Analysis of the macroeconomic development of European and Asia-Pacific countries with the use of connectionist models

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Abstract

The paper applies novel techniques for on-line, adaptive learning of macroeconomic data and a consecutive analysis and prediction. The evolving connectionist systems paradigm (ECOS) is used in its two versions - unsupervised (evolving self- organised maps), and supervised (evolving fuzzy neural networks - EFuNN). In addition to these techniques self-organised maps (SOM) are also employed for finding clusters of countries based on their macroeconomic parameters. EFuNNs allow for modelling, clustering, prediction and rule extraction. The rules that describe future annual values for the consumer price index (CPI), interest rate, unemployment and GDP per capita are extracted from data and reported in the paper for both global - EU-Asia block of countries, and for smaller groups - EU, EU-candidate countries, Asia-Pacific countries. The analysis and prediction models proof to be useful tools for the analysis of trends in macroeconomic development of clusters of countries and their future prediction.

Key words.

neural networks, fuzzy rules, evolving connectionist systems, macroeconomic clusters.

1. Introduction

Complex decision making in a complex, dynamic economic environment is often a very difficult task. Investigation into huge amount of multivariate data is needed to extract and manipulate information distributed within, so that decision making can be soundly sustained. On-line decision support systems (DSS) built for this purpose should have advanced features such as:

- Good explanation facilities, preferably presenting the decision rules used;
- Dealing with vague, fuzzy information, as well, as with crisp information;
- Dealing with contradictory knowledge, e.g. when two experts predict different trends in the stock market;
- Dealing with large data bases with a lot of redundant information, or coping with lack of data.
- Hierarchical organisation, i.e., they can involve different levels of processing, comparing different possible solutions, using alternatives, sometimes in a recurrent way.

Recent advances on artificial neural networks and our latest progress made on evolving connectionist-based systems (ECOS) has suggest that neural network algorithms, especially ECOSs can provide intuitive and robust solutions for economic data analysis and modelling [1].

In this study, we focus on the analysis and prediction of macroeconomic indicators of European and Asia-Pacific countries, with the use of connectionist models.

2. Computational Models

2.1. Self-organizing Maps (SOM)

SOM is a popular neural network algorithm proposed by Kohonen [2] for unsupervised learning. Given a set of data, the SOM algorithm will try to generate a map consisting of nodes usually set in a 2-dimensional lattice. Once the map is set out, given a new pattern of data, or a *feature code* as input, the map will search among its grid nodes, each of which corresponding to a prototype feature code, find the best-matching one, and the new pattern is categorised correspondingly. Therefore the SOM algorithm is also referred as Self-Organizing Feature Map (SOFM) in the sense that it maps features onto prototypes in the map.

With the ability of dimension reduction, clustering and multivariate data visualisation, SOM is closely related to statistical methods like PCA and MDS.

2.2. Evolving Self-organizing Maps (ESOM)

ESOM is an on-line evolving extension of the SOM model [3]. It uses a learning rule similar to SOM, but its network structure is evolved dynamically from input data. ESOM does not hold any pre-assumption on the topology of its feature map. The map topology is evolved from incoming data by dynamically creating prototype nodes and setting out their connections. Simulations carried out have shown that ESOM has better vector-quantisation accuracy, faster learning speed and better visualisation ability compared with SOM.

2.3. Evolving Fuzzy Neural Networks (EFuNN)

The architecture, learning and evolving algorithms, rule extraction and rule insertion algorithms of EFuNN are given in [4]. EFuNNs have the following advantages when compared with traditional MLP or SOM networks:

- An on-line incremental mode capable of one-pass learning. EFuNNs can learn in an incremental, adaptive way through one-pass propagation of any new data examples. EFuNNs start evolving/learning with no rule (hidden) nodes and they grow as data is presented to them. It also has a much faster learning speed.
- Ability to work in a complex environment with changing dynamics. For instance, a stock index system is in a random walk state, then it moves to a chaotic state, and then to quasi periodic state, and an EFuNN that predicts future stock values learns all the time the new behaviour without any human intervention for parameter adjustment.
- Ability to mix expert rules and data as there are algorithms for rule insertion and rule extraction;
- Clustering data in an on-line mode without pre-defining the number of clusters, or the dimensionality and the size of the problem space.

Examples of using EFuNNs for adaptive, intelligent decision support systems for stock prediction and loan approval are given in [5].

3. Experiments

Huge amounts of data in yearly and quarterly time-scales is being collected from many diverse sources like EUROSTAT, Datastream, IMF, World Bank, OECD, statistics departments and central banks of countries for this research. Here we use four macroeconomic indicators throughout all unsupervised mapping and supervised prediction experiments. The indicators are GDP per capita in US dollars, inflation rate, interest rate, and unemployment rate. Data of three groups of countries are collected and analysed: EU countries, candidate countries, and Asia-pacific countries.

3.1 Cluster Analysis of macro-economies

3.1.1. Mapping EU member countries

The data (the four macroeconomic indicators utilised in all the unsupervised mapping) of the fifteen countries joining the European Union have been fed into a Self-Organizing Map. The resulting map is shown in Fig.1 and Fig.2.

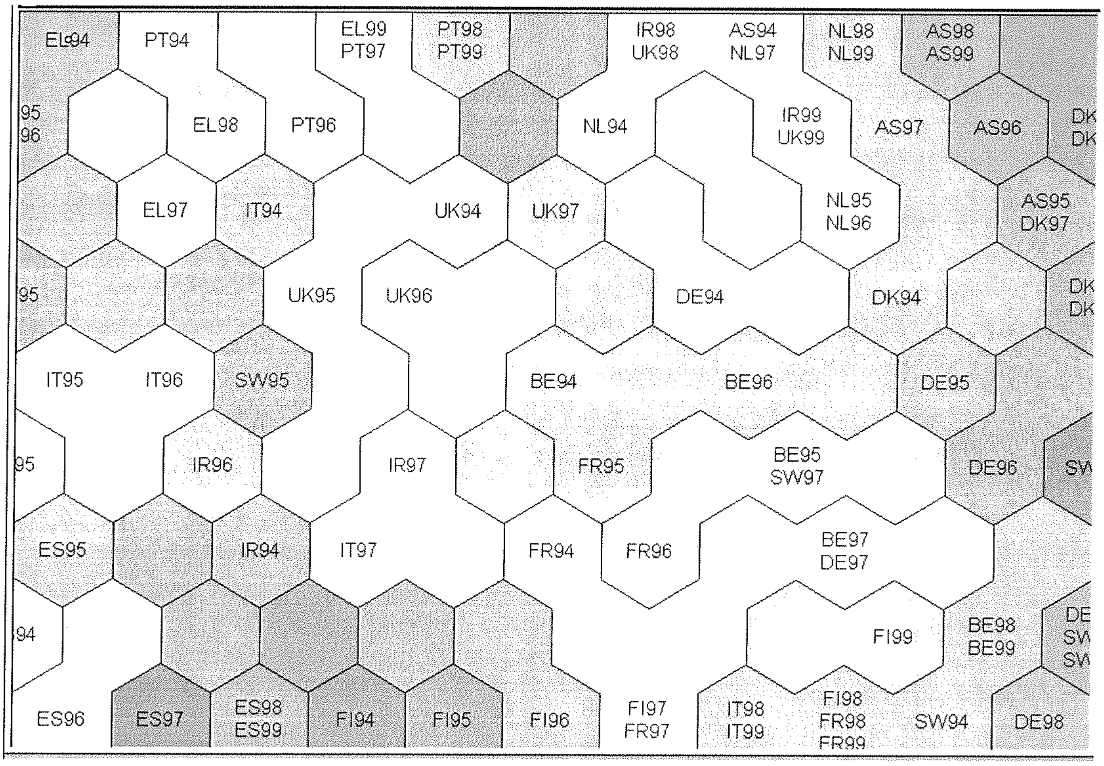


Fig.1 The annual map of 15 European countries according to 4 characteristics

The first feature to be observed in the map is the behaviour of some EM countries that in the last few years has shown considerable improvement in their economy. On of this is of course Ireland that thanks to fundamental structural reforms has reached considerable goals. This virtuous path can be detected in the map in which Ireland is moving from the left side (IR94, IR95, IR96, IR97) to the right one (IR98, IR99). The fact that in the 1999 year Ireland and United Kingdom are grouped in the same cluster is indicative of this improvement in the Ireland economy.

One other country that in the last few years has shown a good economic evolution is Spain. This is indicated by the map positioning Spain in its own cluster in the left-down part of the resulting SOM, quite far from other countries like Italy, France, Belgium and Sweden that in the last few years experienced a more slow economic growth.

The explanation of the different positioning in the map of Spain and Ireland could be explained with some differences in their fast economic growth. Besides, the SOM in mapping the countries has maybe accentuated this feature.

