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ANN Model Identification: A BB-BC Optimization Algorithm Based Approach

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***Abstract*—** This paper proposes a new soft computing approach to artificial neural network (ANN) model identification. The new approach is based upon big bang big crunch (BB-BC) optimization algorithm .To test our approach we have identified two models one from control field namely rapid battery charger and second a rating system for institutes of higher learning. With about 20% of the total data being used for training the proposed approach was able to identify models successfully. In order to validate our proposed approach, we implemented the approach in the MATLAB and compared its training performance with 6 other well known classical training approaches namely Levenberg-Marquardt algorithm (LM), error back propagation(EBP), Resilent prop(RPROP), particle swarm optimization (PSO), ant colony optimization(ACO) and artificial bee colony(ABC). It was observed that BB-BC has faster convergence speed and produced better results than the other approaches.

***Keywords*—** Model Identification, ANN (Artificial Neural Network), Optimization.

I. INTRODUCTION

An ANN is a massively parallel distributive processing system made up of simple processing elements which has the ability to store experiential knowledge and later making it available for the use [1]. ANNs have a property of learning by examples, thus ANNs can be trained with known set of examples for a given problem before they are tested for their inference capability on unknown instances of a problem. These can therefore, identify the objects for which they are not previously trained. ANNs are characterized by properties such as mapping capabilities, pattern association, and generalization for tolerance and higher reliability. ANNs have been widely used in finance and banking, manufacturing, marketing, medicine, environment applications, pattern recognition, and control applications [2].

This paper proposes an iterative method of ANN model identification. The method is general in nature and can be applied to any other problem where ANNs can be applied. Based upon the proposed approach the paper first identifies a model to evaluate the performance of an institution of higher learning. The second example discussed in this paper is of a Rapid Battery Charger (RBC). Shakti et al. [3] presented an ANN based model for a Rapid Battery Charger (RBC). The method had high computational complexity and hence, was not suitable for larger systems. Khosla et al. [4] also discussed fuzzy system modeling for Rapid Battery Charger. Many methods for the ANN system training and design are available in literature [5-6]. In contrast to ANN model identification, literature is rich for fuzzy model identification from the given data set. Fuzzy model identification from given data set, based upon GAs [7-10], based upon bio-geography based optimization (BBO) [11-13], based upon ant colony optimization (ACO) [14-17], based upon particle swarm optimization (PSO) [18-20] and based upon big bang big crunch (BB-BC) [21-22] and parallel BB-BC [23] are available in literature. S Kumar et al. [24] presented fuzzy model identification using BB-BC and parallel BB-BC for overall rating and evaluation of institutions of higher learning. A Kalra et al. [25] proposed an optimized ANN model identification approach using two soft computing based approaches i.e. PSO and ABC for two different problems.

In this paper we present a new soft computing based ANN model identification approach. The approach is based upon BB-BC optimization algorithm. The system identification problem was formulated as minimization problem. The approach is used to find out the optimal values of synaptic weights, number of neurons and number of layers of the ANN based model. To validate our approach, we compare this new soft computing approach with 6 approaches i.e. EBP, LM, RPROP, PSO, ABC and ACO.

This paper consists of VII sections. Section II gives brief introduction to the two problems used for ANN system identification. Section III discusses the modeling process used for implementation. Section IV and V introduces BB-BC theory of evolution of universe and BB-BC based ANN system identification methodology. Section VI discusses the simulation, observations, results and comparison of the system identification by proposed approach. Section VII concludes the paper.

II. Example Used For Ann Model Identification

In this section we discuss ANN system design for two different problems, Rapid Battery Charger (RBC) and performance evaluation of Institutions of Higher Learning from the given training data set. The complete modeling of an ANN system consists of two processes: first the selection of ANN architecture in which number of hidden layers and the number of neurons in each hidden layer is to be decided. Second is the training of this ANN system by the given training data. The problem here is formulated as search and minimization problem. The optimization algorithms are applied in a way to automatically adjust the number of hidden layers, neurons in each of the hidden layer and identified values of synaptic weights in such a way so as to minimize the objective function i.e. MSE.

