SERBIAN JOURNAL OF ELECTRICAL ENGINEERING
Vol. 11, No. 4 (special issue), December 2014, 597-608

UDC: 004.7:519.711]:519.866 **DOI: 10.2298/SJEE1404597A**

Input Data Preprocessing Method for Exchange Rate Forecasting via Neural Network

Dragan S. Antić[1], Miroslav B. Milovanović[1], Staniša Lj. Perić[1], Saša S. Nikolić[1], Marko T. Milojković[1]

Abstract: The aim of this paper is to present a method for neural network input parameters selection and preprocessing. The purpose of this network is to forecast foreign exchange rates using artificial intelligence. Two data sets are formed for two different economic systems. Each system is represented by six categories with 70 economic parameters which are used in the analysis. Reduction of these parameters within each category was performed by using the principal component analysis method. Component interdependencies are established and relations between them are formed. Newly formed relations were used to create input vectors of a neural network. The multilayer feedforward neural network is formed and trained using batch training. Finally, simulation results are presented and it is concluded that input data preparation method is an effective way for preprocessing neural network data.

Keywords: Neural Network, Databases, Forecasting, Input Data, Reduction.

1 Introduction

The economy of a country is a very complex scientific field affected by a large number of parameters. Detailed and comprehensive analysis is required to find some desired dependencies and correlations. Neural networks can be an advantage in processing those huge information databases (compared to classical mathematical approaches). If adequate input parameters are chosen, and the right structure of neural network is selected, desired results can be obtained in a simple and fast way. Fundamental characteristics of neural networks used in economic systems will be presented in Section 2. The purpose of this paper is to present how to optimize input parameters selection and how to do effective data sets processing (Sections 3 and 4). Reduced economic data (for two economic systems) are analyzed in Section 5. Mutual dependences of economic parameters are found and relationships between those parameters and real output values are defined. Network input vectors are formed in Section 5 also. The neural network is formed in Section 6, its structure is presented, and

[1]University of Niš, Faculty of Electronic Engineering, Aleksandra Medvedeva 14, 18000 Niš, Serbia;
E-mails: dragan.antic@elfak.ni.ac.rs; miroslav.b.milovanovic@elfak.ni.ac.rs; stanisa.peric@elfak.ni.ac.rs; sasa.s.nikolic@elfak.ni.ac.rs; marko.milojkovic@elfak.ni.ac.rs

corresponding input and output data vectors are used for network inputs and outputs. Finally, simulation results of designed neural network are presented and analyzed.

2 Neural Networks Usage in Economic Systems

Predictive characteristics of neural networks are the major reasons for their growing presence in economy [1 – 2]. Predicting share prices at the markets and forecasting exchange rates on daily or weekly basis are two of many areas of study in the field of artificial network usage in the economy. Random Walk mathematical model was used at the early beginnings of artificial network usages for monetary forecasting [3]. In [4] the authors use the values of eight economic indicators for predicting daily exchange rates of the Canadian Dollar. In addition to these types of networks, some authors were developing adaptive [5, 6] and recurrent neural networks [7], also with currency predicting purposes. In general, two types of data can be used for predicting exchange rates. The first one is usage of exchange rate history data where vectors (exchange rate values and relevant dates) are used as neural network inputs and outputs [8]. Another type of data that can be applied to the inputs of a network are economic indicators. This is a more complex solution because from the huge number of parameters that affect the economy of a country (and automatically also a currency value) task is to choose only a couple of parameters. However, the most important parameter selection is no guarantee that neural network will provide good predictive results at the network output.

