LEARNING ENHANCEMENT OF RADIAL BASIS FUNCTION NETWORK WITH PARTICLE SWARM OPTIMIZATION

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"To my beloved mother, father, wife, son, brothers and sisters, thanks for your encouragement, support and understanding. To all my lecturers and friends, nice knowing you all and always remember our sweet memory"

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ABSTRACT

Back propagation (BP) algorithm is the most common technique in Artificial Neural Network (ANN) learning, and this includes Radial Basis Function Network. However, major disadvantages of BP are its convergence rate is relatively slow and always being trapped at the local minima. To overcome this problem, Particle Swarm Optimization (PSO) has been implemented to enhance ANN learning to increase the performance of network in terms of convergence rate and accuracy. In Back Propagation Radial Basis Function Network (BP-RBFN), there are many elements to be considered. These include the number of input nodes, hidden nodes, output nodes, learning rate, bias, minimum error and activation/transfer functions. These elements will affect the speed of RBF Network learning. In this study, Particle Swarm Optimization (PSO) is incorporated into RBF Network to enhance the learning performance of the network. Two algorithms have been developed on error optimization for Back Propagation of Radial Basis Function Network (BP-RBFN) and Particle Swarm Optimization of Radial Basis Function Network (PSO-RBFN) to seek and generate better network performance. The results show that PSO-RBFN give promising outputs with faster convergence rate and better classifications compared to BP-RBFN.

ABSTRAK

Algoritma Rambatan Balik (ARB) merupakan kaedah yang lazim digunakan dalam Rangkaian Saraf Buatan (RSB), dan ini termasuk juga Rangkaian Fungsi Asas Terpusat (RFAT). Namun begitu, terdapat banyak kelemahan pada rangkaian ARB seperti kadar penumpuan yang perlahan, dan sering terperangkap di dalam minima tempatan. Bagi mengatasi masalah ini, Pengoptimuman Partikel Berkelompok (PPB) dilaksanakan bagi meningkatkan keupayaan pembelajaran dan prestasi rangkaian RSB dari aspek kadar penumpuan dan ketepatan. Dalam Rangkaian Rambatan Balik Fungsi Asas Terpusat (ARB-RFAT), terdapat banyak elemen yang perlu dipertimbangkan. Ini termasuk penentuan bilangan nod input, nod tersembunyi, nod output, parameter bagi kadar pembelajaran, bias, ralat minimum, dan fungsi keaktifan. Ke semua elemen ini mempengaruhi kepantasan pembelajaran RFAT. Oleh yang demikian, kajian ini melaksanakan teknik PPB yang digabungkan dengan RFAT bagi meningkatkan prestasi pembelajaran rangkaian. Dua algoritma bagi ralat pengoptimuman untuk ARB-FRAT dan PPB-FRAT dibangunkan bagi tujuan menjana dapatan prestasi yang tegar bagi kedua-dua rangkaian tersebut. Hasil kajian mendapati bahawa dapatan daripada PPB-RFAT memberikan keputusan yang menyakinkan dengan kadar penumpuan yang pantas dan ketepatan pengelasan yang baik berbanding ARB-RFAT.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BMI	Body Mass Index
BP	Back Propagation
FPG	Fasting Plasma Glucose
GA	Genetic Algorithm
GAP-RBFN	Growing and Pruning Radial Basis Function Network
HDL	High Density Lipids
HRPSO	Hybrid Recursive Particle Swarm Optimization
LDL	Low Density Lipids
LMS	Least Mean Squares
MIMO	Multi-Input, Multi-Output
NFCM	Normalized Fuzzy C-Mean
OPA	Optimal Partition Algorithm
PSO	Particle Swarm Optimization
PSO-RBFN	Particle Swarm Optimization Radial Basis Function Network
QPSO	Quantum-Behaved Particle Swarm Optimization
RBF	Radial Basis Function
RBFN	Radial Basis Function Network
RLS	Recursive Least Squares
ROLS	Recursive Orthogonal Least Squares
SI	Swarm Intelligence
SOM	Self-Organizing Map
SVD	Singular Value Decomposition

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Radial Basis Function (RBF) Networks form a class of Artificial Neural Networks (ANNs), which has certain advantages over other types of ANNs, such as better approximation capabilities, simpler network structures and faster learning algorithms. The RBF Network is a three layer feed forward fully connected network, which uses RBFs as the only nonlinearity in the hidden layer neurons. The output layer has no nonlinearity and the connections of the output layer are only weighted, the connections from the input to the hidden layer are not weighted (Leonard *et al.*, 1991).