One other thing emerging from the map (and confirmed by the evidence) that has to be stressed is the stability that some EU countries has shown in the last few years. But in this case stability means that countries like Italy and France, because their inability to follow some fundamental structural reform in labour market and in goods market, were not able to catch the train of high growth rate made possible by the new technologies available in the industry and in the information environment.

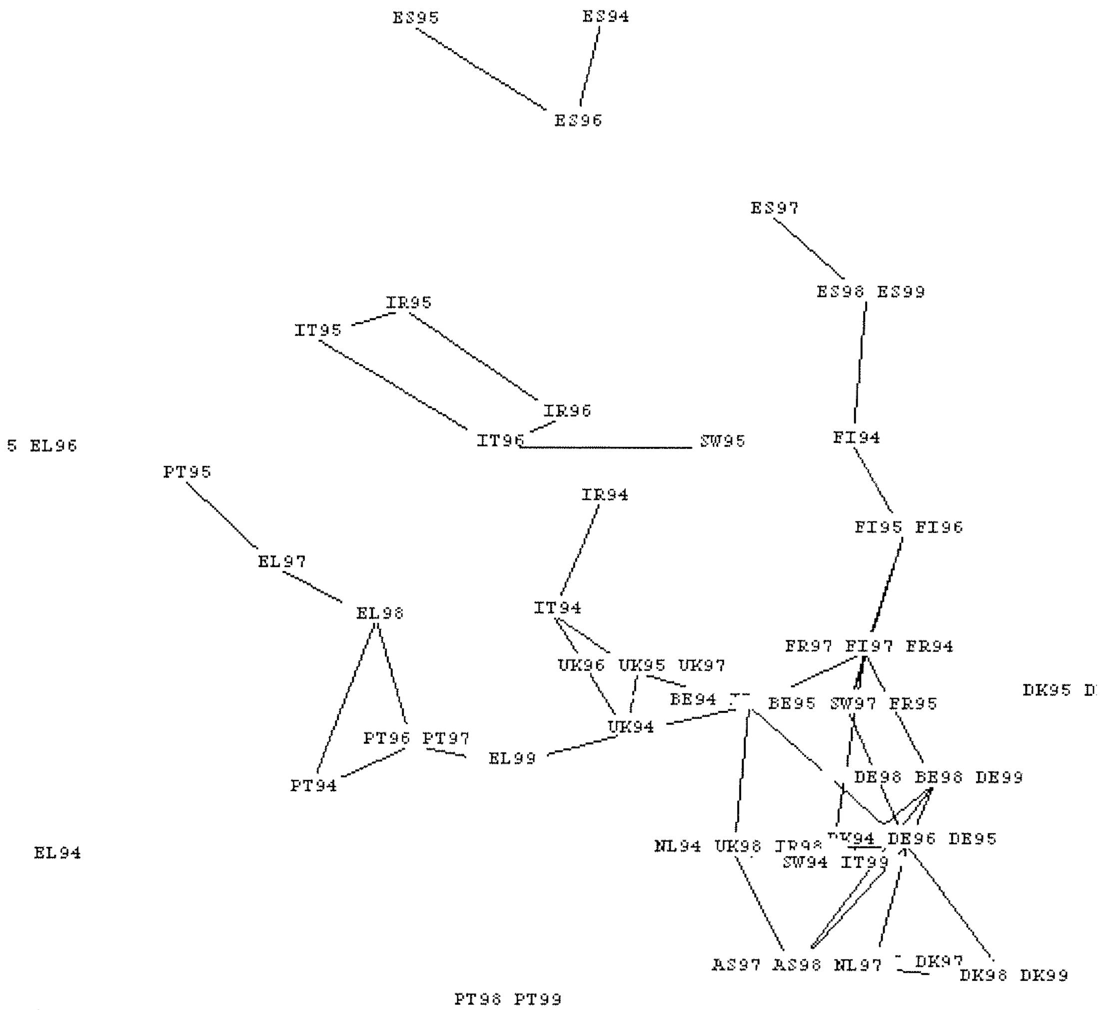


Fig. 2 Macro-economics mapping of EU countries, generated by ESOM with 33 nodes

Finally, the map has correctly shown the path of small economies like Portugal and Greece that in the last two years have been continuously reducing the gap between more advanced European economies.

3.1.2. Mapping EU candidate countries

Bulgaria, Czech Republic, Cyprus, Estonia, Hungary, Latvia, Lithunia, Malta, Poland, Romania, Slovakia, Slovenia and Turkey have presented applications for Membership of the European Union.

On Applications for Membership of the European Union, based on the criteria laid down by the Copenhagen European Council in June 1993, the applicant country must have

- achieved stability of Institutions guaranteeing democracy, the rule of law, human rights and respect for and protection of minorities,
- a functioning market economy, as well as the capacity to cope with competitive pressure and market forces within the EU,
- the ability to take on the obligations of membership, including adherence to the aims of political, economic and monetary union.

For an evaluation of the second criteria of Copenhagen European Council, collected data about macroeconomic indicators of the 11 candidate countries (Cyprus and Malta are not included) have been fed into a Self-Organizing Map. The resulting map is shown in figure 3 and component analysis according to 4 characteristics is shown in Figure 5 a-d.

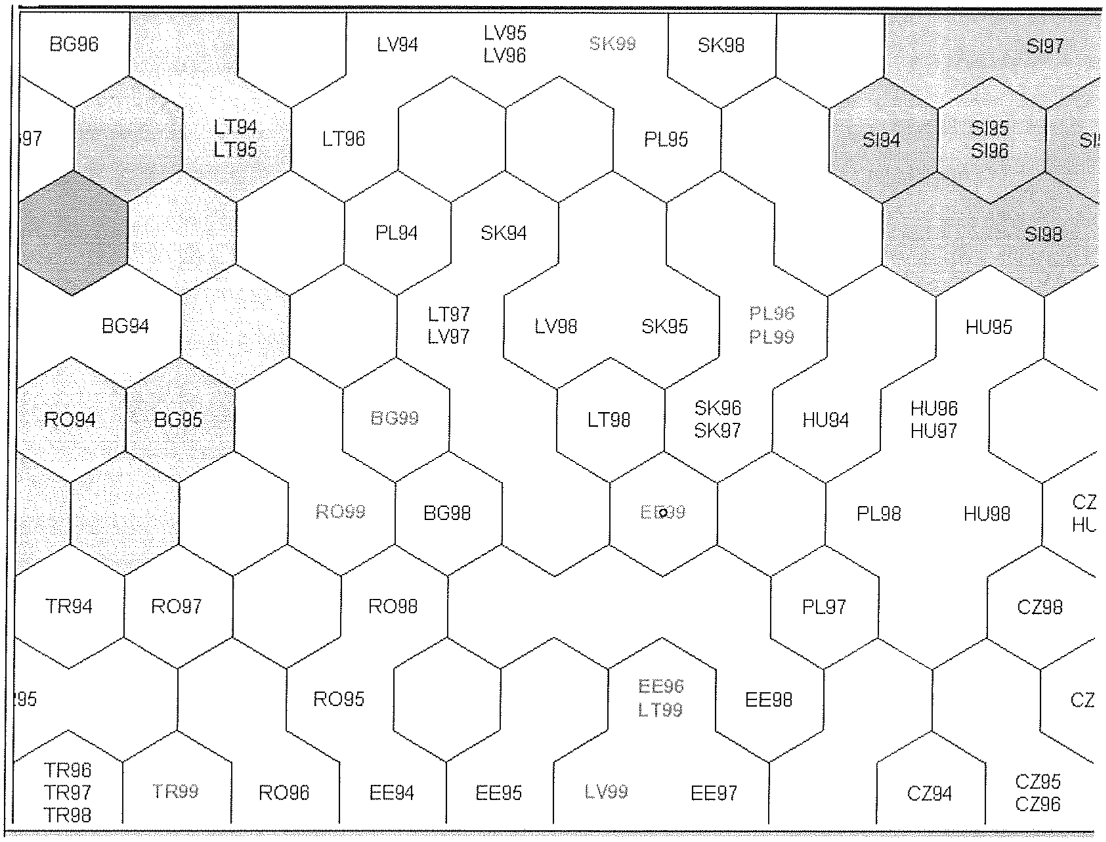


Fig.3. The annual map of the 11 candidate countries according to 4 characteristics.

