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Optimization of Fuzzy Neural Networks using Mine Blast Algorithm for Classification Problem

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ABSTRACT

The integration of Fuzzy Neural Networks (FNNs) with optimization techniques has not only solved the issues "black box" in Artificial Neural Networks (ANNs) but also has been effective in a wide variety of real-world applications. Adaptive Neuro-Fuzzy Inference System (ANFIS) still needs effective parameter training and rules optimization methods to perform efficiently when the number of inputs increases. ANFIS accuracy depends on the parameters it is trained with and the drawbacks of gradients based learning of ANFIS using gradient descent and least square methods in two-pass learning algorithm. Many researchers have trained ANFIS parameters using metaheuristic, however, very few have considered optimizing the ANFIS rule-base. We propose an effective technique for optimizing ANFIS rule-base and training the network parameters using newly Accelerated modified MBA (AMBA) to convergence the speed during exploitation phase. The AMBA optimized ANFIS was tested on real-world benchmark classification problems like Breast Cancer, Iris, and Glass. The AMBA optimized ANFIS has also been employed to model real datasets. The performance of the proposed AMBA optimized ANFIS model was compared with the ones optimized by Genetic Algorithm (GA), Particle Swarm Optimization (PSO), MBA and Improved MBA (IMBA), respectively. The results show that the proposed AMBA optimized ANFIS achieved better accuracy with optimized rule-set in less number of function evaluations. Moreover, the results also indicate that AMBA converges earlier than its other counterparts.

Keywords: ANFIS; neuro-fuzzy; fuzzy system; Mine Blast Algorithm (MBA); optimization

1 Introduction

Various optimization techniques and learning algorithms have been used with Fuzzy Neural Network (FNN) to reduce the cost of learning, and achieving higher accuracy at the same time. Most of these algorithms require substantial gradient information, and may become difficult or unstable when the objective function and the constraints have multiple or sharp peaks. To improve learning capability of FNN, many researchers have optimized the training process by various metaheuristic algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO) or Ant Colonies, which are modeled on swarm intelligence [1, 2].

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In recent years, Adaptive Neuro-Fuzzy Inference System (ANFIS) has gained more attraction than other types of fuzzy expert systems. This is because the results obtained from ANFIS are sturdier than other fuzzy systems [3]. After designing and testing the ANFIS systems, Neshat *et. al.,* [4] found that ANFIS results were comparatively better than other fuzzy expert systems. However, when designing ANFIS based models, the major concern of researchers is to train its parameters efficiently so that enhanced accuracy can be achieved. On the other hand, Liu, Leng [2] and Petković *et. al.,* [5] also agree that tuning membership function (MF) parameters is more complex than the consequent parameters.

Mine Blast Algorithm (MBA) is recently introduced by Sadollah *et. al.,* [6], which has outperformed GA, PSO, and their variants in terms of convergence speed and better optimal solutions. Sadollah *et. al.,* [7] improved MBA and called it Improved MBA (IMBA). This paper further accelerates its convergence speed by modifying exploitation phase and calling the new variant as Accelerated MBA (AMBA).

The following section briefly explains ANFIS and its learning mechanism. Section 3 presents MBA algorithm and the proposed AMBA is introduced, followed by ANFIS training using AMBA in Section 4. The experimental results are given in Section 5. Section 6 makes conclusion of this study.

2 The Concept of ANFIS

Jang introduced ANFIS architecture in 1993 [8], which can approximate every plant with adequate number of rules using adaptive technique to assist learning and adaptation [2, 9]. Figure 1 shows five layer ANFIS architecture:

