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A new hybrid evolutionary based RBF networks method for forecasting time series: A case study of forecasting emergency supply demand time series

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ABSTRACT

Improving time series forecasting accuracy has received considerable attention in recent years. This paper presents a new hybrid evolutionary algorithm for determining both architecture (input variables and neurons of hidden layer) and network parameters (centers, width and weights) of radial basis function neural networks (RBFNNs) simultaneously. Our proposed algorithm generates new architecture applying genetic algorithm (GA). Modified adaptive particle swarm optimization (APSO) is used to determine the training parameters efficiently. Inertia weight and acceleration coefficients in APSO are adapted by swarm status. Since PSO algorithms suffer premature convergence, especially when global best is found, mutation operator is applied to overcome the drawback. Comparing the performance of the proposed approach with several benchmark time series modeling and algorithms shows that the proposed method is able to predict time series more accurately than others. Finally, proposed GA–APSO based RBFNNs method is applied to predict the demand of emergency supplies after earthquake in the East Azerbayjan in 2012 in Iran. The results show that the proposed evolving RBF based method can be applied to forecast the emergency supply demand time series successfully with the automatically selected nodes and inputs.

1. Introduction

A time series is a set of statistics, usually collected at regular intervals. Over the past several decades much research have been done to develop and improve the time series forecasting models (Zhang, 2003). Artificial neural networks (ANNs) have been widely used to forecast time series and solve different engineering problems (Wu and Chau, 2013; Khashei and Bijari, 2012; Sharma and Srinivasan, 2013; Maffini Santos et al., 2014; Ismail et al., 2013). The features of ANNs make them very useful tool, defined by Zhang (2001) as follows: First, ANNs are nonparametric methods and do not need any assumptions about the underlying model. Second, ANNs are nonlinear models. This makes them flexible and powerful tool in modeling complex real world systems which are often nonlinear. Third, ANNs are universal function approximators that they can approximate any complex function with desired accuracy given a large enough input data.

Recently, radial basis function neural networks (RBFNNs) became attractive in practical applications such as forecasting (Yu et al., 2008) fault detection (Chai and Qiao, 2014) and others (Langoni et al., 2006; Park et al., 2011) due to their simpler design process and improved generalization ability compared to neural networks (Yu et al., 2011; Xie et al., 2011). However, there are some drawbacks in architecture selection including: input variables and neurons of hidden layer and determining network parameters (centers, width and weights) of such networks (Pen et al., 2006). Most of the works in the literature consider two phase learning with fixed structure (Schwenker et al., 2001). However, according to the previous works (Pen et al., 2006; Schwenker et al., 2001) considering both architecture and network parameters selection simultaneously has shown better results.

The problem of optimizing the network size and parameters of RBF neural networks is a mixed integer hard optimization problem that there is no analytical method available to solve it and in the literature it has been suggested to be considered (Aladag, 2011). There has been quite a number of papers that only focus on determining the parameters of RBF networks for time series forecasting while optimizing the number of hidden nodes and the input variables is not considered. Evolutionary algorithms have

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also been applied to optimize only the training phase of RBF networks (Lacerda et al., 2005; Leung et al., 2003; Lee and Ko, 2009; Sheta and De Jong, 2001; Harpham et al., 2004; Sheikhan et al., 2013). There are a few papers considering optimization of both structure and network parameters of RBFNNs simultaneously. Yu et al. (2009) propose a hybrid algorithm which combines particle swarm optimization and back propagation algorithm for training RBFNs. Du and Zhang (2008) develop a novel encoding scheme to train RBF networks by GA. This encoding scheme includes both the architecture and the parameters of the RBF networks. Leung et al. (2003) developed an improved GA for tuning the structure and parameters of neural network. They have showed that their proposed GA works better than standard GA.

As noted before, since the problem of optimizing the network size and parameters of RBF neural networks is a mixed integer hard optimization problem, we develop a novel hybrid evolutionary algorithm to optimize architecture and network parameters simultaneously. Genetic algorithm (GA) binary coding scheme recently developed by Du and Zhang (2008) is applied for representing architecture of RBF neural networks. For each chromosome (architecture) modified version of adaptive particle swarm optimization (APSO) algorithm developed by Zhan et al. (2009) is used as the training method of RBF networks. APSO is also incorporated by a mutation operator to overcome the premature convergence of PSO algorithm.

