

## 1º WORKSHOP NACIONAL EM REDES NEURONAIS E 1ª ESCOLA DE REDES NEURONAIS

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**Infraestrutura Básica Disponível (Hardware/Software)**

- IBM-PC Compatible (486, 50 MHz)
- McLeod & Hipel Time Series Package (version 0.62, McLeod & Hipel, 1992)
- Hybrid Backpropagation Software (Lachtermacher, 1991)

**Cooperações Técnico-Científicas Existentes (Nacionais e Internacionais):**

CNPq (Brasil) for Gerson Lachtermacher

NSERC (Canada) - for J.D. Fuller

## **A NEW FORECASTING METHODOLOGY FOR BACKPROPAGATION NEURAL NETWORKS**

As pointed out by Weigend et al. (1990), one of the major constraints to the use of backpropagation neural networks as a practical forecasting tool, is the number of training patterns needed. For example, most business and economic annual series likely have far too few entries for the present procedures. Many authors, (e.g. Baum & Hausler, 1989), suggest that the number of training patterns required is approximately proportional to the number of links in the network. However, there is no general method to determine the optimal size of a network in a particular case. Our proposed methodology deals with this serious constraint, proposing a way in which the data requirement is decreased.

The general idea is to use the validation procedure proposed by Weigend et al. (1990). However, in order to reduce the data requirement we use the Box-Jenkins calibration procedure (Hipel & McLeod 1977, 1992), to identify the "principal components" of a time series. The calibrated ARIMA model suggests the number of input units for the network. This process reduces the size of the network and consequently the data required to train the network.

In order to avoid the overfitting problem, a validation procedure should be performed. The usual way to do that is to split the original time series in two parts. The first part is used to train the network while the second one is used to determine where the training should be stopped. As pointed out by Weigend et al. (1990), some drawbacks are that the validation part of the series is not used directly in the training of the network and the results obtained are dependent on the pair of training and validation sets chosen. The first drawback increases the data requirement to train the network while the second one the uncertainty of the modelling process. In order to deal with the overfitting problem without these drawbacks, Weigend et al. (1990) suggested the weight elimination procedure, which dynamically adjusts the size of the network. However, this increases the complexity of the training process and the overall modelling time.

The new methodology uses the calibrated Box-Jenkins models to generate synthetic time series (McLeod & Hipel, 1978; Hipel & McLeod, 1992), which have the same statistical properties of the original data, and uses it as the validation set. This overcomes the drawbacks pointed out by Weigend et al. (1990) since no split is necessary in the original series.

We tested the new methodology using the U.S. Electricity Consumption time series (1920-1970). The first part (1920-1960) was used to train the network and to calibrate the ARIMA model. The second part of the series was used to for forecasting performance analysis. The ARIMA model suggested that the last two entries be used to forecast the next entry of the series. So, a small two layer (2-4-1) network was used to train the neural network model. All the units used the logistic activation function.

Two types of prediction were tested: one step ahead prediction and multi-step prediction. In the first case the neural network performed as well as the ARIMA model. Both models gave a MAPE (mean absolute percentage error) of 1.2% over ten years. However, for the multi-step prediction the neural network model outperformed the calibrated ARIMA in a ratio of 3:1 (Neural Network MAPE=2%, ARIMA=6%). Similar results were obtained by Weigend et al. (1990) when forecasting the sunspot time series.

The initial results suggest the potential of the new methodology as a practical forecasting tool, by identifying a small network which reduces the data requirements and the overall modelling time, compared with the present neural network approaches. Further test are presently being performed in order to determine the benefits of the new methodology against the traditional method.

**REFERENCES**

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