

# **Forecasting Unemployment Rate Using a Neural Network with Fuzzy Inference System**

**G. Atsalakis<sup>1</sup>, C.I. Ucenic<sup>2</sup>, C. H. Skiadas<sup>1</sup>**

<sup>1</sup>Data analysis and Forecasting Laboratory, Technical University of Crete  
[atsalak@otenet.gr](mailto:atsalak@otenet.gr) , [skiadas@ermes.tuc.gr](mailto:skiadas@ermes.tuc.gr)

<sup>2</sup>Department of Management and Industrial Systems,  
Technical University Cluj Napoca, Romania  
Department of Economics, University of Crete, Greece  
[cameliaucenic@yahoo.com](mailto:cameliaucenic@yahoo.com)

## ***Abstract:***

Greece is a low-productivity economy with an ineffective welfare state, relying almost exclusively on low wages and social transfers. Failure to come to terms with this reality hampers both the appropriateness of EU recommendations and the Greek government's capacity to deal with unemployment.

Rather than finding a job in a family business or through relationship contacts, young people stay unemployed. Nor can people move back to their village of origin so easily. The underground economy, and the mass of small companies which characterize the Greek economy are booming, on paper. One in three members of the workforce are "self-employed", compared to one in seven in the EU as a whole. (International Viewpoint)

An unemployed person in Greece is 2,15 times more likely to suffer poverty than a person in employment. Yet in Greece there are perhaps even more influential factors in determining increased risk of poverty. Thus while unemployment is a crucial factor in the risk of poverty, it is neither the only nor the most significant factor.

The paper presents a new technique in the field of unemployment modeling in order to forecast unemployment index. Techniques from the Artificial Neural Networks and from fuzzy logic have been combined to generate a neuro-fuzzy model. The input is a time series. Classical statistics measures are calculated in order to asses the model performance. Further the results are compared with an ARMA and an AR model.

***Key words:*** *forecasting, neural network, unemployment*

## **1. Introduction**

Unemployment is monthly measured by the Bureau of Labor Statistics. The most important thing to compare is this month's unemployment compared to this time last year. If the comparison is for this month to last month, there could be a reason based on the season, such as the school year ending. The unemployment rate is important as a measure of joblessness. It is also a measurement of the economy growth rate.

The unemployment rate is an indicator used by investors to determine the health of the economy. In addition to the unemployment rate, they also look at which sectors are losing jobs faster. It is very important to estimate and forecast the unemployment rate.

The paper presents a new technique in the field of unemployment modeling in order to forecast unemployment index. Techniques from the Artificial Neural Networks and from fuzzy logic have been combined to generate a neuro-fuzzy model. The input is a time series.

## 2. Unemployment rate

The International Labour Organization (ILO) provides the following definitions for the concepts employment and unemployment:

- employment: employed persons comprises all persons aged 15 years old and over who during the reference week have worked at least one hour for remuneration in the form of wage or salary, for profit or family gain or had a job or an enterprise but were not in work;
- unemployment: unemployed persons comprises all persons aged 15 years old and over, who during the reference interval were without work, currently available for work and, seeking work and had taken specific steps to seek paid employment or self-employment.

Greece is a low-productivity economy with an ineffective welfare state, relying almost exclusively on low wages and social transfers. Failure to come to terms with this reality hampers both the appropriateness of EU recommendations and the Greek government's capacity to deal with unemployment. (Seferiades, 2003)

Statistics unfortunately cannot be taken at face value because earnings of many Greeks and immigrant workers are off-the-books. In addition, the immigrants make up nearly one-fifth of the work force, mainly in menial jobs. Officially, however, Greece, the country with the lowest percent of its population (55.6%) partaking in the workforce, is second only to Spain (11.5%), when it comes to EU unemployment rate. Greek unemployment has been on a downward trend recently (it was 11.9% in 1999). The Centre for Planning and Economic Research (KEPE) reports that the areas where the most jobs are to be found today in Greece are trade, construction, industry and tourism, while most job-seekers are looking for office jobs.

