Hybrid Intelligent Decision Support Systems for Risk Analysis and Prediction of Evolving Economic Clusters in Europe

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Abstract

Decision making in a complex, dynamic environment is a very 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 using methods included in a repository for intelligent connectionist based information systems (RICBIS). A case study project on risk analysis of the European Monetary Union (EMU) is carried out and a framework of system is presented along with some preliminary results.

1 Introduction

Complex decision making in a complex, dynamic 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. Decision support systems (DSS) built for this purpose should have advanced features such as ([8]):

- 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.

Techniques of computational intelligence, such as artificial neural networks, fuzzy logic systems, genetic algorithms, advanced statistical methods, along with traditional statistical and financial analysis methods, have been widely applied on various problems in finance and economics. Some approaches are referenced and explained as follows.

1. Specialised statistical and econometrics models. These models require a reliable knowledge on the underlying rules of the financial and economic systems and can not be easily changed in a new economic or financial situation. They are applicable when crises occur according to recurrent and known patterns. Recent approaches can be found in [3] [23].
2. Symbolic and fuzzy rule-based systems. Rule-based system and fuzzy rule-based system in particular have been used in financial and economic decision making [5][6]. The main advantage of rule-based systems is that their functioning is based on expert rules. The main disadvantage is that these systems are not flexible enough to react to changes in the data.

3. Artificial Neural networks (NNs). Extended studies of using NNs for financial DSS have been done in several books [5][6][25][28]. NN models such as Multilayer perceptron model, Radial Basis Functions etc. have been proved to be competitive in predicting S&P500 futures and option prices [4] [7]. Self- organizing Maps (SOM) [19] are applied to evaluate company performance and predict bankruptcy, evaluate emerging and new markets etc. [1][2][24]. These NN models proved to be efficient, but they do not allow easily for dynamical on-line training, for online adaptive parameter tuning, and for easy interpretation by generating a rule base.
4. Genetic algorithms. There are several studies on using GA for financial decision-making [5][6]. The main advantage of GA is that it requires little knowledge on the underlying rules, formulas, etc. On the other hand, they are computationally slow, and do not necessarily produce the best solution as they are heuristically based.
5. Models based on dynamic system analysis. In [20][21] a stock index prediction problem is considered and prediction at different time scales is performed. Another study on stock market is made in [26].
6. Hybrid systems. Hybrid systems combine several of the above methods into one system. This is done either in a "loose" way, e.g., different modules in the same system use different methods [5][6], or in a "tight" way, where methods are mixed at a low level, say fuzzy neural networks [8][11][22]. These methods are the most promising among the methods discuss 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.

The complexity and dynamics of real-world financial and economical problems require advanced and sophisticated methods and tools to build hybrid intelligent decision support systems (HIDSS) which can deal more powerfully with issues like fast-learning, uncertainty, online adaptability, knowledge capability and hierarchical solution etc.

2 The Computational Models

2.1 RICBIS

RICBIS stands for Repository of Intelligent Connectionist-based Information Systems, which is now under development for our Connectionist-based Information Systems Project. RICBIS features :(i) A number of intelligent computational modules, including Fuzzy Neural Networks (FuNN) [8][10] and Evolving Fuzzy Neural Networks (EFuNN) [12][13], SOM, MLP, etc.; (ii) A platform independent and user-friendly interface running as a Java applet with access to the computational modules included in RICBIS; (iii) An agent-based infrastructure for flexible, seamless integration of computational modules and with other functional modules.

A Java version of rule production system CLIPS is also included so as to collaborate with the ECOS modules [12] and fully explore the knowledge manipulation ability of the system. RICBIS is available from URL http://divcom.otago.ac.nz/infosci/kel/CBIIS.html (*software*).

2.2 EFuNN

In [13][18], the architecture, learning and evolving algorithms, rule extraction and rule insertion algorithms of EFuNN are given. 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 FuNNs and EFuNNs for adaptive, intelligent decision support systems for stock prediction and loan approval are given in [14].

2.3 Evolving Self-organizing Map (ESOM)

ESOM is an ECOS extension of the SOM. It uses a learning rule similar to SOM, but its network structure is evolved dynamically from input data. More details of ESOM can be found in [29].

3 A Case Study on EMU Economics

3.1 The problem

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 [26]. 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 system is to produce a rich informative output consisting of descriptive reports and warning signals. 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.

3.2 The data collection

All EMU macro-economics data, stock indexes and foreign exchange rates employed in this case study is collected at Department of Information Science, University of Trento, Italy, mainly from EUROSTAT, monthly bulletins of European Central Bank, OECS and IMF. These economic and financial data of huge amount are structurally organised to allow for efficient retrieval and manipulation.

