Chapter 17. Hybrid Intelligent Decision Support Systems and Applications for Risk Analysis and Discovery of Evolving Economic Clusters in Europe

N. Kasabov[1], L. Erzegovesi[2], M. Fedrizzi[2], A. Beber[2], and D. Deng[1]

[1] Dept. of Information Science, Univ. of Otago, Dunedin, New Zealand.
E-mail: nkasabov, ddeng@infoscience.otago.ac.nz
[2] Dept. of Informatics and Faculty of Economics, Univ. of Trento, Italy

Abstract. *Decision making in a complex, dynamically changing environment is a difficult task that requires new techniques of computational intelligence for building adaptive, hybrid intelligent decision support systems (HIDSS). Here, a new approach is proposed based on evolving agents in a dynamic environment. Neural network and rule-based agents are evolved from incoming data and expert knowledge if a decision making process requires this. The agents are evolved from methods included in a repository for intelligent connectionist based information systems RICBIS (http://divcom.otago.ac.nz/infosci/kel/CBIIS.html) with the use of financial market data collected in an on-line mode, and with the use of macroeconomic data published monthly in the European Central Bank Bulletin. RICBIS includes different types of neural networks, including MLP, SOM, fuzzy neural networks (FuNN), evolving fuzzy neural networks (EFuNN), evolving SOM, rule-based systems, data pre-processing techniques, standard statistical and financial techniques. A case study project on risk analysis of the European Monetary Union (EMU) is considered and a framework of a system EMU-HIDSS is presented, which deals with different levels of information and users, e.g. the whole world, Europe, clusters of nations, a single nation, companies/banks. It combines modules for final decision making, global and national economic development, exchange rate trend prediction, stock index trend prediction, etc. Some experimental results on real data are presented.*

Keywords. *Intelligent decision support systems, risk analysis, connectionist-based information systems.*

1 Introduction

Complex decision making problems very often require considering enormous amount of information distributed among many variables. The decision support systems (DSS) built to solve these problems should have advanced features such as [19]:

- 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., two experts predict different trends in the stock market;
- Dealing with large databases with a lot of redundant information, or coping with lack of data.
- Having hierarchical organisation, as decision making is usually not a single-level process, but involves different levels of processing, comparing different possible solutions, using alternatives, sometimes in a recurrent way.

Techniques of computational intelligence, such as artificial neural networks, fuzzy logic systems, genetic algorithms, advanced statistical methods, hybrid systems, along with traditional statistical and financial analysis methods, have been widely applied on different problems from finance and economics. Here some of them are references and explained.

1.1 Specialised and Advanced Statistical and Econometric Models

In [45] a model for risk analysis on crashes of currencies is introduced. It considers a crash situation when a currency has been devaluated more than 10% within a month when compared to the US dollar. Four parameters are used to evaluate the likelihood of a crash (a value of 0 or 1) in the following month: measure of currency overvaluation; expected domestic output growth; ratio of federal reserves versus external debt; measures of international financial contagion. The latter is measured in risk appetite (a change in investors preferences before crashes occur), and clusters (whether crashes of currencies from the same block of countries have recently occurred). Other models are presented in [6].

The methods in this group require a reliable knowledge on the underlying rules of the financial and economic systems and can not be easily adjusted to a new economic or financial situation. They are applicable when crises occur according to recurrent and known patterns.

1.2 Symbolic and Fuzzy Rule-Based Systems

Rule-based systems and fuzzy rule-based systems in particular have been used in financial and economic decision making (see papers in [12][13]). The main advantage of rule-based systems is that their functioning is based on human expert rules. The main disadvantage is that these systems are not flexible enough to react to changes in the reality. Changing the rules usually is difficult, and nobody can articulate the perfect set of rules that do not have to change in a future time.

1.3 Artificial Neural Networks (ANN)

Extended studies of using ANN for financial DSS have been done in several books (see for example: [12][13][49][54]). Generally, the so called non-parametric models proved to outperform the statistical methods, especially when the underlying rules were not known, or they change over time. Different types of ANN were used, mainly multi-layer perceptrons (MLP), radial basis functions (RBF), and self-organising feature maps (SOM).

A MLP model and a RBF model on option pricing [16] proved to outperform several other models, that include a direct application of Black-Scholes formula, ordinary least squares, and projection pursuit. The test data was the daily S&P500 futures and option prices. Two input variables – the ratio stock price/strike price and time to maturity, and one output variable - option price, were used. This model was further extended into a multi-modular ANN model with the use of hints [10].

In [5] a substantial study of applying SOM to financial markets is presented. In [3] emerging and new markets are mapped into a SOM that shows groups (clusters) of similar economies.

The so far developed and used ANN models proved to be efficient, but they do not allow easily for dynamic on-line training, for changing the parameters in an on-line mode, for combining data and knowledge (rules) into one system.

1.4 Genetic Algorithms

Genetic algorithms (GA) are heuristic models that are based on generating possible solutions to a problem and evaluating their "goodness" based on a goodness (fitness) function (e.g. goal function) that has to be specified in advance. GA use terminology from the natural selection and evolution of species. There are several studies of using GA for economic and financial decision making (see also chapters in this volume). Software based on GA simulation, that works directly on data in an Excel format has been produced [8].

The main advantage of GAs is that they do not require much knowledge on the underlying rules, formulas, etc., but a goodness function to evaluate how good solutions are. The main disadvantages of GAs are: (i) they are computationally slow; (ii) they do not necessarily provide with the best solution as they are heuristically based; (iii) they do not work in on-line and real time modes.

1.5 Models Based on Dynamic System Analysis

In [50] the stock market is modelled as a complex dynamic system that can be in one of four states projected in a two-dimensional space of group thinking-fundamental bias: random walk, chaotic market, coherent bull market, coherent bear market. In [38][39] a stock index prediction problem is considered as equivalent to the prediction of a chaotic process with different characteristics at different time scales and a high frequency index prediction (e.g. daily prediction) being attempted after the low frequency one (e.g., monthly, or annual prediction) is performed.

1.6 Hybrid Systems

Hybrid systems combine several of the above methods into one system [19][20]. They achieve this combination either in a “loose” way, e.g. different modules in the same system use different methods (see examples of such systems in [12][13]), or in a “tight” way - methods are mixed at a low level, e.g. fuzzy neural networks ([18][29][42]). These methods are the most promising among the methods discussed above, as the hybrid systems integrate the advantages of all the methods combined, e.g. dealing with both data and expert rules, using both statistical formulas and heuristics or hints.

1.7 What is Missing in the Methods from Above?

The six groups of approaches presented above have been partially successful, with major problems as listed below:

- They do not consider the complexity of the problem in a whole with many hierarchical levels for decision making that include applying low-level processing and higher level expert knowledge; or
- They do not consider uncertainties at different levels of information processing and combining them or propagating them in a task dependent way to the final decision making block; or
- They do not apply sufficient variety of techniques and choose the most appropriate for each sub-task; or
- They do not offer adjustment of variable sets, optimisation criteria, rules, even if the real situation changes over time.

2 From DSS to HIDSS

Hybrid systems combine different techniques of computational intelligence with traditional statistical methods. Hybrid systems are especially suitable for building DSS.

Stock market index prediction is a good example of a complex problem that requires a hybrid system, as it is shown on the case study of the NZSE40 stock index in [19][38][39]. Several modules are included in the DSS system presented there as there are several tasks within the global one: data pre- processing (e.g. normalisation, moving averages calculation, etc); predicting the next value for the index; predicting longer-term values for the NZES40, final decision making that takes into account rules on the political and economic situation; extracting trading rules from the system - see Fig.1. A neural network is used to predict the next value of the index based on the current and the previous-day values. The predicted value from the neural network module is combined with expert rules on the current political and economic situation in a fuzzy inference module. These two variables are fuzzy by nature. The final decision is produced as a fuzzy one, and as a crisp one

- after a defuzzification process. Another module in the DSS from Fig.1 is devoted to extracting fuzzy trading rules, which are used to explain the current behaviour of the market.