Natural disasters are full of uncertainties and usually accurate estimation of needed resources is difficult and crucial. In recent years prediction methods have been used to forecast emergency supplies demand after natural disasters. To our knowledge a few of the conducted research uses statistical methods or artificial intelligence for forecasting demand of emergency supplies after disaster such as Xu et al. (2010). Song et al. (1996) also apply fuzzy evaluating techniques for forecasting earthquake damages. Due to complicated structure of the problem the most used technique is expert judgment method (Xu et al., 2010). We apply the proposed GA–APSO based RBFNNs method for forecasting demand of emergency supplies after the earthquake in 2012 in Iran because the corresponding time series contains nonlinearity and irregularity due to characteristics of natural disasters.

The reminder of paper is as follows. In Section 2, we provide a detailed discussion of RBFNNs. Overview of PSO algorithm and proposed modified APSO are presented in Section 3. A novel hybrid evolutionary based RBF networks method is presented in Section 4. Experimental results in real case study and comparison with previous methods are given in Section 5. Section 6 contains conclusion.

2. RBF networks

A neural network is a “massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. ANNs are synthetic networks that imitate biological neural networks” (Haykin, 2007).

Many of ANN based applications use the multi-layer perceptron (MLP) with classic back-propagation (BP) learning algorithm to determine a prediction model. The BP algorithm adjusts ANN's weight parameters in the training phase such that the model outputs are aligned closely with the desired output (target). To predict accurately on unseen data in the problem, part of the available data is stored as the testing set to evaluate ANN's generalization ability. The BP algorithm tends to trap in the local optimum solutions instead of reaching the global optimum (Hegazy and Ayed, 1998).

Recently, RBFNNs became attractive in practical applications (Yu et al., 2011) because of their simple design and more computationally efficient process with improved generalization

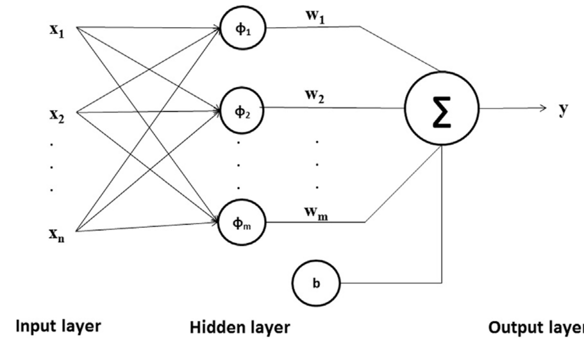

Fig. 1. Architecture of the RBF network.

ability, compared to neural networks (Xie et al., 2011). RBF networks were introduced into the neural network literature by Broomhead and Lowe (1988), in which their main applications are function approximation and time series forecasting, as well as classification or clustering tasks.

2.1. Structure of RBF networks

RBFNNs have architecture similar to one hidden layer perceptron networks and consist of three layers. The input layer is only used to connect the network to its environment. The hidden layer contains a number of nodes, which apply a nonlinear transformation to the input variables, using a radial basis function. The output layer is linear and serves as a summation unit. The typical structure of an RBF neural network with only one output node is depicted in Fig. 1.

Numbers of nonlinear hidden units are usually significantly larger than the number of network inputs, so input space is transformed into higher dimensional space, where patterns become linearly separable (Cover, 1965).

The problem of multivariable time series prediction can be expressed as follows (Yu et al., 2011). For a forecasting problem, the inputs of the network are past lagged observations. Consider a set of N data points in the input space R^d and their target values in R.

$$D = \{(x_i, y_i) \in R^d \times R, \quad i = 1, 2, \ldots, N | f(x_i) = y_i\} \tag{1}$$

This data set can be used to characterize a function with one dimensional output values. The RBF approach to approximate a interpolation function f involves the use of M functions φ_j. The φ_j is a RBF and defined as follows:

$$\varphi_j(u) = \varphi_j(||u - c_j||) \tag{2}$$

The c_js are the locations of the centers of the radial basis functions, ||.|| denotes the norm, and u is the network input vector.

Unlike the randomly generated initial parameters (weights) in traditional neural networks, it is important in RBF networks to find proper initial network parameters such as locations of centers of hidden units because their performances are critically dependent on the choice of the centers (Chen et al., 1991; Huang et al., 2005). Typical approaches to this problem belong to one of the categories introduced by Kalouptsidis and Theodoridis (1993). The approximation of the function f may be expressed as a linear combination of the RBFs

$$\hat{f}(u) = \sum_{j=1}^{M} w_j \varphi_j(||u - c_j||) \tag{3}$$

There are six basis functions, which are recognized as having useful properties for RBF networks (Harpham and Dawson, 2006). Here we use Gaussian basis function which is the most popular and widely used radial basis function used by many other authors for forecasting of time series (Schwenker et al., 2001; Chng et al.,