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AN EARLY-WARNING SYSTEM FOR FINANCIAL PERFORMANCE PREDICTIONS

Abstract. *The Self-Organizing Map (SOM) algorithm is used to assess comparatively the performance of non-banking financial institutions (NFIs) in Romania. The benchmarking model is represented by a - two-dimensional map (a SOM) that can be used to assess visually the performance of NFIs based on different performance dimensions. The SOM is further applied as an early-warning system (EWS) that would accurately forecast the NFIs' future performance. The model is able to correctly predict NFIs' performance movements. Finally, the SOM-based model is compared with a multivariate logit-based model proposed in previous research.*

Keywords*: performance evaluation, non-banking financial institutions, financial ratios, self-organising maps, early-warning systems.*

JEL Classification: C38, C45, D81, G23

1. Introduction

The main objective of all main actors on the financial industry stage is to analyse comparatively financial institutions and what is more, to predict as accurate as possible their performance. Particularly, the major interest of financial industry regulators is maintaining the financial stability of the sector. This can be achieved if the deterioration of financial institutions' performance is correctly and timely predicted. For example, central banks and, especially, their supervision departments are interested in performance prediction models for their supervised entities in order to better allocate their resources (time and personnel).

In this paper, unsupervised neural networks are used for evaluating comparatively the performance of non-banking financial institutions (NFIs) in Romania. The neural networks applied are the Self-Organizing Maps put forward by Kohonen (1997). The main objective is to develop a benchmarking model as a two-dimensional map (a self-organizing map). The resulted self-organizing map can be used to evaluate visually the performance of non-banking financial institutions based on different performance dimensions, such as capital adequacy, assets' quality and profitability. Additionally, the map created is used to build an early-warning system (EWS) for NFIs' performance deterioration. Performance

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deterioration occurs if the NFI is eliminated from the Special Register. The Special Register includes NFIs based on certain performance criteria.

2. Literature review

2.1. Self-Organizing Maps in bankruptcy prediction

The bankruptcy prediction has always raised the interest of both practitioners and macro-policy makers, especially in the aftermath of the global financial crisis. In the specialty literature, the bankruptcy prediction problem is usually approached as a classification task. The objective is to partition the entities in two classes (distressed and healthy) or into a certain number of predefined classes.

So far, a large number of methods have been employed to tackle the bankruptcy prediction problem. Earliest efforts date back to the z-scores developed by Beaver (1966) and Altman (1968). Altman's discriminant analysis has been often used as a benchmark, but in more recent studies it is the logistic regression model initially proposed by Ohlson (1980) that is used to gauge the performance of a chosen method.

However, the state-of-the-art approaches for bankruptcy prediction are represented by neural-network-based models, including the Self-Organizing or Kohonen's Maps.

The Self-Organizing Map is an attractive visualization technique that can be used for bankruptcy prediction models. Its main advantage compared to other methods is the suggestive graphical representation that eases pattern recognition and visual interpretation by decision makers (Chen et al., 2013).

SOM models have also been used for forecasting credit classes. For instance, in Huysmans et al. (2006), the SOM is used for credit scoring on a dataset made up of Benelux financial institutions with 27 variables. The chosen grid gives lower accuracy ratios than what was obtained by several supervised classifiers. Therefore, authors' recommendation is to integrate the SOM with a supervised classifier in order to increase the algorithm's accuracy.

Another string of the literature is focused on using SOM for determining the triggers of financial performance deterioration in companies. For instance, the SOM developed by Severin (2010) on a database with 200 French firms (13 financial ratios) reveals that debt accelerates a decrease in performance for industrial firms with an extensive operating cycle. Furthermore, Chen et al. (2013) use also a sample of small and medium-sized French companies, but consider 29 financial ratios (2003 – 2006). They find that increasing cash-flow, turnover and EBITDA margin could improve companies' financial situations. Some novelty elements of methodology can be found in their study, by integrating two SOMS. The first SOM is trained without taking into account the temporal aspects of the data, each company yielding a trajectory in the SOM neighbourhood grid. Next, the trajectories are visualized and clustered by the second SOM to find the behavioural patterns. Maps to group companies with similar bankruptcy trajectories have also been built by Du Jardin (2017). In a more recent study (Du Jardin, 2018), ensembles of incremental size maps are proposed (where each map has one or several neurons from the previous map). Results obtained from this approach show that this type of maps is more accurate than the one based on single models or models based on an ensemble. Robustness of results have been confirmed by using distinct samples over different time periods.

