FEED-FORWARD NEURAL NETWORKS TRAINING: A COMPARISON BETWEEN GENETIC ALGORITHM AND BACK-PROPAGATION LEARNING ALGORITHM

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ABSTRACT. This study discusses the advantages and characteristics of the genetic algorithm and back-propagation neural network to train a feed-forward neural network to cope with weighting adjustment problems. We compare the performances of a back-propagation neural network and genetic algorithm in the training outcomes of three examples by referring to the measurement indicators and experiment data. The results show that the back-propagation neural network is superior to the genetic algorithm. Also, the backpropagation neural network has faster training speed than the genetic algorithm. However, the back-propagation neural network has the shortcoming of overtraining, while the genetic algorithm does not. The experiment result proves that the back-propagation neural network yields better outcomes than the genetic algorithm.

 ${\bf Keywords:}\ {\bf Back-propagation}\ neural network, Genetic algorithm, Feed-forward neural network$

1. Introduction. Artificial neural networks are biologically inspired classification algorithms that consist of an input layer of nodes, one or more hidden layers and an output layer. Each node in a layer has one corresponding node in the next layer, thus creating the stacking effect [1]. Artificial neural networks are the very versatile tools and have been widely used to tackle many issues [2-6]. Feed-forward neural networks (FNN) are one of the popular structures among artificial neural networks. These efficient networks are widely used to solve complex problems by modeling complex input-output relationships [7,8].

However, FNNs often end up being over trained. They adopt trials-and-errors to seek possible values of parameters for convergence of the global optimum. The learning process of an FNN cannot guarantee the global optimum, sometimes trapping the network into the local optimum. The back-propagation learning algorithm (BPLA) is a widely used method for FNN learning in many applications. It has the great advantage of simple implementation [9]. In addition, many studies have indicated that genetic algorithms (GA) can be successfully applied to identity global optimizations of multidimensional