Time series prediction of the Greek manufacturing index for the non-metallic minerals sector using a Neuro-fuzzy approach (ANFIS)

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Abstract. Business units, which work in a competitive economy, are faced with intensifying pressure. Greek businesses have undergone a rapid economic and political development over the last forty years. The relevant sectors constitute an important object of study. The process industries are forced to adopt advanced techniques to improve their global competitiveness due to the increased competition and increasingly environmental regulations. Long range predictive control algorithms are considered by industry to improve the overall plant operability, efficiency and control performance. Many processes have nonlinear and dynamic character. It is difficult to analyze and model using conventional techniques. A new generation of techniques came as an alternative. Soft computing represents one of them. The objectives of this research were threefold: to analyse the economic development of Greek non-metallic sector, to predict its manufacturing index using an Artificial Network with a Fuzzy Inference System (ANFIS) and to compare its forecasting accuracy with various time-series forecasting methods (AR and ARMA). A data set of monthly observations of the manufacturing index is considered. All data is publicly available, and the concerned factors are generally thought to have potentially explaining or predicting capabilities with respect to the industry growth. The data has been generated by the economic market system. The data were available from 1986 to 2002.
Keywords: ANFIS, Neuro-fuzzy, Forecasting, Manufacturing index.

1 General considerations

Business units, which work in a competitive economy, are faced with intensifying pressure. The soft computing approaches are useful due to a high level of uncertainty in dynamic economic processes. The organization's top management is required to not only assess its position, but also to understand the differences inter-firms and inter-industries [Wu *et al.*, 2001].

Artificial intelligence methods have been developed for many business problems. Recent studies have shown that neural networks represent a forecasting technique which is superior to nearly all existing methods such consensus estimates, statistical modelling and simulation [Milam, 1998].

The use of neural networks in economics is still in its relative initial stages. However, in spite of this, a substantial amount of research has been conducted and the number of publications is very extensive. [Moody, 1993] presented empirical results to forecast the U.S. index of industrial production and argued that superior performance can be obtained using state-of-the-art neural network models than using conventional linear time series and regression methods. [Dilli and Wang, 2002] presented an application of the ARIMA model to forecast the production level of the construction industry. [Dilli and Wang, 2003] applied the neural networks to forecast the production level of construction industry. The objective of their paper has been to develop an empirical model for the construction industry in China, which best fits, the data under study and gives better prediction values with minimum errors. The model has to help the planners and the policy makers to formulate proper policies and programs to promote the industry.

The manufacturing index

The index of manufacturing production (IMP) measures changes in the quantity of commodities produced by different producers. It reflects the trends in a constant basket of goods produced by establishments employing a specific number of workers (for example establishments employing 50 or more workers). Nowadays, in Greece, the manufacturing index is compiled from production data covering more than 1 800 factories, selected by branch according to their size (average annual employment of 10 persons and over) (National Statistical Service of Greece (NSSG).

Olga Christodoulaki [Christodoulaki, 1999] presented an analysis of manufacturing output in Greece during the interwar period. The literature usually sees the 1920s as a landmark in the industrialisation of the country and a time when Greek manufacturing achieved an "unprecedented prominence" [Mazower, 1992]. The Supreme Economic Council constructed the first index of industrial production in Greece in the 1930s. This index is described as a weighted volume index, which includes approximately 80% of the total industrial production. It comprised eleven industrial sectors including electricity after 1925. An index constructed by the National Statistical Service was based on up to 61 items. These goods are primarily agricultural products. A few goods from the secondary sector are included, mainly products of food processing industries as well as some imported foodstuffs.

Non-metallic mineral sector

In recent years, a new business environment has been taking shape. The factors, which played an important role, are higher levels of uncertainty, global competition and the European perspective. Strength refers not only to market share but covers the issue of the production cost. The production centres shifted to cheaper areas. The construction industry affects EU's economy to a large extent. It has attained a significant level of competitiveness at the same level as other sectors in the economy at a national or local level. Exports in metallic mineral and non-metallic mineral products within the EU are double than the level of imports from outside EU.

