ADAPTIVE NEURO-FUZZY MODEL TUNING FOR EARLY-WARNING OF FINANCIAL CRISES[1]

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Abstract:
The paper introduces an early-warning method using multiple financial crises indicators which outputs relevant alerts compared to a precise indication of crisis inception, serving as an effective tool for decision makers. By leveraging fuzzy logic techniques, we design a multi-level fuzzy decision support system based on the evolution of credit growth, housing prices and GDP gap. A neuro-fuzzy approach allows fine tuning of the individual fuzzy sub-systems towards adaptive structures which can follow the particularities of the selected indicators at the individual country level. Simulation results and implementation details are presented, along with conclusion drawn from real economic datasets.

Key words: Early warning indicators, financial crises, fuzzy logic, adaptive neuro-fuzzy inference systems

1. Introduction

Financial crises are extremely costly! The significant losses, which result from them, are linked primarily to the slow-down of the lending process, which leads, as an immediate effect, to a dramatic decrease of the GDP [1], [4], [7]. The same studies reveal that these financial crises are relatively frequent, have long timespans and often represent the underlying factor for other types of crises, such as currency and debt crises, which further amplify their effects. Another aspect to consider is that these crises lead to a lack of trust in that particular economy, resulting in major negative consequences. The above-mentioned factors are the most important effects of banking crises, but besides these, a banking crisis also has other side effects, which are equally important. The global effect of all of these can be devastating for the economy of the affected countries.

The recovery from such a crisis is a cumbersome and lengthy process! Therefore the stringent need for effective early-warning intelligent systems. Following the unfavourable effects of the previous financial crisis, the international supervisory bodies have established the Basel III and CRD-IV regulatory frameworks, which include the implementation of the Counter-Cyclical Buffers (CCBs) to increase the resilience of the banking sector and its ability to absorb shocks arising from financial and economic stress.

The intention is to set aside a financial reserve in the periods of economic growth and to use it during periods of crises in order to reduce their effects. To establish such a capital buffer, banks require an early warning system for determining the moment of emergence of a future crisis. A warning with one year in advance (Late warning) is not considered to be sufficient for setting up this buffer (CCB) and therefore, it is necessary to have a warning two or three years earlier (Early warning). These warning systems have to use the data and the indicators available at a particular moment, they have to be well-grounded and based on scientific methods, in order to benefit from a good credibility and to be able to indicate the beginning of crises with a sufficiently high degree of probability [3].

2. Early-warning indicators

Predicting financial crises represents a complex process due to the stakeholders involved which account for, aside economic and financial factors, on the local and global political context, social phenomena, etc. These are diffcult to quantify and measure in an objective manner.

A number of studies are dedicated to finding relevant indicators which could be used for an early warning system [1], [9], [2]. A selected indicator has to present an evolution with a peak point which can be easily observed with two or three years before the start of a crisis.

In the study published by Jan Babecky et al. in 2012, a number of 30 local and global indicators have been analysed, which could potentially be used as an early warning signal [1]. From the conclusions of the study, we retained that: "growth of domestic private credit, increasing FDI inflows, rising money market rates as well as increasing world GDP and inflation were common indicators of banking crises". The authors of this article have created and tested models with these single indicators, as well as models with multiple indicators and their conclusion was that using a composite early warning index increases the usefulness of the model when compared to using the best single indicator!

As motivation for crisis indicator selection and taking into account the conclusions stemming from [1] and [2], our multi-level warning system outputs a composite early-warning index (CEWI) by processing three basic indicators as inputs: private credit growth, house price growth and private credit to GDP gap. Figure 1 ilustrates the three components of the basic dataset, using aggregated ECB data on a reference timeframe of +/- 16 quarters relative to the outbreak of the recent financial crisis 2008-2009, whose effects are still active to date.