An environment, called FuzzyCOPE/1, that can be used to create hybrid systems, is described in [19] and available from internet URL http://kel.otago.ac.nz/. It consists of the following modules that have compatible interfaces and can be connected in a DSS as a decision making sequence that represents the logic of the real decision making process: data processing modules (normalisation, fuzzification, filtering, etc.); multi-layer perceptron (MLP); self-organising map (SOM); fuzzy neural network (FuNN) as introduced by Kasabov in [18][19][28]; fuzzy logic inference engine (FLIE) based on simple fuzzy rules of Zadeh-Mamdani type (Zadeh, 1965); production rule-based system CLIPS and FuzzyCLIPS in particular. The FuzzyCOPE/1 environment has been extended to FuzzyCOPE/3 with the inclusion of new MLP and SOM learning modes, and new modes for learning, rule extraction and rule insertion in FuNNs. Examples of hybrid systems built with the use of FuzzyCOPE are given in [19]. The two environments FuzzyCOPE/1 and FuzzyCOPE/3 are available from the following WWW site and can be used for building hybrid DSS: http://divcom.otago.ac.nz/infosci/kel/CBIIS.html (Software → FuzzyCOPE).

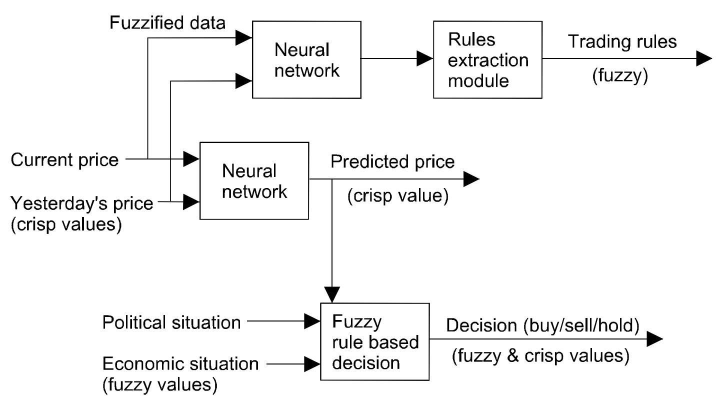

Fig. 1. An example of a hybrid DSS for stock trading (from [19])

The hybrid system environments developed so far, and the hybrid systems built with them, have been very useful techniques, but the complexity and the dynamics of the real-world problems, especially in finance and economics at present, require even more advanced and sophisticated methods and tools for building hybrid intelligent decision support systems (HIDSS). Such systems should be able to change as they operate, always updating their knowledge, and to refine the model through interaction with the environment. Some major requirements to the present day intelligent systems (IS), and to the HIDSS in particular are given in [21]-[25].

A framework for building adaptive intelligent systems, called ECOS (evolving connectionist systems) has been recently introduced in [21]-[25], along with its architecture, learning and evolving algorithms, rule extraction and rule insertion algorithms, of an evolving fuzzy neural network EFuNN [23]-[25]. EFuNNs can learn in an incremental, adaptive way through one-pass propagation of any new data examples. EFuNNs are much faster than FuNNs and MLPs and can learn data in an on-line mode. EFuNNs do not have a fixed structure, on the contrary – they start evolving/learning with no rule (hidden) nodes and they grow as data is presented to them. Pruning of nodes and node reduction is achieved with the use of fuzzy pruning rules, e.g.:

```
IF a node is not much used in a defined period, AND
it is old, THEN probability to prune the node is high.
```

EFuNNs have the following advantages when compared with traditional MLP or SOM networks ([24]:

1. they can learn in an on-line mode any new data as they are made available over time;
2. they can work in a complex environment with changing dynamics, e.g. a stock index system can be 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.
3. they can be used to mix expert rules and data as there are algorithms for rule insertion and rule extraction;
4. they can cluster data in an on-line mode without pre-defining the number of clusters, or the dimensionality and the size of the problem space;
5. they can be used for both supervised and unsupervised learning modes; as supervised systems they can be used to predict future values of the output variables.

Examples of using FuNNs and EFuNNs for adaptive, intelligent decision support systems for stock prediction and loan approval are given in [26]. Other examples include: image recognition [34]; speech and language recognition [24][33]; mobile robot control [24].

Simulators of EFuNN are available from http://divcom.otago.ac.nz/infosci/kel/CBIIS.html (Software).

Another ECOS algorithm, called Evolving Self-organizing Map (ESOM) [4], is proposed as a variation of the SOM algorithm based on the ECOS principles. ESOM uses a learning rule similar to SOM, but its network structure is evolved dynamically from input data. Simulations have shown that ESOM learns faster than SOM with a smaller quantisation error for feature vectors.

ECOS-based modules such as EFuNNs and ESOM are part of the New Zealand Repository of Intelligent Connectionist-Based Systems (RICBIS), which also integrates modules from the FuzzyCOPE environments, a Java version of rule-based system CLIPS (JESS), and a platform independent interface running as a Java applet, which allows for dynamic creation of new modules during the operation of an ECOS, or an HIDSS in particular. RICBIS is available from the following URL:
http://divcom.otago.ac.nz/infosci/kel/CBIIS.html (Software).

A new expert system architecture called Adaptive Intelligent Expert Systems (AIES), based on dynamic generation of interconnected modules (agents) from the RICBIS, is explained in [34]. It is in sharp contrast to the conventional expert systems and DSS that usually have a fixed structure of modules and a fixed rule base. Although traditional expert systems and DSS have been successful in some specific and restricted areas, there was no, or little flexibility left for the expert system to adapt to changes required by the user, or by the dynamically changing environment in which the expert system and the DSS respectively operated.

AIES, or HIDSS in particular, consist of a series of modules which are agent-based and are generated "on the fly" as they are needed. Fig.2 shows a general architecture of an AIES [34]. The user specifies the initial problem parameters and tasks to be solved. The AIES then creates Modules that may initially have no rules or may be set up with rules from the Expert Knowledge Base. The Modules combine the rules with the data from the Environment. The Modules are continuously trained with data from the Environment. Rules may be extracted from trained FuNNs or EFuNNs for later analysis, or for the creation of new Modules. The Modules dynamically adapt their rule sets as the environment changes since the number of rules is dependent on the data presented to the Modules. Modules (agents) are dynamically created, updated and connected in an on-line mode. They can be removed if they are no more needed at a later stage of the operation of the AIES.

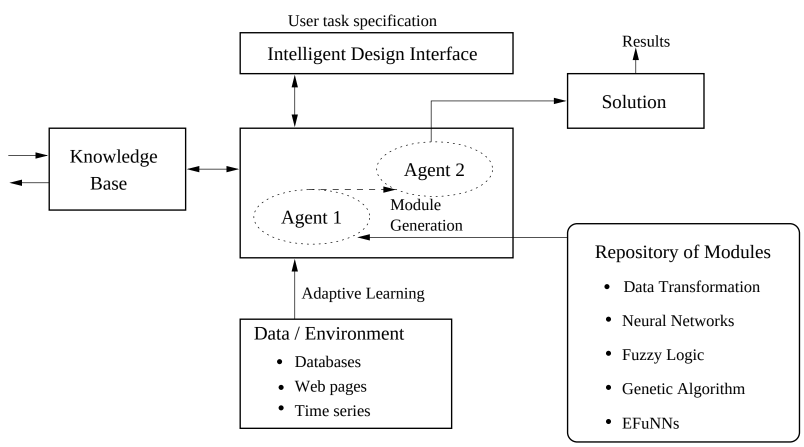

Fig. 2. A block diagram of an agent-based, adaptive intelligent decision support system – HIDSS that uses the architecture of an AIES.

A very complex problem of risk analysis of the European Monetary Union (EMU) system, established in 1999 to unify the currency and the economic development of eleven European countries, is the problem discussed and handled here. The rest of the material here presents first the problem and then a framework of a HIDSS for its solution. It then develops some specific modules and discusses some preliminary experimental and implementation issues.

3 The Problem of Risk Analysis in the European Monetary Union

Since its conception, there have been a lot of materials published on different issues concerning EMU. Global policy requirements exist, such as for each participating country to have a deficit less than 3% of its GDP and external debt less than 60% of the GDP. In the EMU framework, the European Central Bank (ECB) is in charge of the monetary policy, with priority and responsibility for inflation control. The ECB publishes a monthly bulletin containing a rich set of real, monetary and financial data regarding the EMU economies, other countries that would be members of the EMU, USA and Japan, in order to follow the evolution of the EMU in a world-wide context. Important financial and economic parameters are recorded and analysed monthly, quarterly, and annually, e.g.: Reserves and assets (gold, foreign exchange, other); Liabilities; Stock market indexes of the EMU, each country separately and the major world indexes (Dow Jones EURO STOXX, S&P500 – USA, Nikkei225 – Japan); Interest rates; Exchange rates Euro/US$, Euro/JY; Government bond yields (2, 3, 5, 7 and 10 years); Index of consumer prices; Industry and commodity prices; GDP; Employment/unemployment; Saving, deficit/surplus ratio (as a % of GDP); Gross nominal consolidate debt (as a % of GDP); Balance of payments (goods, services, income, capital account).

