MODELLING OF SCENARIOS OF THE CRISIS PHENOMENA TRANSFER AMONG FINANCIAL MARKETS

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Abstract. The phenomenon of crisis transference among financial markets in different countries is especially evident during the global financial crisis of 2007-2009. Abnormal imbalances emerged in the market of secondary financial instruments in the United States in the second half of 2006 and quickly spread to the financial markets of most countries of the world. However, the rate of fall of the main macroeconomic indicators, the duration of the latent period (the time between the date of the beginning of the financial crisis in the source country and date of the recorded fall in GDP of the country that is subjected to "contagion" (Strelchenko, 2016), and recovery period are substantially different. To generate an effective economic policy actually, there is a task of determining the possible scenarios of transferring crisis. *The research subject* is a process of transfer of the crisis phenomena among the financial markets of countries with different levels of economic development. *Methodology*. The paper presents the results of a study on the differentiation of the financial markets reactions to the crisis transfer. To build the corresponding classification model, self-organization Kohonen neural networks are used. *The purpose* of this work is to build a neural network model for clustering economies according to the response to external financial shocks. This model allows predicting the scenarios of transferring crisis among financial markets. *Conclusion*. As a result of the study, there is built a neural network with the architecture of the Kohonen map. The neural network has one hidden layer consisting of six neurons and has a hexagonal structure. Six clusters describe six possible scenarios of the economy dynamics under the impact of the transfer of crises. Cluster number one and two unite countries characterized by a short period of economic recovery and return of the main macroeconomic indicators to the pre-crisis levels. A longer recovery period and high volatility in exchange rates, gross domestic product, and decline in export-import operations characterize the third and fourth clusters of SOM. As for the countries that were in the last two clusters (including Ukraine), then the result of the crisis phenomena transfer is that the average amplitude of the fall in macroeconomic indicators exceeded 15% for the sixth cluster, and 9% for cluster number 5.

Key words: crisis, contagion, macroeconomic indicator, clustering, neural network, Kohonen map, radial basis network.

JEL Classifiaction: C38, C45, G01, G15

1. Introduction

Based on studies of the mechanisms of transboundary transfer of financial crises rests the modern theory of "contagion" (Kaminsky, Reinhart, 2001; Calvo, Reinhar, 1995; Sachs, Tornell, Velasco, 1996). The effect of "contagion" is evident in the atypical fall in exchange rates, stock prices, government bonds, stock indices, etc. (Strelchenko, 2016).

The analysis of researches on the theory of "contagion" reveals the following features specific to the processes of cross-border transfer of financial shocks:

1. The effects of transmission of financial shocks differ significantly depending on the level of economic development, liberalization of the market economy, corruption and shadow economy mode of operation of the exchange rate, etc.
2. In some cases, especially "contagion" exposed country with strong historical trade links. Because of this, the shortest latent period of the reaction is observed in the group of countries that are compactly located near the country – the sources of the crisis. For example, during the "Asian flu" in 1997-1999 – among the new industrialized countries width the Asian development model of the national economy, and the so-called "Tequila effect" in South America (1994).

To identify groups of countries with similar response functions for the spread of financial shocks, promising

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is the use of neural networks, in particular, models with radial basis architecture or Kohonen maps.

2. The advantage of using neural networks in problems of classification

One of the most important applications of neural networks is classification. Often, these tasks do not include final reference values for learning neural networks. Their goal is to divide the original sample into groups according to the specific characteristics of similarity. To address these challenges, self-organizing neural networks are successfully used.

The most famous algorithm for constructing a neural network of this type is the algorithm WTA or "winner takes all" (Kohonen, 2001).

Neural networks, learning without a teacher on the WTA algorithm and implement clustering training samples according to certain criteria, better known as maps, which organize themselves – SOFM (Self-Organizing Feature Map) or Kohonen maps (Kohonen, 2001).

According to problems solved with Kohonen maps, it is necessary to note the following:

- elements within a specific cluster should be similar on certain grounds;
- similar clusters should be located close to each other.