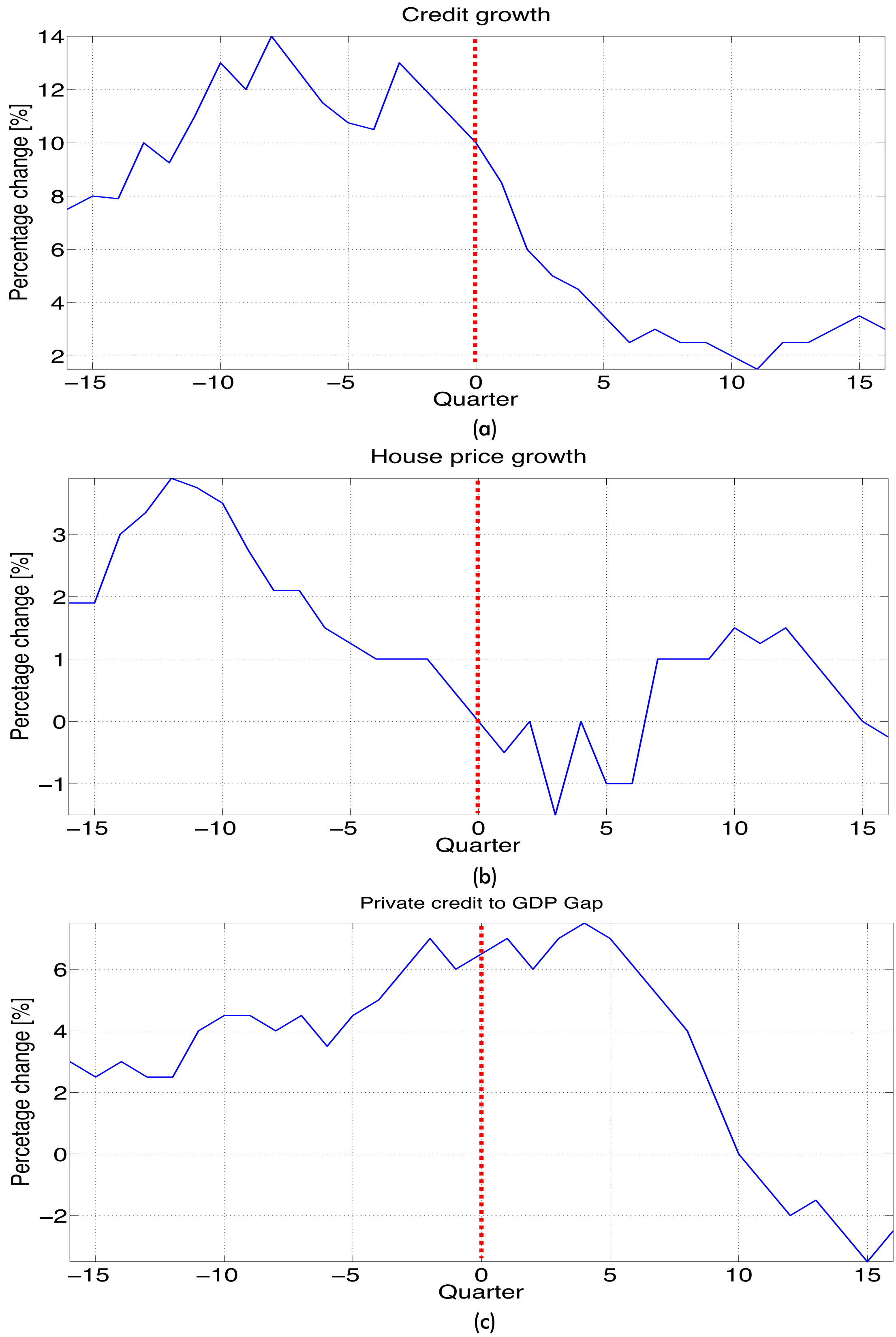

Figure 1. Aggregated reference ECB data: (a) private credit growth – CREDIT, (b) house price growth – HOUSE, (c) private credit to GDP gap - GAP

The private credit to GDP gap is generally acknowledged as one of the most robust crisis indicators [1]. Following its evolution, a value over 2% represents an important warning sign which should not be ignored. Compared to the GAP, which can be seen as a credible crisis indicator, for the other two: CREDIT and HOUSE, extremum points can be detected to be used as early-warning signs of a future crisis. In order to showcase this for the data in Figure 1, the house price growth curve shows a global maximum around three years before the financial crisis of 2008-2009 along with a maximum of the private credit growth indicator around two years before the same event.