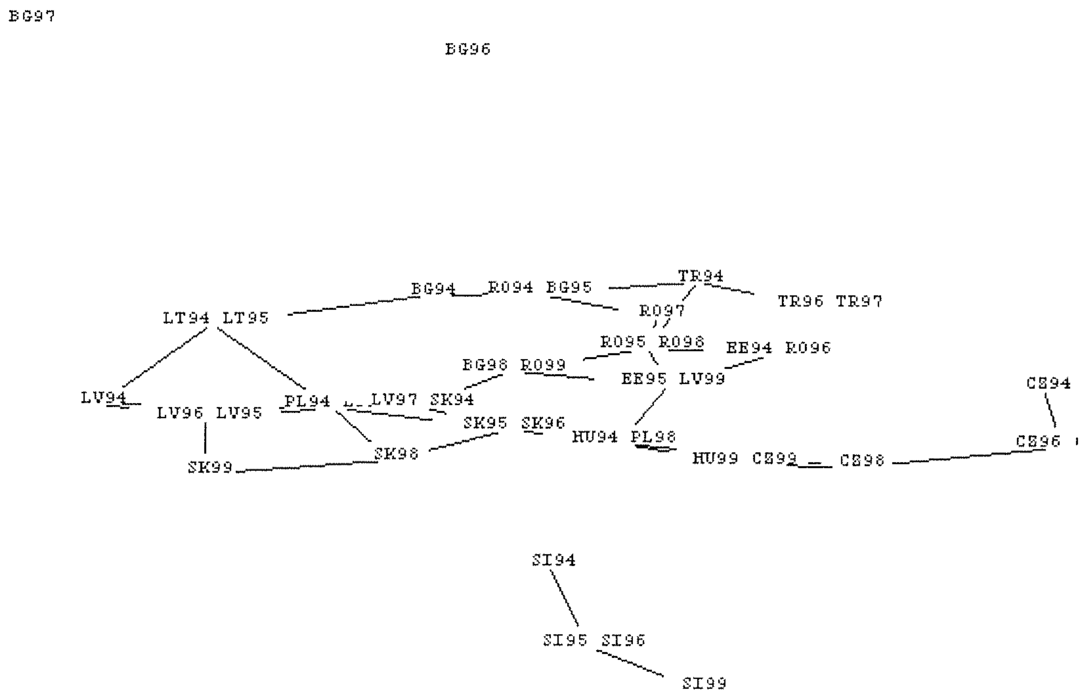


Fig. 4 Visualisation of ESOM on macro-economics of EU candidate countries. (29 nodes).

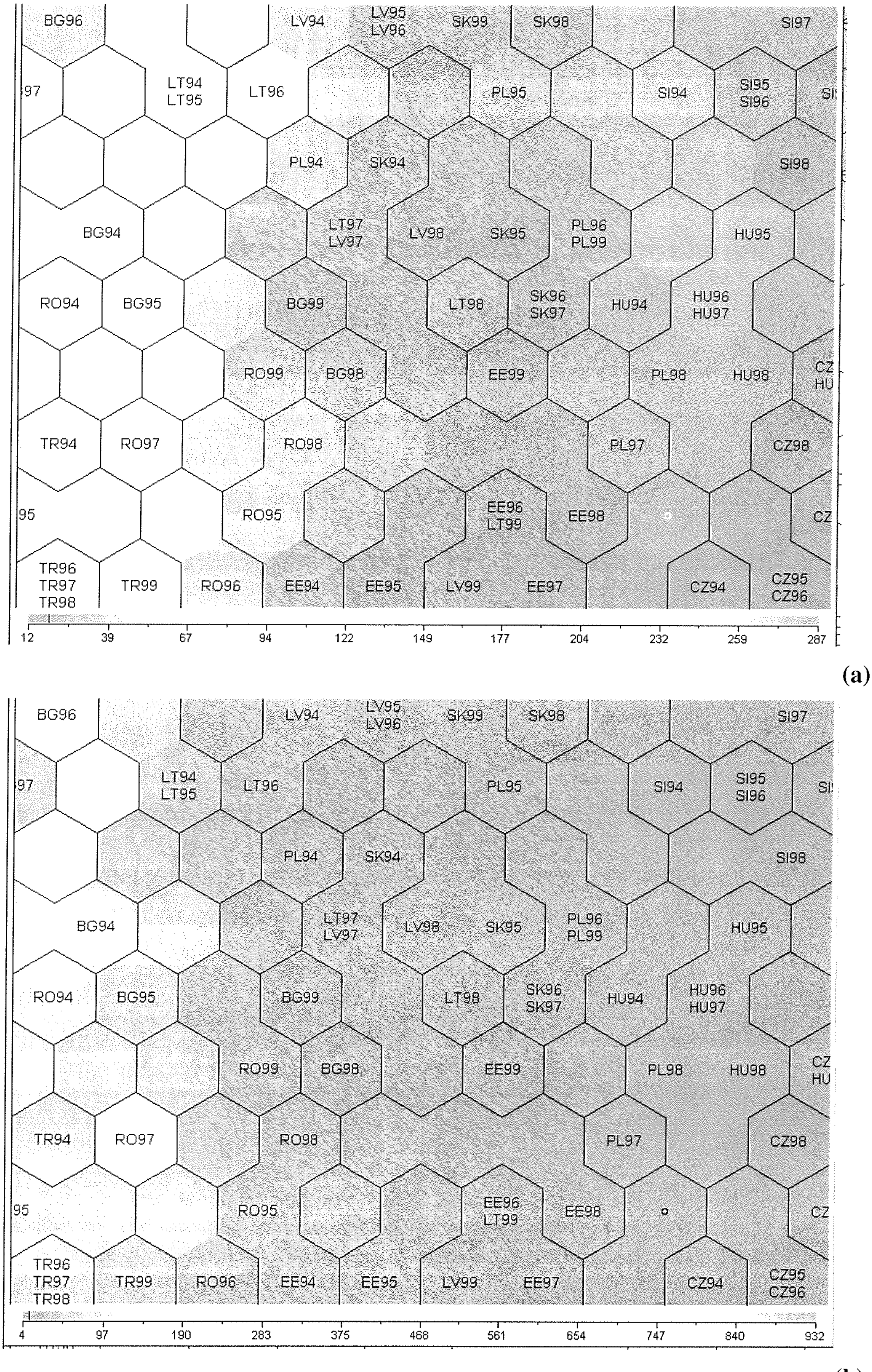
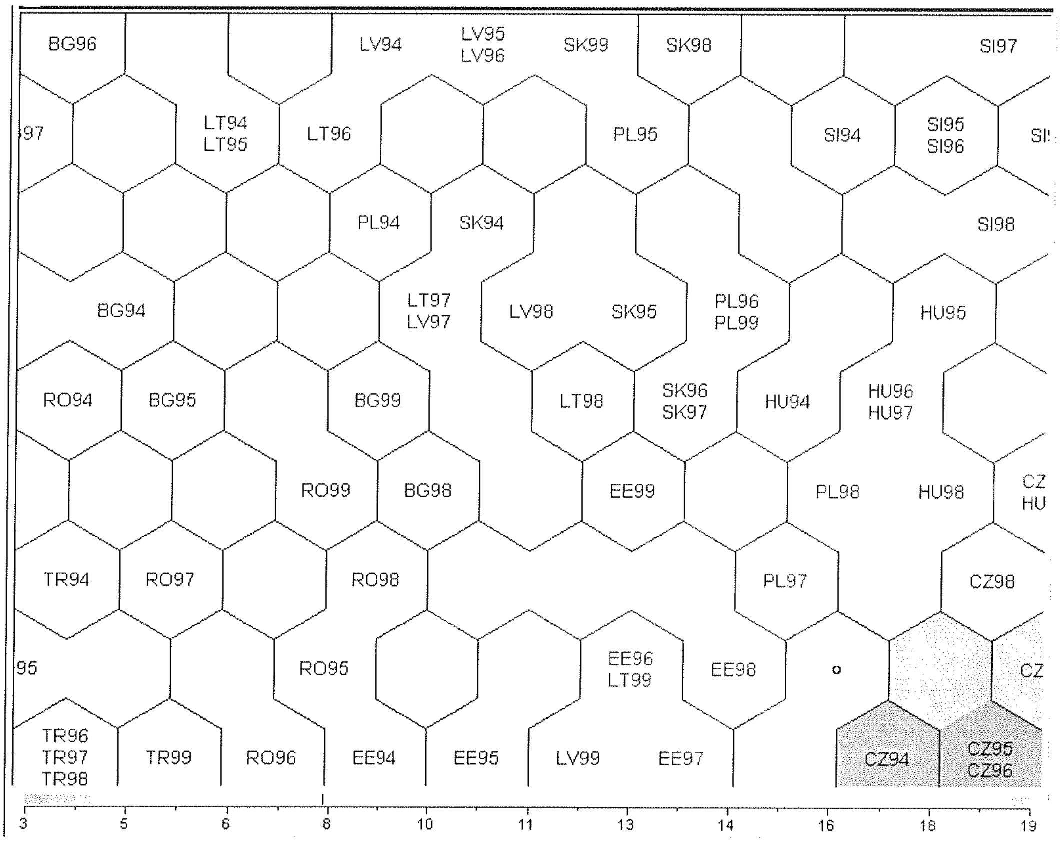
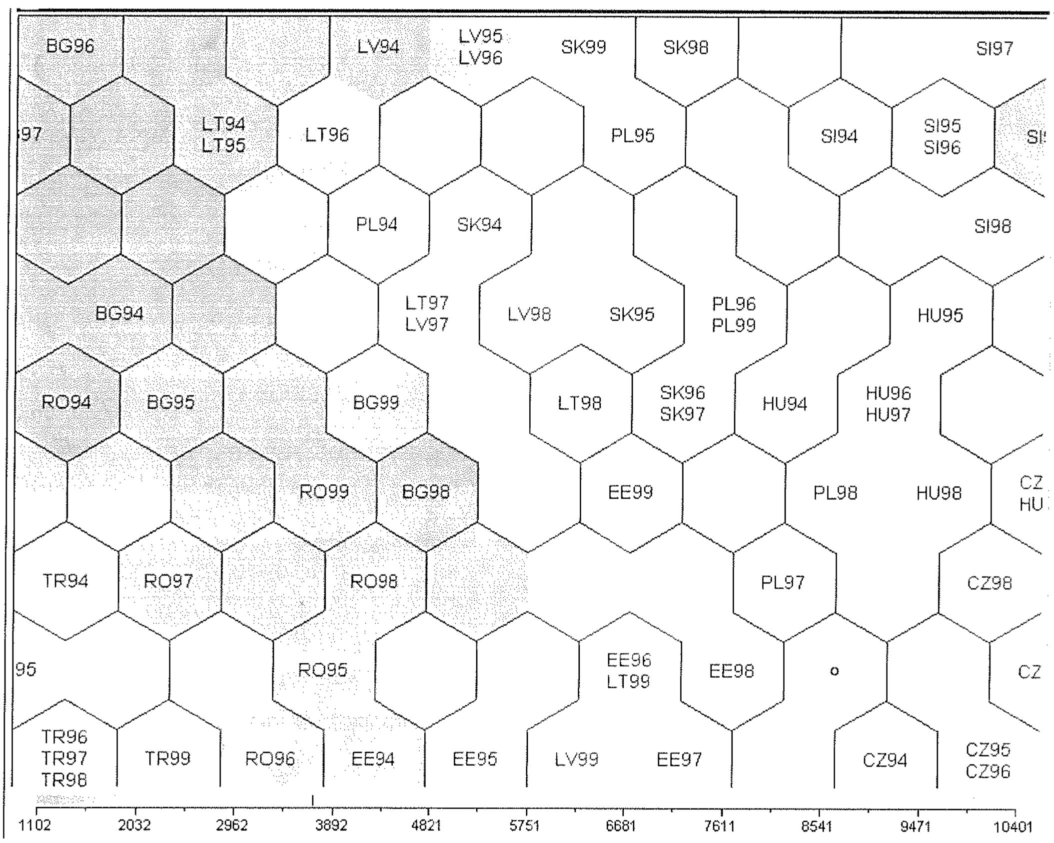