Considering that recent approaches in SOM models focus on identifying the triggers of companies' financial status, the idea of developing an Early-Warning Signs model (EWS model) based on SOM has emerged. This innovative approach would be highly beneficial for practitioners and policy-makers. In the following section, a brief literature review on EWS models is introduced.

2.2. Early-warning signs models

Early-warning signs models were exploited at macroeconomic level for predicting global financial crisis, but also at microeconomic level, for predicting the future bankruptcy of a company. The latter were developed mainly by banking institutions as a supplementary warning system for their companies.

Nonetheless, the EWS established at macroeconomic level represent the vast part of the specialty literature. Their role would be to warn the financial market participants or bank regulators of potential risks and increase the attention of authorities in bank examinations. Moreover, the EWS could be used as a tool to justify policy actions taken as measures needed to avoid a crisis (Davis & Karim, 2008).

Early warning systems have been constructed using a variety of methods. One of the least sophisticated approaches was proposed by Kaminsky & Reinhart (1999). They develop a non-parametric single extraction model starting from evaluating the behaviour of single variables prior to, but, also, during a crisis; a threshold for each variable is established, to distinguish between the normal and the abnormal behaviour. The model is based on minimizing the noise to signal ratio. In other words, they minimize the probability of failing to identify a crisis (type I errors) as well as the probability of false alarms (type II errors) simultaneously. Their data set included 20 countries that were confronted with banking crises in the period 1970 – 1995. The static signal extraction procedure was improved significantly, in terms of predictive power and applicability to different time periods, in the paper of Casu et al. (2012). A dynamic threshold of the indicator variables is introduced instead of the static ones. The dynamic threshold is determined as a certain number of standard deviations from the variables' long-run mean, on a period of 3, 5 or 10 years. The model was applied to a dataset of OECD countries, over a 30-years period.

Other data mining techniques that could be used for an EWS are mentioned by Koyuncugil & Ozgulbas (2012): cluster analysis, hierarchical cluster, SOM, classification and regression tress, Chi-square Automatic Interaction Detector (CHAID).

Although macroeconomic EWS models are usually constructed for emerging economies, Dawood et al. (2017) have proposed a EWS only for developed countries. Multiple leading econometric models are employed and the main conclusion is that a binary logit model (in which the entire crisis period is treated as individual episodes) outperforms the multinomial one.

An innovation in what concerns the variables included as possible warning indicators is presented in Lo Duca & Peltonen (2013). They obtain evidence that combining indicators of domestic and global macro-financial vulnerabilities improves the predictive power of the model. A composite index (Financial Stress Index – FSI) is used to measure a country's level of stress in the financial system. The start of the crisis is considered when the FSI exceeds a certain threshold; the model was developed on a sample of 28 emerging and advanced economies and it would have issued an early warning signal for the US five quarters before the global financial crisis.

An EWS for banking institutions is proposed by Papanikolaou (2018). A dual early warning model is introduced, estimating the joint probability of a distressed bank to go bankrupt or to be bailed out, within a dynamic framework.

The self-organizing map was also used in recent studies (e.g., Sarlin & Peltonen, 2013) for constructing an EWS model. In Sarlin & Peltonen (2013), a Self-Organizing Financial Stability Map (SOFSM) is implemented as a complement to the EWS model proposed by Lo Duca & Peltonen (2013). The map can be used to monitor macro-financial vulnerabilities by identifying a country in the financial stability cycle (pre-crisis, crisis, post-crisis or tranquil). The map can be employed additionally to analyse potential contagions based on similarities in macro-financial vulnerabilities across countries. The model performed similarly to a logit model and managed to identify the start of the global financial crisis (as early as the first quarter of 2006).

EWS have also been constructed for detecting the financial performance of Small and Medium Enterprises (SMEs). Koyuncugil & Ozulgbas (2012) employ the Chi-Square Automatic Interaction Detector (CHAID) to develop a financial EWS that classifies almost 8000 SMEs in 31 different risk profiles. CHAID is particularly popular for its multi-branched characteristic, making it easy to understand and to interpret. Recently, Migdal-Najman et al. (2019) apply SOM to develop an Early warning model against insolvency for companies in construction industry. The proposed model employs 12 financial analysis indicators for a sample of enterprises in Poland. The resulted network has very good classification rates one year before bankruptcy announcement.

