data to identify a fuzzy model with 136 rules. We evolved the models using simple BB-BC as well as parallel BB-BC approaches.

For different parameter stings we conducted model identification experiment for 10 sets each consisting of 10 trials. Whereas for the given set of 136 training examples, simple BB-BC for its best set of trials identified the model with minimum, average and maximum MSE of 0.00, 0.0505 and 0.1861 respectively, parallel BB-BC identified the model with zero minimum, zero average and zero maximum MSE. We further observed that for a given MSE goal of 0.00001 or less over a set of 15 trials parallel BB-BC identified the model in minimum of 51.49 seconds. Average time taken over a set of 15 trials was 53 seconds.

The worst evolution time of the 15 trials was recorded to be 59.2 seconds. With simple BB-BC approach the same readings were observed to be 124.98, 237 and 328 seconds respectively. Thus one could easily conclude that parallel BB-BC is a much faster and more accurate algorithm than the simple BB-BC based approach. Further the both of these were able to evolve over all rating enumeration system from the given training data set. Evolving this model using knowledge driven approach could have been a very time consuming, tedious and tough task.

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