Changes have occurred in the non-metallic minerals market. The Greek cement and building materials market, was expected to be more connected with the technical constructing market as has already happened in other countries. The profits incurred a reduction due to a decline of building activity, recession of the demand regarding products in the European market, and an intensified competition from abroad. Producers were obliged to absorb the biggest part of the incremental production cost when the cost of the production factors increased, in order not to suffer losses in sales and market shares (Federation of Greek Industry, 2000).

2 Methods

Artificial Intelligence forecasting techniques have been receiving much attention lately. They have been cited to have the ability to learn like humans, by accumulating knowledge through repetitive learning activities. Their application in the prediction of economic indicators and financial indices has been demonstrated. [Ranasinghe *et al.*, 1999]

a. Fuzzy logic. Fuzzy logic gives a means of representing uncertainty. It is useful in reasoning with the imprecise data. Fuzzy logic is the convenient way to map the input space to an output space. Fuzzy inference systems (FIS) can express human expert knowledge and experience by using fuzzy inference rules represented in "if-then" statements. The fuzzy inference process has five steps: fuzzify inputs, apply fuzzy operator, apply implication method, aggregate all outputs and defuzzify. In order to obtain a good FIS it is necessary that the researchers possess domain knowledge; the knowledge has to be represented in a symbolic form, be complete, correct and consistent. Unfortunately, fuzzy inference systems tend to become incomplete because experts are reluctant to disclose all the knowledge. In addition it is difficult to express it in a symbolic form. [Nishina and Hagiwara, 1997]

b. Neural networks. Between the biologically inspired computing models there are the artificial neural networks. Artificial NN doesn't approach the complexity of the brain, but have two key similarities: the building blocks are simple computational devices and the connections between neurons determine the function of the network. Layers of neurons form a neural network. A layer includes the weight matrix, the summers, the bias vector b, the transfer function and the output vector [Hagan *et al.*, 1996].

c. Neuro-fuzzy. Neuro-Fuzzy systems use NNs to extract rules and membership functions from input-output data to be used in a Fuzzy Inference System. Using this approach, the black box behaviour of NNs and the problems of finding suitable membership values for FL, are avoided. NFS are suited for applications where user interaction in model design or interpretation is desired. One of the most important NFS is ANFIS.

d. ANFIS. Fuzzy inference systems using neural networks were proposed to avoid the weak points of fuzzy logic. The biggest advantage is that they can use the neural networks' learning capability and can avoid rule-matching time of an inference engine in the traditional fuzzy logic system. Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feedforward type. Due to this minimal restriction, the adaptive network's applications are immediate and immense in various areas. A class of adaptive networks, which are functionally equivalent to fuzzy inference systems, is presented bellow[Jang, 1993]:

We assume the FIS under consideration has two inputs and one output. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type:

Rule1: If x is A_1 and y is B_1 then $f_1 = p_1 \cdot x + q_1 \cdot y + r_1$

Rule2: If x is A_2 and y is B_2 then $f_2 = p_2 \cdot x + q_2 \cdot y + r_2$

The node functions in the same layer are of the same function family as described below:

Layer 1: Every node in this layer is a square node with a node function.

$O_i^1(x) = \mu_{A_i}(x)$ where $x-$ the input to node i, A_i- the linguistic label (small, large, etc.) associated with this node function. In other words, O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i . Usually is chosen $\mu_{A_i}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}}$$

where a_i, b_i, c_i is the parameter set.

As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership function on linguistic label A_i . Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a circle node labeled $\prod$, which multiplies the incoming signal and sends the product out.