An Early-warning model for corporate enterprises has been proposed by Tian & Yu (2017); they use a discrete hazard model for corporate companies in Japan, UK, Germany and France.

The EWS literature has been reviewed for macro-level, as well as for micro-level models. It is found that although there is a large number of studies on EWS at macroeconomic level, for corporate companies and SMEs, the domain of non-banking financial institutions remains rather unexplored. Consequently, several potential contributions to the research field and to the specialty literature of assessing comparatively the performance of different entities were identified:

- applying the algorithms and methods proposed in previous research (Moinescu & Costea, 2014) and other Data Mining methods for elaborating classification/EWS models for NFIs' performance deterioration;
- using clustering as an EWS model;
- using visualization techniques for analysing the evolution over time of the NFIs;
- applying clustering techniques for discovering unusual situations of the NFIs.

All the issues mentioned above are addressed in the present paper. We build on previous results obtained by applying the Self-Organising Map algorithm to the same NFIs' performance dataset as in Costea (2013).

The paper has a significant contribution to the specialty literature. As resulted from the literature review, the application of the SOM algorithm in the classification of non-financial institutions related to their financial performance is an under-researched area. Another novelty element is the use of the Self-organizing Maps for developing an Early-warning signs model for non-financial institutions. In the next Section, the NFIs' performance assessment model proposed in Costea (2013) is introduced. The model is further used to investigate the three worst performing NFIs in Romania.

3. Assessing the performance of non-banking financial institutions

In Costea (2013), the performance of Romanian NFIs is analysed comparatively. The NFIs considered in the mentioned paper are registered in the Special Register, have been active since the introduction of the regulatory framework for this sector in Romania (2007) and are engaged mainly in financial leasing activity. In the above paper, the movements of the three largest NFIs in Romania was assessed. The size of the NFI was considered in terms of average total assets for the period 2007 – 2010. In the present paper, the focus is on the three largest worst performing companies and on their evolution over time. The following indicators are used: for the capital adequacy dimension – Equity ratio (Leverage), for the assets' quality dimension – Loans granted to clients (net value) / total assets (net value) and for the profitability dimension – Return on assets (ROA). Other three dimensions used in evaluating the performance of banks (Cerna *et al.*, 2008) have been excluded from analysis. Two qualitative dimensions (quality of ownership and management) were excluded due to lack of data, while the liquidity indicator was excluded due to its lack of relevance for the NFIs' sector. In Costea (2013), the data were collected annually for 11 NFIs, for the period 2007-2010, totalising 44 observations.

The proposed model is based on the Self-Organising Map (SOM) algorithm introduced by Kohonen in the early 80's (Kohonen, 1997). A two-dimensional map (e.g. 6x4 = 24 neurons) is created from *p*-dimensional input dataset. After training, each cluster/neuron/unit of the map contains observations with similar characteristics, e.g. companies with similar performance. The SOM structure (topology) is rectangular or hexagonal (one cluster/unit can have four or six neighbours – see Figure 1). Each cluster i is represented by the cluster center (set of weights): $C_i = \{FR_{i1}, FR_{i2}, \dots, FR_{ip}\}$ where, FR represents a financial ratio value.

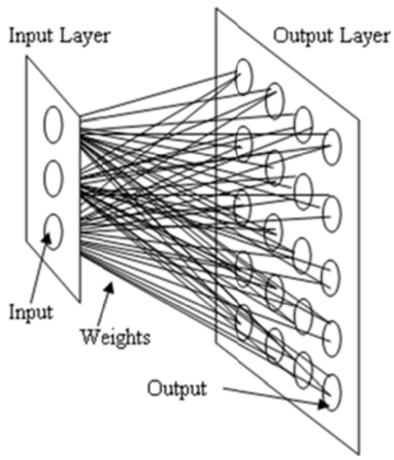

Figure 1. Example of SOM neural network architecture (3 inputs and 5x4 rectangular map)
(Source: Costea, 2005).

