FORCASTING OF RENEWABLE ENERGY LOAD WITH RADIAL BASIS FUNCTION (RBF) NEURAL NETWORKS

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Abstract: This paper focus on radial- basis function (RBF) neural networks, the most popular and widely-used paradigms in many applications, including renewable energy forecasting. It provides an analysis of short term load forecasting STLF performances of RBF neural networks. Precisely, the goal is to forecast the DPcg (difference between the electricity produced from renewable energy sources and consumed), for short- term horizon. The forecasting accuracy and precision, in capturing nonlinear interdependencies between the load and solar radiation of these neural networks are illustrated and discussed using a data based obtain from an experimental photovoltaic amphitheatre of minimum dimension 0.4kV/10kW.

1 INTRODUCTION

Research efforts on artificial neural networks (ANNs) for forecasting are considerable. The literature is vast and growing. In the forecasting works, the term “forecasting” is called also prediction or prognosis. This reveals that there is no consensual acceptation of term. Due to these facts, in this article the forecasting will be associated with the notion of prediction and will determine the future state of the analyzed system the closest possible to the future real state of the system (O. Dragomir. 2010).

Different forecasting time horizons are employed in prediction approaches (day-ahead, hour-ahead) in relation with the application. Short term load forecasting (STLF) samples the information on an hourly (or half hourly) basis, or even a daily basis (for load peak prediction) so is defined as varying from a few minutes up to a few weeks ahead. This type of forecasting is important because the national grid requires DPcg (difference between the electricity produced and consumed) values at any moment in the day. Traditionally, hourly forecasts with a lead time between one hour and seven days are required for the scheduling and control of power systems. From the perspective of the system operators and regulatory agencies, STLF is a source of primary information for safe and reliable operation of the system. For producers also, this type of forecasting is a basic tool for determining the optimal utilization of generators and power stations, as some facilities are more efficient than others.

In this context, this paper provides architecture of RBF, capable to forecast the DPcg for short- term horizon. The proposed structures are applied on a data based obtain from an experimental photovoltaic amphitheatre of minimum dimension (0.4kV/10kW), located in the east-centre region of Romania, more precisely in the city of Targoviste (ICOP- DEMO.

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1998). The paper is organized as follows: first, it provides an overview of RBF neural networks, which are the most popular and widely-used paradigms in many applications, including energy forecasting. Second, a particular RBF architecture is proposed to forecast the DPcg. The forecasting accuracy and precision in capturing nonlinear interdependencies between the load and solar radiation of these one are illustrated and discussed.

2 RBF NEURAL NETWORKS

Actually, the systems are very complexes and the conditioning parameters that influence system functioning are significant. In these cases it is very difficult to determine any sort of model for forecasting purposes. The advantages and the drawbacks of ANNs, leaded us to RBF neural networks as reference tools for our approach of short term energy balance forecasting.

The RBF network is commonly used for the purpose of modeling uncertain and nonlinear functions. Utilizing RBF networks or modeling purposes could be seen as an approximation problem in a high-dimensional space (Zemouri. 2002). A key feature of RBF is that the output layer is nerely a linear combination of the hidden layer signals, there being only one hidden layer.Therefore, RBF networks allow for a much simpler weight updating procedure and subsequently open up greater possibilities for stability proofs and network robustness in that the network can be described readily by a set of nonlinear equations

In RBF networks, determination of the number of neurons in the hidden layer is very important because it affects the network complexity and the generalizing capability of the network. If the number of the neurons in the hidden layer is insufficient, the RBF network cannot learn the data adequately; on the other hand, if the neuron number is too high, poor generalization or an over learning situation may occur (Liu, 2004). The position of the centers in the hidden layer also affects the network performance considerably (Simon. 2002), so determination of the optimal locations of centers is an important task. In the hidden layer, each neuron has an activation function. The gaussian function, which has a spread parameter that controls the behavior of the function, is the most preferred activation function. The training procedure of RBF networks also includes the optimization of spread parameters of each neuron. (Martinez. 2008) studied the best approximation of Gaussian RBF neural networks with nodes uniformly spaced. Afterwards, the weights between the hidden layer and the output layer must be selected appropriately. Finally, the bias values which are added with each output are determined in the RBF network training procedure. In the literature, various algorithms are proposed for training RBF networks, such as the gradient descent (GD) algorithm (Karayiannis, 1999) and Kalman filtering (KF) (Simon. 2002). (Ferrari. 2009) studied the multiscale approximation problem with hierarchical RBF neural networks. But these above RBF methods have the same defects of the backpropagation algorithm. They are either instability or complicate and slow. They have proved that the connection weight of RBF neural networks can be obtained through various learning algorithms; therefore the weight has certain instability.