Of a particular interest is the analysis of the EMU as a dynamic cluster of economies in terms of volatility, variations, change, tendencies, and prediction (e.g., monthly, quarterly, yearly). There are smaller sub-clusters that evolve with the economic development of different groups of European countries and world economies that should be also modelled and predicted in relation to the EMU cluster. All these clusters move quickly in a dynamically changing problem space, thus making the problem of their prediction and risk analysis extremely difficult.

The problem this paper is dealing with as a case study, can be described as risk analysis of the EMU system. Here, more details are given.

With the EMU in effect, countries sharing the Euro as a common currency should overcome the risk of currency crises within the Euro area. However, the European monetary unification has not ruled out possible episodes of financial instability in Europe. The Maastricht Treaty imposes rigid constraints on public budget deficits. These constraints are aimed at preventing an excessive debt burden on national governments, which could lead to a weaker Euro. On the other side, EMU governments could put pressure in order to ease such constraints in the presence of external shocks, such as the crisis in the Balkans. Moreover, European financial markets are not immune from shocks originating in the world economy.

In an extreme scenario, risk of unilateral withdrawal by weaker member countries (otherwise called breakaway risk) cannot be excluded a priori, since the political costs associated with respect of rigid fiscal and monetary constraints in an anchored regime could make withdrawal imperative. Any withdrawal would be a disruptive event, anticipated and/or followed by instability and crashes in credit and asset markets. Credibility of EMU membership will be assessed and priced by financial markets. In the EMU, expectations of breakaway, unlike expected realignments or withdrawals in the Exchange Rate Mechanism operating from 1979 to 1998 under the European Monetary Systems, will no longer translate into wider interest rate differential among currencies, but into variation of credit spreads applied to sovereign debt from different countries. Holders of financial assets will bear a new sort of macro risk, which will be different from plain currency risk and more difficult to identify and measure. Studies on currency crises (e.g. [6]) must be reinterpreted and extended to the new context. Early warning systems used by central banks and speculators, fed with signals of real and financial dis-equilibrium, must be redesigned.

The goal of this project is to develop a computational model for analyzing and anticipating signals of abrupt changes of volatility in financial markets. The system will be aimed at assessing the possibility of speculative attacks against specific EMU member countries, prospective EMU members or the EMU area as a whole. Potential users of the system include monetary authorities, asset managers, traders on money, debt, currency and stock markets and corporate financial managers.

The conceptual model underlying the computational model will be derived from a representation of financial markets as complex dynamic systems, whose stochastic behavior is influenced by exogenous shocks and endogenous uncertainty, the latter caused by interaction among market participants (degree of consensus and tendency to crowd behavior). Inspiration for this approach came from a paper by Tonis Vaga ([50]). The system will be fed with information from different sources, namely:
- macroeconomic and macro-financial indicators, such as the real exchange rate of the Euro against US Dollar and Japanese Yen, inflation differentials, Government deficit, aggregate liquidity and solvency measures (debt/asset ratio, reserve/debt ratio);
- risk spread on debt securities issued by sovereign and private borrowers in EMU countries;
- risk appetite of investors in securities, measured on the basis of correlation between returns in “risky” and “safe” markets (risk appetite is high when riskier markets are rallying versus “safe” markets and the correlation is highly positive);
- returns and historical volatility in financial markets (stock, currency, bond, money, derivatives);
- signals of trend, reversal and change of regime from technical analysis of financial prices (moving averages, resistance and support levels, relative strength indicators, etc.); these signals will serve as proxy variables for endogenous uncertainty;
- implied volatility in option markets and expected distributions extracted from them;
- recent episodes of instability in other currency areas that can exert a contagion effect on the EMU area.

The logic of the system will be designed as an extension of existing event risk models applied to foreign exchange markets ([45]). The system will be tested on a set of recent episodes of market crash, and then extended taking care of unique features of the new EMU monetary regime. The system will produce a rich informative output, consisting of descriptive reports and warning signals.

Firstly, the system will provide an intelligent interface to information currently analyzed by economists and traders. Users will be able to navigate through a rich set of economic and financial data presented in tables and graphs. The presentation will focus on phenomena pertaining to the economic performance in the EMU area, emphasizing divergences among countries and sustainability of Maastricht constraints both at the national and the EMU level.

Secondly, the system will provide signals and indicators reflecting the likelihood of a crash in EMU financial markets. An extensive set of symptoms of financial fragility will be monitored in credit, bond and stock markets. New events will be checked against typical patterns of evolution of financial crises.

The system will provide a valuable support to analysts and decision makers in two ways: (1) selecting relevant information to be subsequently analyzed by human experts and (2) extracting and synthesizing signals from a vast array of information sources.

4 Collecting Relevant Data for Risk Analysis on the EMU. The Trento Financial Data Dictionary

The data collection is an important part of the research project, because the results and the reliability of the hybrid system depend crucially on the quality of the raw data. In fact a huge amount of data is necessary to monitor the so-called breakaway risk in the EMU, in order to detect the solidity of the EMU system, the degree of asymmetry and the potential external shocks.

Huge amount of data is being collected that includes different level of information: macroeconomic information; financial data. Macroeconomic data is available from many sources including EUROSTAT, the European Central Bank Monthly Bulletin, OECS and IMF. A vast amount of macroeconomic data is made available through Datastream. Financial data is available from different on-line sources, such as DataStream and Reuter. Different time-scales of data are present in the data repository (e.g., yearly, quarterly, monthly, daily, irregular time intervals, etc)

It is not easy to deal with this relevant amount of data without preparing at least a general initial structure. For this reason we have built two main prospects: the “sources dictionary” and the “data dictionary”.

The first prospect has a three dimensional structure. In the x-axis we have placed the countries relevant for the EMU risk analysis; we have chosen the eleven participating countries, the potential entrants, the big world players, and some emerging countries to proxy for any contagion effect. In the y-axis we have set all the types of data which could be useful for the research project. The third dimension is concerned with the source of the gathered information; every single variable related to every involved country has been collected by a specific source. This aspect is important to evaluate mainly the reliability of the data, but also the degree of homogeneity in the data set. In fact, choosing the data source which covers the most part of the involved countries allows to achieve high degree of similarity in the modelling procedure and in the updating timing and method. Considering the specific purpose of the analysis, we rely upon official statistics from Eurostat for most of the required data.

The second prospect, named “data dictionary”, is formed as a table with columns reporting the specific features of each data series; the most important ones are the first available date, the frequency of collection, and the mnemonic code, which is an alphanumeric expression useful to automate the information downloading process. We have distinguished two broad categories of data that are being collected. The first level of information is concerned with macroeconomic variables; the second level is more specific and regards financial market data. A third level of information, connected with qualitative knowledge, for example the political situation or particular news, is not formally considered in this first model implementation. The typical feature of the first group of variables – macroeconomic data – is the low frequency of collection, which is monthly, quarterly or even yearly, depending on the specific sector; another important feature is the potential variety of sources for the same kind of data. A third property is the potential different calculus and updating procedure for the same sort of indices. The most relevant macroeconomic data are generally available either as historical time series, or as a consensus forecast.

The financial market variables are collected more frequently, even on a daily basis, and are usually released officially by the exchanges. In our research project we have tried to consider not only the past evolution of the various financial series, but also the market expectations implied in option prices; there is a growing literature dealing with this aspect with two main approaches. The simpler approach is related to the calculation of implied volatility at different monetary degrees as a forecast for expected volatility. In the second approach the underlying risk neutral density function is extracted from option market prices; it is very useful subsequently to monitor the evolution of the various moment of the probability distribution.

5 The EMU-HIDSS: Architecture and Functionality

5.1 A General Framework of the EMU-HIDSS

Here a preliminary design of the EMU-HIDSS is presented (see Fig.3). It is a multi-level, multi-modular structure where many neural network modules (denoted as NNM), rule-based modules and other modules are connected with inter-, and intra-connections. EMU-HIDSS does not have a clear multi-layer structure, but rather a modular, “open” structure. It is an evolving hybrid connectionist-based system ([22]).

The main parts of the EMU-HIDSS are described below.

