models up to a level of full brokers. Such automatic brokers (fixer) will be capable to solve problems independently.

By estimation of the IDC Company the market of public cloud computing in 2009 has made $17 billion or about 5 % from all market of information services [5].

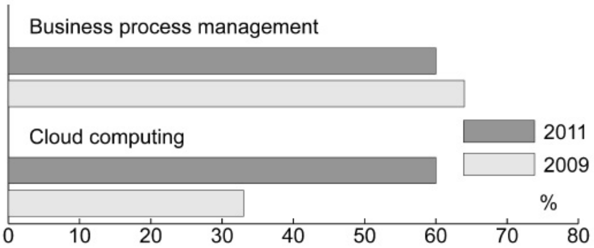

Fig.1. Prospects IT technologies for business

Source: authorial calculation

Among IT technologies for increase of business efficiency CC show the best dynamics of development. More than 3 000 global Chief Information Officer responded in the IBM CIO 2011 study and it showed that 60% of organizations view cloud computing as a way to grow their business and increase their competitiveness, as depicted in Fig. 1 [2, p. 2].

1. Mell P., Grance T. The NIST Definition of Cloud Computing. Recommendations of the NIST NIST Special Publication 800-145, [Online], 2011, http://www.nist.gov/itl/cloud/index.cfm. 2. Acker K., Llaurency S., Green R. Cloud Computing and the Value of zEnterprise [text] / IBM REDP-4763-00, 2011. – 42 p. 3. Kisker H. Cloud Predictions Forrester 2012 [Online], http://blogs.forrester.com/holger_kisker/11-12-13-10_cloud_predictions_2012
4. Gartner. Special Report Cloud Computing [Online], 2012, http://www.gartner.com/technology/research/cloud-computing/index.jsp
5. Fact Sheet IDC_P262 [Online], 2012, http://www.idc.com/prodserv/idc_cloud.jsp

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MODELING OF EUROPEAN STOCK INDEXES RETURNS USING WAVELET ANALYSIS

Проведено кластеризацію доходностей європейських фондових індексів за допомогою методів вейвлет-аналізу. Запропоновано модифікований метод прогнозування доходностей фондових індексів на основі вейвлет-декомпозиції, нейронних мереж та методу SSA.

Ключові слова: вейвлет-аналіз, прогнозування, дохідності фондових індексів.

Проведена кластеризация доходностей европейских фондовых индексов при помощи методов вейвлет-анализа. Предложен модифицированый метод прогнозирования доходностей фондовых индексов на основе вейвлет-декомпозиции, нейронных сетей и метода SSA.

Ключевые слова: вейвлет-анализ, прогнозирование, доходности фондовых индексов.

The paper considers the clustering of European stock indexes returns using the methods of wavelet analysis. The modified method of forecasting of stock index returns based on wavelet decomposition, neural networks and SSA method, is proposed.

Keywords: wavelet analysis, forecasting, stock indexes returns.

Analysis of the financial crises of 90 years of the twentieth century shows that the dynamic of crises displaying in structurally different macroeconomic systems has certain common features. Typically, they are characterized by universal mechanisms of emergence and system instability source. The character of the progress of world crises has some local features at the level of individual national economies. The research of these features allows to estimate the stability of economic systems under exogenous shocks and the ability to quickly recover after the crisis. Systemic problems of economies significantly influence on the behavior of stock markets that is expressed in nonlinearity and non-stationary of stock index time series.

Effective modeling of such time series assumes the application of modern methods of nonlinear dynamics, including the techniques of wavelet transform of signals with complex structure. Wavelet functions are compact waves localized in the time. The decomposition coefficients of waves store the information about the drift parameters of approximated function.

R. Gencay [1], E. Capobianco [2], H. Lee [3] and P. Crowley [4] used the methods of wavelet analysis in the research of behavior of financial markets. The papers of M. Gallegati [5], A. Subbotin [6], K. Minu [7] and T. Kravets [8] are the latest researches of wavelet analysis.

The goal of this paper is to analyze the dynamic of stock indexes in Ukraine, Poland, Russia, Germany, France and the UK using wavelet technology, to localize and describe the identified crises in time and scale, and to forecast stock index returns using a modified method.

The object of the research is returns of European stock indexes such as UX, WIG20, RTSI, DAX30, CAC40 and FTSE100. Research methods are the discrete wavelet transform (DWT), neural networks and Singular Spectrum Analysis (SSA) method.