Procedure of training the SOFM by WTA-rule consists of the following steps (Kroese, 1996):

1. Prior to the training, it is necessary to set the map topology: rectangular or hexagonal (Fig. 1).

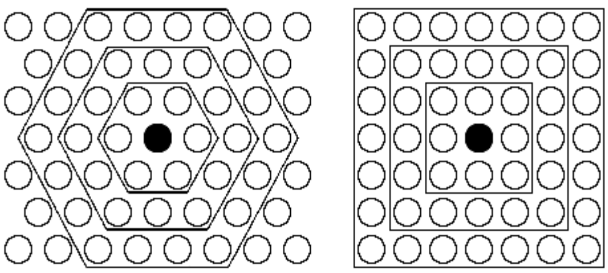


Fig. 1. Possible configurations of Kohonen maps:
a) hexagonal; b) rectangular.

2. Sets the radius update. It defines the range of neighbouring neurons to be training (Fig. 2).
3. Set the initial matrix of synaptic connections
4. For each cluster element calculate the distance to the training vector by the equation:

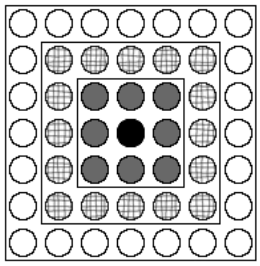
$$d_q = \sum_p \left(w_{pq} - x_p\right)^2, \qquad (1)$$

and choose the winner neuron to a minimum value d_q.

5. For the winning neuron and nodes within a specified radius, update the weights according to the WTA-rule (Kohonen, 2001):

$$w_p(t_i) = w_p(t_{i-1}) + \cdot\eta \cdot \Lambda \cdot [x_p - w_p(t_{i-1})], \qquad (2)$$

where $w_p(t_{i-1})$, $w_p(t_i)$ – p-th neuron setting of Kohonen map before and after correction, respectively; $x_p(t_i)$ – p-th element of input data vector submitted to the t-th training step; η – learning rate, $0<\eta<1$, which changes in the process of self-organization of a neural network (usually the initial value closer to unity and gradually decreasing); Λ – the neighbourhood function between neuron and neuron-winner, which determines the size of the weight adjustment of connections for each neuron (for the winning neuron, neighbourhood function is equal to one and decreases when it moves away from by linear or exponential law).



● – element to be training for r = 0;
● – element to be training for r =1;
⊗ – element to be training for r =2;
○ – element to be training for r =3.

Fig. 2. Choice neighbouring neurons to study, according to the size range:

6. The learning process continues as long as the synaptic weights of the current training cycle compared with the previous one become insignificant.

Compared to other mathematical tools designed to support decision-making in conditions of uncertainty and the large number of influencing factors, neural networks have a number of specific advantages:

1) allow effective modelling of nonlinear processes;
2) no need in strict mathematical specification of the model in solving non-formalized or badly formalized tasks;
3) adaptability for changes influencing factors;
4) parallel data processing;
5) effectiveness in dealing with incomplete or noisy data;
6) the possibility of classification in many ways;
7) the performance of forecasting time series, depending on many factors;
8) the ability to search for hidden patterns in data arrays.

The main drawbacks of neural networks are as follows:

- the lack of a unified theory for choosing the structure of the neural network;
- the practical impossibility of isolating the knowledge-trained neural network, for researchers NN is a "black box."

3. Model construction

To implement Kohonen neural network algorithm in this research, we used the tools of matrix laboratory MatLab.

When building a neural network, it is necessary to solve the problem of the optimal ratio between the number of neurons in the hidden layer and the size of the training set.

Empirical research shows that to achieve high rates of synthesis and learning neural network training set number of elements should be done inequality (Callan, 1998):

$$N_{nv} > \frac{N_w}{\%e}, \quad (3)$$

where N_w – he number of hidden layer neural; N_{nv} – the size of the training set; $\%e$ – is the fraction of errors envisaged in the course of testing.

For Kohonen neural network, the number of neurons in the hidden layer will determine the number of clusters of a future SOM.