In the 1980s, the agricultural sector absorbed many urban workers who would otherwise have been unemployed. But the growing number of job losses, the effects of the EU Common Agricultural Policy, and the regulations of the WTO mean that the countryside can no longer play the shock-absorber role. After ten years of modernization the absorption mechanisms are less responsive.

Rather than finding a job in a family business or through relationship contacts, young people stay unemployed. Nor can people move back to their village of origin so easily. The underground economy, and the mass of small companies which characterize the Greek economy are booming, on paper. One in three members of the workforce are "self-employed", compared to one in seven in the EU as a whole. (International Viewpoint)

An unemployed person in Greece is 2.15 times more likely to suffer poverty than a person in employment. Yet in Greece there are perhaps even more influential factors in determining increased risk of poverty. Thus while unemployment is a crucial factor in the risk of poverty, it is neither the only nor the most significant factor.

Among the measures to combat unemployment and increase employment are:

- involvement of local authority enterprises in new jobs programs;
- part-time employment in the provision of social services;
- conversion of passive policies (benefit-centred policies) to active policies for the unemployed.

The promotion of entrepreneurship is one of the major keys to growth and a precondition for the creation of more and better jobs. More specifically, support for entrepreneurship in SMEs is a central axis of the policy we are implementing through

Meanwhile efforts have been under way to reorganize the Manpower Employment Organization (OAED), with a review of the progress of the restructuring program and the recent

adoption of new targets. The new institutions recently introduced into the labour market are private employment agencies and the contracted-out labour system.

The restructuring of labour market institutions has not yet led to widespread implementation of systems of individualized approach for the prevention and cure of unemployment. Moreover, legislative interventions to promote employment and flexibility have not yielded their full effect. Opportunities for part-time employment remain limited. While the trend towards the creation of new full-time jobs is welcome, the lack of part-time opportunities may well discourage certain groups from seeking paid employment. (Greek Ministry of Labour and Social Security, 2003)

Other weak aspects are a high youth and female unemployment rates, a persistent long-term unemployment and persisting regional differences. A comparison between Athens and Thessaloniki in 2001, for instance, reveals that while new jobs increased in Attica, due mainly to major Olympic Games construction projects, Thessaloniki's unemployment started at 10.7% and reached 11.5%. Youth unemployment is also regional, swelling up to 40.2% in Central Greece. The unemployment ranges from 15.7% in the region of Western Macedonia to 4.8% in Crete. ([www.interkriti.org](http://www.interkriti.org)). There would not be such gaps if the workforce could adjust to changing technological demands.

Though unemployment was down in 2003, Greece was still trying to catch up to European levels of participation in the workforce. In 2002, Greece, Italy and Spain registered the lowest employment rate and female employment rates in the EU. Eurostat pointed out that Greece's employment rate, 56,9%, was lower than the EU average of 64,2%. It will be harder for the country to catch up to the EU-wide targets of 65% in 2010 and 70% by 2010, as set out by the European Council. The gender gap in Greece was pronounced, with a 71,7% male employment rate and a 42,7% female employment rate in 2003.

A 2003-2008 employment action plan includes measures for the state to provide some 25,000 part-time jobs, more subsidies and tax incentives, greater social services (especially for women), training programs for the long-term unemployed, rent assistance and breaks unemployment rate to drop to 8.9% in the second quarter of 2003 – a full percentage point lower than it was in 2002 and 0,7% down from the first quarter of 2003.

The evolution of unemployment rate during 1990-2003 is graphically presented next.