Time-frequency analysis of the wavelet theory is the fundamental tool to research the frequency domain characteristics of nonstationary signals. Wavelet analysis involves the projection of a signal onto an orthogonal set of components named wavelets. A wavelet fluctuates around zero, the fluctuations of a wavelet's function go rapidly down to zero and they are localized in time and space. Wavelet representations have finite energy over the entire real line. The functions used in wavelet analysis have wide support. More importantly, they are not necessarily homogeneous over time. Hence, wavelets are a very powerful tool in handling dynamic patterns that may change rapidly over time.

Wavelet decomposition of the signal allows to delete a noise and to make a forecast. Neural networks and SSA [9,10] method are used to make the forecasts in the considering research.

A number of assumptions and significant simplifications, demonstrating the properties of the study through the experience, generalization, getting significant data from the redundant information are made in the process of neural networks definition. Neural networks can change their behavior depending on the state of their surrounding environment. After analyzing the input signals, the neural networks can self-adjust and train to provide the correct response. The trained network can be stable to some deviations of output that allows the correct identifying of the image that contains a variety of barriers and distortions.

The basic version of SSA method is to convert a one-dimensional time series in the multivariate one using one parametric procedures of the shift and to research the received multidimensional procedure using the method of principal components (singular decomposition) and reduction (approximation) of a series by selected principal components. Thus, the result of the method is the decomposition of time series into simple components: slow trends, seasonal and other periodic or fluctuation components and noise components. The resulting decomposition can be a basis for the forecasting of both the time series and its individual components.

The research was conducted by analyzing non-stationary time series of logarithmic stock index returns for the period from 08/01/2007 to 11/01/2011 (1200 points). Stock index returns were calculated on the basis of closing prices, their absolute values were used as a measure of volatility. There was experimentally obtained, that the discrete wavelet transform in the application of wavelet sym2 with 5 level of decomposition defines the best phase transitions of systems.

As a result of research, indexes were grouped into two clusters depending on the amplitude and characteristic features of the wavelet decomposition components. The first cluster includes indexes DAX30, FTSE100, WIG20 and CAC40, their approximation series amplitudes (except DAX30) are in the range from -10 to +10. Figure 1 presents the components of signals recovered by the approximation coefficients after the decomposition DAX30, CAC40, FTSE100 and WIG20 returns using wavelet sym2(5). There is a small instability zone of specified indexes in late 2007, followed by an abrupt sharp decrease of returns in mid-2008.

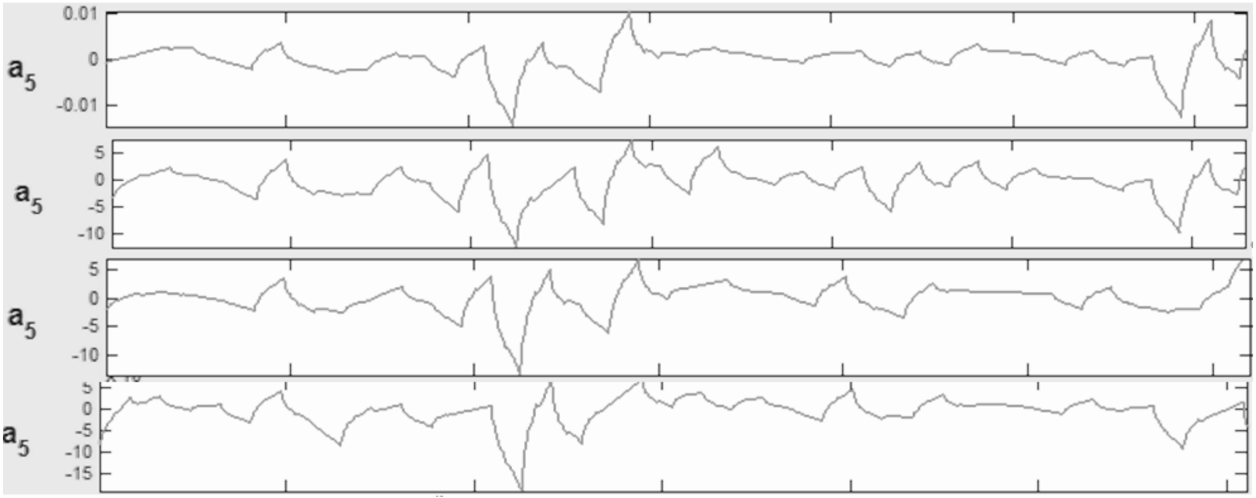

Fig. 1. Trend charts of DAX30, CAC40, FTSE100, WIG20 returns, recovered by the approximation coefficients at the 5th level of decomposition

Source: authorial calculation

Let us characterize the local features of individual indexes. FTSE100 index has a more international character than DAX30. Therefore, FTSE100 is over DAX under the condition of cheap pound sterling, falling interest rates, low levels of economic growth and decline of world stock markets. It is well known that DAX has more volatility than FTSE100, but the amplitude of fluctuations of FTSE100 returns is greater than the scale of fluctuations of the German index returns (from -10 to 5 and from -0.01 to 0.01, respectively). This result does not contradict the general trend, because there is an increased volatility of decomposition components recovered by detail coefficients at different levels. In addition, the indexes repeat trends of each other with some slight time lags. Usually DAX is more cyclical than the FTSE100, since its dynamics is highly dependent on German exporters and the European Bank policy.