Before training the SOM, these clusters' centers are randomly initialized (default initialization). The observations are presented one by one to the algorithm during the training phase. The closest cluster for each observation is calculated by the algorithm and this cluster is called the *best matching unit* (m_u). A particular observation is denoted by O_j and by m_u the cluster center for which the Euclidean distance is minimized:

$$m_u = \left\{ C_i \middle| min\left(\sqrt{\sum_{k=1}^{p}\left(O_{jk} - C_{ik}\right)^2}\right)\right\} \quad (1)$$

Once the best matching unit for a particular observation is found, the center of that winning cluster u is changed by incorporating the new won observation. Also, the neighbouring clusters change their centers:

$$C_i(t+1) = \begin{cases} C_i(t) + \alpha(t)\left[O_j - C_i(t)\right], i \in N_u \\ C_i(t), \qquad\qquad\qquad\quad i \notin N_u \end{cases} \quad (2)$$

where O_j is observation j which is randomly selected at moment t, N_u is a set of clusters in the vicinity of the winner neuron u and $\alpha(t) \in (0, 1)$ is the learning rate function. The $\alpha(t)$ function decreases monotonically with t (Kohonen 1997, pp. 86-88). The learning rate $\alpha(t)$ can be a linear function (the default):

$$\alpha(t) = \alpha(0) \cdot \left(1 - \frac{t}{rlen}\right) \quad (3)$$

or an inverse-type function:

$$\alpha(t) = \alpha(0) \cdot \frac{C}{C+t} \quad (4)$$

where $\alpha(0)$ is the initial value for the learning rate function, $C = \frac{100}{rlen}$ and $rlen$ is the number of steps chosen for training. Regardless of the type, the learning rate function $\alpha(t)$ decreases to 0. The set N_u depends on the radius length N (the radius of the circle, which defines the vicinity of the winner neuron u). N can be defined as a decreasing function of time:

$$N(t) = 1 + [N(0) - 1](1 - t/rlen) \quad (5)$$

where $N(0)$ is the initial value for the radius. Obviously, $N(t)$ decreases linearly to 1.

By default the SOM algorithm stops training when a predefined number of training steps has been reached. Another possible stopping criterion: the training stops if the improvement in the overall *average quantisation error* (E) is very small. The formula below gives the overall average quantisation error:

$$E = \sqrt{\frac{\sum_{j=1}^{n} \sum_{k=1}^{p} \left(O_{jk} - C_{ik}\right)^2}{n}} \quad (6)$$

where C_i is the winner cluster u (the cluster that wins the observation). It is the cluster closest to the observation O_j.

The final output of training the SOM is a matrix with the set of clusters' centers (weight vectors). *U-matrix* (unified distance matrix) is a method proposed by Ultsch (1993) to visualize the SOM output (the weights matrix). This method calculates the distances between all neighbouring clusters. Then, these distances are used to construct the borders between neurons: large distances between neurons are highlighted using dark borders, while light borders correspond to small distances (see the bottom of Figure 2). Consequently, the neurons ("raw" clusters) that are close to each other can be visually grouped to form supra-clusters ("real" clusters). In Figure 2, we used a dashed line to represent these „real" clusters. In addition to the application of *U-matrix* method, we could use for each individual financial variable a so-called *component plane (feature plane)*. For each feature plane, light colours for the neurons correspond to high values, while dark colours correspond to low values (see the top of Figure 2).