3 Economic Parameters and Principal Component Analysis

Neural network in this paper will be used to predict exchange rate of the Russian currency Ruble against the U.S. Dollar on a quarterly basis (four month prediction interval). The Author's idea is to place focus on relevant indicators of both economic systems (Russian and American). Let's reconsider that only parameters of the Russian Federation are used for determining exchange rates. If Russia achieves GDP growth of 2% at some point, this would result improvement of many economic indicators, directly affecting the exchange rate strengthening of their currency against the dollar. The drawback of this method can be seen immediately because the method is based on the state of a single economic system, without consideration of economic indicators in the other relevant system. Specifically, in this case, the value of the Ruble exchange rate is assumed with no knowledge of whether in the United States has happened some global economic changes that would affect dependence of two currencies. It would be credible to use only one economic system for input parameters only if it is considered that U.S. economic indicators are constant. The aim of this paper is to present a method for selecting input parameters that will take into consideration the both economic systems and their mutual dependencies that effect on the exchange rate values. What would that mean specifically? For example, further is found that GDP in the U.S. grew up by 5% for the same time period. That directly means that the Russian economy strengthened in a given time period, but tells also that the U.S. economy has progressed more than it was case in Russia. This will certainly imply by the falling value of the Ruble against Dollar, which is opposed to the earlier conclusion (when only one economic system was observed). Seventy economic parameters grouped into six categories are taken for initial input parameters: Main Economic Indicators Category (15 parameters), Real Sector Indicators Category (14 parameters), External Sector Indicators Category (2 parameters), Financial Sector Indicators Category (19 parameters), Government Finance Sector Indicators Category (5 parameters) and Market Sector Indicators Category (15 parameters). Information and names for each of these parameters are taken from relevant sites [9 – 11]. Those parameters are chosen on the basis of their presence at [9 – 11]. Parameters from six categories are used for analysis of Russian and American markets. This allows direct parameter comparisons of two economic systems and development of mutual dependencies and relations. All parameter values are taken quarterly (four month period) for the period 2008 – 2012. Since this is the initial system with 140 input variables (70 for every economic system), where each of them is changing dynamically, it is estimated that quarterly changes of each parameter have sufficient informations for analysis. After performing first analysis and initial input parameters selection, next task is the optimization of selected inputs. The aim of the optimization process is to reduce significantly the initial number of input parameters within each category and to obtain new vectors. The new vectors present combination of selected input vectors and they are based on mutual dependencies and weight coefficients which will be proposed in the paper.

Principal Component Analysis (PCA) is a data processing method which will be performed in this paper. PCA is widely used mathematical method that has a huge applicative area: processing large amount of data, signal processing, statistical data analysis, face recognition, data set identification, motion analysis, data clustering, and dimension reduction [12]. The main task of dimension reduction is to use PCA process on a data with a certain amount of redundancy. This redundant data will be removed from the initial database and that way dimension of data matrix will be reduced. Quality of informations which were provided by matrix will be kept, but with a smaller number of variables (Fig. 1). Task of PCA in this paper is to perform dimensionality reduction within each category for two economic systems. After finishing analysis and establishing relations between reduced variables, input vectors of neural network will be formed (Fig. 1). Thus, the main objectives of the PCA method are the most important informations extraction (from the database), and unnecessary, redundant parameters removal.

PCA is forming new variables called principal components which are obtained as a linear combination of original initial variables [13] during the process. The method involves data set projection to a new coordinate system by specifying unit vectors and unit matrix. Basic operations for PCA implementation are mean value of a data set, standard deviation, variance and covariance.

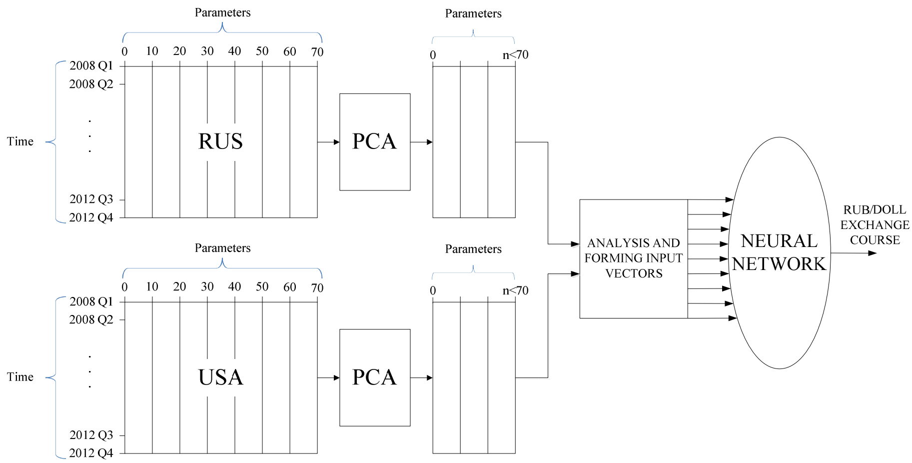

Fig. 1 – *Graphical display of neural network optimization procedure.*

PCA directly determines unit vectors and unit values from covariance matrix. Covariance matrix determines how much parameter values are varying with respect to the mean value, depending on the other parameters. The most sensitive parameters will be required further (parameters with the largest number of variations) and their identification is the beginning of the input vector selection.