(1) Feature selection part. It performs filtering of the input information, feature extraction and forming input vectors. Typical features extracted from the input data either in an on-line mode or from the already stored data in files are:

- Basic statistical parameters;
- Probability distribution and cluster information;

- Moving averages;
- Wavelet transformations;
- Power spectrum and FFT frequency characteristics;
- Main frequencies;
- Lyapunov coefficients;
- Fractal dimensions;
- First and second derivatives;
- Skewness measures.

The above transformations are performed in the pre-processing (feature extraction) modules of the system applied to certain information input streams.

(2) Learning and memory part, where information (patterns) are stored. It is a multi-modular, evolving structure of neural network modules (NNM). These modules can be built with the use of MLP, SOM, ESOM, FuNNs, EFuNNs, etc. There are several levels of processing in these modules in terms of timing:

- Daily updated modules, these are modules that deal with daily financial prediction and daily input data, e.g. MIB30 prediction, Euro/US$ exchange rate prediction, etc.
- Weekly updated modules
- Monthly updated modules
- Yearly updated modules, e.g. long trend prediction, and in terms of the produced results that are passed to the next level higher decision modules:
- One day ahead prediction results
- Monthly prediction results
- Yearly prediction results
- Longer term predicted results

This part of the system will include several modules to deal with different levels and scales of prediction for each of the European countries, the big economies and the emerging economies. Different modules will deal with:

- Predicting values (differences in values)
- Predicting short term trends, e.g. one week trend if a stock value will be going up extremely high, or moderately down.
- Predicting long term trends, e.g. one-year trend if a stock value will be going up extremely high, or critically down.

(3) Higher-level decision part that consists of several modules, each taking decision on a particular problem. The modules receive input from the NNMs, inputs form other variables in the data, qualitative input from users, and make decisions on possible critical situations that might occur in the EMU. These modules can send a feedback to the NNM and the feature extraction part of the system in terms of requiring more information, different scenarios to be explored, different features extracted, etc. The modules here are mainly rule based with the use of production

systems, flat fuzzy rules, FuNNs and EFuNNs that can represent both fuzzy rules and data. There are several groups of in this part that interact between each other, for example:

(a) A group of modules that deal with a global risk evaluation problems, e.g.:

- Module evaluating the degree of stability in the EMU;
- Module evaluating the degree of symmetry / asymmetry between the economies within the EMU;
- Module evaluating the political sustainability in the EMU;
- Module evaluating the degree of suitability of a new country joining the EMU;
- Module evaluating the degree of instability in the EMU based on external factors (USA; Asia, Japan, India, Russia, wars, etc.)
- others

(b) A group of modules that deal with important economic factors and their results can be used either separately, or by the modules of type (1) above:

- GDP
- Rate of unemployment
- Internal debt
- External debt
- Short term global economic trends
- Long term global economic trends
- Solvency ratio of households, business, banks and government
- Indication of reallocation of investments by global asset managers
- Sharp movements of a certain commodity in a short or in a long term pattern
- Sharp falls in short term or long term trends
- Evaluating and indication of consecutive phases happening over a period of time, for example an economy has been in three consecutive phases that signal a critical situation for this economy and will be influential for the EMU

(4) Action modules, that take the output from the higher-level decision modules and produce output results or send output (control) information in an on-line or in an off-line mode to institutions that should be alerted on a critical situation.

(5) Self-analysis, and rule extraction modules. This part extracts compressed abstract information from the NNMs and from the decision modules in different forms of rules, abstract associations, etc. Here FuNNs' and EFuNNs' rule extraction capabilities will be utilised.

Initially the EMU-HIDSS will have a pre-defined structure of modules and very few connections between them defined through prior knowledge. Gradually, the system will become more and more "wired through self-organisation, and through creation of new NNM and new connections.

Each of the modules in the system are built, or automatically generated from the agent modules available from RICBIS, e.g.: data processing modules (e.g. normalisation, moving averages, FFT, filtering, wavelet transformation, fractal analysis, chaos analysis, etc); production rules in JESS; fuzzy inference rules, MLP, SOM, ESOM, FuNNs, EFuNNs, Hidden-Markov Models, etc.

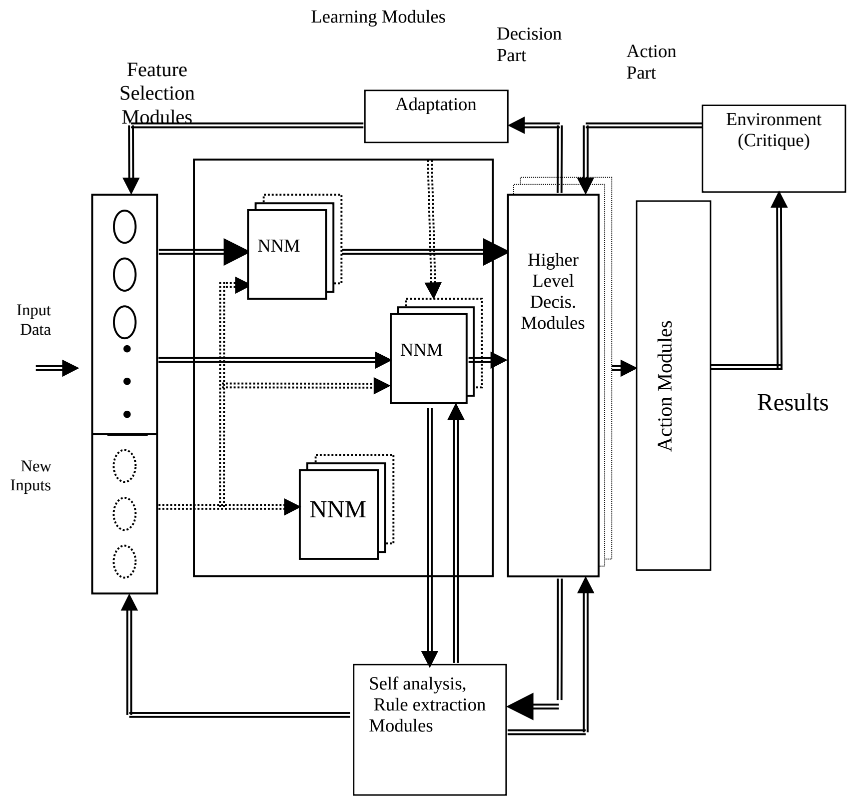

Fig. 3. A block diagram of the general framework of the EMU-HIDSS as an evolving connectionist-based system (adapted from [22]).

5.2 EMU-HIDSS/1

Here, the first version of the EMU-HIDSS is presented that includes a small number of modules and groups connected between each other as described below.

Group 1: Modules for higher-level risk analysis

Here are modules that make decision on the discrepancy/risk of a single country to develop in a direction away from the expected development of the EMU. Fuzzy production rules are used for the implementation of these modules, such as:
IF a country is politically unstable, or in war, AND the trend of its macroeconomic development in the last two periods is away from the centre of the EMU cluster, THEN the risk that this country will go even further away from the EMU is high.

Group 2: Modules for discovering trends in the macroeconomic development of the EMU cluster related to the development of other clusters and other countries.

Here the concept of EMU cluster is introduced based on the EMU aggregated data projected from a multidimensional space into a two (or a three) dimensional topological map with the use of self-evolving, self-organising maps. The vectors of the used 8 parameters for the last 5-6 year of all the EMU countries, the other European countries, some emerging market countries, and also the USA and Japan, are mapped into one SOM or ESOM.

The neuron (the point in the two-dimensional map space) where the current-period EMU vector is projected is considered to be the center of the EMU cluster. The cluster incorporates all points where the data of the individual EMU countries are mapped. The form of the cluster and its movement from one period to the next one can be observed on the maps and the information will be quantified based on the distance between the points. The shape of the EMU cluster and its dynamics can suggest further political and economic development in the EMU.

The movement of the center of the EMU cluster can be compared with the movement of the points where the different countries are mapped. A quantitative measure on the difference (the distance in the topological space) between different countries from the EMU, and outside the EMU, is evaluated that is used as a separate information results as well as an input information to the higher- level decision making modules.

Different clusters are formed on a SOM: the EMU cluster; the emerging economies cluster (e.g., Poland); the cluster of the non-European developed countries (e.g. the USA, Japan, Canada, Australia, New Zealand); the cluster of underdeveloped countries; the cluster of the developed non-EMU countries (e.g. the UK); the cluster of the developing non-EMU countries (e.g., Bulgaria, Romania). A vector of fuzzy membership degrees to which each country belongs to each of the clusters is calculated and traced over time.