Layer 3: Every node in this layer is a circle node labeled N. The $i-th$ node calculates the ratio of the $i-th$ rules firing strength to the sum of all rules' firing strengths:

$$\overline{w_i} = \frac{w_i}{w_1 + w_2},\ i = 1, 2$$

For convenience, output of this layer will be called *normalized firing strengths.*
Layer 4: Every node i in this layer is a square node with a node function

$$O_i^4(x) = \overline{w_i} \cdot f_i = \overline{w_i}(p_i \cdot x + q_i \cdot y + r_i)$$

where: $\overline{w_i}$ is the output of layer 3 and $p_i,\ q_i,\ r_i$ is the parameter set. Parameters in this layer will be referred to as consequent parameters.
Layer 5: The single node in this layer is a circle node labeled $\sum$ that computes the overall output as the summation of all incoming signals, i.e.,

$$O_i^5(x) = \sum_i \overline{w}_i \cdot f_i = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i}$$

3 Results and discussions

The object of this research consists of forecasting the manufacturing index for the non-metallic minerals sector from Greece. The forecasting was done using an adaptive neural network with fuzzy inference system. ANFIS uses a hybrid-learning algorithm to identify the membership function parameters of single-output, Sugeno type fuzzy inference systems (FIS). The model was applied for the period 1986-2002. The minimum value of the manufacturing index was 62,1 and the maximum 132,6. The index was less than 100 in 87 months and between 100 and 120 in 43 months. The sector established significant development, reflected in an index greater than 120 only in 26 months in the analyzed interval.

It worked with different numbers of membership functions: two, three, four, five and seven. Different types of membership functions were also chosen - gbellmf, gaussmf, trimf and trapmf The model has one input - the previous value of the manufacturing index of the analyzed sector. The linguistic expressions (small, big, low, high) were transformed into fuzzy sets using membership functions. However, a weak point was the volume of data. Had it been possible to obtain more data, the results could have been more accurate. The model almost always predicted the correct trend of the manufacturing index.

The final model was chosen according to the smallest value of errors. The best results were obtained working with four triangular membership functions. The characteristics of the model for the case of the minimum errors are 20 nodes, 8 linear parameters, 12 nonlinear parameters, 155 training data pairs, 59 checking data pairs and 4 fuzzy rules (their number being obtained with the formula $2^2 = 4 -$ number of membership functions$^{\text{number of imputs}}$).

The scatter plot (figure 1) is a powerful tool, which allows viewing entire data set at once. It displays the relationships between the input and output and identifies the outliers.

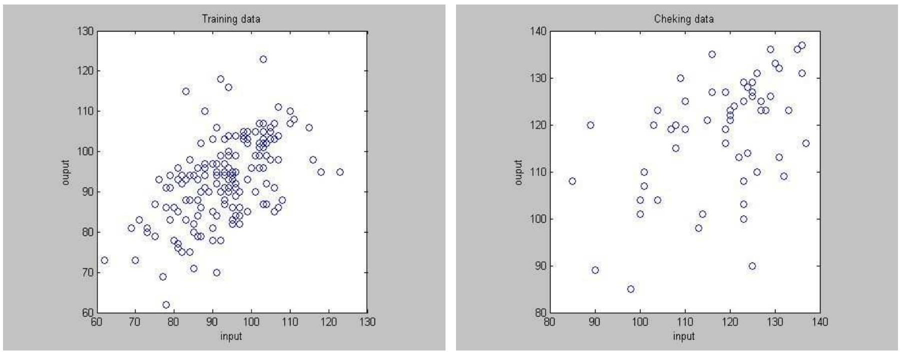

Fig. 1. Scatter plot of input data

The values predicted by the adaptive neural network with fuzzy inference system were compared with the data set. The forecasting accuracy was evaluated by undertaking the comparison with the AR and ARMA methods. The graphical representation of the errors and the comparison between the actual values and the ANFIS predicted values are presented in figure 2