We can view the design of a RBF Network as a curve-fitting (approximation) problem in a high-dimensional space. From this viewpoint, learning is accomplished by finding a surface in a multi-dimensional space. This surface is used to interpolate the test data. RBF Network is a fully connected network and generally is used as a classification tool. In a RBF model, the layer from input nodes to hidden neurons is unsupervised and the layer from hidden neurons to output nodes is supervised (Bishop, 1995). The transformation from the input to the hidden space is nonlinear, and the transformation from the hidden to the output space is linear. The hidden neurons provide a set of “functions” that constitute an arbitrary “basis” for the input patterns. These are the functions known as called radial basis functions (Qu *et al.*, 2003).

Due to their better approximation capabilities, simpler network structures and faster learning algorithms, RBF Networks have been widely applied in many science and engineering fields. RBF Network is three layers feedback network, where each hidden unit implements a radial activation function and each output unit implements a weighted sum of hidden units' outputs. Its training procedure is usually divided into two stages. First, the centers and widths of the hidden layer are determined by clustering algorithms such as K-means, vector quantization, decision trees, and self-organizing feature maps. Second, the weights connecting the hidden layer with the output layer are determined by Singular Value Decomposition (SVD) or Least Mean Squares (LMS) algorithms (Liu *et al.*, 2004).

The primary significance for ANN is the ability of the network to learn from its environment and to improve its performance through learning (Haykin, 1999). Learning is a process of modifying the weights and biases to the neurons and continued until a preset condition is met such as defined error function. Learning process is usually referred as training process in ANN. The objective of training process is to classify certain input data patterns to certain outputs before testing with another group of related data. The back Propagation (BP) algorithm is commonly used learning algorithm for training ANN (Zweiri *et al.*, 2003). BP algorithm is used in ANN learning process for supervised or associative learning. Supervised learning learns based on the target value or the desired outputs. During training, the network tries to match the outputs with the desired target values. Other algorithm that usually use is Genetic Algorithm (GA) which is one of the famous evolutionary technique in ANN learning.

Clustering algorithms are able to find cluster centers best representing data distribution. Hence clustering algorithms have been successfully used in training RBF Networks. Optimal Partition Algorithm (OPA) is used to determine the centers and widths of RBFs. The research is compared in terms of the performance of the RBF Networks evolved by seven different clustering techniques (Chen and Qin, 2006). In most traditional algorithms, such as the K-means, the number of cluster centers need to be predetermined, which restricts the real applications of the algorithms. In addition to the K-means algorithm, several algorithms, such as

Genetic Algorithm (GA) and Self-Organizing Maps (SOM) have been used in clustering. Another computational intelligence method is called Particle Swarm Optimization (PSO) has been applied to data clustering (Cui, 2005).

PSO algorithm was originally designed by Kennedy and Eberhart in 1995, the idea was inspired by the social behavior of flocking organisms. The algorithm belongs to the broad class of stochastic optimization algorithm that may be used to find optimal (or near optimal) solutions to numerical and qualitative problems. PSO uses a population of individuals to probe promising regions of the search space. The population in this context is called a "swarm" and the individuals are called "particles". Each particle moves in the search space with a velocity that is dynamically adjusted according to its own flying experience and its companions' flying experience and retains the best position it ever encountered in memory. The best position ever encountered by all particles of the swarm is also communicated to all particles. Depending on the topology, in the local variant, each particle can be assigned to a neighborhood consisting of a predefined number of particles.

1.2 Problem Background

In this section, RBF Network and PSO will be discussed in terms of their usage from the previous studies.

1.2.1 RBF Network

RBF Network is defined as an ANN, which uses RBF as activation functions. They are used in function approximation, time series prediction, and control. RBF Network forms special neural network architecture is constructed of three layers, namely input, hidden, output layer. The input layer is made up of source nodes that connect the network to its environment. The second layer, the only hidden layer of the network, applies a non-linear transformation from the input space to a hidden space. The nodes in the hidden layer are associated with centers, which character the structure of network. The response from a hidden unit is activated through a RBF, such as Gaussian function. The output layer is linear supplying the response of the network to the activation pattern applied to the input layer and serves as a summation unit.