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}[\mathrm{OA} - \mathrm{OC}]2 \quad \ldots\ldots\ \ldots\ldots\ (1)$$

where OA is the actual output or desired output, OC is the computed output, N is the number of training examples used for model identification.

In the first example we discuss the evaluation system for the institutes of higher learning [24]. Figure 1 represents the block diagram of the desired model. This is a multi-input single output system. The names of input variables and other details of the system are mentioned in table 1. The second example is of Rapid Battery Charger (RBC) design problem [26].

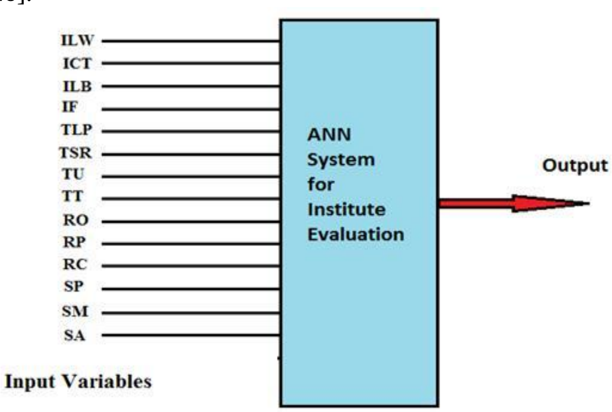

Figure 1. Block Diagram of ANN System for IRS

Table 1. Input variables for Institute Rating system (IRS)

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

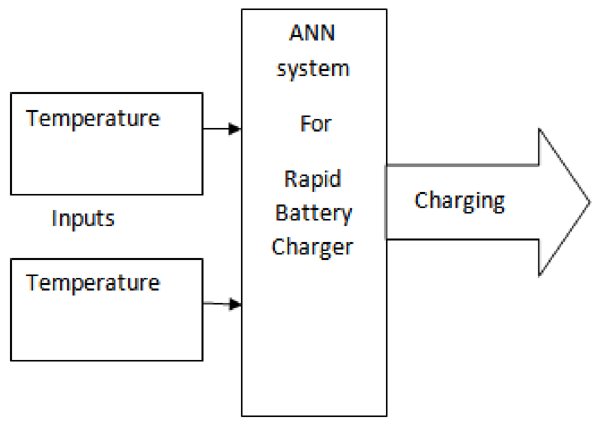

Figure. 2 Block Diagram of the Required ANN System for RBC

This is a two input and single output system and belongs to the control system category. The two inputs are (1) temperature (2) temperature gradient (temp_grad.) and charging current is the output for the system. Figure 2 shows the block diagram of the system to be identified.

III. Methodology

Modeling an ANN System is a complex process involving number of steps. This complexity further increases with the increase in the number of input parameters and number of hidden layers. The main steps to be followed for modeling a complete ANN model are given as below:-

1. Begin with number of hidden layers NH = 0.
2. Fix the number of neurons in each hidden layer. (Maximum hidden layers are 2).
3. Randomly initialize the weights of ANN.
4. For each training pattern, evaluate output and error between the computed and desired output.
5. Compute mean square error for the model (MSE).

6. Minimize the objective function (MSE) by adjusting the weights using proposed approach by embedding following modules for training: BB-BC, ACO, ABC, PSO, LM, EBP and RROP.
7. If MSE is acceptable (termination criterion is met) then go to step 9, else if number of hidden layers are non zero then increase the number of neurons in the hidden layers. After an upper limit of the number of neurons in the hidden layers has reached and if the performance is still not acceptable we increase the number of hidden layers.
8. Go to step 4.
9. Stop.

