AN ADAPTABLE TIME-DELAY NEURAL NETWORK TO PREDICT THE SPANISH ECONOMIC INDEBTEDNESS

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Keywords: Neural Network, Training, Time-Delay Neural Network, Levenberg-Marquardt

Abstract: In this paper, we study and predict the economic indebtedness for the autonomic of Spain. In turn, we use model of neural network. In this study, we assess the feasibility of the Time-Delay neural network as an alternative to these classical forecasting models. This neural network permits accumulate more values of pass and a best prediction of the future. We show the MSE assignment to check the good forecasting of indebtedness economic.

1 INTRODUCTION

Artificial Neural Networks (ANNs) have been deployed in a variety of real world problems (Haykin (1998)). The success of ANNs for a particular problem depends on the adequacy of the training algorithm regarding the necessities of the problem. The existing gradient-based techniques in particular the Back-propagation algorithm, have been widely used in the training of ANNs.

A feed-forward neural network with an arbitrary number of neurons can approximate some uniformed continuous functions (Hornik et at.(1989)). These arguments permit us the basic motivation to use neural network for forecasting time series.

In this paper, we study the way to predict the Spanish economic indebtedness for 2001 year. We use the gross inner product of each community.

This paper is organized as follows. Section 2 we introduce Time-Delay neural network. In Section 3, we expose the adaptation algorithm, Levenberg-Marquardt**.** So, Section 4 we show ours experimental results in the application of this model with autonomous Spain indebtedness. Finally, our conclusions are presented in Section 5.

2 A TIME DELAY NEURAL NETWORK

The traditional model of multi-layers neural network is formed by a set of layers with artificial neurons. Neurons of one layer is connected with each one of neurons the following layers, so they are completely connected. In figure 1, we show a neuron that it appertains to layer l+1 of the network. The inputs x_i^l to the neuron in layer l are multiplied by the weights w_{ij}^l . These weights represent the synaptic connection between the neuron **i** in previous layer and neuron **j** in layer **l+1**. The output of neuron is calculated through a sigmoidal function of the weighty sum of its inputs:

$$x_j^{l+1} = f\left(\sum_i w_{ij}^l x_i^l\right) \qquad (1)$$

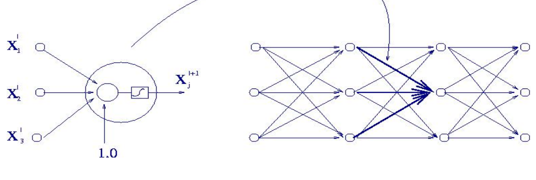

Figure 1: Representation of a neuron

P. Cuellar M., Fajardo W., C. Pegalajar M., Pérez-Pérez R. and Navarro M. (2004).
AN ADAPTABLE TIME-DELAY NEURAL NETWORK TO PREDICT THE SPANISH ECONOMIC INDEBTEDNESS.
In *Proceedings of the Sixth International Conference on Enterprise Information Systems*, pages 457-460
DOI: 10.5220/0002628604570460

The x_0^l =1 is the bias for neuron. The training of network is realized through the Back-Propagation algorithm.

To handle the temporal information (time patterns) for the times series data, a neural network must be "short-term memory", the primary role of is to remember the past signal. There are two attributes of memory structure: depth and resolution. The memory depth defines the length of the time window available in the memory structure to store past information. The deeper the memory, the further it holds information from the past. Memory resolution defines how much information will be remembered in a given time window. The so-called "tapped delay line" is the simplest and most commonly used form of "short-term memory".

A popular neural network that uses ordinary time delays to perform temporal processing the so-called *time delay neural network* (TDNN), which was first described in Lang and Hinton (1988) and Waibel et al. (1989). The TDNN is a multilayer feedforward network whose hidden neurons and output neurons are *replicated across time*. It was devised to capture explicitly the concept of symmetry time as encountered in the recognition of an isolated word (phoneme) using a spectrogram.

The main goal in development of TD-neural networks was to have a neural network architecture for non-linear feature invariant classification under translation in time or space. TD-Networks uses built-in time-delay steps to represent temporal relationships. The invariant classification translation is realized by sharing the connection weights of the time delay steps. The activation of each TD-neuron is computed by the weighted summation of all activations of predecessor neurons in a input window over time and applying a non-linear function (i.e. a sigmoid function) to the sum.