3. Multi-level Fuzzy System for Early Warning

Fuzzy logic represents a powerful tool for quantitative method assesment [4-6]. Previous work [10] has dealt with the application of fuzzy logic for early warning of financial crises. As follow up and significant improvement of that approach, one of the main contributions of this work is the design, implementation and evaluation of a multi-level decision support system for early warning, based on fuzzy logic. This has the task of effectively combining the information offered by the three chosen indicators described in the previous section: GAP, CREDIT and HOUSE, by two fuzzy blocks, as first level, generating early-warning signals: EW1 and EW2, which are subsequently interpreted, in the second level, to give the final output. Additionally, using an adaptive neuro-fuzzy inference system (ANFIS) a neural network is trained for each of the individual fuzzy systems, in order to adapt the model to the particularities of a specific country upon departing from the aggregated data used in the design phase. The overall system diagram of the proposed approach is shown in Figure 2. It represents a two level fuzzy system for generation of the early warning signal based on the three input paramenters, evaluated as crisis indicators. The three main blocks are: fuzzy system 1 (FZ1), fuzzy system 2 (FZ2), composing the first processing, input, level and fuzzy system 3 (FZ3) as second processing, output, and level.

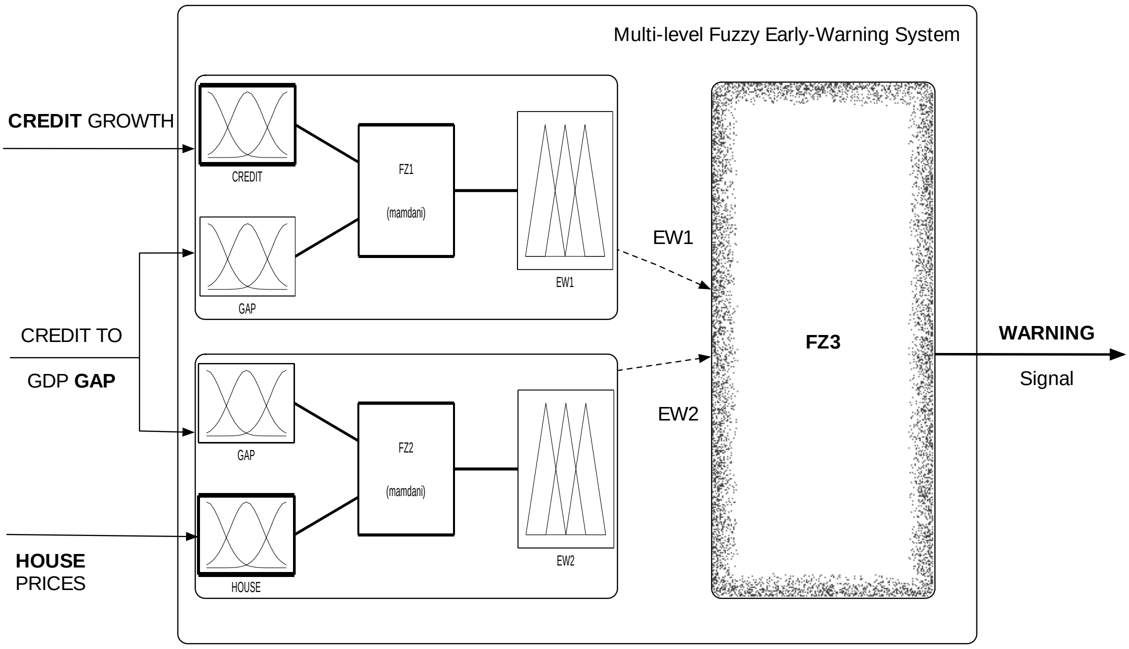

Figure 2. Multi-level Fuzzy Early-Warning System Diagram

The processing block FZ1 takes as input parameters the private credit growths and the private credit to GDP gap and outputs a synthetic, intermediary, warning indicator, denoted EW1. The second processing block of the input level, FZ2, has the private credit to GDP gap and the house price growth. The output signal is denoted EW2.