To separate the training sample into six groups corresponding to the migration scenarios of the crisis phenomena among the financial markets, the size of the training sample will be determined from the relationship (3):

$$N_{nv} > \frac{6}{0{,}1} = 60\,.$$

The size of the training set should cover statistics for more than 60 countries.

A neural network structure represented by blocks Simulink is presented in Figure 3.

The configuration of Kohonen maps is hexagonal.

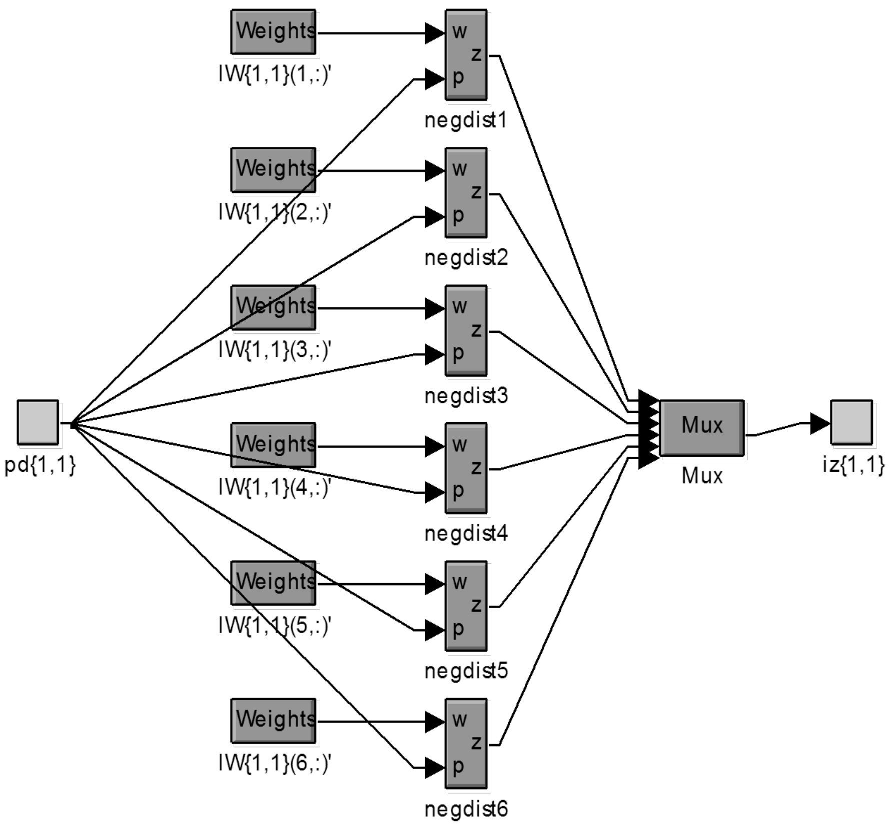


Fig. 3. A neural network structure represented by blocks Simulink

4. Modelling of scenarios of the crisis phenomena transfer among financial markets

Training sample – array of dimension , where the number of rows – the number of countries included in the training sample, and the number of columns – macroeconomic indicators:

- GDP;
- the exchange rate of the national currency;
- part of the country international investment position that characterizes the external liabilities of residents to non-residents;
- foreign exchange reserves; the value of government bonds.

The training sample of sixty-six countries represented countries in each group of IMF classification. Namely:

1. Advanced Economies: Euro Area (1), Estonia (2), Lithuania (3), Australia (4), Canada (5), Special administrative region of China Hong Kong (6), China, P.R.: Macao (7), Czech Republic (8), Denmark (9), Iceland (10), Israel (11), Japan (12), South Korea (13), New Zealand (14), Norway (15), Singapore (16), Sweden (17), Switzerland (18), United Kingdom (19), United States (20).
2. Emerging and Developing Economies: Bangladesh (21), Bhutan (22), Brunei Darussalam (23), Cambodia (24), China P.R.: Mainland (25), Fiji (26), India (27), Indonesia (28), Kiribati (29), Lao People's Democratic Republic (30), Malaysia (31), Mongolia (32), Myanmar (33), Nepal (34), Papua New Guinea (35), Philippines (36), Samoa (37), Solomon Islands (38), Sri Lanka (39), Thailand (40), Tonga (41), Vanuatu (42), Vietnam (43), Albania (44), Bosnia and Herzegovina (45), Bulgaria (46), Croatia (47), Hungary (48), Latvia (49), Macedonia (50), Montenegro (51), Poland (52), Romania (53), Serbia Republic (54), Turkey (55), Armenia (56), Azerbaijan (57), Belarus (58), Georgia (59), Kazakhstan (60), Kyrgyz Republic (61), Moldova (62), Russian Federation (63), Tajikistan (64), Ukraine (65).