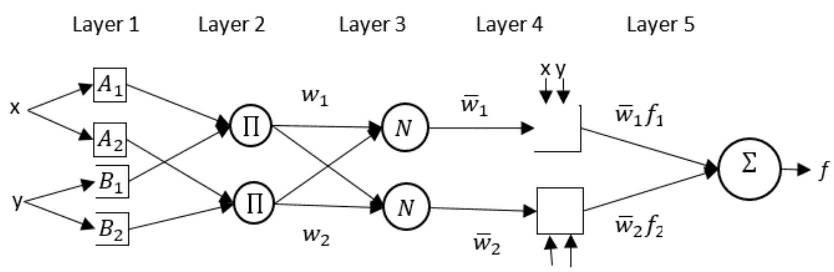

Figure 1. ANFIS Architecture (M. A. Shoorehdeli et al., 2009)

Layer 1: Every node i in this layer is adaptive MF, i.e., Triangle, Trapezoidal,

Gaussian, or generalized Bell function.

$$O_{1,i} = \mu_{A_i}(x), \qquad i = 1,2 \tag{1}$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \qquad i = 3,4 \tag{2}$$

Layer 2: These nodes are fixed and represent simple product ∏ to calculate firing

strength of a rule.

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2 \tag{3}$$

In this paper, the rules are generated using grid partitioning. The number of rules is m^n where m is the number of MFs in each input variable and n is the number of inputs to ANFIS.

Layer 3: Each node is fixed and represented as N in Figure 1. It normalizes firing strength of a rule from previous layer by calculating the ratio of the ith rule's firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \qquad i = 1,2. \tag{4}$$

where $\overline{w}$ is referred to as normalized firing strength of a rule.

Layer 4: These are consequent nodes which are identified during training. Each node has node function

$$f_i = p_i x + q_i y + r_i$$

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i), \qquad i = 1,2. \tag{5}$$

Layer 5: It is output node which does the summation of rules output

$$O_{5,i} = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\sum_{i=1}^{2} \overline{w_i} f_i}{w_1 + w_2} \tag{6}$$

ANFIS learns by adjusting all modifiable parameters using gradient descent (GD) and least squares estimator (LSE). The parameter update process uses a two pass learning algorithm as presented in Table 1.

Table 1. Two Pass Hybrid Learning Algorithm for ANFIS

	Forward Pass	**Backward Pass**
Antecedent Parameters	Fixed	GD
Consequent Parameters	LSE	Fixed
Signals	Node Outputs	Error Signals

In forward pass, consequent parameters are updated by LSE, and in backward pass, the premise parameters are updated using GD. Backward pass is influenced by back propagation (BP) algorithm of ANN which has the drawback to be likely trapped in local minima [9]. This paper explores the applicability of MBA after modifying its exploitation phase; calling it Accelerated MBA (AMBA). This paper presents an overview of MBA in the following section. The proposed AMBA is explained in the next section.

3 Mine Blast Algorithm – MBA

Sadollah et. al., [6] recently developed MBA as an optimization technique for handling complex optimization problems. This method is derived from the idea of explosion of mines, and thrown shrapnel pieces explode other mines by colliding with them. The most explosive mine (min or max f(x)) located at the optimal point X* is considered as optimal solution. The solution individuals in a population are shrapnel pieces (Ns).

The initial population is created by first shot point, represented by X_0^f

$$X_0 = LB + rand \times (UB - LB) \tag{7}$$

where X0, LB and UB are the generated first shot point, lower, and upper bounds of the problem, respectively. rand is a uniformly distributed random number between 0 and 1. Explosion of a landmine generates shrapnel pieces Ns which collide with other landmine at location X_{n+1}. The user of MBA can decide to start with multiple first shot points.

$$X^f_{n+1} = X^f_{e(n+1)} + \exp\left(-\sqrt{\frac{m^f_{n+1}}{d^f_{n+1}}}\right) X^f_n, \qquad n = 0,2,3,\ldots \tag{8}$$

$$X^f_{e(n+1)} = d^f_n \times rand \times \cos(\theta), \quad n = 0,2,3,\ldots \tag{9}$$

$$d^f_{n+1} = \sqrt{(X^f_{n+1} - X^f_n)^2 + (F^f_{n+1} - F^f_n)^2} \tag{10}$$

$$m^f_{n+1} = \frac{F^f_{n+1} - F^f_n}{X^f_{n+1} - X^f_n}, \qquad n = 0,2,3,\ldots \tag{11}$$

where $X^f_{e(n+1)}$, d^f_{n+1} and m^f_{n+1} are the location of exploding mine, the distance and the direction of the thrown shrapnel pieces in each iteration, respectively. In (9), θ is the angle of the shrapnel pieces. F is the objective function value for the point X in (10) and (11).