IV. Big Bang –Big Crunch Theory

The Big Bang Big Crunch (BB-BC) theory is an optimization technique based upon the theory of the evolution of the universe. In the Big Bang phase, energy dissipation produces disorder and in the Big Crunch phase, randomly distributed particles are drawn into an order. An optimization algorithm was proposed based on this called the Big Bang-Big Crunch optimization algorithm [27].The pseudo code of BB-BC is shown below:-

Begin

/* Big Bang Phase */

Generate a random set of NC candidates (population);

/* End of Big Bang Phase */

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

Compute the fitness value of all the candidate solutions;

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

/* Big Crunch Phase */

For guiding the new search compute the center of mass (x^c) using equation 2;

$$x^c = \frac{\sum_{i=1}^{np} \frac{1}{f^i} x^i}{\sum_{i=1}^{np} 1/f^i} \tag{2}$$

Where x^c = position of the CoM;

x^i = position of candidate i;

f^i = fitness function value of candidate i;

np = The population size in Big Bang phase.

Best fit individual can be chosen as the center of mass instead of using equation 2;

/* End of Big Crunch 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 3;

$$x^{new} = x^c + l(rand)/k \tag{3}$$

End while

End

V. BB- BC Optimization Based Algorithm for ANN System Identification

Big Bang-Big Crunch is one of the simplest optimization algorithms used in the soft computing. In this we discuss the algorithm for design and training ANN models for the above said two problems using this approach.

Nomenclature

Size of the individual = S

Number of individuals in each population = N Number of Inputs = NI

Number of Hidden Layers = NH

Max number of Hidden Layers = NHmax = j

Number of data points = NDP

Number of Neurons = NNI = kj Where I = 1 to j

Number of iterations = NT

Number of populations = NP

5.1 BB-BC optimization based ANN system identification Algorithm

1. Begin
   % initialize number of hidden layers%
2. for NH = 0: j (number of hidden layers: j<= 2)
   NN1max= NDP/3
3. for NN1 = 2: NN1max
   (number of neuron in the 1st hidden layer)
   NN2max = floor (NNmax*0.6)
4. for NN2 = 2 : NN2max
   (number of neuron in the 2nd hidden layer)

   Compute the size of individual as per the equations/criteria given below
5. If NH=0
   S = Number of inputs + 1= NI+1
6. elseif NH = 1
   S= NN1*(NI+2) + 1
7. elseif NH = 2
   S= NN1* (NI+1) + NN2 (NN1+2)+ 1
8. End
   /* Big Bang Phase Starts */
   % Initialize the Population %
   Generate a random set of N candidates (population); each individual consists of S genes
   /* End of Big Bang Phase */
9. for jj = 1: NT (number of iterations)
10. for ii = 1: N (population size)
11. for mm = 1: NDP (Number of Data points) for each data point evaluate the output of ANN and calculate the error between the desired and the computed output.
12. end (end of mm loop)
    Compute the MSE for each individual.
13. end (end of ii loop)

Sort the population from best to worst based on fitness (MSE) value.

14. For guiding the new search compute the center of mass (CoM) using equation 2 (mentioned above).
15. Best fit individual can be chosen as the center of mass instead of using Equation 2.
16. fitness of best fit individual = best_MSE
17. if best_MSE<= acceptable value then exit and display results

    Generate the next population around the best fit candidate by adding or subtracting normal random number whose value decreases as the iterations elapse using Equation 3(mentioned above).
18. end (end of jj loop)
19. end (NN2 = 2 : NN2max loop)
20. end (NN1 = 2: NN1max loop)
21. end (NH =1: J loop)

Display best fit candidate and its fitness.

The best fit candidate gives the optimum values of the weights for each layer such that MSE is minimal for the entire training set.

VI. Simulation Results And Discussions

To validate our proposed approach we implemented these algorithms in MATLAB on a DEL Laptop with Intel core i3 processor, running on Windows 7 platform. We have taken both data sets i.e RBC and IRS data from computational laboratory (CI lab) available at www.cilab.in. We used a battery data set consisting of total of 561 patterns and institute rating system data set consisting of 135 patterns to evolve the architecture as well as for training purpose. We used only about 20% data for training purpose. For each of the implemented approach we took 15 trials with 500, 1000, 2000, 5000 and 10,000 iterations and recorded the MSE of each evolved model. Table 2 shows the different parameters considered for ANN model identification. Table 3 and Table 4 compare the performance of proposed algorithm with EBP, RPROP, LM, ACO, ABC and PSO based model identification approaches for Rapid Battery Charger (RBC) and institute rating system (IRS). The value of MSE with this proposed approach has been found to be far superior then the other 6 algorithms.