Modules from group 2 cover different time-scales: annual macroeconomic mapping, quarterly macroeconomic map and monthly macroeconomic mapping.

The following variables describe the macroeconomic state of a country in a given period and all the vectors for all the relevant periods (years, quarters, months) are used in the unsupervised training: GDP, debt, deficit, inflation rate, interest rate, unemployment, balance of payment, production gap.

Group 3: Modules for evaluating trends in the exchange rate Euro/US$

The main module here predicts the trend of the exchange rate between Euro and the US dollar, but other modules deal with national currencies that are not part of the EMU.

The following 10 input variables for example can be used to predict the rate R(t+1) of Euro/US$, where t is the current period: R(t), R(t-1), Euro/JY(t), Euro/JY(t-1), ratio inflation rate in EMU/inflation rate in the USA for both (t) and (t-1) periods; ratio interest rates in EMU/interest rates in USA for both (t) and (t-1) periods; ratio GDP in EMU/GDP in USA for both (t) and (t-1) periods.

Two types of models are used - FuNNs and EFuNNs. The two models use different techniques for extracting rules and the meaning of the extracted rules is different.

In the rules extracted from FuNNs the condition and conclusion elements have importance factors attached to them pointing to the importance of the different parts of a rule. The rules extracted from EFuNNs are also fuzzy, but they point to the clusters in the input and the output space that are linked together in the rule. EFuNNs require less time for training and can be updated very quickly with new data in an on-line mode.

The predicted trends of the exchange rates can be used either as separate output results, or as input values for the higher-level decision modules for both quarterly and monthly trends prediction.

Group 4: Modules for evaluating trends in major stock indexes and stock markets

Here a map of the different states of a stock market according to [50] is created. The transition between random walk state, chaotic state, or a coherent state will be modelled by the use of different techniques, that include: hidden Markov models; evolving fuzzy neural networks EFuNNs; production rules.

Another module from this group evaluates the volatility of monthly trends in the Dow Jones Euro STOXX50 index (DJE). Other modules evaluate weekly trends and daily values. The following 14 input variables can be used to evaluate the DJE$(t+1)$, where t is the current time period: DJE(t); DJE$(t-1)$; $S\&P500(t)$; $S\&P500(t-1)$; Euro/US\$$(t)$; Euro/US\$$(t-1)$; Euro/JY$(t)$; Euro/JY$(t-1)$; Inflation rate (t); Inflation rate $(t-1)$; GDP(t); GDP$(t-1)$; Interest rate (t); Interest rate $(t-1)$.

Other modules evaluate the trends in major European stock markets, such as the Italian MIB30 index (Milano).

6 Implementation and Current Experimental Results with the EMU-HIDSS

The implementation of the conceptual model of the EMU-HIDSS from section 5 is a very complicated task and a long-term objective. Here, different modules from the EMU-HIDSS/1 conceptual model that follow the general description and the logical links presented in the previous section, are developed and results are explained.

6.1 Group 1 Module for Statistically-Based Higher-Level Risk Analysis

This module takes dynamic input information from the cluster maps of the previous level of processing and calculates the Euclidean distance between each country's representation vector and the center of the EMU cluster over consecutive periods of time (years, quarters). In this way the countries that are moving away from the EMU cluster are indicated along with the speed at which they are moving. For example the distance between the cluster center of the main EMU countries and Italy for 1997 can be evaluated as 3.8 and for 1998 as 3.3, while the same distance between IT and JP for the same periods can be evaluated as 1.2 and 0.7 respectively (see Fig.4).

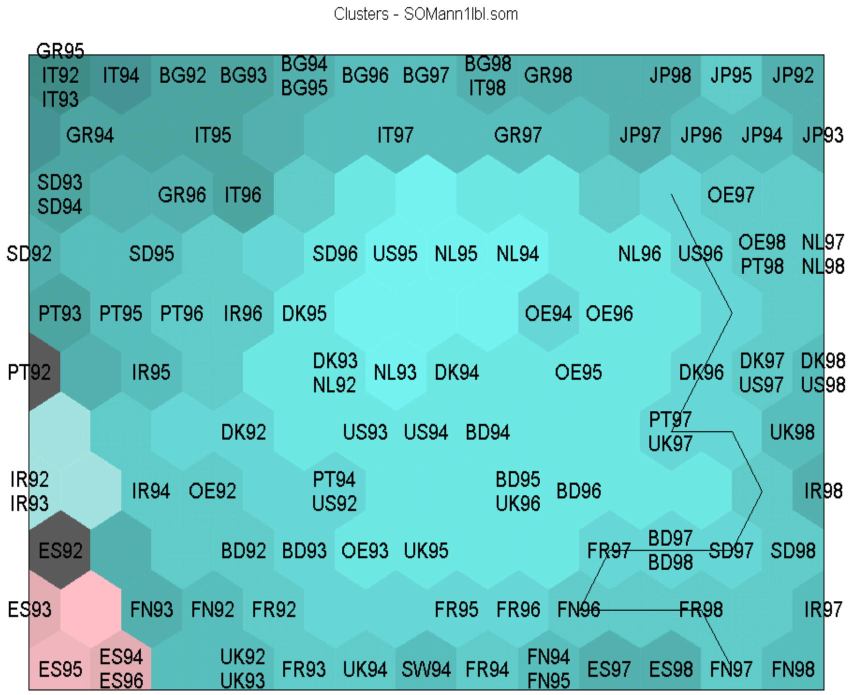

Fig. 4. The annual map of the 15 countries according to 5 characteristics (DBT/GDP, DEF/GDP, Inflation rate, Interest rate, Unemployment). The contour shows the center of the EMU cluster for 1998.

6.2 Group 2, SOM Modules for Visual Exploration of the Annual and Quarterly Macroeconomic Development of the EMU Cluster Related to the Development of Other Clusters and Other Countries

The following 5 variables describe the annual macroeconomic state of a country: DBT/GDP, DEF/GDP, Inflation rate, Interest rate, Unemployment. The SOM model was trained on 15 countries data from 1992 till 1998. It is seen how the points of the map of the main EMU countries and USA are moving from left to right. Fig.4 shows also the contour surrounding the centre of the EMU cluster for 1998. It is obvious that the following EMU countries are within the cluster: OE, NL, DK, IR, UK, SD, BD, FR in addition to the USA and the UK. But four countries are outside it (IT, BG, GR, ES) with only ES moving into the right direction towards the EMU cluster center.

Fig.5 shows the direction in which Italy (IT) is moving over the years from 1992 till 1998.

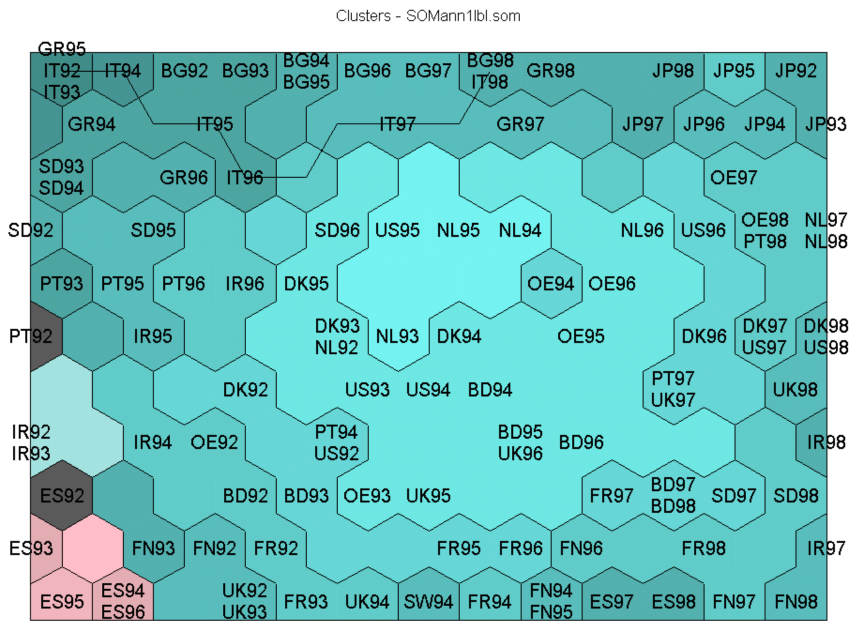

Fig. 5. Iso-graphs of the 15 countries annual development map and the direction of the development of Italy.