What is the problem in RBF Network? In RBF Network, different layers perform different tasks. Therefore, it is useful to separate the optimization of the hidden unit and output layer of the network by using different techniques. The parameters of the RBF Networks are the center and the influence field of the radial function and the output weight (between the intermediate layer's neurons and those of the output layer).

So we can take a two-step training strategies to train them respectively. The First step is called unsupervised learning used to determine the center and widths of the RBF (structure identification stage) by different algorithms such as k-mean clustering and the nearest neighbor's algorithms respectively. The Second step is called supervised learning used to determine the connections weights between the hidden layer and the output layer (parameters estimation stage) by different algorithms such as least mean squares algorithm and gradient based methods. This is a time consuming procedure, as it requires evaluation of many different structures based on trial and error procedure.

Another drawback is the centers of hidden units are determined only based on local information. It is desirable combined the structure identification with parameters estimation as a whole optimization problem. However, this problem cannot be solved easily by the standard optimization methods. An interesting alternative for solving this complicated problem can be offered by recently developed swarm intelligent strategies. Genetic algorithms (GA), the typical representative among others, have been successfully utilized for the selection of the optimal structure of RBF Network. But GA have some defects such as more predefined parameters, more intensive programming burden etc. (Ding *et al.*, 2005).

Venkatesan *et al.* (2006) have used RBF Network for pattern recognition and classification for diagnosis of diabetes mellitus and compare the results with MLP Network and logistic regression. Based on their results, it is proven that RBF Network has a better performance than other models. On the other hand, Zhang *et al.* (2004) had applied two real problems in biomedical domain which were breast cancer and gene to RBF Network with GAP algorithm called Growing and Pruning Radial Basis Function Network (GAP-RBFN). The Results showed that, for the classification problems with continuous low dimensional input samples, GAP-RBF can achieve a better or at least a similar generalization performance with a much more compact structure and a higher training speed compared with other ANN methods.

The application RBF Network for time series forecasting has been done by Huang *et al.* (2003). He used a divide-and-conquer learning approach for RBF Network (DCRBF), which was a hybrid system consisting of several sub-RBF Networks. Since this system divided a high-dimensional modeling problem into several low dimensional ones, its structural complexity was generally simpler than a conventional RBF Network. The results showed that the proposed approach had faster learning speed with slightly better generalization ability.

1.2.2 Particle Swarm Optimization (PSO)

PSO is a heuristic technique suited for search of optimal solutions and based on the concept of swarm. Kennedy and Eberhart originally designed the PSO algorithm in 1995. PSO has roots in two methodologies. Its links to Artificial Life in general, and to bird flocks, fish schools and swarm theory in particular are very evident. Nonetheless, PSO is also tied to Evolutionary Computation, namely to Genetic Algorithms (GAs) and Evolutionary Programming. Particle Swarm has two primary operators: Velocity update and Position update. During each generation each particle is accelerated toward the particles previous best position and the global best position. At each iteration, a new velocity value for each particle is calculated based on its current velocity, the distance from its previous best position, and the distance from the global best position.

Why PSO is an attractive and important for Learning? PSO is an optimization tool, combines local search methods with global search methods, attempting to balance exploration and exploitation. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust.

PSO has been used to face the problem of classification of instances in multiclass databases by Falco *et al.* (2006). A class prototype is represented in a multi-dimensional space by a centroid; PSO is used to find the optimal positions of all the class centroids. The results show that PSO is on average quite effective in facing classification problems. Lee *et al.* (2005) have used PSO and GA for excess return evaluation in stock market. Based on their experiment, it is proven that PSO algorithm is better compared to GA. PSO can reach the global optimum value with less iteration; keep equilibrium versus GA and show the possibility to solve the complicated problem using only basic equation without crossover, mutation and other manipulation as in GA.

Mohaghegi *et al.* (2005) have used BP and PSO for training a RBF Network based on neuroidentifier for power system. The training algorithms have been applied only for updating the output synaptic weight matrix, and in both cases the centers and widths of the neurons in the hidden layer are derived using an offline clustering method. The results show that PSO algorithm is better compared to BP in terms of robustness and the efficiency in finding the optimal weights for the RBFN neuroidentifier, Furthermore, PSO algorithm has proven to be efficient even for a reduced number of particles, thus the computational effort is comparable and even less significant than BP. PSO as a reliable algorithm for training such a neural network.