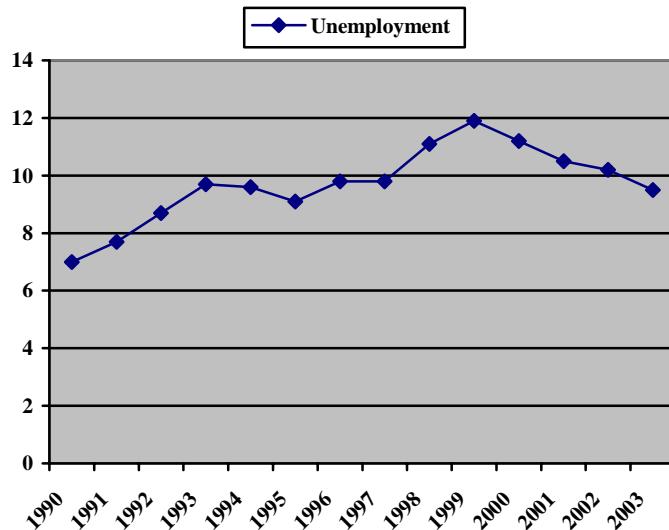


Figure 1: Evolution of unemployment rate 1990-2003 (OECD data)

### 3. Using soft computing in time series forecasting

Among the biologically inspired computing models are artificial neural networks (ANN). ANN does not approach the complexity of the brain, but both of them have two key similarities: the building blocks are simple computational devices and the connections between neurons determine the function of the network.

A neural network is formed by layers of neurons. A layer includes the weight matrix, the summers, the bias vector  $b$ , the transfer function and the output vector  $a$ . A layer whose output is the network output is named the output layer. All the other layers are called hidden layers.

A neuro-fuzzy system is defined as a combination of Artificial Neural Networks (ANN) and Fuzzy Inference System (FIS) in such a way that neural network learning algorithm are used to determine the parameters of FIS. Adaptive Neural Fuzzy Inference System (ANFIS) is a system that belongs to neuro-fuzzy category.

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. In the subsequent section is presented a class of adaptive networks, which are functionally equivalent to fuzzy inference systems.

Fuzzy reasoning type-3 is illustrated in the next figure.

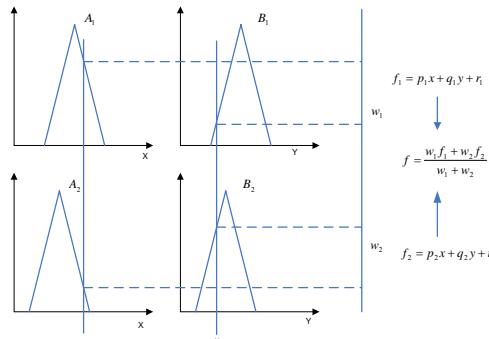


Figure 2. Fuzzy reasoning type 3

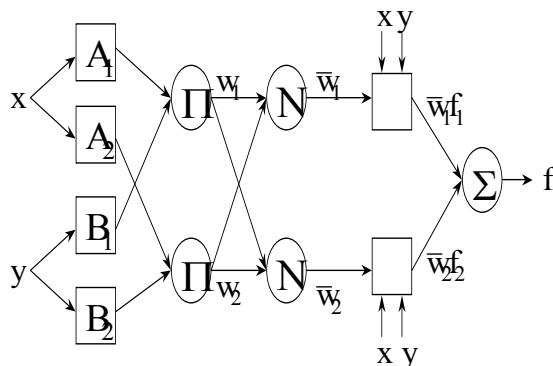


Figure 3. ANFIS architecture

For simplicity, it is assumed the fuzzy inference system under consideration has two inputs "x" and "y" and one output "z". Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type:

Rule1: If

$$x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1 \cdot x + q_1 \cdot y + r_1$$

Rule2: If

$$x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2 \cdot x + q_2 \cdot y + r_2$$

then the type-3 fuzzy reasoning is illustrated in the figure 2, and the corresponding equivalent ANFIS architecture (type-3 ANFIS) is shown in the figure 3. The node functions in the same layer are of the same function family as described below:

**Layer 1** Every node  $i$  in this layer is a square node with a node function.

$$O_i^1(x) = \mu_{A_i}(x) \text{ where } x - \text{the input to node } i$$

$A_i$  - the linguistic label associated with this node function.

$O_i^1$  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 bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function or the Gaussian function

**Layer 2** Every node in this layer is a circle node labeled  $\pi$ , 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: 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. Parameters in this layer will be referred to as consequent parameters.