The two intermediary outputs are further processed at the second level through the FZ3 block. Establishing the processing rules requires expert knowledge of the underlying process and we base our design on some assumptions listed below:

The exact date of the outbreak of a financial crisis cannot be reasonably established in practice due to the lack of an universally accepted notion for how it is defined, with a diversity of opinions among economists. Therefore we found it more suitable that instead of outputing a crisp value in years for the crisis start estimation, to use a warning singal instead from fuzzy processing. Three levels have been defined as outputs of the FZ3 block: NORMAL, DANGER and CRITICAL. The NORMAL signal is generated when the economic indicators taken into consideration follow a predictable evolution, between adequate limits leading to the assumption that there is no impending danger of a financial crisis. The DANGER signal is associated to an early warning prediction. It will be basically generated when yearly credit growth surpasses 15-20% along with credit gap values over 2% or a housing price growth of over 5-6% associated to a similar increase in the GAP value. In this context the early warning given by the DANGER indicator signals a high probability of a financial crisis in the next 2 to 3 years. The third, CRITICAL, signal points to a crisis situation where already the economic situation is out of control. We associate this to a late warning signal. Tables 1-3 synthesize the definition of the membership functions for the input and output variables of the fuzzy systems.

Table 1. CREDIT input fuzzy membership functions

Slow credit	SL	0-6%
Moderate credit	MO	5% -10%
Medium credit	ME	8%-12%
Big credit	MR	11%-15%
Alarming credit	AL	14%-20%

Table 2. HOUSE input fuzzy membership function

Decrease	DC	-4%-0%
Stationary	ST	-1%-1%
Moderate growth	MG	0%-2%
Growth	GR	1.5%-4%
High growth	HG	3.5%-6%

Table 3. GAP input fuzzy membership function

Normal	NO	0%-1.8%
Dangerous	DS	1.5%-3%
Critical	CS	2%-8%

To exemplify the implementation of the system, carried out by means of the MATLAB Fuzzy Logic Toolbox [11], with triangular membership functions. The definition of the CREDIT input variable is illustrated in Figure 3.

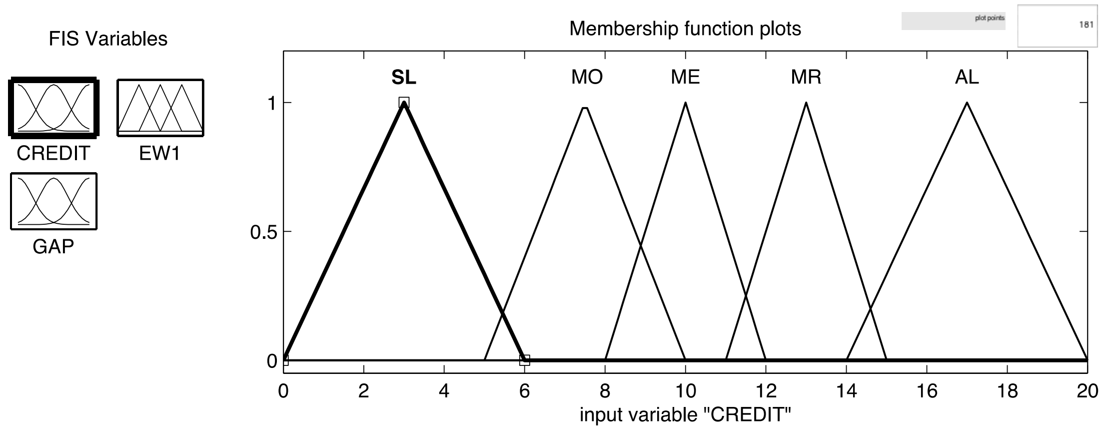

Figure 3. CREDIT membership function definition for FZ1

The results obtained by applying this approach on aggregated ECB data are shown in Figure 4. It can be seen how the average of the two indicators EW1 and EW2 correctly converges upon the starting point of the financial crisis of 2008-2009.