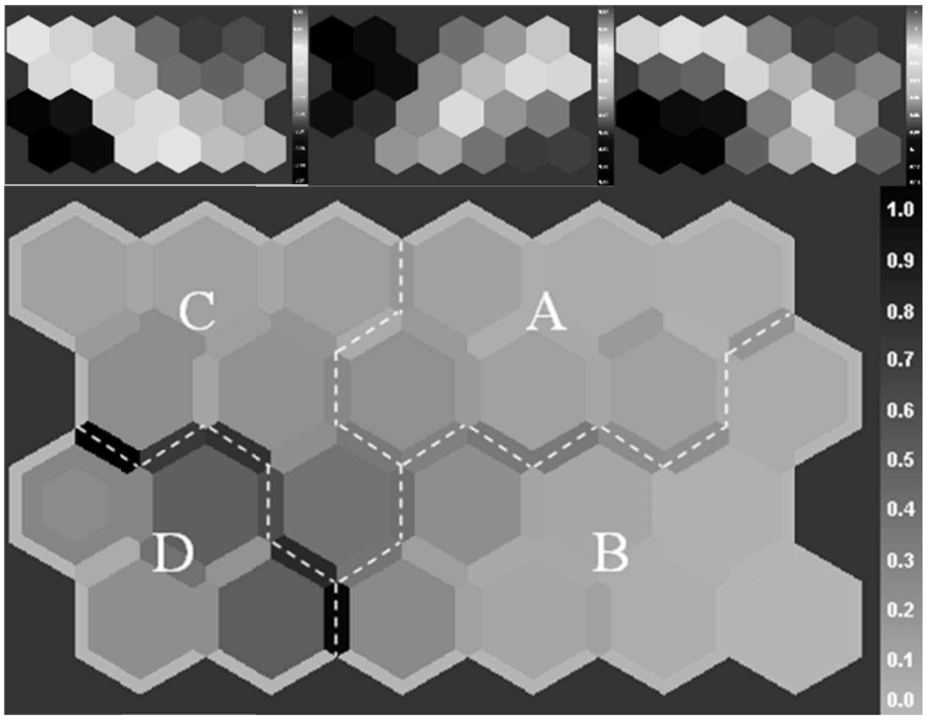

Figure 2. The SOM based on NFIs performance dataset: 24 "raw" clusters and 4 identified "real" clusters. On the top of the figure we display the component planes for the 3 variables: Leverage, Loans/Asstes and ROA
(Source: adapted from Costea, 2013).

Considering the advantages of the *U-matrix* method, the procedure unfolds with two stages: in the first stage, the SOM algorithm is applied and the 2-dimensional map is built from the input space. For the first stage of the methodology, several maps were trained by selecting different values for the above SOM algorithm parameters. No preprocessing procedures were necessary for the dataset given that the values of the ratios are already standardised in a [-1; 1] interval. Hence, the potential negative impact that the Euclidean distance calculations would have on the clustering is diminished. The right choice of the algorithm parameters is both problem and data dependent. However, whatever data is used for training, the algorithm works best when the results of a first training session are accompanied by another training session where we fine-tune the parameters (Kohonen *et al.*, 1996, p. 16). The final map chosen (shown on the bottom of Figure 2) was the one with the smallest quantisation error (E = 0.074522). The map dimensionality was set to 6x4 (24 "raw" neurons or clusters) and not higher in order to minimize the number of empty clusters. The clusters centers were *randomly* initialized and a *hexagonal* map structure was chosen. Equation (3) was used as *the learning rate function* and equation (5) as *the neighborhood function*. Next, as reported elsewhere (e.g., Kohonen, 1997), two training phases followed: in the first training phase (rough training) the clusters' centers are ordered. Consequently higher initial learning rate and higher initial vicinity were used: $rlen$ = 1000, $\alpha(0) = 0.05$, and $N(0) = 6$. In the second training phase the clusters' centers are fine-tuned. Therefore, lower learning and neighborhood parameters are applied, but higher number of training steps: $rlen$ = 10000, $\alpha(0) = 0.02$, and $N(0) = 2$.

The final 6x4 map contains 24 "raw" clusters or neurons (in Figure 2, a "raw" cluster is any of the 24 hexagons in the map). After the training completes, each cluster/neuron consists of a number of observations or none. The final map obtained in Costea (2013) is used, shown in Figure 2.

In the second stage of the methodology the "raw" clusters are grouped to form "real clusters". The *U-matrix* method is used to accomplish this stage, looking at the borders between neurons, by analysing the component plane for each input variable and the observations that belong to each cluster. Thus, four "real" clusters are identified (clusters A, B, C, and D in Figure 2) which are briefly described below.

Cluster A contains the NFIs with the highest values for the financial variables measuring capital adequacy and profitability dimensions and medium values registered for the variable measuring the assets' quality dimension. Eight observation are included in this "real" cluster. The average values for the input variables are: Leverage – 14.77%, Loans/Assets – 63.48%, ROA – 0.88%. This is the only cluster with positive average profitability ratios.