Fig. 5 Component Analysis for the EU Candidate Countries: (a) Inflation rate (b) Interest rates



(c)



(d)

Fig. 5 Component Analysis for the EU Candidate Countries: (c) Unemployment rate (d) GDP per capita in US$.

According to the map in Figure 3, the component analysis in Figure 5 a-d and the ESOM visualisation in Fig. 4 can be observed 3 sub clusters. Czech Rep., Hungary and Slovenia are grouped in the first subcluster and among the EU candidate countries they have best economies. In the second subcluster may be thought 3 Baltic countries Estonia, Latvia and Lithuania. The economies of Poland and Slovakia may be seen in this second subcluster, too. Poland's economy is closer to the first and Slovakia's economy is closer to the third cluster.

The third one - Bulgaria (99/98) – is in between the second cluster and Bulgaria (94-97), Romania and Turkey. Turkey placed in the bottom left corner of the map because of its chronic inflation. The earthquake which struck Turkey in August 1999 caused considerable economic damage and Turkey has undergone a period of recession in 1999. In recent years, Bulgaria has made considerable progress in macroeconomic stabilisation, whereas Romania's economic situation has deteriorated in 1998.

3.1.3 Pacific Countries

The first observation from the map in Figure 6 and Figure 7 is the effects of Asian crisis in 1997. From Japan to Hong Kong, Asia's economies are placed in a deep recession and this situation can be observed for the years 1997 and 1998 in the map. According to the basic macroeconomic indicators used in this research, the Pacific financial story for 1999 is the happy end.

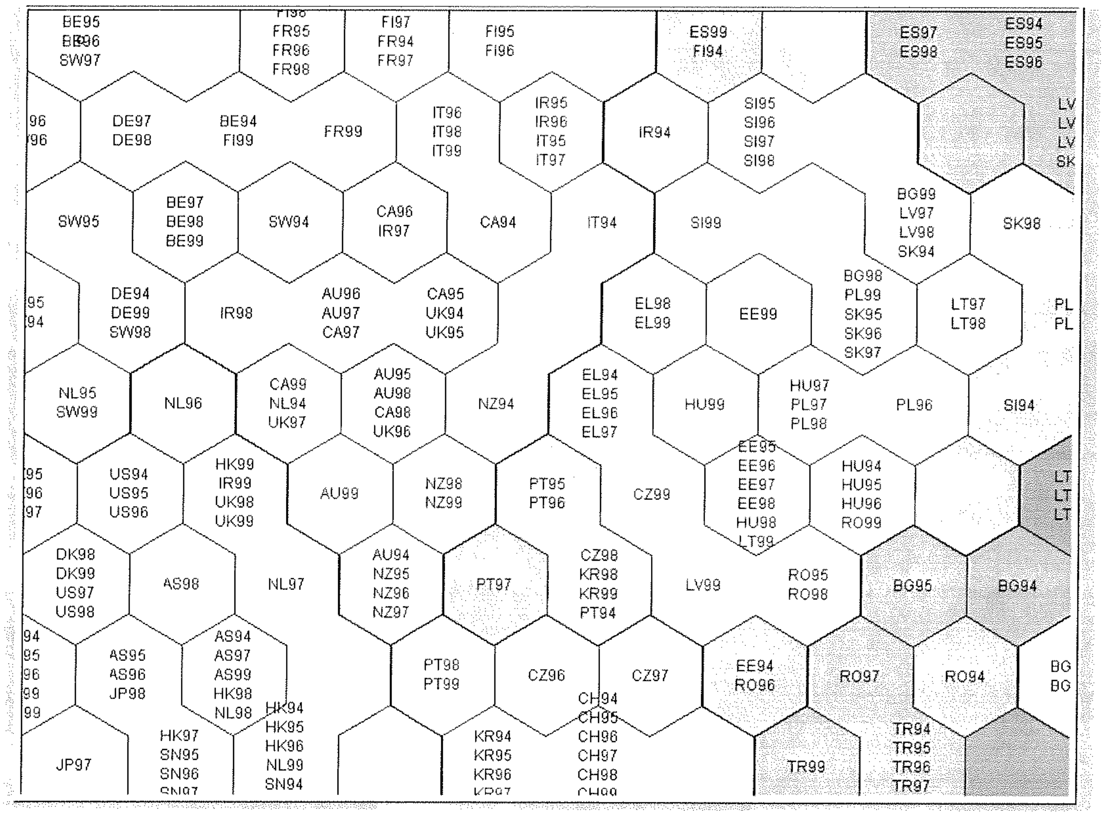


Fig.6. The annual map of the 32 countries (14 EU Member, 11 EU Candidate Countries, Australia, China, Hong Kong, Korea, Singapore, New Zealand and the United States) according to 4 characteristics (GDP Per Capita in US$, Inflation rate, Interest rate, Unemployment rate).