In MBA, the user defined parameter, called exploration factor μ, allows to randomly search for optimal solutions at small and large distances using (12) and (13).

$$d^f_{n+1} = d^f_n \times (|randn|)^2, n = 0,2,3,\ldots \tag{12}$$

$$X^f_{e(n+1)} = d^f_{n+1} \times \cos(\theta), \qquad n = 0,2,3,\ldots \tag{13}$$

Sadollah, Yoo [7] improved MBA to find optimal cost design for water distribution systems. The exploitation phase, defined in MBA, is modified by IMBA, which focuses on the solution closest to the best one so far. IMBA modifies (8) as below:

$$X^f_{n+1} = X^f_{e(n+1)} + \exp\left(-\sqrt{\frac{1}{D}}\right) \times \{rand\} \otimes \{X_{Best} - X_{best-1}\}, \; n = 0,1,3,\ldots \tag{14}$$

In (14), the perception of direction is replaced by moving to the best solution. The exponential term in this equation improves the obtained exploded point by including information from current best solution X_{Best} and previous best solution X_{best-1} and Euclidean distances between them in m dimensions.

$$D = \left[\sum_{i=1}^{m} (X_{iBest} - X_{i(best-1)})^2\right]^{1/2} \tag{15}$$

Unlike MBA, distance between shrapnel pieces are reduced by (16), only when there is no change in the value of the cost function.

$$d_n^f = \frac{d_{n-1}^f}{\exp\left(\frac{k}{\alpha}\right)}, \qquad n = 1,2,3, \ldots \tag{16}$$

where α and k are reduction constants and iteration number index, respectively.

3.1 Accelerated Mine Blast Algorithm – AMBA

The modification in exploitation equation by IMBA improves results, more quicker results could be achieved by having distance between current exploded point $X_{e(n+1)}$ and current best solution so far. The proposed modifications in (14) and (15) are illustrated below:

$$X_{n+1}^f = X_{e\,(n+1)} + \exp\left(-\sqrt{\frac{1}{D}}\right) \times \{rand\} \quad \otimes \{X_{Best} - X_{e\,(n+1)}\}, \quad n = 1,2,3, \ldots \tag{17}$$

$$\mathrm{D} = \left[\sum_{i=1}^{m} (\mathrm{X_{iBest}} - \mathrm{X_{e\,(n+1)}})^2\right]^{1/2} \tag{18}$$

where D represents Euclidean distances between current best solution $\mathrm{X_{iBest}}$ and current point of explosion $X_{e(n+1)}$ in m dimensions. The proposed approach did not use information of previous best location; therefore it accelerated the convergence of the algorithm. Hence, this new variant of MBA is referred to as Accelerated MBA (AMBA). To validate its performance, when training ANFIS network on benchmark classification problems, the results are compared with MBA and IMBA.

3.2 ANFIS Training using AMBA

In this paper, AMBA is employed to tune premise and consequent parameters of ANFIS. Each shrapnel piece of mine in AMBA represents a set of parameters comprising of both the MF parameters and the consequent part of the fuzzy rule. The performance validation criterion mainly focused on three measures: optimized rule-set of ANFIS, accuracy of ANFIS, and convergence speed of optimization algorithms. Optimized rule-set consisted of the potentially contributing rules which were extracted from the overall knowledge-base of ANFIS. The accuracy was measured in terms of Mean Square Error (MSE) between actual and the desired output. The speed of convergence of optimization algorithms was measured in number of iterations.