Table 2. Parameters of RBC and IRS

Parameters	**Values for RBC**	**Values for IRS**
Size of population	10	10
Number of hidden layers	2	2
Number of neuron in first hidden layer	5	5
Number of neuron in first hidden layer	3	3
Number of iterations	500,1000, 2000 5000 , 10,000	500,1000, 2000 5000 , 10,000
Number of input variables	2	14

Table 3. Performance comparison of MSE with different approaches for Rapid Battery Charger (RBC) data

Performance Measures	**Iterations=500**						
	Model identification approach						
	PSO	**BBBC**	**ACO**	**EBP**	**RPROP**	**LM**	**ABC**
maximum MSE	**0.0401**	**0.0154**	**0.0193**	**0.1178**	**0.1171**	**1.0415**	**0.1191**
Mean MSE	**0.01893333**	**0.005422**	**0.014427**	**0.11756**	**0.1164**	**0.41166**	**0.113933**
Minimum MSE	**0.0046**	**0.000727**	**0.0118**	**0.117**	**0.1105**	**0.0212**	**0.1098**
Elapsed Time (sec)	**1.73358667**	**4.571813**	**5.940047**	**9.48534**	**8.492327**	**0.070707**	**16.14322**

	Iterations=1000						
	Model identification approach						
Performance Measures	**PSO**		**PSO**		**PSO**		**PSO**
maximum MSE	**0.0356**	**0.0224**	**0.0157**	**0.1177**	**0.117**	**0.2383**	**0.1182**
Mean MSE	**0.01741333**	**0.009638**	**0.01326**	**0.11742**	**0.11546**	**0.08066**	**0.1127**
Minimum MSE	**0.0059**	**0.000666**	**0.0114**	**0.1171**	**0.1043**	**0.0091**	**0.1077**
Elapsed Time (sec)	**4.24708**	**9.248847**	**10.54223**	**16.37903**	**14.74454**	**0.023947**	**37.54106**

Performance Measures	Iterations=2000						
	Model identification approach						
	PSO		PSO		PSO		PSO
maximum MSE	0.0418	maximum MSE	0.0418	maximum MSE	0.0418	maximum MSE	0.0418
Mean MSE	0.01432	Mean MSE	0.01432	Mean MSE	0.01432	Mean MSE	0.01432
Minimum MSE	0.0029	Minimum MSE	0.0029	Minimum MSE	0.0029	Minimum MSE	0.0029
Elapsed Time (sec)	7.27198	Elapsed Time (sec)	7.27198	Elapsed Time (sec)	7.27198	Elapsed Time (sec)	7.27198

Performance Measures	Iterations=5000						
	Model identification approach						
	PSO		PSO		PSO		PSO
maximum MSE	0.041	maximum MSE	0.041	maximum MSE	0.041	maximum MSE	0.041
Mean MSE	0.017727	Mean MSE	0.017727	Mean MSE	0.017727	Mean MSE	0.017727
Minimum MSE	0.0066	Minimum MSE	0.0066	Minimum MSE	0.0066	Minimum MSE	0.0066
Elapsed Time (sec)	36.71967	Elapsed Time (sec)	36.71967	Elapsed Time (sec)	36.71967	Elapsed Time (sec)	36.71967

Performance Measures	Iterations= 10000						
	Model identification approach						
	PSO		PSO		PSO		PSO
maximum MSE	0.0453	0.0165	0.0214	0.1177	0.1169	0.6716	0.1222
Mean MSE	0.02098	0.008527	0.01472	0.117407	0.113667	0.138187	0.114267
Minimum MSE	0.0023	0.0018	0.0118	0.1171	0.0967	0.0061	0.1088
Elapsed Time (sec)	109.5225	90.37113	98.74841	2423.294	173.4092	0.063533	270.8297