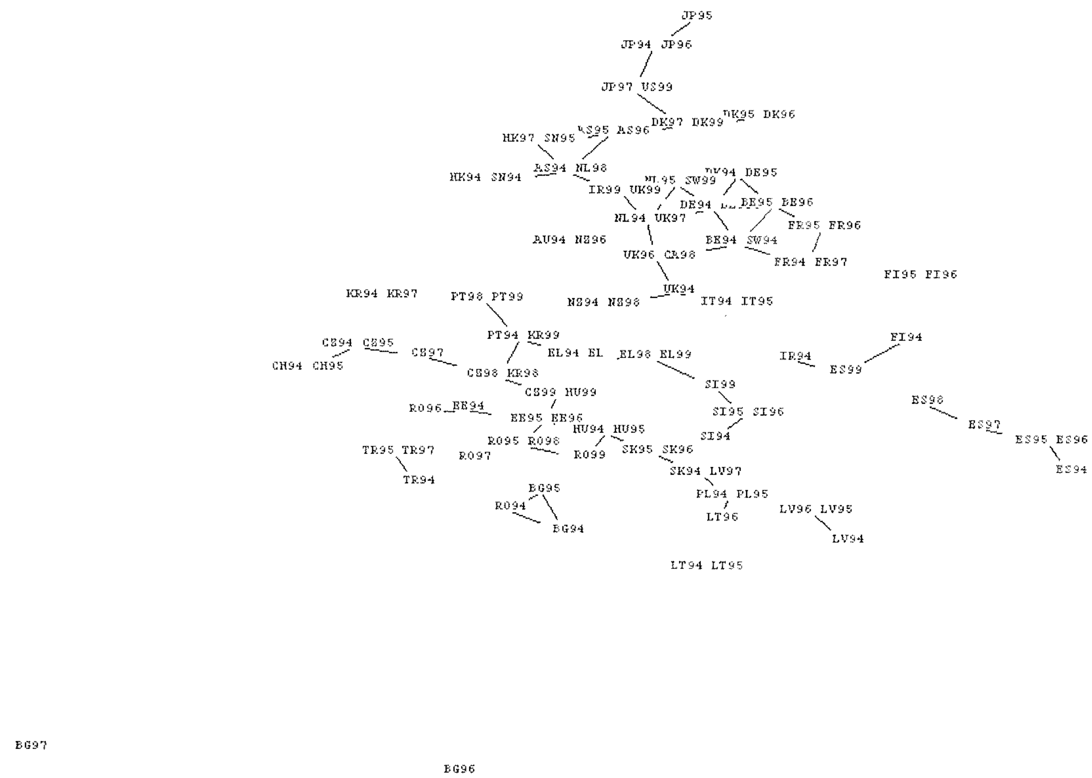


Fig. 7 Macro-economic performance map generated using ESOM and Sammon's Projection

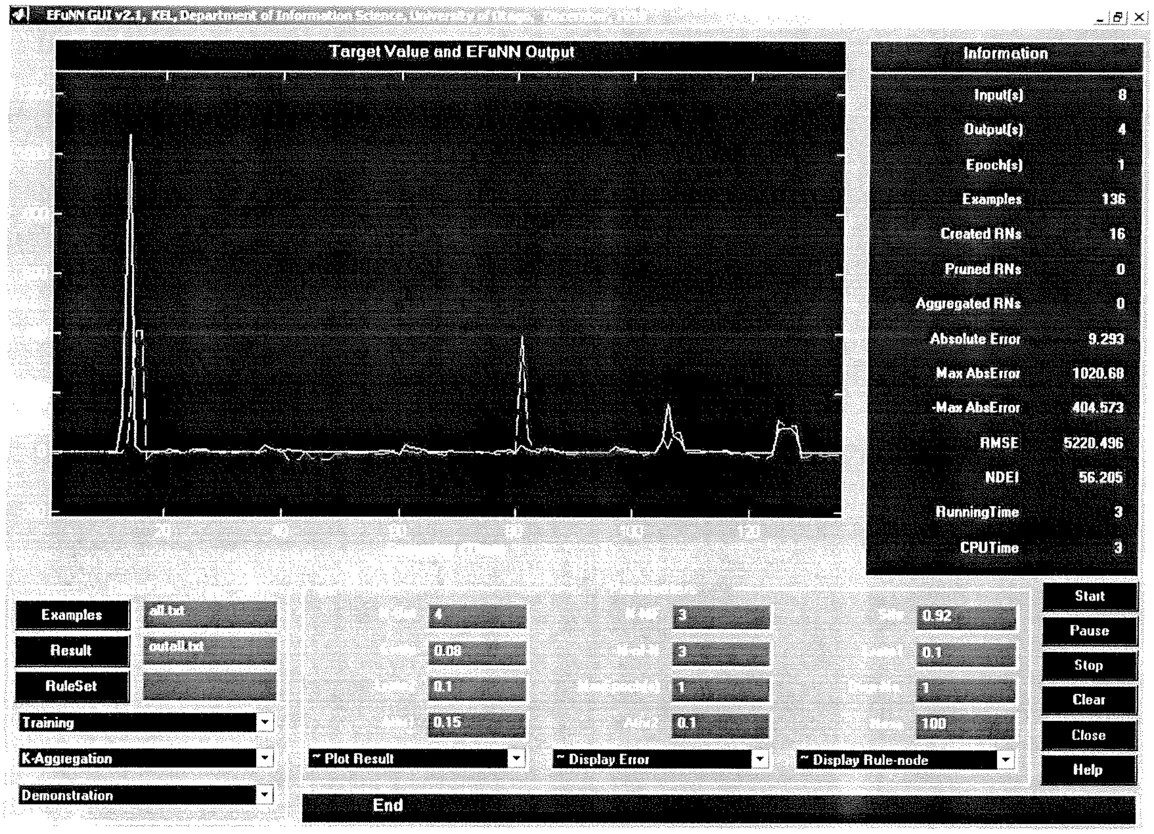


Fig.8. Experiment – EFuNN, all countries, by country order, GDP per capita prediction (in US$) – output # 4

3.2. Prediction of macro-economics with the use of EFuNNs

Experiments on prediction of macro-economic indexes have also been carried out. Good on-line prediction accuracy is gained in all EFuNN modules, as shown in Fig.8, Fig.9, and Fig.11.

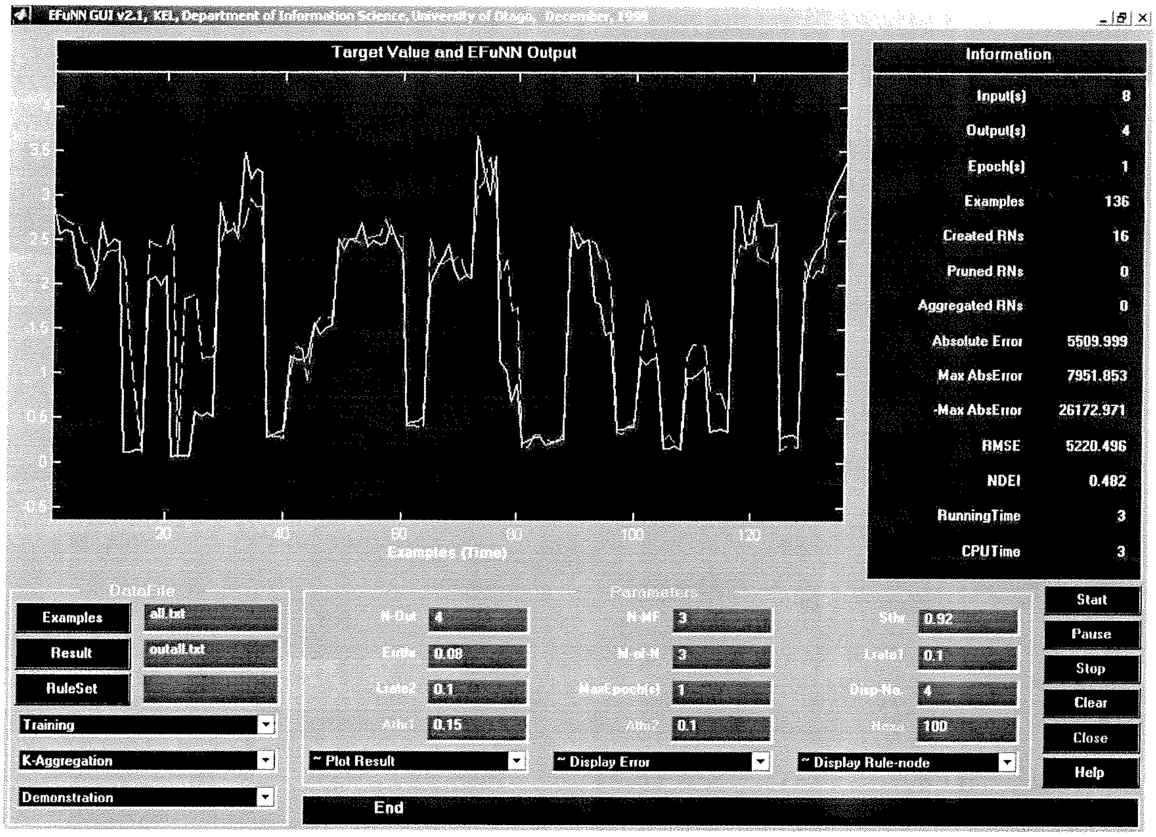


Fig.9. CPI on-line learning and prediction (output #1)

3.3. Extracting rules for macroeconomic development

Fig. 10 and Fig. 12 present the rule sets extracted from corresponding EFuNN modules.

The rules are of the form of:

IF (macroeconomic parameters) (t) is (....)

AND (macroeconomic parameters) (t-1) is (....)

THEN (macroeconomic parameters) (t+1) is (....)

where (t) is the currently month. Three membership functions are used.