3 PERFORMING STLF WITH RBF

The forecasting performances of RBF neural networks in load forecasting, are illustrated using a dataset with 240 data points {y(t), u(t)}, representing the radiation [W/m2] (mean value=0.9255 and standard deviation= 97.6705) and the DPcg [kW] (mean value=0.8156 and standard deviation= 130.9313) , obtained from a Solar Amphitheatre (ICOP-DEMO. 1998) and (F. Dragomir *et al*. 2010). The data used are normalized before starting the training session and de-normalized at the end of the training.

RBF neural network, used for performing STLF, has an input layer, one hidden layer and an output layer. The neurons in the hidden layer contain Gaussian transfer functions, whose outputs are inversely proportional to the distance from the center of the neuron (see Table 1).

Table 1: RBF parameters.

Architecture	RBF
Number inputs	1
Number layers	1 hidden layer with 5 radbas neurons 1 output layer with with purelin neurons
Transfer functions	gaussian - hidden layer purelin- output layer
Performance functions	MSE (Mean Squared Error) MAE (Mean Absolute Error)
Initial MSE goal	0.0098
Initial spread	0.02719

For the dataset, simulations are repeated 8 times.

Dataset is divided into train and test subsets. 60% of the data set is selected as the training data and remained data set is selected as the testing data. For each run, the number of neurons, deviations of the radial units, MAE (Mean Absolute Error) and MSE (Mean Square Error) are computed in order to reach the MSE goal 0.0115. The measurements based on MSE are suggestive, because it penalizes the huge forecasting errors. The MAE is considered that would be an adequate error measure if the loss function were linear (and linear in percentage, not in absolute error); however, recent studies and the experience of system operators indicates that the loss function in the load forecasting problem is clearly nonlinear, and that large errors may have disastrous consequences for a utility.

The goal of the tests is, given training and test data, to choose the input parameters MSE goal, spread and Hmax (hidden layer neurons number) to minimize MSE value.

The input parameters have been initialized with: MSE goal= 0.0098, the minimum distance between clusters of different classes MNDST =0.8156, spread0 = 0.2719 and Hmax0 = 60.

In training phase the following steps are repeated until the network's mean squared error falls below goal or the maximum number of neurons are reached: 1) the network is simulated, 2) the input vector with the greatest error is found 3) a radbas neuron is added with weights equal to that vector and 4) the purelin layer weights are redesigned to minimize error.

Table 2: Train and test results of RBF simulations.

Train			Test	
Spread	H	MSE (*10-3)	MAE (*10-1)	MSE (*10-1)
0.027	25	7.4966	4.9542	6.4668
0.127	15	7.8996	1.9653	1.4197
0.227	11	9.6653	0.6805	0.1354
0.327	8	6.4121	0.5751	0.0766
0.427	7	9.3638	0.5456	0.0786
0.527	7	8.6819	0.8884	0.1448
0.627	6	8.8989	0.5706	0.0730
0.727	7	6.1955	0.9046	0.1332

The general characteristics of the RBF training are illustrated in Table 2.

Firstly, it was investigated how the spread of the hidden layer base function affects the network's performance (see Figure 1). The initial downward trend of MSE due to spread growth isn't the same all over training set. This indicates the need for consideration of a second parameter in the evaluation of RBF training performance. This is the number of neurons in the hidden layer.