Another SOM module is trained on quarterly data of the following three variables: Inflation rate, Interest rate, Unemployment. Fig.7 shows the map and the line of the quarterly development of Germany (BD).

The SOM modules are suitable for visual exploration as SOMs provide with an efficient tool for vector quantisation, i.e. turning an n-dimensional space usually into two dimensional space preserving the similarity between the input vectors across all the attributes as topological distance between points of the map. SOMs have some difficulties, mainly: (a) they have a fixed structure; (b) they can not tolerate missing values; (c) learning usually takes a long time.

In order to overcome the limitations of the SOMs, here evolving SOM modules are also used.

6.3 Group 2, ESOM Module for Dynamic Mapping of Macroeconomic Analysis

Another annual map is evolved with the same data set as in the SOM modules and is shown in Fig.8. The map is first clustered using ESOM algorithm, and then projected onto a two-dimensional plane for visualisation using Sammon's algorithm. Hence both clustering and data structure are available within the map. The layout of labelled nodes is very similar to that of Fig.4, but the ESOM map gives more

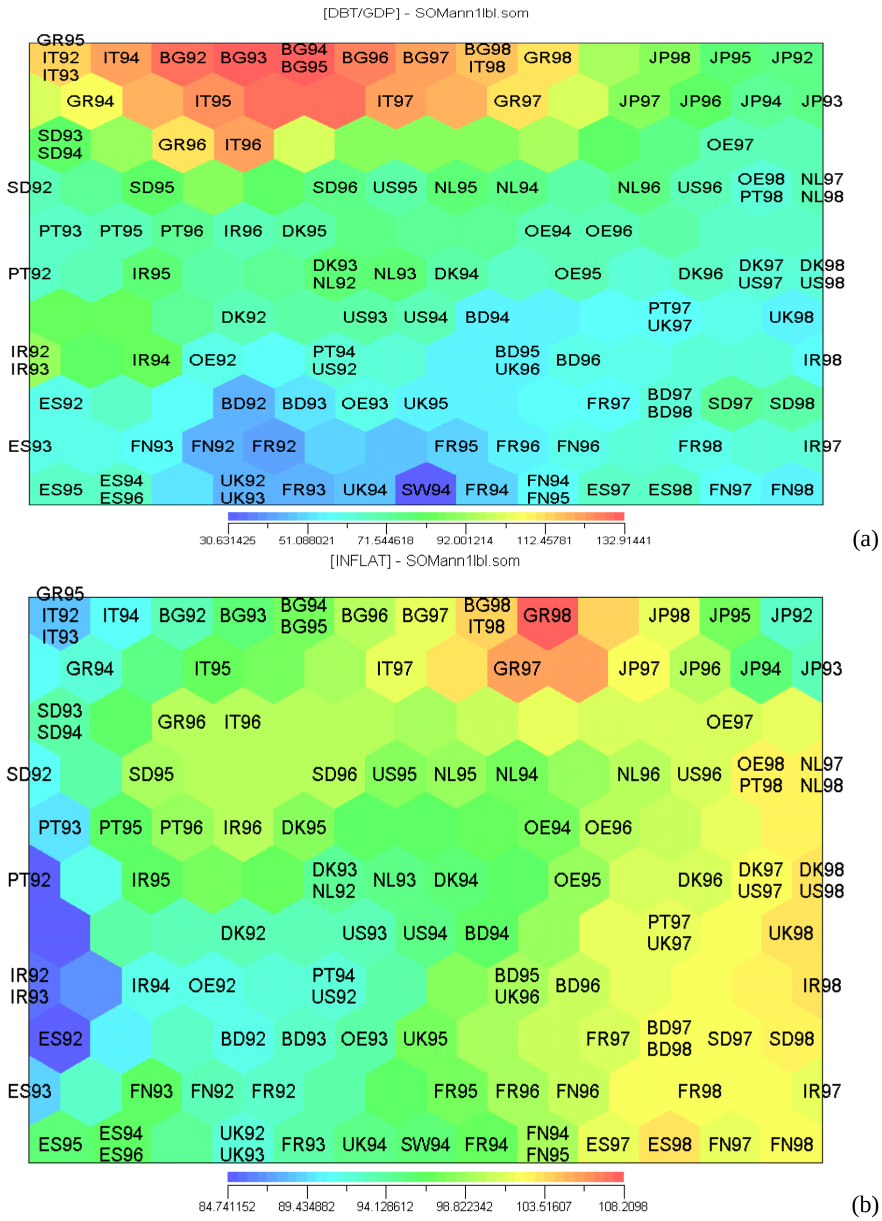

Fig. 6. Component analysis: (a) The first component (DBT/GDP) from the map of figs.4 and 5 show that in this respect BG, IT and GR are in a similar position. SD97 and SD98 form an “island” in the EMU cluster with a good tendency. (b) The Inflation component shows a dramatic increase in Greece from 1996 to 1997 and 1998.

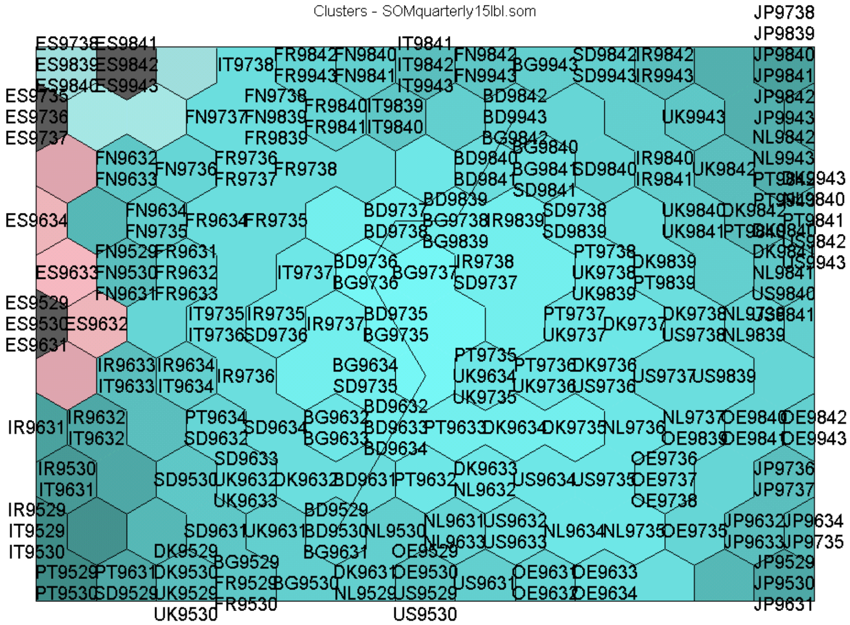

Fig. 7. The complete map of the quarterly development of the 15 countries from 1995 till 1999 and the line of the development of Germany (DB).

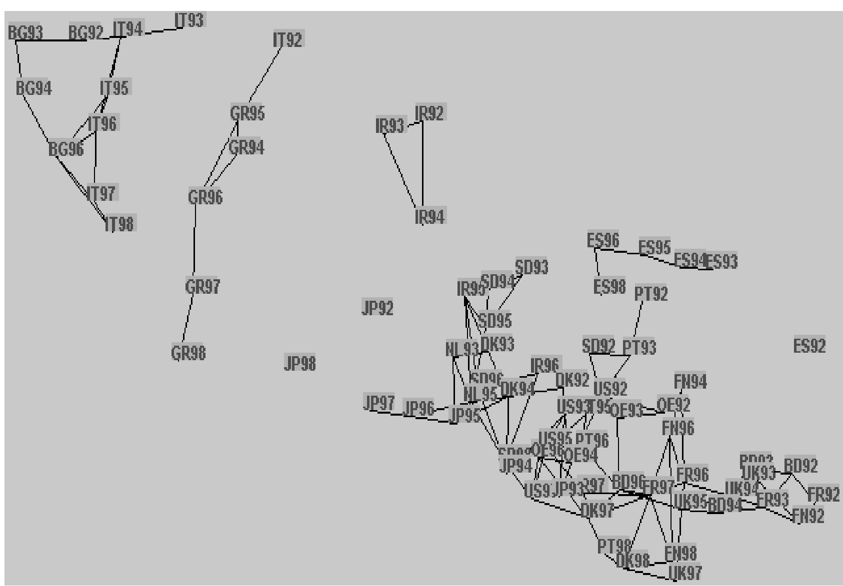

Fig. 8. The ESOM clusters of the macroeconomies of EMU countries.