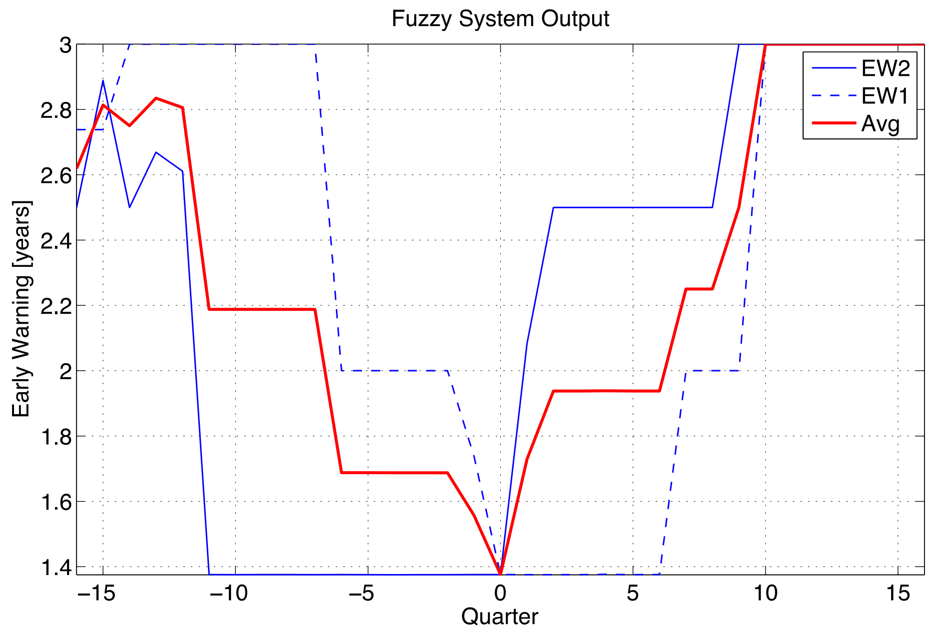

Figure 4. Synthetic output warning signals for FZ1 and FZ2

At the output level, the warning signal of the system is computed based on the intermediary warning signals EW1, based on CREDIT and GAP, and EW2, based on HOUS and GAP. The classification of the two signals is carried out according to Table 4.

Table 4. Output signal fuzzy classification

	Crises starts in	EW1	EW2
Iminent crises	1-1.75 years	IM	IK
Crises in two years	1.5-2.5 years	C2	K2
Crises between 2 and 3 years	2-3 years	2P	23
Crises in three years	2.5-3.5 years	C3	K3
Evolution without crises	3-5 years	FC	FK

An option for the implementation of the output decision block FZ3 is based on the combination of EW1/EW2 by means of an OR operator as described in Table 5. The output variables representing direct early warning signals: Late Warning – LW, Early Warning – EW, and No Crisis – NO, are classified by means of an intensity map as in Figure 5.

Table 5. FZ3 decision block output

	IM	C2	2P	C3	FC
IK	**LW**	**LW**	**LW**	**LW**	**LW**
K2	**LW**	**EW**	**EW**	**EW**	**NO**
23	**LW**	**EW**	**EW**	**EW**	**NO**
K3	**LW**	**EW**	**EW**	**EW**	**NO**
FK	**LW**	**NO**	**NO**	**NO**	**NO**

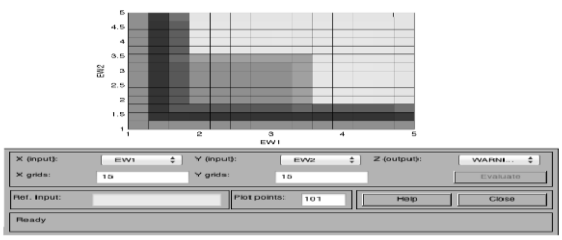

Figure 5. Warning signal of the multi-level structure

4. Adaptive neuro-fuzzy model tuning approach

In order to fine-tune our approach and provide for a more flexible way of adapting the fuzzy-inference systems to country specific variations, we build an adaptive neuro-fuzzy model. ANFIS systems were initially proposed by Jang [8] and offer neural-network based training for fuzzy logic membership function intervals. This requires an initial data set based on which the modelling of the neural network is carried out using a hybrid: backpropagation and linear lest squares, learning method.