Cluster B is the largest cluster and it contains half of the total number of observations (22 observations). This cluster contains the NFIs with medium values for capital adequacy and profitability dimensions and highest value for the variable measuring assets' quality dimension. In this case, we registered the following average values for the financial variables: Leverage – 2.98%, Loans/Assets – 81.13%, ROA – (2.24%).

The average values of the ratios for the observations included in cluster C are: Leverage – 1.39%, Loans/Assets – 53.23%, ROA – (2.50%). However, the NFIs in this cluster present a lower performance compared to the ones in cluster B. These two clusters (B and C) present on average negative values for the profitability dimension.

Cluster D includes the companies that performed worst compared to their pairs. The values for all financial variables are very poor: Leverage – (52.15%), Loans/Assets – 57.33%, ROA – (13.24%). In parentheses we included negative values. As for the other clusters, cluster D presents negative profitability values.

Next, in Figure 3 the movements of the worst performing NFIs are analysed. These NFIs have been classified in one of the four years in cluster D. They are denoted with Company X, Y and Z, in decreasing order of average assets (X – 687,298,550 RON, Y – 521,088,420 RON, and Z – 148,508,941 RON).

In Figure 3 we show the trajectories for the three NFIs that present the worst performance: the largest underperformer denoted with X (dark), the second largest underperformer denoted with Y (grey) and the third largest underperformer denoted with Z (white), between 2007 and 2010.

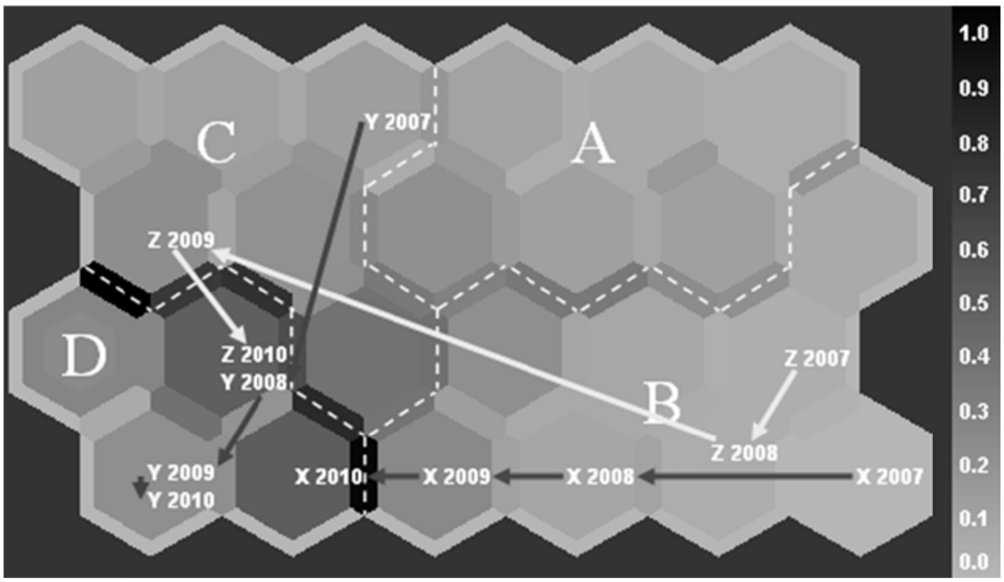

Figure 3. The final 6x4 map with identified "real" clusters and the trajectories between 2007 and 2010 for the worst performers ("dark" for company X, "grey" for company Y, and "white" for company Z)

Company X was located in cluster B in 2007 and 2008, and continued in this cluster in 2009. In the next year the company' situation deteriorated and it dropped to cluster D. This was partially due to constant deterioration of its own capital with the highest deterioration encountered for the year 2010, while the decrease in total assets was smaller. Moreover, in 2010 company X encountered a sharp decrease in the loans granted, compared to those from 2007 (a 65% decrease).

Company Y is the second largest underperformer and during the analysed period its performance indicators presented the lowest values as compared to its pairs. It started in cluster C in 2007, and it dropped in cluster D where it remained for the following three years. Company Y encountered the worst capital adequacy (-90%) mainly due to an important decrease of its total assets in 2010 (61% decrease as compared to 2007). For the first three consecutive years (2007-2009) this company presented negative values for the profitability variable (ROA), recording the highest value in 2009. In 2010, the profitability ratio turned positive as a consequence of the company's restructuring measures.