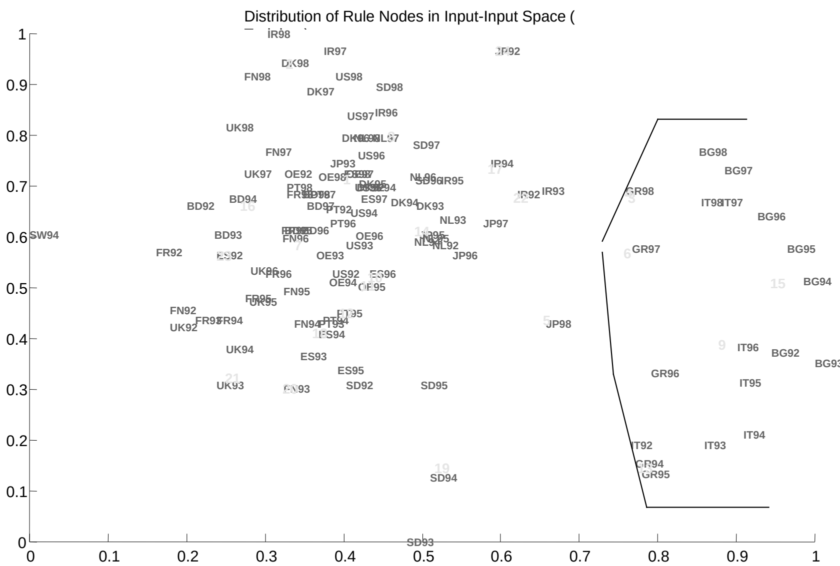

Fig. 9. Clustering of annual data with EFuNN.

explicit information on similarity of country performance which can be represented by distance between the nodes.

By clipping weak connections using a distance threshold, as shown in Fig.8, clusters in the annual macroeconomic performance data can be revealed. Here we find two major clusters, the EMU cluster with countries like FR, BD, FN, PT etc. plus UK and US, and the fall-out cluster with GR, IT, and BG.

6.4 Group 2, EFuNN Based Module for Prediction and Clustering of the Annual and Quarterly Economic Development of the 15 Countries

Here EFuNNs are used to develop modules that can predict values for all the five selected attributes in the annual development and the three selected attributes for the quarterly development. Such modules are the annual module and the quarterly module. The first one takes two input vectors each of 5 variables (at the time moment t and $t-1$) and calculates one output vector of 5 elements predicting what the values for these variables will be. Fig.9 shows the clustering of the annual data (displayed with the first two variables DBT/GDP and Deficit/GDP) achieved in the rule nodes of an evolved EFuNN. It is clear that IT, GR and BG form a cluster with high DBT/GDP value and DEF/GDP running from low to high values. The clustering of data samples are quite similar to that of the SOM module, but it is much more quickly learned in the one-pass learning EFuNN module.

Fig.10 shows the annual EFuNN predictor for the 15 countries run in an on-line mode to predict the DBT/GDP values annually.

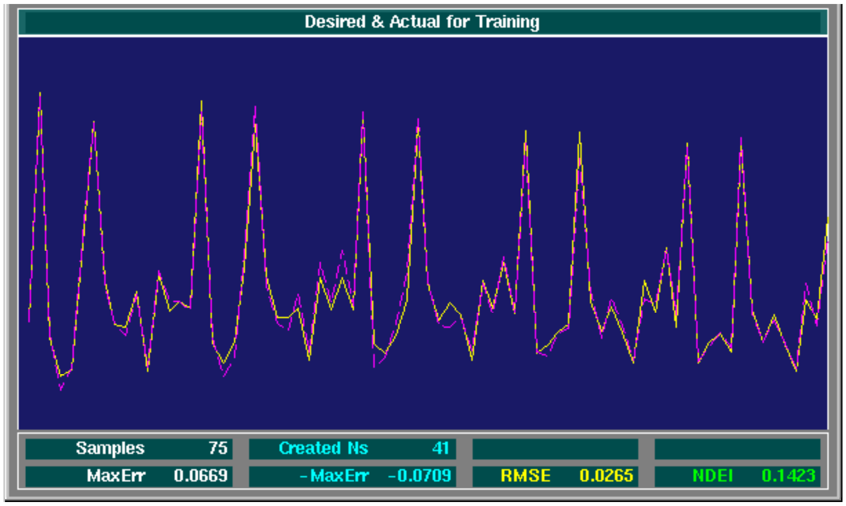

Fig. 10. Annual EFuNN predictor for prediction of annual DBT/GDP values.

Fig. 11. Quarterly predictor for the 15 countries and the on-line prediction of the first variable (Inflation rate).

Rules can be extracted from EFuNNs that are fuzzy, and they point to the clusters in the input and the output space that are linked together in the rule. EFuNNs require less time for training and can be updated very quickly with new data in an on-line mode.

Fig.11 shows the 15 countries quarterly predictor, which can predict values of the three selected variables Inflation rate, Interest rate, Unemployment for any of the countries in the following quarter given the data for the current and previous quarter and also the annual DBT/GDP and the previous year DBT/GDP are entered. The first output variable is shown as predicted in an on-line mode. The system improves its prediction over time.

6.5 Group 4, EFuNN Module to Evaluate Trends in the Exchange Rate Euro/US$

The main module here predicts the monthly trend of the exchange rate between Euro and the US dollar. The following 10 input variables are used in order to predict the rate $R(t+1)$ of Euro/US$, where t is the current period: $R(t)$, $R(t-1)$, Euro/JY(t), Euro/JY$(t-1)$, ratio inflation rate in EMU/inflation rate in the USA for both (t) and $(t-1)$ periods; ratio interest rates in EMU/interest rates in USA for both (t) and $(t-1)$ periods; ratio GDP in EMU/GDP in USA for both (t) and $(t-1)$ periods.

6.6 Group 4, EFuNN Module to Evaluate Trends in the DJE501 Major Stock Index

This module evaluates the monthly trends in the Dow Jones Euro STOXX50 index (DJE). The following 14 input attributes are used to evaluate the DJE$(t+1)$, where t is the current time period: DJE(t); DJE$(t-1)$; $S\&P500(t)$; $S\&P500(t-1)$; Euro/US(t); Euro/US$(t-1)$; Euro/JY(t); Euro/JY$(t-1)$; Inflation rate (t); Inflation rate $(t-1)$; GDP(t); GDP$(t-1)$; Interest rate (t); Interest rate $(t-1)$.

Besides the modules listed above, several other modules are currently under development.

7 Conclusions and Directions for Further Research

A framework of hybrid intelligent decision system is presented in the paper. By applying a repository of intelligent information processing modules implemented in an agent-based architecture, a case study system EMU-HIDSS is built for risk analysis and prediction of evolving economic clusters in Europe.

The EMU-HIDSS is designed to be used at different levels of analysis and decision making about the EMU and about the relevant changes in the economic clusters of Europe and the world, that includes: the European Union level; the global world economies level; national level; company and bank level. Data and some of the developed models are available from internet URL http://divcom.otago.ac.nz/infosci/kel/CBIIS.html (Software - Financial Risk Analysis and Prediction).

Acknowledgements

This work is supported by a research grant of the Department of Computer and Management Sciences, University of Trento, and also by a grant PGSF-UOO808 funded by the New Zealand Foundation for Science, Research and Technology (FRST).