The second cluster consists of Ukrainian UX and Russian RTSI. The German index has added to the graphs in Figure 2 because of the similarity in the amplitudes of the fluctuations of trend component. In this case UX and RTSI have some similarity, namely, the Ukrainian index follows the trend of Russian index with a certain time lag.

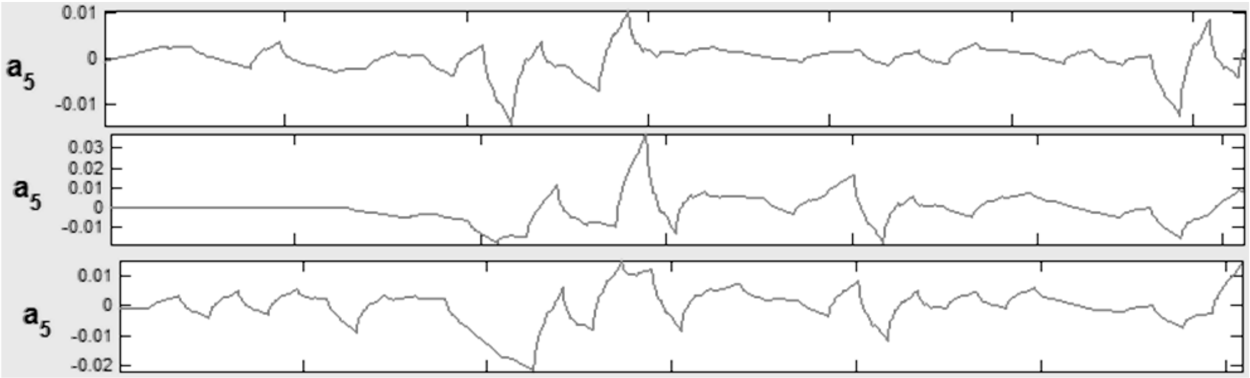

Fig. 2. Trend charts of DAX30, UX, RTSI returns, recovered by the approximation coefficients at the 5th level of decomposition

Source: authorial calculation

UX and RTSI are beginning to fall sharply in the summer of 2008. Besides, the decrease of RTSI returns is deeper than the decrease of UX returns and held before. This is a consequence of sharp decline of oil prices, which is the engine of the Russian economy, and of oil prices attaining a 12-month minimum in October 2008. In March 2010, a small returns decrease of both indexes also was observed, that coincided with the Parliamentary elections in Russia and political instability in Ukraine.

The application of the method of window transformation at all scale levels by DWT of research signals confirms the conclusions made above about the nature and characteristics of the identified crises' waves in the stock markets. Figure 3 presents the dynamics or volatility of returns of FTSE100, DAX30, CAC40, WIG20 on the third level of decomposition. The dynamics has a clearly defined variance wave for all indexes and another zone of instability for the CAC40 and DAX30 with further sharp increase of variance for all indices at end of period. A similar picture is observed at other scale levels.

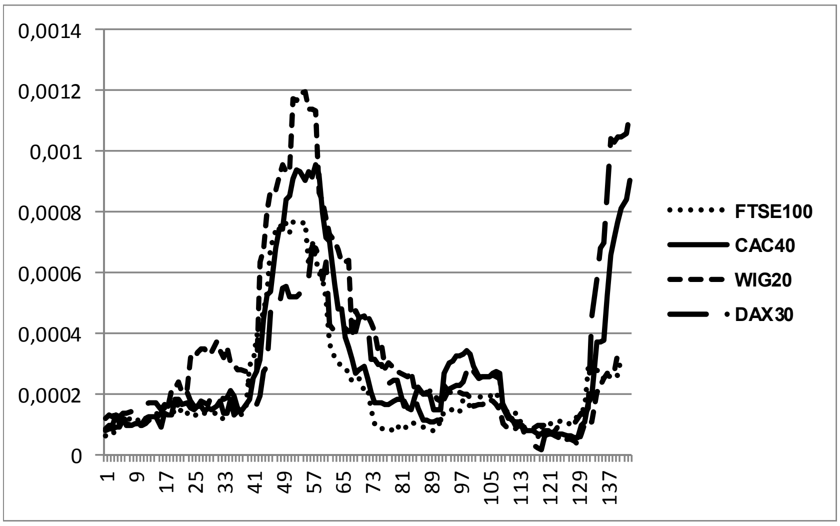

Fig. 3. Smoothed squares of detail coefficients at 3-rd level of decomposition for indexes DAX30, CAC40, FTSE100, WIG20