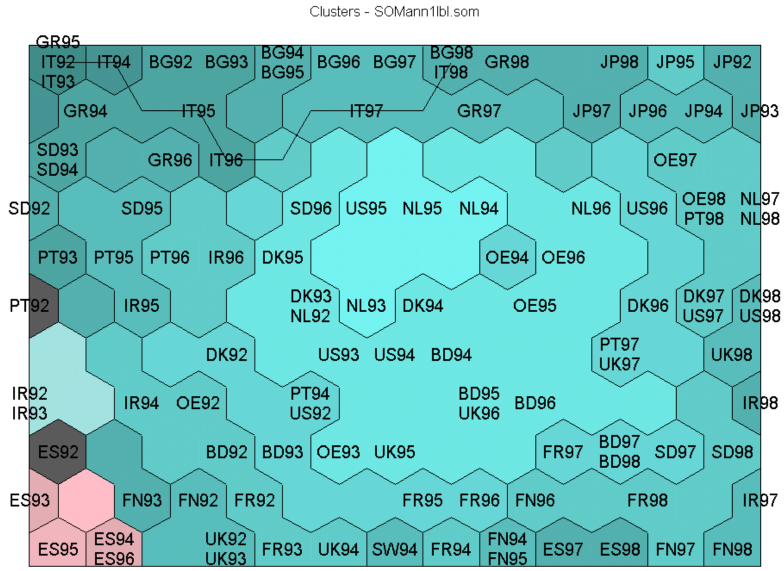

Fig. 1 *The annual dynamics of Italy in the background of EMU country annual map and the moving direction of Italy.*

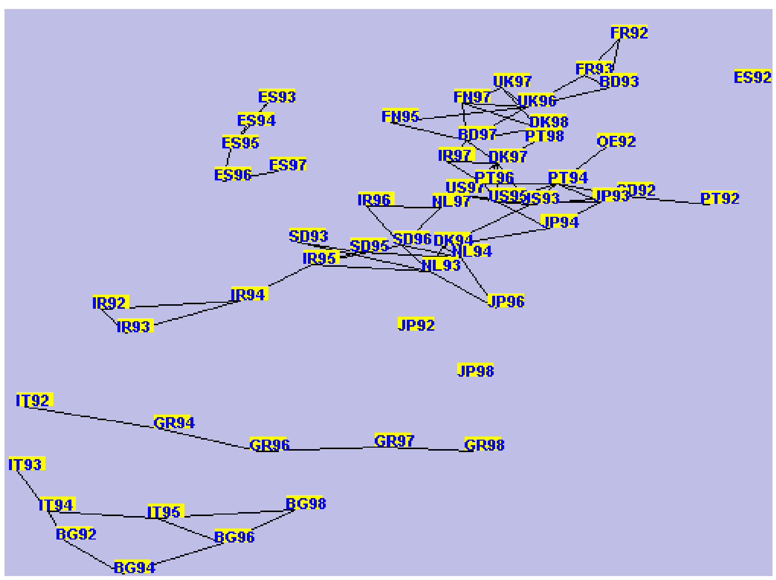

Fig. 2 *The annual EMU macroeconomics map generated by ESOM.*

3.3 Implementation and experiment results

A case study system EMU-HIDSS is constructed with the RICBIS environment. Various modules are developed to evaluate macroeconomic performance of EMU countries, and to predict the EMU stock market and foreign exchange rates for Euro against other currencies. Two major groups of modules are presented here:

1. SOM/ESOM 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. Five variables are used to describe the annual macroeconomic state of a country: Debt/GDP, Deficit/GDP, inflation rate, interest rate, and unemployment.

   The SOM solution, shown in Fig.1, was trained on the 15-country data from 1992 till 1998. It is obvious that the following EMU countries are within the cluster: OE, NL, DK, IR, UK, SD, BD, and FR, in addition to the USA and the UK. But four countries are outside it (IT, BG, GR, and ES) with only ES moving into the right direction towards the EMU cluster centre. The figure also shows the direction in which Italy (IT) is moving over the years from 1992.

Fig. 2 shows the map obtained by ESOM. The map structure is very similar to that of Fig.1, but the cluster structure are clearer with information on distances between clusters.

2. EFuNN modules to evaluate trends in the EMU macroeconomic indicators, exchange rate Euro/USD and Dow Jones Euro STOXX50 index (DJE). Fig.3 shows the prediction of the quarterly inflation rate of Italy.

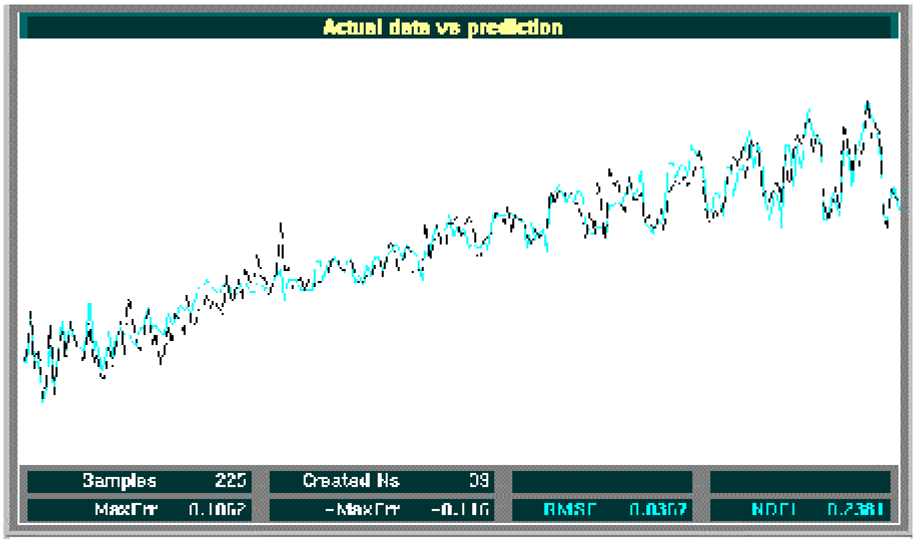

Fig. 3 *Predict the quarterly inflation rate of Italy*

4 Conclusion

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 the relevant changes in the economic clusters in Europe and the world, that includes: European Union level; global world economies level; national level; company and bank level.

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