References

1. Amari, S., Kasabov, N., Eds. (1998) Brain-like Computing and Intelligent Information Systems. Springer Verlag.
2. Bollacker, K., Lawrence S., Giles L. (1998) CiteSeer: An autonomous Web agent for automatic retrieval and identification of interesting publications. Proc. of the 2nd International ACM conference on autonomous agents. ACM Press, 116-123.
3. Deboeck, G. (1999) Investment maps for emerging markets. In: N.Kasabov and R.Kozma Eds. Neuro-fuzzy techniques for intelligent information systems. Physica Verlag (Springer), 373-395.
4. Deng, D., Kasabov, N. (1999) Evolving Self-organizing Map and its Application in Generating A World Macroeconomic Map. Proc. of ICONIP/ANZIIS/ANNES'99 International Workshop, University of Otago, 7-12.
5. Deboeck, G., Kohonen, T. (1998) Visual exploration in finance with self-organizing maps, Springer Verlag.
6. Eichengreen, B., Rose, A., Wyplosz, C. (1995) Exchange market mayhem: the antecedents and aftermath of speculative attacks. Economic Policy, 251-312.
7. Monthly Bulletin (1999) European Central Bank.
8. Evolver software package for Excel, http://www.palisade.com/html/evolver_body.html.
9. Farmer, J.D., Sidorowitch J. (1987) Predicting chaotic time series. Phys. Rev. Lett., 59, 845-848.
10. Garcia, R., Gencay R. (1997) Pricing and hedging derivative securities with neural networks and a homogeneity hint. Technical Report, Department of Science and Economics, University of Montreal, Canada.
11. Goodman, R., Higgins, C.M., et. al. (1992) Rule-based neural networks for classification and probability estimation. Neural Computation, 14, 781-804.
12. Goonatilake, S., Khebbal S. Eds. (1995). Intelligent Hybrid Systems. John Wiley & Sons London.
13. Goonatilake, S., Trelevan P. (1995) Intelligent Systems for Finance and Business. John Wiley & Sons.
14. Hashiyama, T., Furuhashi, T., Uchikawa, Y. (1992) A decision making model using a fuzzy neural network. Proceedings of the 2nd International Conference on Fuzzy Logic & Neural Networks, Iizuka, Japan, 1057-1060.
15. Heskes, T.M., Kappen B. (1993) On-line learning processes in artificial neural networks. Mathematical foundations of neural networks, Elsevier, Amsterdam, 199-233.
16. Hutchinson, J., Lo A., Poggio T. (1994) A nonparametric approach to pricing and hedging derivative securities via learning networks. The Journal of Finance, vol.XLIL, No.3, 851-890.

17. Ishikawa, M. (1996) Structural learning with forgetting. Neural Networks, 9, 501-521.
18. Kasabov, N. (1996) Adaptable connectionist production systems. Neurocomputing, 13(2-4) 95-117.
19. Kasabov, N. (1996) Foundations of Neural Networks, Fuzzy Systems and Knowledge Engineering. The MIT Press, CA, MA.
20. Kasabov, N. (1996) Learning fuzzy rules and approximate reasoning in fuzzy neural networks and hybrid systems. Fuzzy Sets and Systems, 82(2), 2-20.
21. Kasabov, N. (1998) The ECOS Framework and the ECO Learning Method for Evolving Connectionist Systems. Journal of Advanced Computational Intelligence, 2(6), 1-8.
22. Kasabov, N. (1998) ECOS: A framework for evolving connectionist systems and the ECO learning paradigm. Proc. of ICONIP'98, Kitakyushu, Japan, IOS Press, 1222-1235.
23. Kasabov, N. (1998) Evolving fuzzy neural networks - algorithms, applications and biological motivation. In Yamakawa and Matsumoto Eds., Methodologies for the Conception, Design and Application of Soft Computing. World Scientific. 271-274.
24. Kasabov, N. (1999) Evolving connectionist and fuzzy connectionist systems for on-line adaptive decision making and control. In: Advances in Soft Computing - Engineering Design and Manufacturing, R. Roy, T. Furuhashi and P.K. Chawdhry Eds. Springer, London.
25. Kasabov, N. (1999) Evolving fuzzy neural networks for adaptive, on-line intelligent agents and systems. In: O. Kaynak, S.Tosunoglu and M.Ang Eds. Recent Advances in Mechatronics. Springer, Berlin.
26. Kasabov, N. Fedrizzi, M. (1999) Fuzzy neural networks and evolving connectionist systems for intelligent decision making. Proc. of the 8th International Fuzzy Systems Association World Congress, Taiwan, 17-20.
27. Kasabov, N., Kozma, R. (1999) Multi-scale analysis of time series based on neuro-fuzzy-chaos methodology applied to financial data. In Refenes, A., Burges, A. and Moody, B. Eds. Computational Finance 1997. Kluwer Academic.
28. Kasabov, N., Kim J.S. et.al. (1997) FuNN/2- a fuzzy neural network architecture for adaptive learning and knowledge acquisition. Information Sciences, 101(3-4), 155-175.
29. Kasabov, N., Kozma, R. (1997) Neuro-fuzzy-chaos engineering for building intelligent adaptive information systems. In: Intelligent Systems: Fuzzy Logic, Neural Networks and Genetic Algorithms. Da Ruan Eds. Kluwer Academic Boston/London/Dordrecht, 213-237.
30. Kasabov, N., Israel, S., Woodford, B. (1999) Methodology and evolving connectionist architecture for image pattern recognition. In: Pal, Ghosh and Kundu Eds. Soft Computing and Image Processing, Physica-Verlag(Springer) Heidelberg, accepted.
31. Kasabov, N., Song, Q. (1999) Dynamic, evolving fuzzy neural networks with 'm-out-of-n activation nodes for on-line adaptive systems. Technical Report TR99-04, Department of Information Science, University of Otago.
32. Kasabov, N., Watts M. (1997) Genetic algorithms for structural optimisation, dynamic adaptation and automated design of fuzzy neural networks. In: Proc. of the Inter. Conf. on Neural Networks (ICNN97), IEEE Press, Houston.
33. Kasabov, N., Watts, M. (1999) Spatial-temporal evolving fuzzy neural networks STE-FuNNs and applications for adaptive phoneme recognition, Technical Report TR99-03, Department of Information Science, University of Otago.
34. Kasabov, N., Woodford, B. (1999) Rule insertion and rule extraction from evolving fuzzy neural networks: algorithms and applications for building adaptive, intelligent expert systems. Proc. of Int. Conf. FUZZ-IEEE, Seoul.
35. Kawahara, S., Saito, T. (1996) On a novel adaptive self-organising network. Cellular Neural Networks and Their Applications, 41-46.

36. Kohonen, T. (1990) The Self-Organizing Map. Proceedings of the IEEE, 78, 1464-1497.
37. Kohonen, T. (1997) Self-Organizing Maps, second edition. Springer.
38. Kozma, R., Kasabov, N. (1998) Chaos and fractal analysis of irregular time series embedded into connectionist structure. In: Brain-like Computing and Intelligent Information Systems. S. Amari, N. Kasabov Eds. Springer Singapore, 213-237.
39. Kozma, R., Kasabov, N. (1999) Generic neuro-fuzzy-chaos methodologies and techniques for intelligent time-series analysis. In: Soft Computing in Financial Engineering, R. Ribeiro, R. Yager, H.J. Zimmermann, J. Kacprzyk (Eds.), Physica-Verlag Heidelberg.
40. Krogh, A., Hertz, J.A. (1992) A simple weight decay can improve generalisation. Advances in Neural Information Processing Systems 4, 951-957.
41. Le Cun, Y., Denker J.S., Solla, S.A. (1990) Optimal Brain Damage. In Touretzky, D.S. Ed. Advances in Neural Information Processing Systems, 2, 598-605.
42. Lin, C.T., Lee C.S.G. (1996) Neuro Fuzzy Systems. Prentice Hall.
43. Mitchell, M.T. (1997) Machine Learning, MacGraw-Hill.
44. Moody, J., Darken, C. (1989) Fast learning in networks of locally-tuned processing units. Neural Computation, 1, 281-294.
45. Persaud, A. (1998) Global foreign exchange research. In: Event Risk Indicator Handbook, JP Morgan, London, 44-171.
46. Saad, D. Ed. (1999) On-line Learning in Neural Networks. Cambridge University Press.
47. Sankar, A., Mammone, R.J. (1993) Growing and pruning neural tree networks. IEEE Trans. Comput., 42(3), 291-299.
48. Swope, J.A., Kasabov, N., Williams, M. (1999) Neuro-fuzzy modelling of heart rate signals and applications to diagnostics. In: Szepanjuk Ed., Fuzzy Systems in Medicine, Physica Verlag, accepted.
49. Trippi, R., Turban E. Eds. (1993) Neural Networks in Finance and Investing. Irwin Professional Publications, New York.
50. Vaga, T. (1990) The coherent market hypothesis. Financial Analysts Journal, November-December, 36-49.
51. Watts, M., Kasabov, N. (1998) Genetic algorithms for the design of fuzzy neural networks. In: Proc. of ICONIP'98, Kitakyushu, Japan, 21-23.
52. Watts, M., Kasabov, N. (1999) Neuro-genetic tools and techniques. In: Neuro-Fuzzy Techniques for Intelligent Information Systems, N.Kasabov and R.Kozma, Eds., Physica Verlag Heidelberg, 97-110.
53. Woldrige, M., Jennings, N. (1995) Intelligent agents: Theory and practice. The Knowledge Engineering Review, 10.
54. Zirilli, J. (1997) Financial Prediction Using Neural Networks. Thomson Computer Press, London.