Source: authorial calculation

Figure 3 represents the time frame match of the first wave of crisis in all countries of the cluster that became apparent in March 2008. It should not be considered the first fluctuation of the Polish index, which was held in July 2007. The fluctuation was a result of Poland and Ukraine declaration as the two countries for Euro 2012 that greatly improved the investment expectations.

A similar analysis was performed for the second cluster together with the Polish index to compare the effectiveness of economic policies of the last 20 years. The dynamics of volatility returns of UX, RTSI, WIG20 on the third level of decomposition is presented in Figure 4.

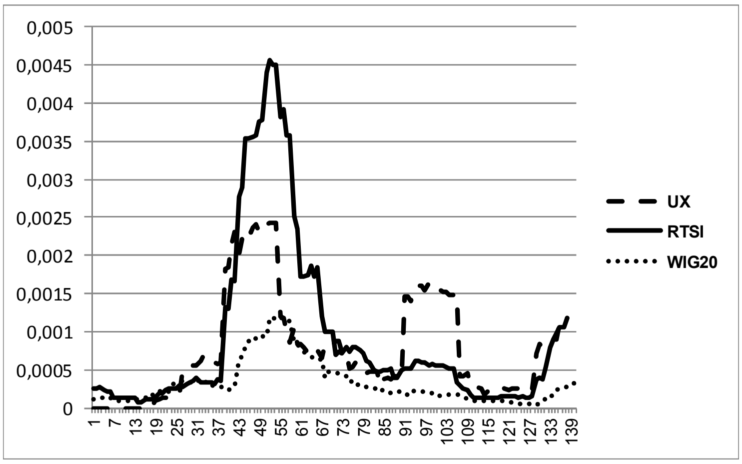

Fig. 4. Smoothed squares of detail coefficients at 3-rd level decomposition of UX, RTSI, WIG20

Source: authorial calculation

Figure 4 shows that neither Poland nor Russia had clearly expressed the second wave of crisis. In the Polish case it is due to its successful economic reforms. The lack of significant instability in the Russian market is a result of the strong dependence of the Russian economy on the current prices of commodity (oil and gas). The second wave of crisis in Ukraine started in mid-September 2010, the increase of consumer prices and high debt economy were observed in this period.

The modified method of forecasting of stock index returns based on wavelet decomposition, neural networks and SSA method are considered. Calculations were performed using the package Matlab, Alyuda NeuroIntelligence 2.2 (577), CaterpillarSSA 3.4.

In the first forecasting case, the maximum scale of the historical time series was selected to build the forecast of closing price for the next day. The maximum scale of the time series influences on the forecasted value, which has reserve of 32 trading days. Multiple scale wavelet analysis was conducted for the sliding window of length of 32. The selection of components of the vector of wavelet coefficients, which most affect the predicted value, was conducted on the base of calculations of the absolute value of the corresponding linear correlation coefficient. The neural network with one hidden layer was used to make the forecast. The most significant wavelet coefficients were the input of network, and the forecasted value of returns was obtained as an output.

In the second forecasting case, the noise component was deleted from the signal using the selected wavelet in order to forecast the returns of stock indexes. The procedure of noise deleting was performed by filtering the coefficients of wavelet decomposition and further recovery of series using significant coefficients. Then the denoised signal was processed by SSA.

German index DAX30 has been selected to demonstrate the proposed forecasting method. Experimentally it was found that wavelet db4 with two levels of decomposition was the best for this case. There is a forecast of DAX30 returns based on sym2(5) and db4(2) decomposition to demonstrate the need of informed wavelet and level of decomposition.

Figure 5 shows the graph of the dynamics of DAX30 returns and different forecasting results of the application of neural networks and SSA method.