Main results were obtained macro-economic data represented in percentage variation quarterly series for Hungary over 42 quarters starting in 1997. Figure 6 shows the input data for the three variables of choice: credit, house and gap. It can be seen how the need to adjust the fuzzy models designed initially for the aggregated data, appears due to significant country specific variations.

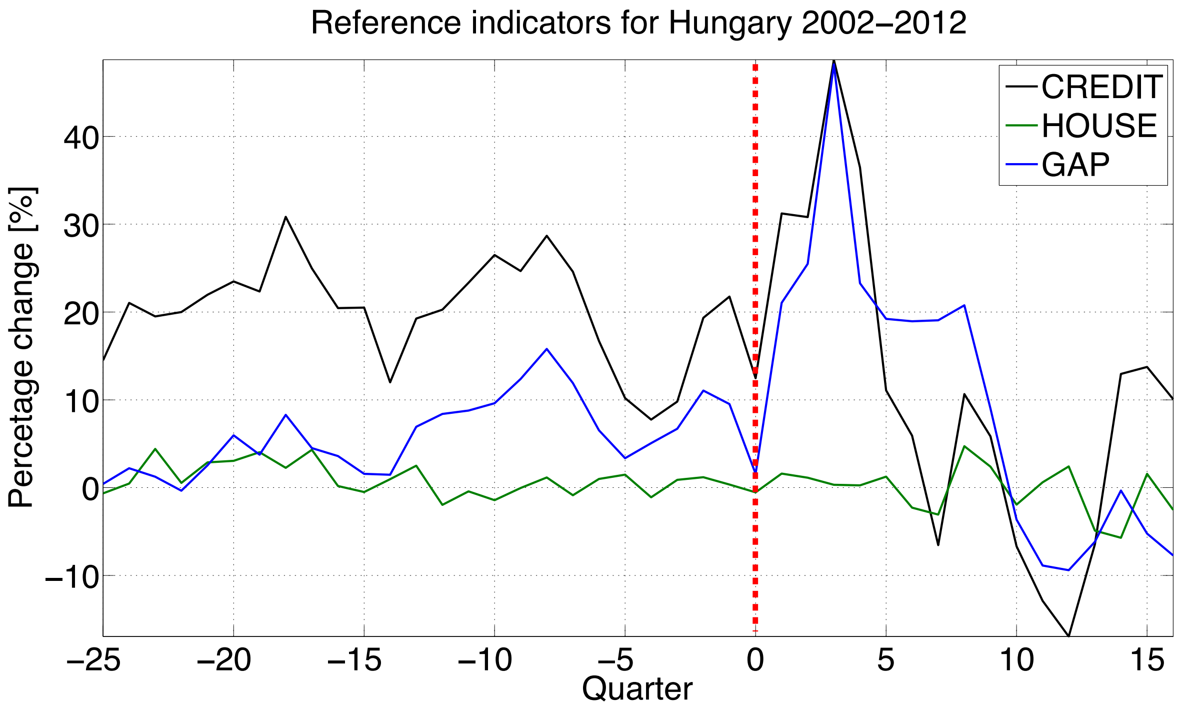

Figure 6. Input variables for Hungary 2002-2012

The neural network used for training of the fuzzy logic blocks is shown in Figure 7. Figure 8 lists the numeric results of the ANFIS training stage.