Sierakowski *et al.* (2005) have used PSO algorithm for multi-step-ahead prediction using RBF Network using k-means for clustering and optimized by pseudo-inverse and PSO. The results show that RBFN can be a powerful tool to predict temporal series and to study complex and chaotic behavior. It's possible to realize that the use of PSO in optimizing the centers generated by k-means has considerably increased the results, increasing the robustness of RBFN.

Ding *et al.* (2005) have used a novel PSO algorithm with matrix encoding for training RBF Network models in nonlinear system identification. The results showed that the RBF Networks produced by the PSO algorithm possess more parsimonious structure and achieve smaller prediction error compared with those obtained using the k -means two stage training algorithm.

Chen *et al.* (2006) were proposed supervised mean subtractive clustering algorithm to evolve RBF Networks and the evolved RBF acts as fitness evaluation function of PSO algorithm for feature selection. The method performs feature selection and RBF training simultaneously. Experimental results show that the proposed methods are effective in reducing the feature size, the structural complexity of the RBF Network, and even the classification error rates.

1.3 Problem Statement

In BP-RBF Network, there are many elements to be considered such as the number of input, hidden and output nodes, learning rate, momentum rate, bias, minimum error and activation function. All these elements will affect the convergence of RBF Network learning. As mentioned before, PSO can be used to determine some parameters and provide the best pattern of weight in order to enhance the RBF Network learning.

The whole optimization problem requires minimization of the error function. This is rather difficult using the traditional optimization techniques, especially due to the presence of the number of units in the hidden layer. PSO algorithm can be implementing to obtain the convergence speed and the classification accuracy of RBF Network learning as well as other type of optimization problems. Therefore this study will investigate the performance of the PSO-based learning algorithm for RBF Network in terms of individual structure and fitness function related to the learning behavior.

The research questions of this study can be stated as:

1. Could PSO algorithm enhance learning capability of RBF Network?
2. How significant is PSO in optimizing the RBF Network?
3. How effective is the PSO fitness function in enhancing the performance of RBF Network?

1.4 Project Aim

This study aims to investigate the effective of PSO in RBF Network compared to BP-based RBF Network in terms of convergence rate, correct classification and fitness function related to the RBF Network learning enhancement.

1.5 Project Objectives

The objectives of this study have been identified as below.

1. To develop PSO-based learning algorithm for RBF Network.
2. To analyze the significant of PSO parameters in optimizing the Network by minimizing the cost function.
3. To enhance RBF Network learning by integrating PSO error function minimization.

4. To compare the results between PSO-RBFN and BP-RBFN in terms of convergence rate and classification result.

1.6 Project Scope

In order to achieve the objectives stated above, the scope of this study is limited to the following:

1. Five datasets which are XOR, Balloon, Cancer, Iris and Ionosphere have been used to get the results for both algorithms.
2. The performance of PSO learning algorithm for RBF Network will be compared to BP algorithm.
3. The PSO and BP programs are customized, developed and applied to RBF Network using Microsoft Visual C++ 6.0.

1.7 Significance of Project

The performance between PSO-based RBF Network and BP-based RBF Network is analysed, thus we can determine which method is better for RBF Network learning. This is important to show that PSO can be successfully used to solve difficult problems.

1.8 Report Organization

This report is divided into five chapters: Chapter 1 provides an introduction of the project including the problem background, the problem statement, objectives and the scope. Chapter 2 reviews the literature on previous studies related to the project, it discusses RBF Network, PSO and learning problems. Chapter 3 covers the methodology of the research, which focuses on the application of the PSO algorithm on optimization of RBF Network learning. Chapter 4 presents and discusses the data analysis and explains the experiments. The conclusions and suggestions for future work are explained in Chapter 5.

REFERENCES

Ahmed T. (2004). *Adaptive Particle Swarm Optimizer for Dynamic Environments.* The University Of Texas: Master Thesis.

Al-kazemi B. and Mohan C.K. (2002). Training Feedforward Neural Network Using Multi-phase Particle Swarm Optimization. *Proceeding of the 9th International Conference on Neural Information Processing*. 5: 2615-2619.

Arisariyawong S. and Charoenseang S. (2002). Dynamic Self-organized Learning in Complexity Growing of Radial Basis Function Networks. *Industrial Technology, 2002. IEEE ICIT '02. 2002 IEEE International Conference*. 1: 655-660.

Ben Kröse and Patrick van der Smagt (1996). *An Introduction to Neural Networks*. The University of Amsterdam.