**Layer 5** The single node in this layer is a circle node labeled  $\Sigma$  that computes the overall output as the summation of all incoming signals. Consider using all possible parameters which the number is function of both, the number of inputs and the number of membership function then can be defined number of all rules.

#### 4. Literature review

There are many works that aim to forecast unemployment index using soft computing methodology. Some of them are mentioned below.

a. Freisleben and Ripper applied neural networks trained with the backpropagation algorithm to predict the future values of three time-series relevant to assess the German economy: the gross national product, the unemployment rate, and the number of employees. The performance of the networks is evaluated by comparing them to appropriate linear regression techniques and ARIMA models. The comparison shows that the networks produce good results which are superior to those obtained by linear regression; the ARIMA models are better for predictions one time period ahead, but they are outperformed by the networks when predictions for several time periods ahead are made

b. Vasantha Kandasamy and Subhaashree used multivalent fuzzy cognitive maps to study the unemployment problems. The unemployment problem is one, which is faced by all sections of people rich as well as poor educated as well as uneducated. The various reasons given are increase in population, craze only on certain special courses in education, dignity of labour among educated, pay, preference for government job. As most of the notions are uncertain and dominated by strong feelings, the Multivalent Fuzzy Cognitive Maps (MFCM) were appropriate.

c. Kasabov predicted the unemployment for the next quarter based on past data. The following attributes have been used: Time; Quarter; Private consumption expenditure; Government expenditure; Exports of Goods & Services; Number of people unemployed (in thousands) at the previous quarter; Number of people unemployed at the current quarter. The data set was divided into three sets A,B, and C. The experiments show that updated fuzzy neural networks through the MTZ are more robust to forgetting, faster and better at adaptation and provide a good generalisation. They can be used for building practical real-time adaptable systems. It may be possible now to control the level of adaptation and forgetting through using different thresholds for fuzzy rules extraction.

d. Arzu N. made use of fuzzy equations for unemployment and GDP Data. This data set contains two variables which are unemployment and gross domestic product ( $x_1$ ) in UK between 1955 and 1969. ANFIS yields smaller training errors than ANFIS Unfolded in time. This was an expected result, since during the training phase, the model used online learning. The error obtained for a sample is a cumulative error containing the error in the whole time interval.

e. Moshiri S. and Brown L. presented a comparison of forecasting methods for unemployment variation. They applied two ANN models, a back-propagation model and a generalized regression neural network model to estimate and forecast postwar aggregate unemployment rates in the US, Canada, UK, France, and Japan.

They compared the out-of-sample forecast results obtained by the ANN models with those obtained by several linear and non-linear times series models currently used in the

literature. It is shown that the artificial neural network models are able to forecast the unemployment series as well as, and in some cases, better than, the other univariate econometrics time series models in their test.

f. Hampel and Kunz presented structural-component models for regional unemployment forecasting. They forecasted regional unemployment in the 176 German labour-market districts using an augmented structural-component (SC) model and comparing the results from this model with those from basic SC and autoregressive integrated moving average (ARIMA) models. Using unemployment data from the Federal Employment Services in Germany for the period December 1997 to December 2005, they first estimated basic SC models with components for structural breaks and ARIMA models for each spatial unit separately.

In a second stage, autoregressive components were added into the SC model. The results show that the SC model with autoregressive elements is not superior to basic SC and ARIMA models in most of the German labour-market districts. The SC model with spatial autocorrelation performs better than the other models in labour-market districts which have a low seasonal span and a relatively high unemployment rate.

g. Pattueli et all forecasted regional employment using neural networks. a set of neural network (NN) models is developed to compute short-term forecasts of regional employment patterns in Germany. The paper compared two NN methodologies. First, it uses NNs to forecast regional employment in both the former West and East Germany. Next, additional forecasts are computed, by combining the NN methodology with shift-share analysis (SSA).