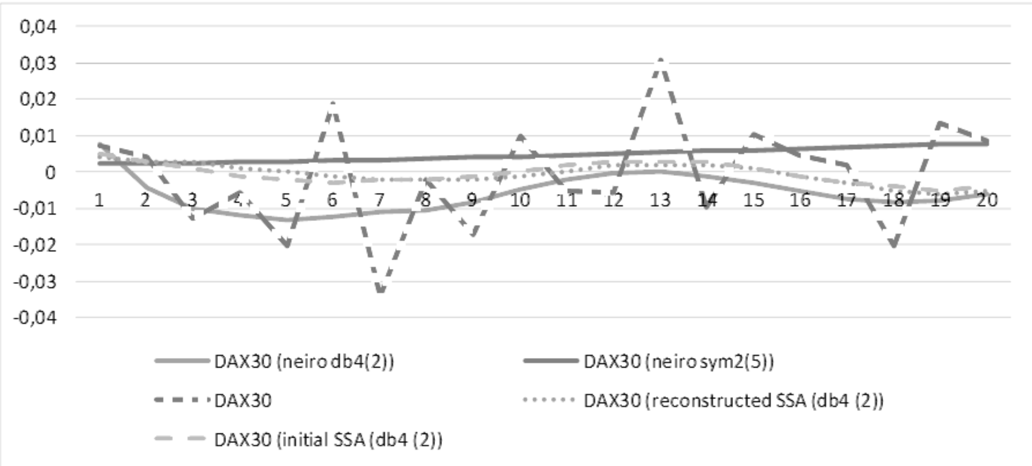

Fig. 5. The dynamics of DAX30 returns and forecasting results

Source: authorial calculation

Figure 5 shows that the using of sym2(5) wavelet gives a less accurate value than the decomposition by wavelet db4(2) in the process of neural networks forecasting. A similar result is observed when SSA is used. The best forecast, in comparison with real data, was obtained by using of neural networks for the signal, which if free of noise under wavelet db4(2).

We live in an era when the astronomical amount of speculative money turns at the world market. This process is based not on fundamental but on technical analysis, which is hardly affected by macroeconomic indicators. Therefore, fluctuations of stock indexes (including their returns) ceased to be reliable indicators of macroeconomic processes.

The question of the second wave of global crisis is urgent, because the situation at the financial sector of the world economy does not only not improving, but rather continues to deteriorate in some areas. There are reasons to believe that these problems are the result of superficiality and lack of the stated reforms. At the same time there is the tendency of correction of the foundations of economies, which wavered, without using of cardinal measures.

The conducted research focuses two clusters of stock indexes that are similar by the returns dynamics. The first cluster includes DAX30, CAC40, FTSE100, WIG20, and the second cluster includes RTSI and UX. It should be also noted that the local characteristics of each stock index are clear defined despite the close relationship between the considerable indexes.

The paper considered a comprehensive application of wavelet transform and neural networks of the problem of stock index returns forecasting. The best results are obtained by using the forecasting capabilities of neural networks, the input of which is time series, previously deprived of the noise component using properly chosen wavelet transform. The obtained results allow to forecast the value of stock index returns in the short term under very high accuracy.

1. Gencay R. Scaling properties of foreign exchange volatility / R. Gencay, F. Selcuk, B. Whitcher // Physica A, 2001b. – P. 249–266. 2. Capobianco E. Multiscale analysis of stock index return volatility / E. Capobianco // Computational Economics, 2004. – Vol. 23, No. 3. – P. 219-237. 3. Lee H. International transmission of stock market movements: A wavelet analysis / H. Lee // Applied Economics Letters, 2004. – Vol. 11. – P. 197-201. 4. Crowley P.M. A guide to wavelets for economists / P.M. Crowley // Journal of Economic Surveys, 2007. – Vol. 21. – P. 207-267. 5. Gallegati M. Wavelet analysis of stock returns and aggregate economic activity / M. Gallegati // Computational Statistics and Data Analysis, 2008. – Vol. 52, No 6. – P. 3061-3074. 6. Subbotin A. A Mutli-horizon Scale for Volatility / A. Subbotin // CES Working Papers Series, University of Paris-1 (Pantheon-Sorbonne), 2008. – Vol. 20. – P. 1-44. 7. Minu K. K. Wavelet Neural Networks for Nonlinear Time Series Analysis / K. K. Minu, M. C. Lineesh, C. J. John // Applied Mathematical Sciences, 2010. – Vol. 4, No. 50. – P. 2485-2495. 8. Kravets T. Wavelet analysis of stock indexes of Ukraine and Poland in economic crisis and relaxation/ T. Kravets, A. Sytyenko // Visnyk of Taras Shevchenko National University of Kyiv: Economics, 2012. – Vol. 132. – P. 39-43. 9. Golyandina N. Analysis of Time Series Structure: SSA and related techniques / N. Golyandina, V. Nekrutkin,