Bishop C. M. (1995). *Neural Networks for Pattern Recognition*, Oxford University Press, Oxford, p. 164.

Castellanos A., Blanco A. M. and Palencia V. (2007). Application of Radial Basis Neural Networks for Area Forest. *International Journal "Information Theories & Applications"*. 14: 218-222.

Chen C.-Y., Feng H.-M. and Ye F. (2007), Hybrid Recursive Particle Swarm Optimization Learning Algorithm in the Design of Radial Basis Function Networks. *Journal of Marine Science and Technology*. 15(1): 31-40.

Chen J. Y. and Qin Z. (2006). Training RBF Neural Networks with PSO and Improved Subtractive Clustering Algorithms. *Springer-Verlag*. 4233: 1148 – 1155.

Chi W., Zhou B., Shi A., Cai F., and Zhang Y. (2004). Radial Basis Function Network for Chaos Series Prediction. *Springer-Verlag*. 3174: 920-924.

Cui X. H., Polok T. E. (2005). Document Clustering Using Particle Swarm Optimization. *Swarm Intelligence Symposium, 2005. SIS 2005. Proceedings 2005 IEEE*. IEEE: 185-191.

Ding H., Xiao Y., and Yue J. (2005). Adaptive Training of Radial Basis Function Networks Using Particle Swarm Optimization Algorithm. *Springer-Verlag*. 3610: 119 – 128.

Eberhart R. and Shi Y. (2001). Particle swarm optimization: Developments, applications and resources. *In Proceedings of the 2001 Congress on Evolutionary Computation*. IEEE. 1: 81-86.

Falco D. I., Cioppa D. A. and Tarantino E. (2007). Facing classification problems with Particle Swarm Optimization. *Applied Soft Computing*. 7: 652 – 658.

Gao H., Feng B., Hou Y. and Zhu L. (2006). Training RBF Neural Network with Hybrid Particle Swarm Optimization. *Springer-Verlag*. 3971: 577 – 583.

Guerra F. A. and Coelho L. d. S. (2005). Radial Basis Neural Network Learning Based on Particle Swarm Optimization to Multistep Prediction of Chaotic Lorenz's System. *Proceedings of the Fifth International Conference on Hybrid Intelligent Systems*. IEEE: 521-523.

Guerra F. A., Coelho L. d. S. (2008). Multi-step ahead nonlinear identification of Lorenz's chaotic system using radial basis neural network with learning by clustering and particle swarm optimization. *Chaos, Solutions and Fractals*. ScienceDirect. 35(5): 967-979.

Gudise V. G. and Venayagamoorthy G. K. (2003). Comparison of Particle Swarm Optimization and Backpropagation as Training Algorithms for Neural Networks. *Swarm Intelligence Symposium, 2003. SIS '03. Proceedings of the 2003 IEEE*. IEEE: 110 - 117.

Haykin S. (1999). *Neural Network. A Comprehensive Foundation*. 2nd Ed: Prentice Hall.

Huang R. and Cheung Y. (2003). A Fast Implementation of Radial Basis Function Networks with Application to Time Series Forecasting. *Springer-Verlag*. 2690: 143–150.

Kennedy J. and Eberhart R. (2001), Swarm Intelligence. Morgan Kaufmann Publisherrs, Inc. San Franscisco California

Lee S. J., Lee S., Chang S. and Ahn H. B. (2005). Comparison of GA and PSO for Excess Return Evaluation in Stock Markets. *Springer-Verlag*. 3562: 221-230.

Leonard J.A., Kramer M. A. (1991). Radial basis function networks for classifying process faults. *Control Systems Magazine*. IEEE. 11(3): 31-38.

Lin L. I. (2005). *Particle Swarm Optimization for Solving Constraint Satisfaction Problems*. Simon Eraser University: Master Thesis.

Liu Y., Zheng Q., Shi Z., and Chen J. (2004). Training Radial Basis Function Networks with Particle Swarms. *Springer-Verlag*. 3173: 317-322.

Luger George F. (2002). *Artificial Intelligence: Structures and Strategies for Complex Problem Solving*. 4th ed. Addison-Wesley/Pearson Education Limited, Harlow, England: 417-473.

Merwe D. V. D. and Engelhrecht, A. (2003). Data Clustering using Particle Swarm Optimization. *The 2003 IEEE congress on Evalutionary computation*. December 8 12. IEEE. 1: 215–220.