Since SSA aims to identify variations observed among the labour districts, its results are used as further explanatory variables in the NN models. The data set used consisted of a panel of 439 German (NUTS 3) districts. The out-of-sample forecasting ability of the models is evaluated by means of several appropriate statistical indicators.

h. Partridge M. D. and Rickman D.S. (1998) presented a regional interindustry employment forecasting. The Bayesian vector autoregression (BVAR) employment-forecast approach was generalized using data for the state of Georgia. This study advances previous regional BVAR approaches by incorporating regional input-output coefficients, using the coefficients both to specify the prior means in one model and to weight the variances of a Minnesota-type prior in a second model, and including final-demand effects and links to national and world economies. Out-of-sample forecasts produced by the generalized BVAR models are compared to forecasts produced from an autoregressive model, an unconstrained VAR model, and a Minnesota BVAR model.

i. Pelaez and Rolando F. (2006) applied neural networks in order tp forecast unemployment rate. This paper identified leading indicators of the unemployment rate. Forecasts of the unemployment rate were obtained with an econometric model, and with an artificial neural network. Both model-based forecasts outperform forecasts from the Survey of Professional Forecasters. This was important because the unemployment rate forecast from the Survey of Professional Forecasters has outperformed

## 5. Model presentation

The forecasting of unemployment rate was done with an adaptive network with fuzzy inference system (ANFIS). The model predicts in a one step ahead prediction scheme. The method of trial and error was used in order to decide the type of membership function that describe better the model and provides the minimum error.

The gauss membership function made available better results than gbellmf. It was noticed that the increase of the number of membership function determined a decrease of errors for all type of membership functions. Finally six-membership functions of gauss shape were chosen.

The training data is represented in figure 4.

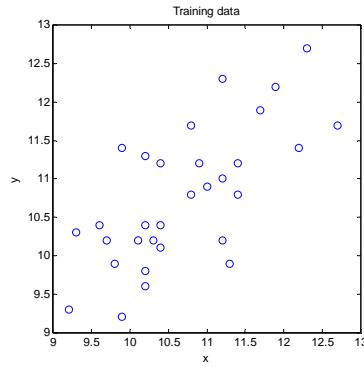


Figure 4: Training data

The comparison between initial and final membership functions shows a slight change in their shape.

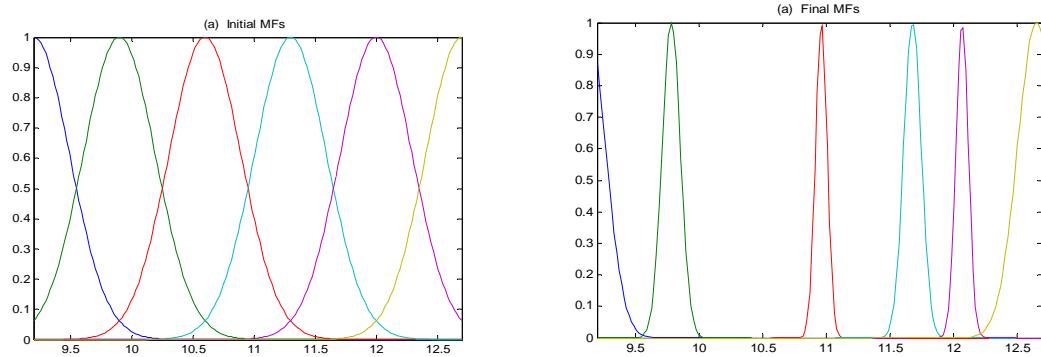


Figure 5: Comparison initial - final membership functions

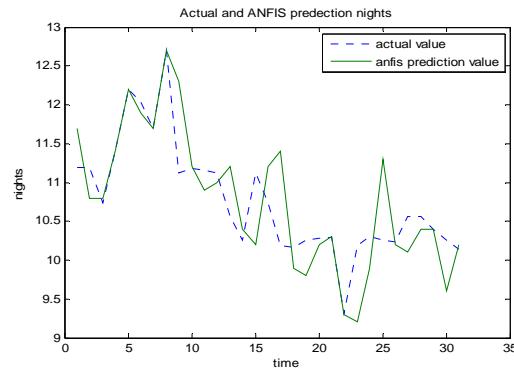


Figure 6: Comparison actual – ANFIS prediction values

The analysis of model quality was done related to four main types of errors: MSE, RMSE, MAE and MAPE. A comparison of the results for the case of six gauss membership functions (minimum error) is presented bellow.