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Rule   1:
if    [1] ( 1   0.711 ) ( 2   0.289 )
      [2] ( 1   0.693 ) ( 2   0.307 )
      [3] ( 1   0.432 ) ( 2   0.567 ) ( 3   0.000 )
      [4] ( 1   0.021 ) ( 2   0.774 ) ( 3   0.204 )
      [5] ( 1   0.711 ) ( 2   0.289 )
      [6] ( 1   0.694 ) ( 2   0.306 )
      [7] ( 1   0.464 ) ( 2   0.536 ) ( 3   0.000 )
      [8] ( 1   0.018 ) ( 2   0.764 ) ( 3   0.217 )
then  [1] ( 1   0.675 ) ( 2   0.279 )

      [2] ( 1   0.667 ) ( 2   0.286 )

      [3] ( 1   0.440 ) ( 2   0.508 ) ( 3   0.005 )

      [4] ( 2   0.675 ) ( 3   0.287 )

Rule   2:
if    [1] ( 1   0.708 ) ( 2   0.292 )
      [2] ( 1   0.678 ) ( 2   0.320 ) ( 3   0.002 )
      [3] ( 1   0.207 ) ( 2   0.775 ) ( 3   0.017 )
      [4] ( 1   0.108 ) ( 2   0.865 ) ( 3   0.027 )
      [5] ( 1   0.707 ) ( 2   0.292 ) ( 3   0.002 )
      [6] ( 1   0.678 ) ( 2   0.320 ) ( 3   0.003 )
      [7] ( 1   0.214 ) ( 2   0.769 ) ( 3   0.017 )
      [8] ( 1   0.078 ) ( 2   0.887 ) ( 3   0.035 )
then  [1] ( 1   0.689 ) ( 2   0.287 )

      [2] ( 1   0.668 ) ( 2   0.304 ) ( 3   0.000 )

      [3] ( 1   0.202 ) ( 2   0.767 ) ( 3   0.002 )

      [4] ( 1   0.005 ) ( 2   0.883 ) ( 3   0.085 )

Rule   3:
if    [1] ( 1   0.712 ) ( 2   0.288 )
      [2] ( 1   0.691 ) ( 2   0.309 )
      [3] ( 1   0.179 ) ( 2   0.801 ) ( 3   0.021 )
      [4] ( 1   0.006 ) ( 2   0.769 ) ( 3   0.225 )
      [5] ( 1   0.712 ) ( 2   0.288 )
      [6] ( 1   0.693 ) ( 2   0.307 )
      [7] ( 1   0.158 ) ( 2   0.825 ) ( 3   0.017 )
      [8] ( 1   0.002 ) ( 2   0.793 ) ( 3   0.206 )
then  [1] ( 1   0.688 ) ( 2   0.285 )

      [2] ( 1   0.678 ) ( 2   0.294 )

      [3] ( 1   0.145 ) ( 2   0.794 ) ( 3   0.033 )

      [4] ( 2   0.660 ) ( 3   0.312 )

Rule   4:
if    [1] ( 1   0.590 ) ( 2   0.410 )
      [2] ( 1   0.239 ) ( 2   0.761 )
      [3] ( 1   0.042 ) ( 2   0.932 ) ( 3   0.026 )
      [4] ( 1   0.687 ) ( 2   0.313 )
      [5] ( 1   0.630 ) ( 2   0.370 )
      [6] ( 1   0.345 ) ( 2   0.655 )
      [7] ( 1   0.113 ) ( 2   0.863 ) ( 3   0.024 )
      [8] ( 1   0.677 ) ( 2   0.323 )
then  [1] ( 1   0.539 ) ( 2   0.447 )
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      [2] ( 2   0.273 ) ( 3   0.714 )

      [3] ( 2   0.951 ) ( 3   0.042 )

      [4] ( 1   0.695 ) ( 2   0.292 )

Rule   5:
if    [1] ( 1   0.566 ) ( 2   0.370 ) ( 3   0.064 )
      [2] ( 1   0.275 ) ( 2   0.642 ) ( 3   0.083 )
      [3] ( 1   0.092 ) ( 2   0.875 ) ( 3   0.033 )
      [4] ( 1   0.682 ) ( 2   0.318 )
      [5] ( 1   0.529 ) ( 2   0.413 ) ( 3   0.058 )
      [6] ( 1   0.088 ) ( 2   0.369 ) ( 3   0.543 )
      [7] ( 1   0.002 ) ( 2   0.953 ) ( 3   0.046 )
      [8] ( 1   0.693 ) ( 2   0.307 )
then  [1] ( 2   0.300 ) ( 3   0.714 )

      [2] ( 2   0.677 ) ( 3   0.415 )

      [3] ( 2   0.854 ) ( 3   0.106 )

      [4] ( 1   0.673 ) ( 2   0.287 )

Rule   6:
if    [1] ( 1   0.495 ) ( 2   0.433 ) ( 3   0.071 )
      [2] ( 2   0.329 ) ( 3   0.671 )
      [3] ( 1   0.029 ) ( 2   0.965 ) ( 3   0.006 )
      [4] ( 1   0.692 ) ( 2   0.308 )
      [5] ( 1   0.069 ) ( 2   0.288 ) ( 3   0.643 )
      [6] ( 1   0.066 ) ( 2   0.682 ) ( 3   0.252 )
      [7] ( 1   0.002 ) ( 2   0.903 ) ( 3   0.095 )
      [8] ( 1   0.694 ) ( 2   0.306 )
then  [1] ( 1   0.666 ) ( 2   0.321 )

      [2] ( 1   0.614 ) ( 2   0.335 ) ( 3   0.038 )

      [3] ( 2   0.986 ) ( 3   0.001 )

      [4] ( 1   0.678 ) ( 2   0.309 )

Rule   7:
if    [1] ( 2   0.286 ) ( 3   0.714 )
      [2] ( 2   0.720 ) ( 3   0.280 )
      [3] ( 2   0.936 ) ( 3   0.064 )
      [4] ( 1   0.690 ) ( 2   0.310 )
      [5] ( 1   0.688 ) ( 2   0.312 )
      [6] ( 1   0.658 ) ( 2   0.342 )
      [7] ( 1   0.017 ) ( 2   0.983 )
      [8] ( 1   0.686 ) ( 2   0.314 )
then  [1] ( 1   0.705 ) ( 2   0.295 )

      [2] ( 1   0.660 ) ( 2   0.340 )

      [3] ( 2   0.887 ) ( 3   0.113 )

      [4] ( 1   0.684 ) ( 2   0.316 )

Rule   8:
if    [1] ( 1   0.690 ) ( 2   0.310 )
      [2] ( 1   0.640 ) ( 2   0.360 )
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        [3] ( 1   0.521 ) ( 2   0.479 )
        [4] ( 1   0.621 ) ( 2   0.379 )
        [5] ( 1   0.693 ) ( 2   0.307 )
        [6] ( 1   0.646 ) ( 2   0.354 )
        [7] ( 1   0.516 ) ( 2   0.484 )
        [8] ( 1   0.607 ) ( 2   0.393 )
   then [1] ( 1   0.686 ) ( 2   0.279 )

        [2] ( 1   0.651 ) ( 2   0.314 )

        [3] ( 1   0.692 ) ( 2   0.273 )

        [4] ( 1   0.575 ) ( 2   0.372 ) ( 3   0.019 )

Rule   9:
if      [1] ( 1   0.648 ) ( 2   0.352 )
        [2] ( 1   0.525 ) ( 2   0.475 )
        [3] ( 1   0.129 ) ( 2   0.804 ) ( 3   0.067 )
        [4] ( 1   0.629 ) ( 2   0.371 )
        [5] ( 1   0.653 ) ( 2   0.347 )
        [6] ( 1   0.555 ) ( 2   0.445 )
        [7] ( 1   0.080 ) ( 2   0.848 ) ( 3   0.072 )
        [8] ( 1   0.619 ) ( 2   0.381 )
   then [1] ( 1   0.668 ) ( 2   0.318 )

        [2] ( 1   0.573 ) ( 2   0.395 ) ( 3   0.019 )

        [3] ( 1   0.038 ) ( 2   0.856 ) ( 3   0.093 )

        [4] ( 1   0.581 ) ( 2   0.405 ) ( 3   0.001 )

Rule   10:
if      [1] ( 1   0.711 ) ( 2   0.289 )
        [2] ( 1   0.699 ) ( 2   0.301 )
        [3] ( 1   0.521 ) ( 2   0.479 )
        [4] ( 2   0.655 ) ( 3   0.345 )
        [5] ( 1   0.711 ) ( 2   0.289 )
        [6] ( 1   0.696 ) ( 2   0.304 )
        [7] ( 1   0.525 ) ( 2   0.475 )
        [8] ( 2   0.644 ) ( 3   0.356 )
   then [1] ( 1   0.670 ) ( 2   0.277 )