The statistical information used to calculate contained in the public domain at the International Monetary Fund (IMF, 2017).

Using the function tool built Kohonen self-organizing map, which splits the original sample into six clusters based on the pattern data selected quarterly macroeconomic indicators for the period 2007-2009. The classification results are shown in Figure 4.

As a result of the simulation, we received six groups of countries with similar characteristic dynamics of macroeconomic indicators: GDP; the exchange rate of the national currency; a part of the country international investment position that characterizes the external liabilities of residents to non-residents; foreign exchange reserves; the value of government bonds.

The simulation gave a distribution of economies in the following way (presented according to the structure of SOM):

1. Euro Area (1), Estonia (2), Lithuania (3), Czech Republic (8), Denmark (9), Israel (11), Singapore (16), Switzerland (18), United States (20), Brunei Darussalam (23), Malaysia (31), Myanmar (33), Philippines (36), Thailand (40), Albania (44), Bosnia and Herzegovina (45), Bulgaria (46), Croatia (47), Latvia (49), Macedonia (50), Montenegro (51).
2. Australia (4), Canada (5), New Zealand (14), Norway (15), Sweden (17), Indonesia (28), Kiribati (29), Samoa (37), Tonga (41), Vanuatu (42), Hungary (48), Poland (52), Serbia Republic (54).
3. Bangladesh (21), Armenia (56), Georgia (59), Moldova (62).
4. Iceland (10), South Korea (13), United Kingdom (19), Bhutan (22), India (27), Nepal (34), Solomon Islands (38), Romania (53), Turkey (55).
5. Special administrative region of China Hong Kong (6), China, P.R.: Macao (7), Japan (12), China P.R.: Mainland (25), Lao People's Democratic Republic (30), Papua New Guinea (35), Azerbaijan (57).
6. Cambodia (24), Fiji (26), Mongolia (32), Sri Lanka (39), Vietnam (43), Kazakhstan (60), Belarus (58), Kyrgyz Republic (61), Russian Federation (63), Tajikistan (64), Ukraine (65).

Analysis of the obtained results indicates the high quality of the constructed model. The average characteristics of classification within each group are very similar.

It is also important to note that the neural network is included in one cluster of countries that are close geographically and historically folded close economic ties.

To clarify the results obtained, the author considers it necessary to further work to supplement output data rates for a longer period and to compare the results of clusters with the radial base neural network.

5. Conclusions

As a result of the study, there is built a neural network with the architecture of the Kohonen map. It allows

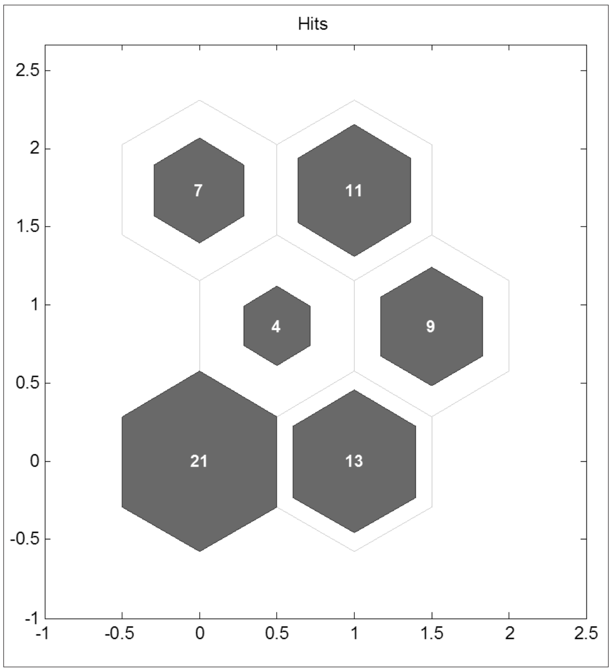


Fig. 4. Kohonen self-organizing map that reflects the clustering of countries' economies on the dynamics of the chosen indicators for 2007-2009