$$\begin{aligned} \text{MSE\_anfis} &= 0.2598 \\ \text{RMSE\_anfis\_c} &= 0.5097 \\ \text{MAE\_anfis\_c} &= 0.3449 \\ \text{MAPE\_anfis\_c} &= 3.2295 \end{aligned}$$

$$\begin{aligned} \text{MSE\_ar} &= 0.4424 \\ \text{RMSE\_ar} &= 0.6651 \\ \text{MAE\_ar} &= 0.5116 \\ \text{MAPE\_ar} &= 4.7870 \end{aligned}$$

$$\begin{aligned} \text{MSE\_arma} &= 0.4172 \\ \text{RMSE\_arma} &= 0.6459 \\ \text{MAE\_arma} &= 0.5297 \\ \text{MAPE\_arma} &= 4.9429 \end{aligned}$$

As it can be seen, ANFIS provides better results (smaller error values).

## 6. Conclusion

The paper presents an ANFIS forecasting model. The results were presented and compared based on four different kinds of errors: MSE, RMSE, MAE and MAPE. The ANFIS model gives the best results for the case of six gauss membership functions and 250.000 epochs.

This research aimed to prove that a neuro-fuzzy approach can be used to forecast the unemployment rate. 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 can be used in the ANFIS with relative ease.

Without having the claim that was solved the entire problem of unemployment rate forecasting, one allow noting that the findings of this study have managerial and practical implications. Further improvements are still possible if much information could be inserted in the learning algorithm.

## **ACKNOWLEDGEMENT**

The authors are grateful for financial support from the Mary Curie Transfer of Knowledge of the European Communities 6th Framework Program under contract MTKD-CT-014288.

## **References**

Arzu N. (2003) – A Temporal Neuro-Fuzzy Approach For Time Series Analysis, The Middle East Technical University

Freisleben, B. Ripper, K. (1998) - Economic forecasting using neural networks, Neural Networks, Proceedings., IEEE International Conference on Volume 2, Issue , Nov/Dec, Page(s):833 - 838 vol.2

Hampel K. and Kunz M.(2006) - Regional Unemployment Forecasting Using Structural-Component Models with Spatial Autocorrelation, European Regional Science Association in its series ERSA conference papers with number ersa06p196.

Kasabov N. - Investigating the Adaptation and Forgetting in Fuzzy Neural Networks Through a Method of Training and Zeroing, University of Otago, P.O.Box 56, Dunedin, New Zealand

Moshiri S. and Brown L. (2008) - Unemployment Variation over the Business Cycles: A Comparison of Forecasting Models, Journal of Forecasting, Forthcoming

Pattuelli et all (2006) - New Neural Network Methods for Forecasting Regional Employment: an Analysis of German Labour Markets, Journal of Spatial Economic Analysis, Volume (Year): 1 Issue (Month): 1 (June), Pages: 7-30

Partridge M. D. and Rickman D.S. (1998) - Generalizing the Bayesian Vector Autoregression Approach for Regional Interindustry Employment Forecasting, American Statistical Association in its journal Journal of Business and Economic Statistics, Volume (Year): 16 (1998) Issue (Month): 1 (January), Pages: 62-72

Pelaez and Rolando F. (2006) - Using Neural Nets To Forecast The Unemployment Rate: A Promising Application Of An Emerging Quantitative Method, Publication: Business Economics Date: Sunday, January 1 2006

Seferiades S. (2003) - The European Employment Strategy Against a Greek Benchmark: A Critique, European Journal of Industrial Relations, Vol. 9, No. 2, 189-203, SAGE Publications

Vasantha Kandasamy, Subhaashree S. (2000) - Multivalent fuzzy cognitive maps to study the unemployment problems, Symposium on mathematical methods and Applications, Indian Institute of Technology, Chennai, India