Company Z had a similar evolution to the one of company X: it started in cluster B in 2007 and 2008, migrated to cluster C one year later and, finally, dropped to cluster D in 2010. Similar to company X, in 2010 company Z registered a significant decrease of all its financial variables: high negative value for the own capital and a sharp loan decrease of about 70% compared to 2008. However, the ratios decrease was slightly smaller than the decrease in absolute values as the total assets (the denominator) decreased substantially as well (around 45%).

4. Applying the SOM model

The descriptive SOM model obtained in the previous Section can be used in order to accommodate new companies on the map as data becomes available. This is done by calculating the Euclidean distances of each new raw data, after preprocessing, to the previously obtained clusters' centers. The observations are then assigned to the closest cluster: the cluster for which the smallest distance from the observation to its center is obtained. Furthermore, a probability of default for each performance cluster can be calculated by simply dividing the number of default NFIs in the cluster to the total number of observations within the cluster. By doing this we actually simulate an early-warning system (EWS). Quarterly data between Q1 2007 and Q4 2012 was considered, for a sample of around 68 NFIs registered in the Special register kept at National Bank of Romania. Approximately 1140 data points were thus obtained. Only part of the NFIs from the General register that meet certain criteria of performance in terms of loans and borrowings are included in the Special Regiter. If the NFIs meet these criteria for three reporting-periods in a row or three quarters, then they are entered in the Special register. On the contrary, if a NFI from the Special register does not match the criteria for three consecutive quarters, it will be de-classified in the General register. Therefore, a NFI was considered "defaulted" in the current quarter if it was removed from the Special register three quarters later. Consequently, a number of data points had to be discarded from the initial dataset: if one NFI "defaulted" in the current quarter, the data point associated with that NFI was discarded in the subsequent quarters until the removal from the Special register. In this way, the final number of available observation was 1111 (Q1 2007 : Q4 2012). These 1111 observations were further divided in two parts: the data between Q1 2007 and Q1 2012, totalising 958 observations, were used to recalculate the clusters' centers of the SOM model proposed in the previous Section. Out of these 958 observations, 18 were "defaults". The data from the last three quarters (Q2:Q4 2012) were used to run the forecasts for the period Q1 2013 : Q3 2013. In this way, any performance deterioration or improvement can be signalled early, as early as three quarters in advance.

The distribution of the 958 observations to the 4 "real" clusters obtained in previous Section is presented in Table 1.

As it is shown in Table 1, the probabilities of default for each cluster can now be calculated. They are labelled in the increasing order of default risk. Moreover, new centers for the four clusters can be calculated based on the allocation of the 958 observations (see Table 2).

Table 1

The structure of the SOM model clusters after allocation

# of obs. before allocation	Leverage	Earning power	ROA	# of obs. after allocation	# of defaults	Probability of default	Performance Class (in increasing order of risk)
8	0.148	0.635	0.008	116	1	0.86%	A
22	0.030	0.811	-0.022	773	12	1.55%	B
9	0.014	0.532	-0.025	56	4	7.14%	C
5	-0.522	0.573	-0.132	13	1	7.69%	D

Table 2

The new clusters' centers after the allocation of the 958 observations

# of obs. after allocation	Leverage	Earning power	ROA	Performance Class (in increasing order of risk)
116	0.3272741	0.6086303	0.0072292	A
773	0.0571001	0.9691945	-0.0130159	B
56	0.0721848	0.2989939	-0.0076201	C
13	-1.7056216	2.5638340	-1.4398967	D

However, this approach would not have the same result (in terms of the observations' distribution within the clusters) as that obtained if the SOM algorithm and the procedure described in the previous Section would have been applied directly to all 958 observations. The problem with retraining a SOM model is that the algorithm is heavily parameterized and choosing the right setting can sometimes be very challenging. Moreover, generally, more data implies more noise within data which leads to some critical choices related to the SOM algorithm: the preprocessing method, the way the outliers and abnormal values are handled. O more stable approach to building classification/EWS models so as to accommodate newly available data and to make accurate predictions related to the performance class for these data would be to invoke a classification algorithm instead of using the prescriptive capabilities of a clustering one (e.g., SOM clustering algorithm) which is done in Moinescu & Costea (2014). The authors propose a logistic regression-based EWS for classifying the NFIs considering their financial performance. A comparative analysis between the current results and those from Moinescu & Costea (2014) is provided in this paper in a separate Section.