The fitness is defined as mean squared error (MSE) between actual output and the desired output, it can expressed as:

$$MSE = \frac{\sum_{i=1}^{m}(O - O_m^t)^2}{m}, \tag{19}$$

where MSE, O, O_m^t, and m are mean square error, ANFIS output, target output of mth training pair, and the size of training dataset, respectively.

The ANFIS network trained by AMBA algorithm is outlined as below Figure 2:

```
ANFIS Training using AMBA

begin
Initialize AMBA: N_s, μ, α, maxItr

Randomly initialize first shot point

while(maxItr, or the stopping criterion is not met)

for n=1 to N_s (Each shrapnel contains all ANFIS parameters)

  if n < μ then (Exploration phase)
      Calculate the updated position of shrapnel pieces using (12) and (13)
   else (Exploitation phase)
     Calculate the position of exploded mines using (9)

     Calculate the Euclidean distance between mines using (18)
     Update the position of shrapnel pieces using (17)
    end if
  Evaluate function value of shrapnel pieces and update CurrentBest using (19)
  Update θ

next
Reduce the distance of the shrapnel pieces adaptively using (16)
next explosion until stopping criterion
end
```

Figure 2. AMBA Algorithm

The datasets are partitioned into two sets: training and testing set. The partitioning of is performed randomly such that 75% reserved for training and 25% for testing purpose. For training ANFIS with standard MBA, IMBA and the proposed AMBA, Table 2 presents the initialization values.

Table 2. Specification of ANFIS and AMBA Algorithm MBA, IMBA, AMBA

Parameters	Value	ANFIS Parameters	Value
Number of first shot points ( )	1	Number of inputs	As per datasets mentioned in Table 2
Number shrapnel pieces ( )	15	Number of MFs for each input	3
Exploration Factor (		Type of MF	Guassian
Reduction Factor ( ) Maximum Iterations			
Objective Function	Mean Square Error (MSE)		

4 Experimental Results

This section provides the analysis and discussion on the performance of the proposed Accelerated Mine Blast Algorithm (AMBA) optimized ANFIS. The performance of the optimized ANFIS was evaluated in terms of accuracy while AMBA was evaluated based on convergence rate. The efficiency was evaluated using three real world classification problem datasets which were breast cancer, iris, and glass. These datasets were taken from University California Irvine Machine Learning Repository (UCIMLR) at Center for Machine Learning and Intelligent Systems. To validate superiority over other optimization methods, the proposed AMBA optimized ANFIS was compared with the one optimized by GA, PSO, MBA, and IMBA, respectively. For further evaluation, the ANFIS-based AMBA model was first trained and then tested on industry data acquired from SME Corporation Malaysia. The data was taken from SCORE (SME Competitiveness Rating for Enhancement), a software diagnostic system developed by SME Corporation Malaysia for ranking SMEs. The summarization drawn from the results is presented as follow.

Table 3 proves that the proposed AMBA outperformed other optimization algorithms in the list. AMBA optimized rule-set from 16 rules to 7 for achieving accuracy of 99.777%. Even though, the optimized rule-set of AMBA and IMBA was equal but AMBA achieved this rule-set in just 16 iterations as compared to IMBA did in 30. Moreover, the accuracy of IMBA was lesser than the proposed algorithm. This shows the proposed AMBA exhibited more speed of convergence than other algorithms. Here, MBA and PSO obtained 5 rules each in their optimized rule-set but the accuracy of PSO was better than MBA due to better membership functions parameters identified by PSO. GA performed least in this case as well. It was able to bring only 4 rules therefore losing accuracy.