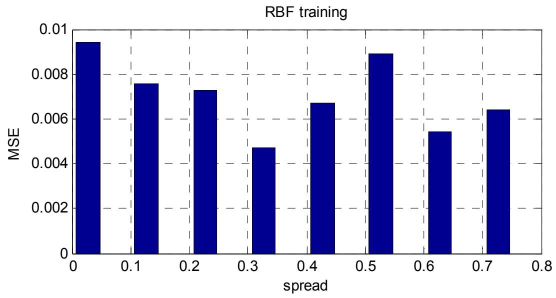

Figure 1: MSE in relation with spread for training phase.

The number of neurons in the hidden layer is very important in design issue of an RBF network. Therefore, the experiments have been conducted on different RBF networks which has 6 neurons to 25 neurons located in the hidden layer. Using more neurons than that is needed causes an over learned network and moreover, increases the complexity of the RBF network (see Table 2).

The predictions made by RBF neural network over the test dataset in relation with the measured outputs (targets) are illustrated in Figure 3. The small number of test data has a bad influence over the forecasting accuracy (see Figure 2). The output of the RBF network is a measure of distance from a decision hyper plane, rather than a probabilistic confidence level The quality of the possible solutions are calculated using MSE and MAE.

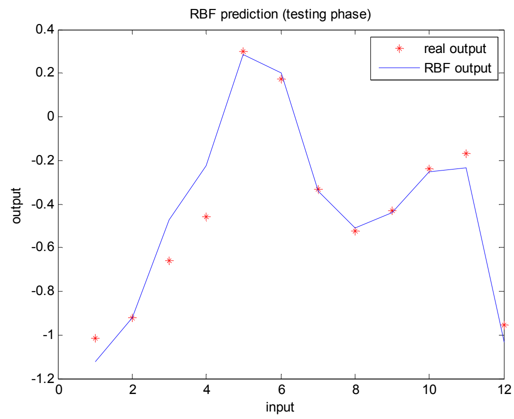

Figure 2: RBF outputs vs. targets in testing phase.

Figure 3 indicates the RBF testing errors with the help of MAE and MSE. The Figure 3 shows that, the growth of spread values until 0.3 has a big influence over MAE and MSE values. These ones decreas a lot, from 4.9542 to 0.5751 MAE and from 6.4668 to 0.0766 MSE. The trend change when the spread reach 0.327 value. The error values increase and indicate that the optimal values for spread and number of neurons in hidden layer has to be locate.

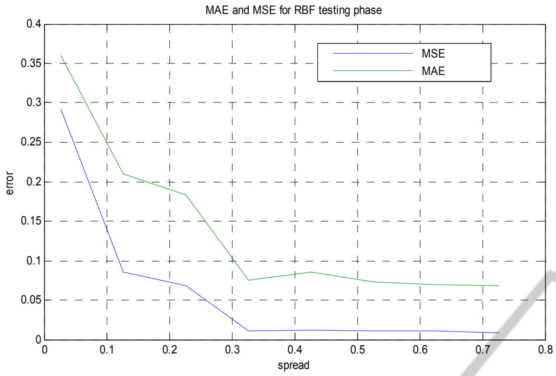

Figure 3: MAE and MSE values of RBF in testing phase.

At the beginning, Hmax was equal with the number of training points. The training tests with variable number of neurons in hidden layer have showed that 8 is the optimum number for the neurons in hidden layer, much less than the number of training points. At the end of RBF training, the optimum spread value found is 0.327.

4 CONCLUSIONS AND WORK IN PROGRESS

This paper focus on a particular neural network, the radial basis function neural network. Considering a data based obtain from an experimental photovoltaic amphitheatre and MSE and MAE metrics for forecasting performance evaluation , the simulations and tests made in this article, put in evidence the accuracy and precision of the particular proposed RBF structure in capturing nonlinear interdependencies between inputs and outputs. Due to its good capabilities to forecast the DPcg in relation with solar radiation, this architecture in well suited in STLF energy applications.

The work is still in progress and the developments are at present extended to: training the radial layer (the hidden layer) of RBF using the Kohonen and LVQ training algorithms, which are alternative methods of assigning centres to reflect the spread of data, training the output layer (whether linear or otherwise) using any of the iterative dot product algorithms and improving the interpretability of the obtained predictive system.

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