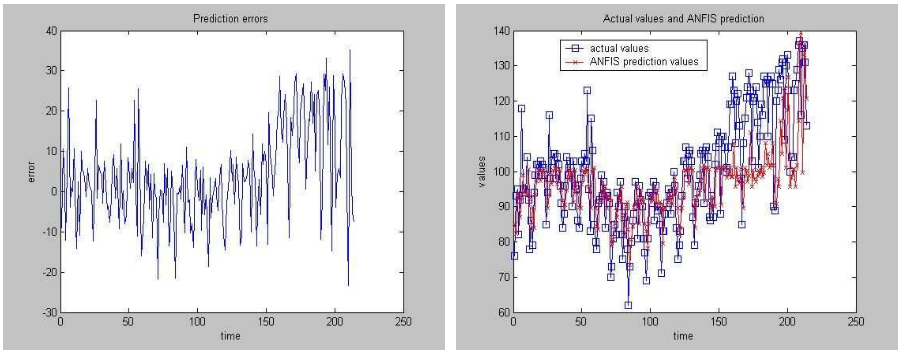

Fig. 2. Error evolution (a) and the comparison between the actual values and the ANFIS values (b) non-metallic

The model displayed a high degree of prediction of the correct trend. The results are better in the first part. Another observation is that at the beginning, the model more accurately forecasted the decrease of the manufacturing index, but afterwards it was able to predict its growth.

The training error, checking error and the step-size are illustrated in figure 3. The training errors are comprised in the interval (8,55; 8,6). The checking errors decreased after 5 epochs by increasing the number of epochs and remained constant after 20 epochs.

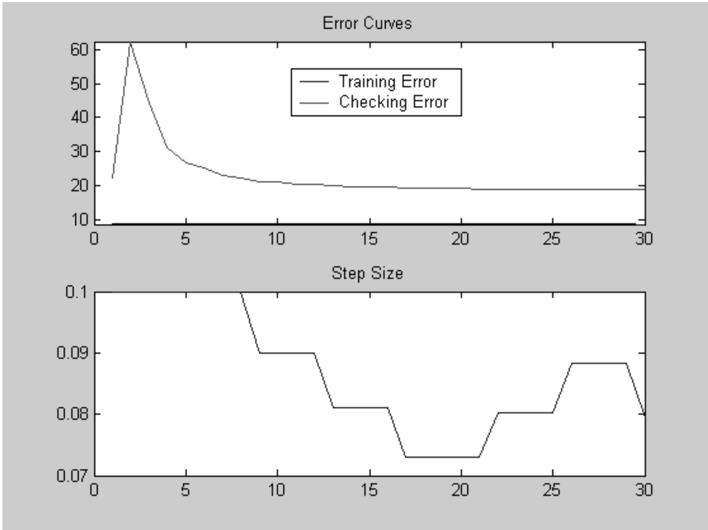

Fig. 3. The error curves and the step-size

The results derived from the application of the adaptive network with fuzzy inference system were compared with those obtained with the use of traditional methods. The comparison of the ANFIS model with the AR and ARMA models is presented in table 1. The comparison was done using relative measures of forecasting accuracy dealing with errors. The measures used in the comparative study are the root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). These measures and their application to forecasting have been discussed by many authors [Makridakis *et al.*, 1983][Goh, 1996].

The following ideas can be drawn from the above analysis:

- the application of ARMA took on the smallest RMSE. AR ranked second, followed by the adaptive neural network with fuzzy inference system;
- from the point of view of MAE, the situation was the same. ARMA was ranked first. The second MAE value was obtained for AR, while ANFIS gave the worst value;

Errors	ANFIS	AR	ARMA
RMSE	12.3264	10.6575	10.4546
MAE	9.3513	8.1903	8.1755
MAPE	9.0386	8.4242	8.4588

Table 1. Comparison ANFIS - AR - ARMA for the non-metallic sector

- from the point of view of MAPE, the order of ranking remained unchanged comparing with RMSE and MAE.

4 Conclusions

This research aimed to prove that a neuro-fuzzy approach could be used to forecast the manufacturing index. The weak aspects of other forecasting methodologies for time series could be overcome with the proposed adaptive network with fuzzy inference system (ANFIS). The data available in the form of input output pairs could be used in the ANFIS with relative ease.

Finally, it goes without saying that one of the major limitations of this study is that the practical implementation of the aforementioned approach requires further study and experimentation.

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