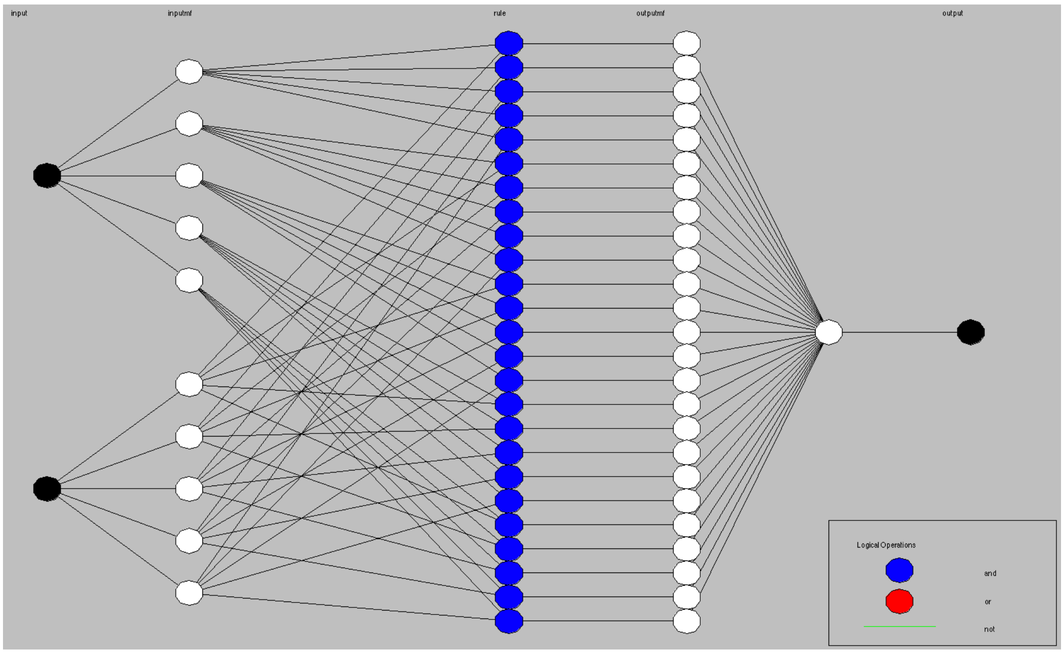

Figure 7. Neural-network based training of fuzzy systems

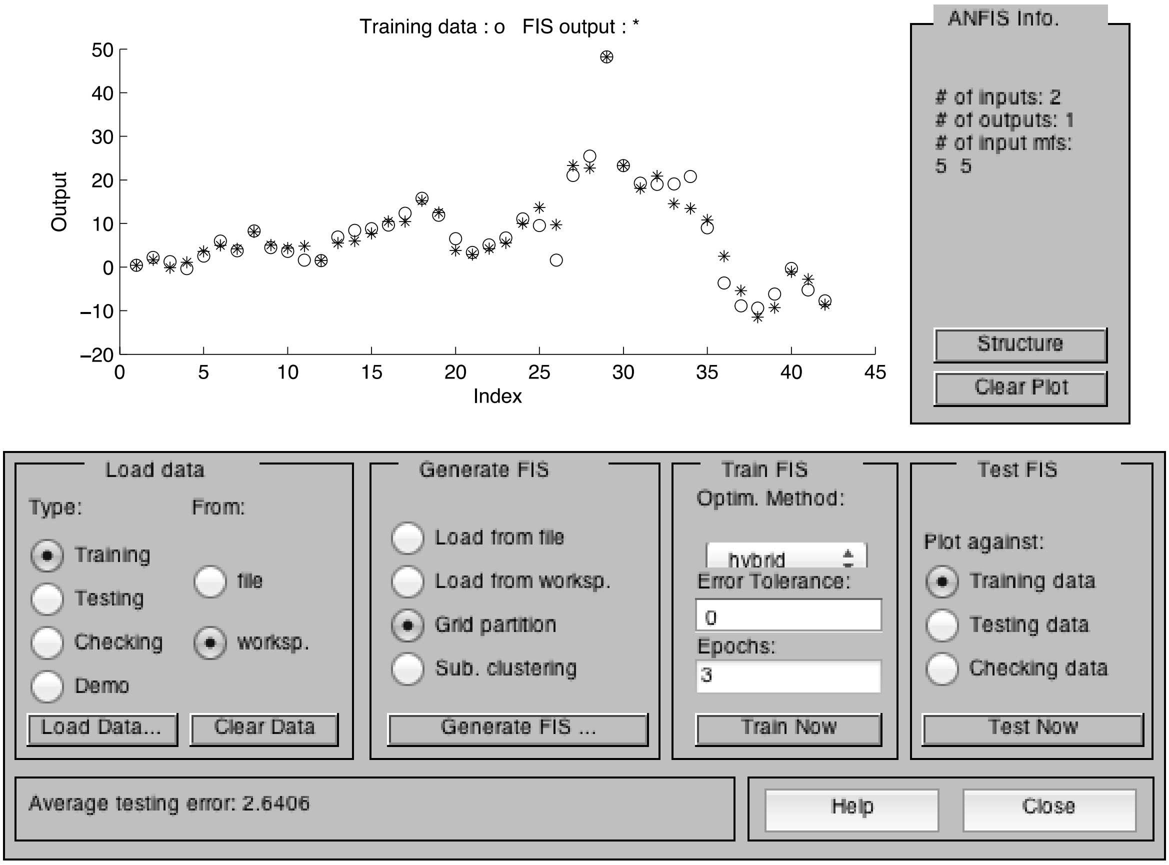

Figure 8. ANFIS training results

The final result is shown in Figure 9. It illustrates the surface view on an equivalent FZ1 fuzzy system with CREDIT and GAP as input1 and input2 respectively. An important observation is that the ANFIS modelling process generates Sugeno-type fuzzy systems which generate the output as a weighted average of the individual rule evaluation.

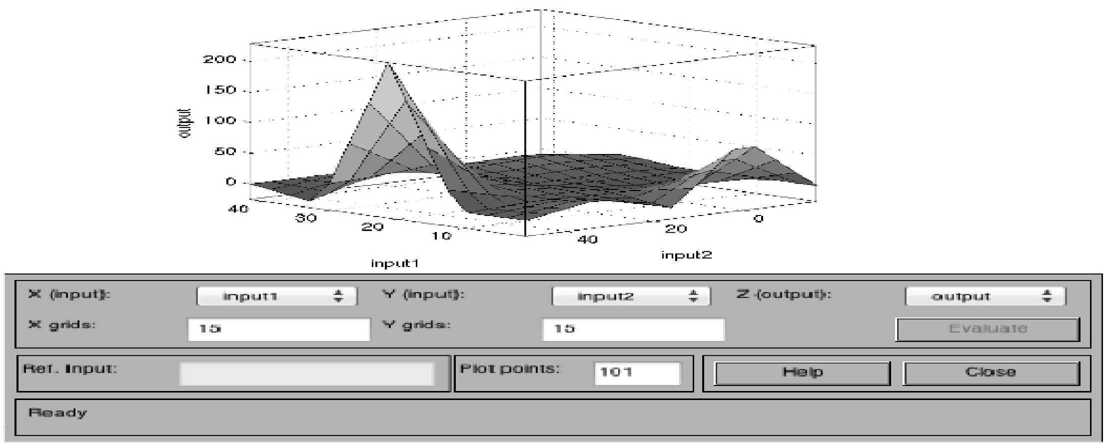

Figure 9. Surface view of Sugeno-type fuzzy system output

5. Conclusions

The paper discussed the application of fuzzy logic structures for decision support in early warning of financial crises scenarios. A multi-level fuzzy structure has been designed, implemented and validated using aggregated ECB macroeconomic indicators. Leveraging ANFIS modeling methods for fuzzy logic membership tuning has shown promising results in the scenario of early warning systems, adapted to specific socio-economic conditions of individual countries.

Main findings resulted in defining fuzzy variables and rule bases for a two level system able to offer reliable indices for financial crises forecasting. This allows incorporating expert knowledge into a flexible prediction framework which can be adjusted depending on country-level characteristics as well as the global economic environment e.g. by selecting different indicators as inputs.

Future work will be focused on developing the global model and application to Romania, subject to availability of extensive datasets to use as input variables.

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[1] **Acknowledgements**
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