        [2] ( 1   0.670 ) ( 2   0.277 )

        [3] ( 1   0.354 ) ( 2   0.593 )

        [4] ( 2   0.302 ) ( 3   0.650 )

Rule   11:
if      [1] ( 1   0.705 ) ( 2   0.295 )
        [2] ( 1   0.656 ) ( 2   0.344 )
        [3] ( 1   0.185 ) ( 2   0.758 ) ( 3   0.057 )
        [4] ( 1   0.387 ) ( 2   0.613 )
        [5] ( 1   0.706 ) ( 2   0.294 )
        [6] ( 1   0.667 ) ( 2   0.333 )
        [7] ( 1   0.180 ) ( 2   0.755 ) ( 3   0.065 )
        [8] ( 1   0.372 ) ( 2   0.628 )
   then [1] ( 1   0.689 ) ( 2   0.293 )

        [2] ( 1   0.662 ) ( 2   0.316 ) ( 3   0.004 )
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       [3] ( 1   0.193 ) ( 2   0.773 ) ( 3   0.016 )

       [4] ( 1   0.299 ) ( 2   0.683 ) ( 3   0.000 )

 Rule   12:
 if    [1] ( 1   0.708 ) ( 2   0.292 )
       [2] ( 1   0.686 ) ( 2   0.314 )
       [3] ( 2   0.324 ) ( 3   0.676 )
       [4] ( 1   0.251 ) ( 2   0.749 )
       [5] ( 1   0.708 ) ( 2   0.292 )
       [6] ( 1   0.679 ) ( 2   0.321 )
       [7] ( 2   0.331 ) ( 3   0.669 )
       [8] ( 1   0.202 ) ( 2   0.798 )
 then  [1] ( 1   0.693 ) ( 2   0.292 )

       [2] ( 1   0.667 ) ( 2   0.318 )

       [3] ( 2   0.203 ) ( 3   0.782 )

       [4] ( 1   0.105 ) ( 2   0.880 )

 Rule   13:
 if    [1] ( 1   0.714 ) ( 2   0.286 )
       [2] ( 1   0.708 ) ( 2   0.292 )
       [3] ( 1   0.637 ) ( 2   0.363 )
       [4] ( 2   0.369 ) ( 3   0.631 )
       [5] ( 1   0.713 ) ( 2   0.287 )
       [6] ( 1   0.711 ) ( 2   0.289 )
       [7] ( 1   0.622 ) ( 2   0.378 )
       [8] ( 2   0.393 ) ( 3   0.607 )
 then  [1] ( 1   0.703 ) ( 2   0.291 )

       [2] ( 1   0.707 ) ( 2   0.287 )

       [3] ( 1   0.617 ) ( 2   0.377 )

       [4] ( 2   0.349 ) ( 3   0.645 )

 Rule   14:
 if    [1] ( 1   0.709 ) ( 2   0.291 )
       [2] ( 1   0.681 ) ( 2   0.319 )
       [3] ( 1   0.527 ) ( 2   0.473 )
       [4] ( 1   0.298 ) ( 2   0.672 ) ( 3   0.030 )
       [5] ( 1   0.709 ) ( 2   0.291 )
       [6] ( 1   0.685 ) ( 2   0.315 )
       [7] ( 1   0.536 ) ( 2   0.464 )
       [8] ( 1   0.302 ) ( 2   0.661 ) ( 3   0.037 )
 then  [1] ( 1   0.692 ) ( 2   0.292 )

       [2] ( 1   0.669 ) ( 2   0.314 )

       [3] ( 1   0.600 ) ( 2   0.383 )

       [4] ( 1   0.261 ) ( 2   0.709 ) ( 3   0.014 )

 Rule   15:
 if    [1] ( 1   0.686 ) ( 2   0.314 )
       [2] ( 1   0.604 ) ( 2   0.396 )
       [3] ( 1   0.016 ) ( 2   0.759 ) ( 3   0.225 )
       [4] ( 1   0.642 ) ( 2   0.358 )
       [5] ( 1   0.692 ) ( 2   0.308 )
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        [6]  ( 1    0.618 )  ( 2    0.382 )
        [7]  ( 2    0.672 )  ( 3    0.328 )
        [8]  ( 1    0.637 )  ( 2    0.363 )
then    [1]  ( 1    0.690 )  ( 2    0.310 )

        [2]  ( 1    0.644 )  ( 2    0.356 )

        [3]  ( 2    0.530 )  ( 3    0.470 )

        [4]  ( 1    0.631 )  ( 2    0.369 )

Rule    16:
if      [1]  ( 1    0.592 )  ( 2    0.408 )
        [2]  ( 1    0.310 )  ( 2    0.690 )
        [3]  ( 1    0.320 )  ( 2    0.680 )
        [4]  ( 1    0.651 )  ( 2    0.349 )
        [5]  ( 1    0.617 )  ( 2    0.383 )
        [6]  ( 1    0.360 )  ( 2    0.640 )
        [7]  ( 1    0.363 )  ( 2    0.637 )
        [8]  ( 1    0.647 )  ( 2    0.353 )
then    [1]  ( 1    0.585 )  ( 2    0.403 )

        [2]  ( 1    0.395 )  ( 2    0.593 )

        [3]  ( 1    0.357 )  ( 2    0.631 )

        [4]  ( 1    0.649 )  ( 2    0.340 )
```

Fig.10. Rules of GDP prediction for all countries.

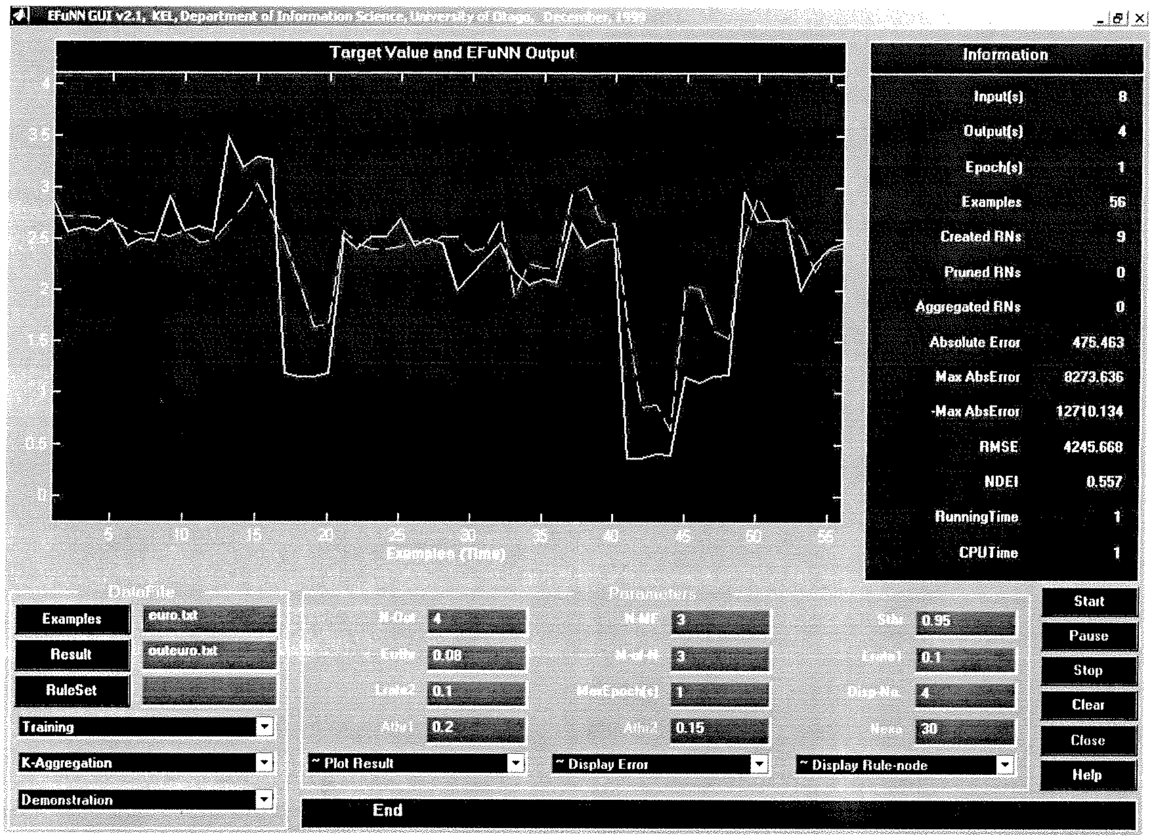

Fig.11. EU member countries – GDP on-line learning and prediction