Table 4. Performance comparison of MSE with different approaches for IRS (institute rating system)

Performance Measures	Iterations=500						
	Model identification approach						
	PSO		PSO		PSO		PSO
maximum MSE	0.0351	maximum MSE	0.0351	maximum MSE	0.0351	maximum MSE	0.0351
Mean MSE	0.024273	Mean MSE	0.024273	Mean MSE	0.024273	Mean MSE	0.024273
Minimum MSE	0.0158	Minimum MSE	0.0158	Minimum MSE	0.0158	Minimum MSE	0.0158
Elapsed Time (sec)	1.074487	Elapsed Time (sec)	1.074487	Elapsed Time (sec)	1.074487	Elapsed Time (sec)	1.074487

Performance Measures	Iterations=1000						
	Model identification approach						
	PSO		PSO		PSO		PSO
maximum MSE	0.0349	maximum MSE	0.0349	maximum MSE	0.0349	maximum MSE	0.0349
Mean MSE	0.02206	Mean MSE	0.02206	Mean MSE	0.02206	Mean MSE	0.02206
Minimum MSE	0.0129	Minimum MSE	0.0129	Minimum MSE	0.0129	Minimum MSE	0.0129
Elapsed Time (sec)	3.181193	Elapsed Time (sec)	3.181193	Elapsed Time (sec)	3.181193	Elapsed Time (sec)	3.181193

Performance Measures	Iterations=2000						
	Model identification approach						
	PSO		PSO		PSO		PSO
maximum MSE	0.0336	maximum MSE	0.0336	maximum MSE	0.0336	maximum MSE	0.0336
Mean MSE	0.022127	Mean MSE	0.022127	Mean MSE	0.022127	Mean MSE	0.022127
Minimum MSE	0.0117	Minimum MSE	0.0117	Minimum MSE	0.0117	Minimum MSE	0.0117
Elapsed Time (sec)	7.302653	Elapsed Time (sec)	7.302653	Elapsed Time (sec)	7.302653	Elapsed Time (sec)	7.302653

Performance Measures	Iterations=5000						
	Model identification approach						
	PSO		PSO		PSO		PSO
maximum MSE	0.0372	maximum MSE	0.0372	maximum MSE	0.0372	maximum MSE	0.0372
Mean MSE	0.02316	Mean MSE	0.02316	Mean MSE	0.02316	Mean MSE	0.02316
Minimum MSE	0.0103	Minimum MSE	0.0103	Minimum MSE	0.0103	Minimum MSE	0.0103
Elapsed Time (sec)	42.92591	Elapsed Time (sec)	42.92591	Elapsed Time (sec)	42.92591	Elapsed Time (sec)	42.92591

Performance Measures	Iterations=10000						
	Model identification approach						
	PSO		PSO		PSO		PSO
maximum MSE	0.0322	maximum MSE	0.0322	maximum MSE	0.0322	maximum MSE	0.0322
Mean MSE	0.02026	Mean MSE	0.02026	Mean MSE	0.02026	Mean MSE	0.02026
Minimum MSE	0.0095	Minimum MSE	0.0095	Minimum MSE	0.0095	Minimum MSE	0.0095
Elapsed Time (sec)	176.154	Elapsed Time (sec)	176.154	Elapsed Time (sec)	176.154	Elapsed Time (sec)	176.154

Observations for RBC data:

The evolved model for RBC is simulated for 500, 100, 2000, 5000 and 10000 iterations. We conducted 15 trials for each of the iterations set. The performance of RBC model is placed as Table 3. For the set simulated with 500 iterations we observe that the BB-BC based proposed approach yielded the best results with mean MSE of 0.005422 followed by ACO with mean MSE of 0.014427. Further we observe that for the sets consisting of 500, 1000, 2000, 5000 and 10000 iterations BB-BC produced the best performance with mean MSE of 0.005422, 0.009638, 0.006124, 0.005959 and 0.008527.BB-BC was followed by ACO and PSO. We also observe that though LM algorithm was far behind as for as the accuracy was concerned. It converges quickly to a given performance. Figure 3 depicts the simulation graph of MSE Vs iterations for RBC data set with reference to Table 3 .This shows the comparison of BBBC approach with all other 6 algorithms on the basis of mean MSE.