Time-Delay neural network (TDNN) is a dynamic neural network structure that is constructed

by embedding local memory (tapped delay line memory) in both input and output layers of a multilayers feed forward neural network. Both, its input and output are time series data.

3 GRADIENT DESCENDENT: LEVENBERG-MARQUARDT

Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as

$$\mathbf{H} = \mathbf{J}^T\mathbf{J}$$

and the gradient can be computed as

$$\mathbf{g} = \mathbf{J}^T\mathbf{e}$$

where the Jacobian matrix that contains first derivatives $\mathbf{J}$ ` the network errors respect to the weights anu oiases, and **e** is a vector of network errors. The Jacobian matrix can be computed through a standard Backpropagation technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - [\mathbf{J}^T\mathbf{J} + \mu\mathbf{I}]^{-1}\mathbf{J}^T\mathbf{e}$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm.

We use the algorithm implemented by MATLAB. TRAINLM can train any network as long as its weight, net input, and transfer functions have derivative functions. We use the version 6.5 of MATLAB and toolbox of neural network with a license of campus available in Universidad of Granada.

4 RESULTS

To continue, we apply this model of neural network to resolve the problem of forecasting of indebtedness economic of the autonomous community Spanish in the period between year 1986 and 2000. We have a set of values of each community. These values reflect the ratio of indebtedness. The TDNN utilized is formed by 20 neuron input and a neuron output. Moreover, we utilized three step delay in the input layer.

In the following figure are represented the real values (blue) and the predicted values (red). The sixteen value is the prediction to year 2001. The axis

X represents the year of data and axis Y represents the gross inner product.

The results obtained after of training can be consulted in the following figures:

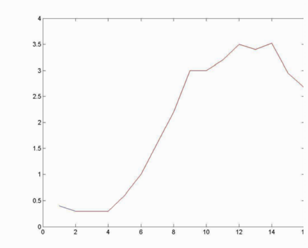

Figure 8: Castilla-Leon

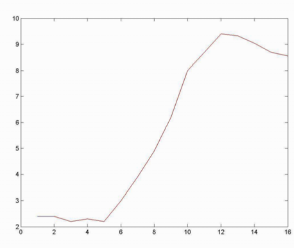

Figure 9: Cataluña

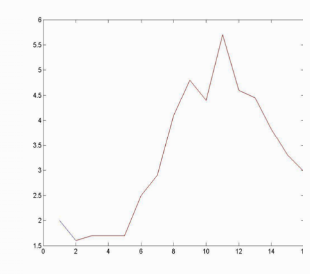

Figure 6: Canarias

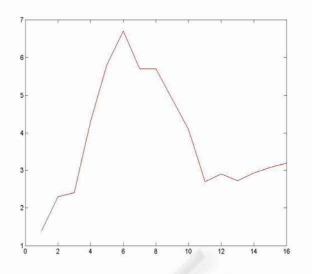

Figure 7: Cantabria

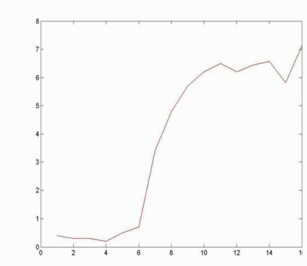

Figure 10: Extremadura

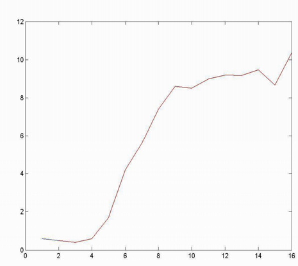

Figure 11: Galicia

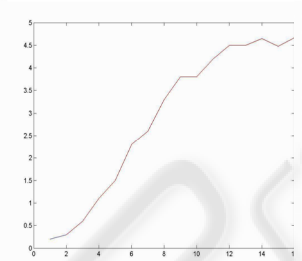

Figure 12: Madrid

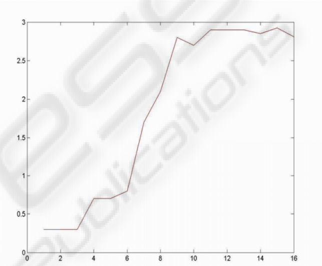

Figure 13: Castilla-Mancha

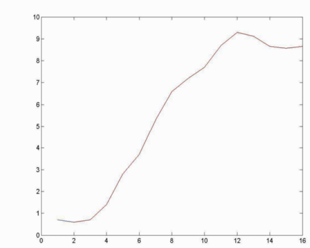

Figure 2: Andalucia

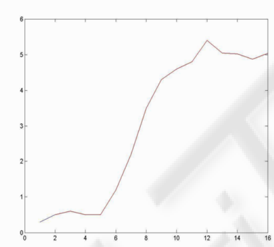

Figure 3: Aragón

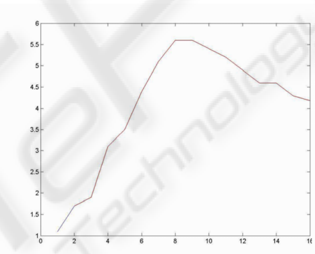

Figure 14: Murcia

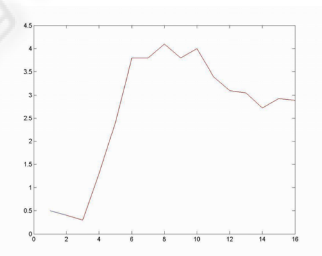

Figure 15: Rioja

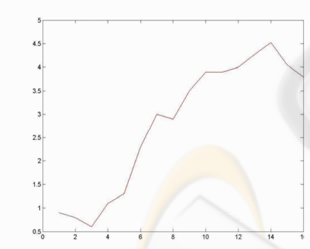

Figure 4: Asturias

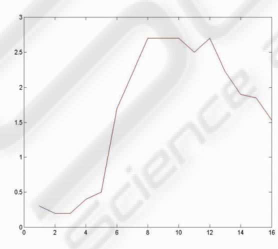

Figure 5: Baleares

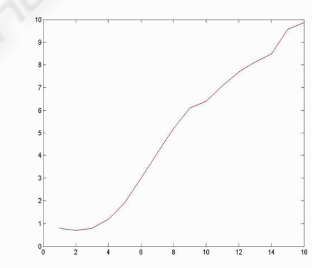

Figure 16: Valencia

As we can observe the level the learning is very high. In the following table (table 1) where we show the MSE commited in the train, the values are very low. Therefore, we realized a good approximation to the functions.

Table 1: The midle MSE of ten ejecution the algorithm over Time-Delay Neural Network

COMMUNITY	Medium Square Error
Andalucía	9.12219e-025
Aragón	3.40256e-023
Asturias	1.76825e-023
Baleares	2.27909e-024
Islas Canarias	9.21784e-023
Cantabria	4.14689e-027
Castilla León	3.61551e-024
Cataluña	1.86823e-022
Extremadura	1.88568e-023
Galicia	1.2120e-022
Madrid	1.32362e-022
Castilla-La Mancha	9.95153e-024
Murcia	1.97685e-023
Rioja	4.97758e-026
Valencia	1.84428e-023

The following table (table 2) shows the inference for 2001 year:

COMMUNITY	RATE OF INDEBTEDNESS
Andalucía	8.741354
Aragón	5.114635
Asturias	2.888294
Baleares	1.498553
Islas Canarias	2.266441
Cantabria	3.356926
Castilla León	3.237302
Cataluña	8.366449
Extremadura	7.838027
Galicia	10.958742
Madrid	4.669944
Castilla-La Mancha	2.814105
Murcia	4.371530
Rioja	2.810956
Valencia	10.338479

5 CONCLUSIONS

In this paper, we show that the assignment MSE committed is very low.

Therefore, we show how TDNN and Levenberg-Marquardt act over the values of Spanish economic indebtedness. The error commited is very low and therefore the ajust is very good. The new approximate with TDNN- Levenberg-Marquardt give better result as other work with Finite Impulse Response Neural Network (M.P. Cuellar et al. 2003). We obtain the best solution for time-series predictions in case of indebtedness in comparison with other neural network topology and studies.

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