Mohaghegi S., Valle Y. d., Venayagamoorthy G. K. and Harley R. G. (2005). A Comparison of PSO and Backpropagation for Training RBF Neural Networks for Identification of A Power System With Statcom. *Swarm Intelligence Symposium, 2005. SIS 2005. Proceedings 2005 IEEE*. IEEE: 381-384.

Omran H. G. M., Engelbrecht P. A. and Salman A. (2005). Dynamic Clustering using Particle Swarm Optimization with Application in Unsupervised Image Classification. *Transactions on Engineering, Computing and Technology*. 9: 199-204.

Osuna R.G. (2005). *Lecture 13: Validation, Intelligent Sensor System, Wright State University*. http://research.cs.tamu.edu/prism/lectures/iss/iss_l13.pdf.

Palmer A., Mantano J.J. and Sese A. (2005). Designing an artificial neural network for forecasting tourism time series. *Tourism Management*. ScienceDirect. 27(5): 781-790.

Qu M., Shih F. Y., Jing J., Wang H. (2003). Automatic Solar Flare Detection Using MLP, RBF and SVM. *Springer-Verlag*. 217(1): 157-172.

Qin Z., Chen J., Liu Y. and Lu J. (2005). Evolving RBF Neural Networks for Pattern Classification. *Springer-Verlag*. 3801: 957 – 964.

Reynolds C. W. (1987). Flocks, herds and schools: a distributed behavioral model. Comput. Graphics. 21 (4): 25–34.

Rumelhart D.E. and McClelland J.L. (1986). *Parallel Distributed Processing: Explorations in The Microstructure of Cognition*. Vol 1. MIT press, Cambridge, MA.

Shi Y. and Eberhart R. (1998). A Modified Particle Optimizer. *Proceedings of the 1998 IEEE World Congress on Computational Intelligence*. May 1998. IEEE: 69-73.

Shi Y. (2004). Particle Swarm Optimization. *IEEE Neural Network Society*: 8-13.

Sierakowski C. A., Guerra F. A. and Coelho L. d. S. (2005). Particle Swarm Optimization Approach for Multi-Step-Ahead Prediction Using Radial Basis Function Neural Network. *Proceedings of 16th IFAC World Congress*.

Sun J., Xu W., and Liu J. (2006). Training RBF Neural Network via Quantum-Behaved Particle Swarm Optimization. *Springer-Verlag*. 4233: 1156 – 1163.

Vakil-Baghmishah M. T. and Pavesic N. (2004). Training RBF networks with selective backpropagation. *Nerocomputing*. ScienceDirect. 62: 39 – 64

Van den Bergh F. (1999). Particle Swarm Weight Initialization In Multi-Layer Perceptron Artificial Neural Networks. *Accepted for ICAI*. Durban, South Africa.

Van den Bergh F. and Engelbrecht A. P. (2000). Cooperative Learning in Neural Networks using Particle Swarm Optimizers. *South African Computer Journal*. (26): 84-90.

Venkatesan P. and Anitha S. (2006). Application of a radial basis function neural network for diagnosis of diabetes mellitus. *Current Science*. 91(9): 1195-1199.

Wang X. G., Tang Z., Tamura H. and Ishii M. (2004). A modified error function for the backpropagation algorithm. *Neurocomputing*. 57: 477-488.

Yao X. (1993). A review of evolutionary artificial neural networks. *International Journal of Intelligent Systems*. 4: 203-222.

YU D.L., Gomm J.B. and Williams D. (1997). A Recursive Orthogonal Least Squares Algorithm for Training RBF Networks. *Neural Processing*. 5: 167–176.

Zhang C., Shao H., Li Y. (2000). Particle Swarm Optimization for Evolving Artificial Neural Network. *Systems, Man, and Cybernetics, 2000 IEEE International Conference* . 4: 2487-2490.

Zhang G., Patuwo B.E. and Micheal Y.H. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*. 14: 35-62.

Zhang R., Sundararajan N., Huang G., and Saratchandran P. (2004). An Efficient Sequential RBF Network for Bio-Medical Classification Problems. *Neural Networks, 2004. Proceedings. 2004 IEEE International Joint Conference.* 3: 2477-2482.

Zweiri Y.H., Whidborne J.F. and Sceviratne L.D. (2002). A Three-term Backpropagation Algorithm. *Neurocomputing*. 50: 305-318.