including a certain economy to a class for the four macroeconomic indicators:

- GDP;
- exchange rate of the national currency;
- part of the country international investment position, that characterizes the external liabilities of residents to non-residents;
- foreign exchange reserves; the value of government bonds.

The neural network has one hidden layer consisting of six neurons and has a hexagonal structure.

Six clusters describe six possible scenarios of the economy dynamics under the impact of transfer crises. Cluster number one and two unite countries characterized by a short period of economic recovery and return of the main macroeconomic indicators to the pre-crisis levels. A longer recovery period and high volatility in exchange rates, gross domestic product, and decline in export-import operations characterize the third and fourth clusters of SOM. As for the countries that were in the last two clusters (including Ukraine), then the result of the crisis phenomena transfer is that the average amplitude of the fall in macroeconomic indicators exceeded 15% for the sixth cluster, and 9% for cluster number 5.

To clarify the results obtained, the author considers it necessary to further work to supplement output data rates for a longer period and to compare the results of clusters with the radial base neural network.

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Инна СТРЕЛЬЧЕНКО

МОДЕЛИРОВАНИЕ СЦЕНАРИЕВ ПЕРЕНОСА КРИЗИСНЫХ ЯВЛЕНИЙ МЕЖДУ ФИНАНСОВЫМИ РЫНКАМИ

Аннотация. Явление переноса кризисных явлений между финансовыми рынками разных стран особенно ярко проявилось в период мирового финансового кризиса 2007-2009 гг. Аномальные дисбалансы появились на рынке вторичных финансовых инструментов в Соединенных Штатах во второй половине 2006 года и быстро распространились на финансовые рынки большинства стран мира. Тем не менее, темпы падения основных макроэкономических показателей, продолжительность латентного периода (промежуток времени между датой начала финансового кризиса в стране-источнике и датой зафиксированного падения ВВП страны, подверженной «инфекции» (Strelchenko, 2016) и период восстановления существенно различаются. Для создания эффективной экономической политики актуальной является задача определения возможных сценариев переноса кризиса. *Предметом исследования* являются процессы переноса кризисных явлений между финансовыми рынками стран с разным уровнем экономического развития. *Методология*. В статье представлены результаты исследования дифференциации реакции финансовых рынков перенос кризисных явлений. Для построения соответствующей модели классификации использовалась нейронная самоорганизующаяся сеть Кохонена. *Цель* этой работы – построить модель нейронной сети для кластеризации экономики в соответствии с реакцией на внешние финансовые потрясения, которая позволит прогнозировать сценарии переноса кризиса между финансовыми рынками. *Выводы*. В результате исследования – построена нейронная сеть, имеющая архитектуру карты Кохонена. Нейронная сеть имеет один скрытый слой, состоящий из шести нейронов, и гексагональную структуру. Шесть кластеров описывают шесть возможных сценариев динамики экономики под воздействием переноса кризисных явлений. Кластер номер один и два объединяют страны, характеризующиеся коротким периодом восстановления экономики и возвратом основных макроэкономических показателей до докризисного уровня. Более длительный период восстановления и высокая волатильность обменных курсов, валового внутреннего продукта, сокращение экспортно-импортных операций, характеризуют третий и четвертый кластеры самоорганизующейся карты. Что касается стран, которые попали в два последних кластера (включая Украину), то в результате переноса кризисных явлений средняя амплитуда падения макроэкономических показателей превысила 15% для шестого кластера, и 9% для кластера номер 5.