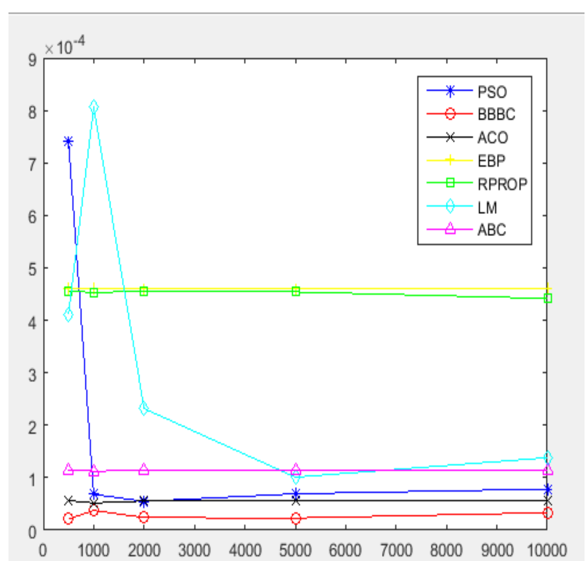

Figure 3. MSE v/s Iterations for Rapid Battery charger with BB-BC Algorithm

Observations for IRS data:

For IRS, we again observed the algorithm performance with the sets consisting of 500, 1000 and 2000 iterations. The observations are presented in table form. We observe that BB-BC approach produced the most accurate results with 0.000113, 5.22e-05, 0.000125, 0.000114 and 6.94e-05 for 500, 1000, 2000, 5000 and 10000 resp. Though LM was far behind on account of accuracy yet it was fastest to converge. Figure 4 depicts the simulation graph of MSE Vs iterations for IRS data set with reference to

Table 4 .This shows the comparison of BBBC approach with all other 6 algorithms on the basis of mean MSE.

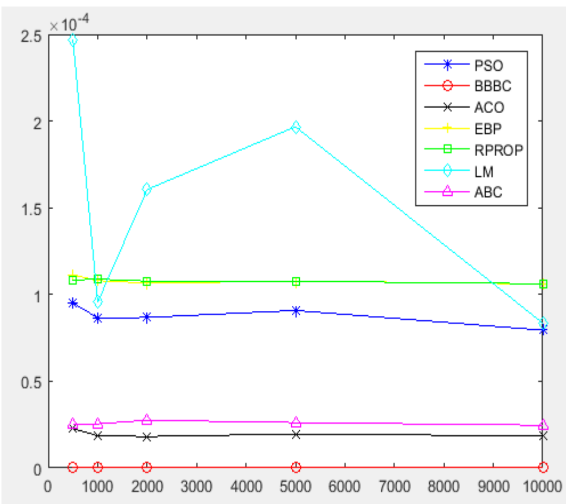

Figure 4. MSE v/s Iterations for Institutes Rating system with BB-BC Algorithm

VII. Conclusion and Future Scope

The paper presented a new BB-BC based model identification approach. We applied this approach to identify two models; the first one was a 2 input single output RBC chosen from the control system field. The second example was 14 input single output institute rating model. From the simulation results it is evident that for control system modeling problem the BB-BC based training gave the best performance as far as the accuracy was concerned. For the institute rating system example, for the all the sets of observations with 500, 1000, 2000, 5000 and 10000 iterations the BB-BC based training approach performed best with minimum MSE. Still when the numbers of iterations were raised to 5000 and 10000 we observed that BBBC based approach outperform all other approaches and produced best results with minimum MSE. This was followed by ACO based approach. As far as convergence time was concerned we observed that in all cases though LM based training approach was far behind on account of MSE it produced quickest of the results. Thus we conclude that for both the examples, on MSE performance parameter, BB-BC approach outperformed all of the other 6 algorithms.

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