Table 3: Summary of optimization algorithms' performances in Iris classification problem

CRITERIA	GA	PSO	MBA	IMBA	AMBA
Optimized Rule-Set	4	5	5	7	7
MSE	0.15533	0.089008	0.13505	0.034896	0.0044512
Accuracy %	92.233%	95.5496%	93.248%	98.255%	99.777%
Iterations To Converge	30	30	30	30	16

From the results shown in Table 4, it is worth noticing that AMBA performed better than GA, PSO, MBA, and IMBA. AMBA reduced the number of rules in the total rule-set of 512 rules to 58 and achieved 98.433% accuracy. It achieved highest accuracy among others optimization algorithms in just 9out of 30 iterations. PSO attained second best accuracy among others which was 97.636% with 24 rules. It consumed 23 iterations out of 30 to reach the target error for overall ANFIS output. MBA and IMBA consumed all 30 iterations and could not reach the target error. They demonstrated 97.347% and 97.086% accuracies with 59 and 62 rules, respectively. GA was once again lowest performer with 96.679% accuracy in this classification problem as well.

Table 4: Optimization algorithms' performances in Breast Cancer classification problem

CRITERIA	GA	PSO	MBA	IMBA	AMBA
Optimized Rule-Set	25	24	59	62	58
MSE	0.14643	0.047274	0.053058	0.058273	0.03134
Accuracy %	92.679%	97.636%	97.347%	97.086%	98.433%
Iterations To Converge	30	23	30	30	9

In Table 5, the performance of AMBA is compared with GA, PSO, MBA, and IMBA while training and optimizing ANFIS network. Even though AMBA and IMBA took same number of iterations (6) to meet target error tolerance (0.01) and both the algorithms brought 21 out of 512 rules in their optimized rule-set, but AMBA was able to achieve better accuracy than IMBA. MBA also reached error tolerance in 8 iterations unlike PSO and GA which consumed maximum iterations limit of 30. MBA, PSO, and GA reached the accuracy of 99.524%, 97.935%, and 97.837%, respectively, whereas they optimized the rule-set to 20, 13, and 7, respectively.

Table 5: Optimization algorithms' performances in Glass classification problem

CRITERIA	GA	PSO	MBA	IMBA	AMBA
Optimized Rule-Set	7	13	20	21	21
MSE	0.043267	0.041296	0.0095231	0.0087719	0.0027582
Accuracy %	97.837%	97.935%	99.524%	99.561%	99.862%
Iterations To Converge	30	30	8	6	6

As shown by the results in Table 6 below, the proposed AMBA optimized ANFIS network effectively than other optimization algorithms. It obtained optimum number of rules with higher accuracy in less number of iterations as compared to the original MBA, its variant IMBA, and GA and PSO as well. Table 4.3 reveals that AMBA retrieved 98 rules out of total 128 in forward pass with rule tolerance 0.0001. It achieved 99.764% which is higher than original MBA and its variant IMBA. As compared to the proposed AMBA, MBA and IMBA achieved less accuracy with less number of rules in more iterations; 99.681% with 96 rules and 99.613% with 91 rules, respectively, with 30 iterations each. However, they performed better than GA and PSO. GA performed least in this problem and could only reach to 42.251% with 34 rules. PSO showed better accuracy than GA, reaching 90.735% with 58 rules. Both the optimizers spent30 iterations.

Table 6: Optimization algorithms' performances in SME Classification problem

CRITERIA	GA	PSO	MBA	IMBA	AMBA
Optimized Rule-Set	29	58	96	91	98
MSE	0.4321	0.1853	0.0063873	0.0077464	0.0047279
Accuracy %	78.395%	90.735%	99.681%	99.613%	99.764%
Iterations To Converge	30	30	30	30	16

5 Conclusion

A new variant of MBA, so called AMBA, has been proposed in this paper. AMBA is integrated with ANFIS for training the premise and consequent parameters to achieve minimum error difference between the desired and actual output. The findings from the results, obtained from several experiments conducted on real-world benchmark problems, indicate that the proposed AMBA can efficiently train ANFIS network. The proposed AMBA reduces the computational cost by eliminating the cost of maintaining the previous best solution. It only uses current best solution and the available candidate solution. Because of this modification, AMBA shows the ability of converging quicker as compared to the standard MBA, and the improved variant IMBA. Even though, MBA is a potential optimization algorithm, it can still be improved by modifying exploitation phase and distance reduction policy.

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