In Table 3 data for the last three quarters in 2012 is used (153 observations, 51 for each quarter) and show what are the results of applying our EWS model to predict the performance class in the first three quarters for 2013 (whether the observation is classified under the performance class A, B, C or D).

Table 3

Allocation of NFIs into performance classes using the SOM model

Performance Class (in increasing order of risk)	Q1 2013	Q1 2013 (%)	Q2 2013	Q2 2013 (%)	Q3 2013	Q3 2013 (%)
A	9	18	9	18	8	16
B	39	76	39	76	40	78
C	1	2	2	4	2	4
D	2	4	1	2	1	2
Total	51	100	51	100	51	100

According to the SOM model the majority of the NFIs are classified in the B performance class which is a medium risk performance class. However, this class has a rather low probability of default (1.55%, see Table 1) which signals a low risk of default. The results show a moderate deterioration of NFIs' performance in the first three quarters of 2013. This corresponds to the reality since, during 2013, there were only 3 NFIs' defaults.

5. Comparative analysis with previously reported results

In Moinescu & Costea (2014) the authors proposed an early warning system for the NFIs' defaults based on a multinomial logistic regression (MLR) approach. Recently, some authors proposed multiple-criteria decision-making methods for evaluating the clustering/classification algorithms (e.g., Kou *et al.* 2014). Comparing the results of our SOM-based EWS model with those reported using the logit-based model (see Table 4), it can be said that the SOM model performs worse in discriminating the NFIs' performance. This happens since the performance classes are not clearly defined: it is difficult to make a hierarchy between class A and class B since, as stated previously, the companies in class A are the only ones that in average have positive profitability. Companies in class B, however, have in average the highest values for the assets' quality dimension. Nonetheless, in both cases (MLR- and SOM-based approaches), if the first two classes from a low risk super-class and the last two from a high-risk one are taken into account, the results are similar. In both cases around 90% of the cases are concentrated in the first super-class, while the rest remain in the second one, for all three quarters.

Another drawback in using the SOM model as a performance forecasting mechanism is the lack of interpretability of how the model has yield a certain class performance for a (new) observation. In this respect the logistic regression model is richer in information since it provides an individual default probability for each new observation. What is more, the logistic regression coefficients can be used to interpret how this probability has been obtained.

Table 4

Allocation of NFIs into performance classes using the multinomial logistic regression (MLR-) and SOM-based models

Performance Class (in increasing order of risk)	Q1 2013 (%)		Q2 2013 (%)		Q3 2013 (%)	
	MLR	SOM	MLR	SOM	MLR	SOM
A	18	18	27	18	18	16
B	75	76	65	76	64	78
C	6	2	4	4	10	4
D	2	4	4	2	8	2
Total	100	100	100	100	100	100

However, our performance classification experiments clearly show the advantages of using both techniques at the same time (the vizualization capabilities of SOM model and the interpretability of logistic regression results).

6. Conclusions

This paper presented a neural-network-based model to evaluate comparatively the performance of non-banking financial institutions (NFIs) in Romania. Based on the SOM algorithm, four performance classes were built and the probabilities of default for each class were estimated. The dataset consisted of quarterly data for 68 NFIs, the time span being 2007 – 2012. The set of NFIs' performance indicators employed captured three of the most important performance dimensions: capital adequacy, assets' quality and profitability. The three worst-performing NFIs are analysed using the visualization capabilities of the SOM model and the underlying trajectories. Finally, the SOM model is applied to estimate the allocation into performance classes for the NFIs in the first three quarters in 2013. The SOM model accurately classified the NFIs showing a moderate deterioration (which corresponded to reality) of these entities. The results of our SOM-based model were compared with those obtained by applying a multivariate logit-based model proposed in Moinescu & Costea (2014). The SOM model performed worse in discriminating the NFIs' performance: the performance classes were not clearly defined and the model lacked the interpretability of the results. On the contrary, the multivariate logit coefficients have accessible interpretability and an individual default probability estimate is obtained for each new observation. However, we can highlight the advantages of each of the two techniques: the visualization capabilities of the SOM model and the interpretability of the multivariate logit-based EWS model.

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