```
Rule   1:
if   [1] ( 1   0.640 ) ( 2   0.360 )
     [2] ( 1   0.611 ) ( 2   0.389 )
     [3] ( 1   0.295 ) ( 2   0.704 ) ( 3   0.002 )
     [4] ( 1   0.018 ) ( 2   0.731 ) ( 3   0.250 )
     [5] ( 1   0.620 ) ( 2   0.380 )
     [6] ( 1   0.647 ) ( 2   0.353 )
     [7] ( 1   0.380 ) ( 2   0.619 ) ( 3   0.002 )
     [8] ( 1   0.018 ) ( 2   0.678 ) ( 3   0.304 )
then [1] ( 1   0.584 ) ( 2   0.393 )

     [2] ( 1   0.587 ) ( 2   0.391 )

     [3] ( 1   0.372 ) ( 2   0.602 ) ( 3   0.002 )

     [4] ( 2   0.638 ) ( 3   0.341 )

Rule   2:
if   [1] ( 1   0.588 ) ( 2   0.400 ) ( 3   0.012 )
     [2] ( 1   0.534 ) ( 2   0.454 ) ( 3   0.011 )
     [3] ( 1   0.064 ) ( 2   0.846 ) ( 3   0.090 )
     [4] ( 1   0.050 ) ( 2   0.785 ) ( 3   0.165 )
     [5] ( 1   0.591 ) ( 2   0.400 ) ( 3   0.009 )
     [6] ( 1   0.544 ) ( 2   0.446 ) ( 3   0.009 )
     [7] ( 1   0.047 ) ( 2   0.827 ) ( 3   0.126 )
     [8] ( 1   0.043 ) ( 2   0.775 ) ( 3   0.182 )
then [1] ( 1   0.600 ) ( 2   0.380 )

     [2] ( 1   0.517 ) ( 2   0.467 )

     [3] ( 1   0.041 ) ( 2   0.767 ) ( 3   0.172 )

     [4] ( 1   0.029 ) ( 2   0.762 ) ( 3   0.190 )

Rule   3:
if   [1] ( 1   0.361 ) ( 2   0.584 ) ( 3   0.054 )
     [2] ( 1   0.447 ) ( 2   0.499 ) ( 3   0.053 )
     [3] ( 1   0.215 ) ( 2   0.722 ) ( 3   0.062 )
     [4] ( 1   0.434 ) ( 2   0.566 )
     [5] ( 1   0.374 ) ( 2   0.586 ) ( 3   0.040 )
     [6] ( 1   0.350 ) ( 2   0.599 ) ( 3   0.051 )
     [7] ( 1   0.157 ) ( 2   0.785 ) ( 3   0.058 )
     [8] ( 1   0.409 ) ( 2   0.591 )
then [1] ( 1   0.363 ) ( 2   0.600 ) ( 3   0.003 )

     [2] ( 1   0.342 ) ( 2   0.631 )

     [3] ( 1   0.094 ) ( 2   0.846 ) ( 3   0.026 )

     [4] ( 1   0.323 ) ( 2   0.640 ) ( 3   0.002 )

Rule   4:
if   [1] ( 1   0.700 ) ( 2   0.300 )
     [2] ( 1   0.635 ) ( 2   0.365 )
     [3] ( 2   0.364 ) ( 3   0.636 )
     [4] ( 2   0.812 ) ( 3   0.188 )
     [5] ( 1   0.698 ) ( 2   0.302 )
     [6] ( 1   0.639 ) ( 2   0.361 )
     [7] ( 2   0.352 ) ( 3   0.648 )
     [8] ( 2   0.719 ) ( 3   0.281 )
```

```
then [1] ( 1   0.670 ) ( 2   0.328 )

     [2] ( 1   0.578 ) ( 2   0.419 )

     [3] ( 2   0.397 ) ( 3   0.600 )

     [4] ( 2   0.756 ) ( 3   0.241 )

Rule   5:
if   [1] ( 1   0.564 ) ( 2   0.436 )
     [2] ( 1   0.580 ) ( 2   0.420 )
     [3] ( 1   0.007 ) ( 2   0.873 ) ( 3   0.121 )
     [4] ( 1   0.023 ) ( 2   0.977 )
     [5] ( 1   0.470 ) ( 2   0.530 )
     [6] ( 1   0.417 ) ( 2   0.583 )
     [7] ( 1   0.012 ) ( 2   0.737 ) ( 3   0.252 )
     [8] ( 2   0.982 ) ( 3   0.018 )
then [1] ( 1   0.444 ) ( 2   0.547 )

     [2] ( 1   0.321 ) ( 2   0.670 )

     [3] ( 1   0.023 ) ( 2   0.582 ) ( 3   0.386 )

     [4] ( 2   0.853 ) ( 3   0.137 )

Rule   6:
if   [1] ( 2   0.286 ) ( 3   0.714 )
     [2] ( 2   0.286 ) ( 3   0.714 )
     [3] ( 2   0.353 ) ( 3   0.647 )
     [4] ( 1   0.714 ) ( 2   0.286 )
     [5] ( 2   0.286 ) ( 3   0.714 )
     [6] ( 2   0.286 ) ( 3   0.714 )
     [7] ( 2   0.311 ) ( 3   0.689 )
     [8] ( 1   0.714 ) ( 2   0.286 )
then [1] ( 2   0.286 ) ( 3   0.714 )

     [2] ( 2   0.286 ) ( 3   0.714 )

     [3] ( 2   0.475 ) ( 3   0.525 )

     [4] ( 1   0.714 ) ( 2   0.286 )

Rule   7:
if   [1] ( 1   0.004 ) ( 2   0.683 ) ( 3   0.313 )
     [2] ( 2   0.731 ) ( 3   0.269 )
     [3] ( 2   0.585 ) ( 3   0.415 )
     [4] ( 1   0.672 ) ( 2   0.328 )
     [5] ( 1   0.007 ) ( 2   0.842 ) ( 3   0.151 )
     [6] ( 2   0.809 ) ( 3   0.191 )
     [7] ( 2   0.747 ) ( 3   0.253 )
     [8] ( 1   0.694 ) ( 2   0.306 )
then [1] ( 2   0.775 ) ( 3   0.230 )

     [2] ( 2   0.283 ) ( 3   0.714 )

     [3] ( 2   0.788 ) ( 3   0.209 )

     [4] ( 1   0.704 ) ( 2   0.293 )

Rule   8:
if   [1] ( 1   0.072 ) ( 2   0.928 )
```

```
     [2] ( 2   0.929 ) ( 3   0.071 )
     [3] ( 2   0.967 ) ( 3   0.033 )
     [4] ( 1   0.664 ) ( 2   0.336 )
     [5] ( 1   0.132 ) ( 2   0.868 )
     [6] ( 2   0.828 ) ( 3   0.172 )
     [7] ( 2   0.845 ) ( 3   0.155 )
     [8] ( 1   0.678 ) ( 2   0.322 )
then [1] ( 1   0.204 ) ( 2   0.796 )

     [2] ( 2   0.797 ) ( 3   0.203 )

     [3] ( 2   0.450 ) ( 3   0.550 )

     [4] ( 1   0.701 ) ( 2   0.299 )

Rule   9:
if   [1] ( 1   0.600 ) ( 2   0.400 )
     [2] ( 1   0.534 ) ( 2   0.466 )
     [3] ( 1   0.344 ) ( 2   0.656 )
     [4] ( 1   0.329 ) ( 2   0.671 )
     [5] ( 1   0.595 ) ( 2   0.405 )
     [6] ( 1   0.625 ) ( 2   0.375 )
     [7] ( 1   0.413 ) ( 2   0.587 )
     [8] ( 1   0.345 ) ( 2   0.655 )
then [1] ( 1   0.557 ) ( 2   0.441 )

     [2] ( 1   0.600 ) ( 2   0.398 )

     [3] ( 1   0.437 ) ( 2   0.561 )

     [4] ( 1   0.355 ) ( 2   0.643 )
```

Fig. 12. Rules for the European Union

4. Conclusions and Directions for Further Research

Future work is planned with the use of quarterly macroeconomic data. This is expected to result in a more precise models developed. A further analysis of the trends in the development of the EU-candidate countries will be conducted. The preliminary analysis shows a trend of development towards the centre the EU cluster. A more precise comparative analysis on the trends of development of the three major groups of countries - EU, EU-candidates and Asia-Pacific will be attempted.

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Appendix-A: Legends

AS	Austria	IT	Italy
AU	Australia	JP	Japan
BE	Belgium	KR	Korea, Rep.
BG	Bulgaria	LT	Lithunia
CA	Canada	LV	Latvia
CH	China	NL	Netherlands
CZ	Czech Rep.	NZ	New Zealand
DE	Germany	PL	Poland
DK	Denmark	PT	Portugal
EE	Estonia	RO	Romania
EL	Greece	SI	Slovenia
ES	Spain	SK	Slovakia
FI	Finland	SN	Singapore
FR	France	SW	Sweden
HK	Hong Kong	TR	Turkey
HU	Hungary	UK	U. Kingdom
IR	Ireland	US	USA