The next step after obtaining the covariance matrix is the computation of unit vectors and unit values. Their sorting in descending order is done and components are classified according to their importance. Unit vector with the highest unit value is considered to be the most dominant component of the analysed data set. The goal of this first analysis is to extract the most dominant parameters and prepare them for further processing.

If reduction is well-performed the error is negligible, so reduced matrix will represent an adequate replacement for the original data set. In the next section results of applied PCA method will be shown.

4 The Results of Applied PCA

Dominant economic parameters of two systems are obtained by performing PCA method on six categories from Section 3. This analysis is done by *IBM SPSS Statistics* software usage. In Fig. 2 are shown comparisons between two economic systems for every category separately. Dominant components (parameters) with the highest unit values are easy to observe from the figure. X-axes on the graphs present list of components, while Y-axes represents unit values for each of these components. Categories which will be undergone to additional analysis are Main Economic Indicators, Real Sector Indicators and Market Sector Indicators for both economic systems; and separately Financial Sector Indicators for Russia and Government Finance Sector Indicators for U.S. It will be considered that graphical representation in Fig. 2 is sufficient for determining dominant parameters of other categories.

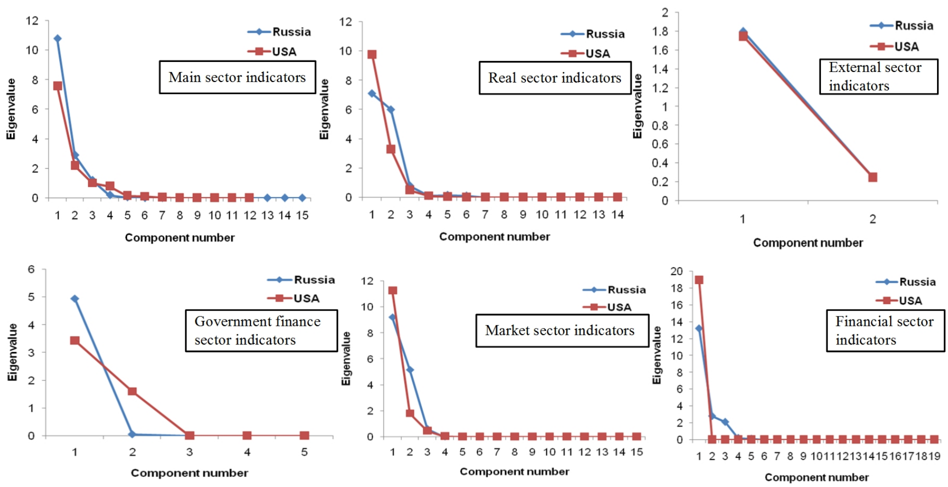

Fig. 2 – *Graphical display of dominant economic parameters within 6 categories – RUSSIA and USA.*

The task of second analysis is to evaluate the importance of each selected dominant component from Fig. 2. This will determine whether it is possible to make a further reduction of extracted components. This analysis was performed using matrix components (**Tables 1** and **2**) where dependence for each dominant component was found (dependence with other components from categories they are belonging to). In **Tables 1** and **2** are shown dependences only for the strongest correlations (because of paper compactness).

Table 1
Correlations between dominant and non-dominant components – Russian economic system.

Main Economic Indicators	Dominant Component			
	1	2	3	4
Reserves - Fine Troy Ounces	0.996	–0.069	0.023	0.051
Reserves- SDRs - Total Reserves	0.994	–0.010	–0.009	–0.082
Reserves - Total Reserves Minus Gold	0.994	–0.010	–0.009	–0.083
…………………………………….	……	……	……...	……...
Financial sector indicators	1	2	3	
UAAL - Other	0.989	0.048	0.086	
UAAL - Other Residents	0.988	0.048	0.086	
UAAL - Total	0.987	0.124	0.064	
……………………………………..	….....	……..	………	
Market Sector Indicators	1	2	3	
Lending Rate	–0.997	0.067	0.041	
Total Retail Trade	0.983	–0.033	0.182	
…………………………………….	……..	……..	……….	
Real Sector Indicators	1	2	3	
Gross Domestic Product - Deflator	0.846	0.401	0.041	
Gross Domestic Product (Volume) -	0.838	0.530	0.511	
…………………………………….	……..	…….	………	

Table 2
Correlations between dominant and non-dominant components – U.S. economic system.

