ABSTRACT

The performance of Neural Networks (NN) depends on network structure, activation function and suitable weight values. For finding optimal weight values, recently, computer scientists show the interest in the study of social insect's behavior learning algorithms. Chief among these are, Ant Colony Optimization (ACO), Artificial Bee Colony (ABC) algorithm, Hybrid Ant Bee Colony (HABC) algorithm and Global Artificial Bee Colony Algorithm train Multilayer Perceptron (MLP). This paper investigates the new hybrid technique called Global Artificial Bee Colony-Levenberg-Marquardt (GABC-LM) algorithm. One of the crucial problems with the BP algorithm is that it can sometimes yield the networks with suboptimal weights because of the presence of many local optima in the solution space. To overcome GABC-LM algorithm used in this work to train MLP for the boolean function classification task, the performance of GABC-LM is benchmarked against MLP training with the typical LM, PSO, ABC and GABC. The experimental result shows that GABC-LM performs better than that standard BP, ABC, PSO and GABC for the classification task.

Keywords: Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Global Hybrid Ant Bee Colony, Hybrid Ant Bee Colony (HABC) Algorithm, Swarm Intelligence

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INTRODUCTION

Artificial Neural Networks (ANNs) are the most novel and powerful artificial tool suitable for solving combinatorial problems such as prediction, forecasting and classification (Daqi & Yan, 2005; de A. Araújo, 2011; Ghazali, Jaafar Hussain, Mohd Nawi, & Mohamad, 2009). NNs are being used extensively for solving universal problems intelligently like continuous, discrete, telecommunications fraud detection and clustering (Charalampidis & Muldrey, 2009; Hilas & Mastorocostas, 2008; Mielenzuk & Tyrych, 1993). Ns are being applied for different optimization and mathematical problems such as classification, object and image recognition, signal processing, temperature and weather forecasting and bankruptcy (Aussem, Murtagh, & Sarazin, 1994; Chaudhuri & Bhattacharya, 2000; Chen, Duan, Cai, & Liu, 2011; Uncini, 2003).

There are several techniques used for NNs favourable performance for training ANN such as evolutionary algorithms (EA), Multi-objective hybrid evolutionary algorithms (Qasem, Shamsuddin, & Zain, 2012; Tallón-Ballesteros & Hervás-Martínez, 2011), Genetic algorithms (GA) (Blanco, Delgado, & Pegalajar, 2001; García-Pedrajas, Ortiz-Boyér, & Hervás-Martínez, 2006; Geretti & Abramo, 2011), Particle swarm optimization (PSO) (Al-Shareef & Abbod, 2010; Hong-Bo, Yi-Yuan, Jun, & Ye, 2004; Hongwen & Rui, 2006), deferential evolution (DE) (Slowik & Bialko, 2008; Subudhi & Jena, 2011), an colony optimization (ACO) (Ashena & Moghadasi, 2011; Blum & Socha, 2005), BP d improved BP algorithm (Nawi, Ransing, & Ransing, 2006; Yan, Zhongjun, & Jiayu, 2010). These techniques are used for initialization of optimum weights, parameters, activation function, and selection of a proper network structure.

The main task of BP algorithm is to update the network weights for minimizing output error using BP processing because the accuracy of any approximation depends upon the selection of proper weights for the neural networks (NNs). It has high success rate in solving many complex problems, but it still has some drawbacks, especially when setting parameter values like initial values of connection weights, value for learning rate, and momentum. If the network topology is not carefully selected, the NNs algorithm can get trapped in local minima, or it might lead to slow convergence or even network failure. In order to overcome the disadvantages of standard BP, much global optimization population-based technique[20], GA (Geretti & Abramo, 2011), improved BP (Nawi, et al., 2006), DE (Slowik & Bialko, 2008), BP-ant colony (Chengzhi, Yifan, Lichao, & Yang, 2008), and PSO (Hongwen & Rui, 2006).

Artificial Bee Colony (ABC) (D. Karaboga & Akay, 2007), he Hybrid Ant Bee Colony (HABC) (H. SHah, R. Ghazali, N. M. Nawi, & M. M. Deris, 2012b), Improved Artificial Bee Colony (IABC) (H. Shah & Ghazali, 2011), G-HABC (H. Shah, R. Ghazali, N. M. Nawi, & M. M. Deris, 2012b); Hybrid Global Artificial Bee Colony Algorithm (Rozaida et al., 2013) and the Global Hybrid Ant Bee Colony (HABC) algorithm (Habib SHah, et al., 2012b), ar population-based algorithms that can provide the best possible solutions for different mathematical problems by using inspiration techniques from nature. A common feature of population-based algorithms is that the population consisting of feasible solutions to the difficulty is customized by applying some agents on the solutions depending on tuipon information of their robustness. Therefore, the population is encouraged towards improved solution areas of the solution space.

Population-based optimization algorithms are categories into two sections namely evolutionary algorithm (EA) (Xinyan & Jianguo, 2011), and I-based algorithm (Aydin, Wu, & Liang, 2010). In EA, the major plan underlying this combination is to take the weight matrices of the ANNs as individuals, to change the weights by some operations such as crossover and mutation, and to use the error produced by the NNs as the fitness measure that guides selection (Yan-fei & Xiong-min, 2010). In S based algorithm, ABC has the advantage of global optimization and easy recognition. It has been successfully used.
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