Main Economic Indicators	Dominant Component				
	1	2	3	4	5
National currency per SDR	–0.6	–0.3	–0.6	–0.2	0.31
Real Effective Exchange Rate	–0.7	–0.6	0.07	–0.1	–0.2
....	...	...	...	...	...
Real Sector Indicators	1	2	3		
Gross Domestic Product - Nominal	0.99	0.05	0.11		
Gross Domestic Product - Deflator	0.98	-0.1	0.11		
....	...	...	...		
Market Sector Indicators	1	2	3		
Interest	0.24	0.95	–0.1		
....	...	...	...		
Government	1	2			
Revenue	0.92	0.4			
Taxes	0.94	0.35			
....	...	...			

Good parameter is considered to be the one whose correlations with the other parameters are as close as possible to numerical value 1, for each comparison. If a correlation between two elements is closer to one, their relationship to each other is stronger. Furthermore, as mutual relationship is stronger, dominant parameter will better represent parameters which are not dominant. Finally, the worst correlation coefficients from **Tables 1** and **2** will be excluded from further analysis. After completion of the dimension reduction procedure, from 140 initial parameters (for both economic systems), the 12 most dominant components of the Russian economic system and 9 components of the U.S. economic system are formed and can be seen in **Table 3**. In the next section, a procedure for establishing relations and dependencies between the most dominant components will be proposed. Also, after establishing principles of mutual relationships between components, network input vectors will be formed.

Table 3
The most dominant components for two economic systems.

	Category	Russia	United States	
1	Main Sector Indicators	Market Rate	Market Rate	1
2		Real Effective Exchange Rate	Real Effective Exchange Rate	2
3		Discount rate - Interest Rates		
4	Real Sector Indicators	Gross Domestic Product - Nominal	Gross Domestic Product - Nominal	3
5		Gross Domestic Product - Deflator	Gross Domestic Product - Deflator	4
6	External Sector Indicators	Total Reserve Assets	Total Reserve Assets - Economic concept	5
7	Financial Sector Indicators	Total Central Bank Assets	Total Central Bank Assets	6
8		Other Depository Corporations		
9		General Government		
10	Government Sector Indicators	Revenue	Revenue	7
			Taxes	8
11	Market Sector Indicators	Interest	Interest	9
12		Short-term Policy Rate		

5 Mutual Relations and Input Vector Forming Procedure

Once the selection of dominant components is done, the next task is to design neural network input vectors. Parameter influence adjustments will be made according to their significance. Parameter influences will be presented by coefficients α_1, α_2, α_3, α_4, α_5, α_6 for each category respectively. Importance of parameters within initial categories is the main reason for coefficients induction. For example, if three dominant parameters are selected from category with 19 parameters, these parameters are going to have a higher coefficient compared to three dominant parameters that are selected from category with 5 parameters. Coefficients are calculated using the equation:

$$\alpha_i = \frac{K_i}{70}, \tag{1}$$

where variable K_i is the number of parameters of i-th category, while 70 is the total number of parameters of one economic system. Numerical values of coefficients according to (1) are: $\alpha_1 = 0.241$, $\alpha_2 = 0.2$, $\alpha_3 = 0.029$, $\alpha_4 = 0.271$, $\alpha_5 = 0.071$, $\alpha_6 = 0.214$.

The last step at a procedure of input vector forming is the optimization of dominant parameters. The author's desire was to form a single input vector for each of 6 categories. It would reduce the network input dimension, and network speed would increase. In order to achieve the desired quality of input vectors, the standard deviation method will be applied on dominant parameters (within each category separately). The entire range of values of dominant parameters will be expressed this way. Also, the high variability of input vector values will be achieved. The standard deviation will be determined according to the formula:

$$s^2 = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}{n-1} = \frac{\sum_{i=1}^{n}\left(X_i - \frac{\left(\sum_{i=1}^{n} X_i\right)}{n}\right)^2}{n-1}, \tag{2}$$

where X_i is i-th dominant parameter and n is the number of dominant parameters within each category. The standard deviation for each category is found according to this formula. The number of dominant parameters within each category was determined in the previous section. After finding standard deviation values for each category, final input vector values are obtained by their multiplication with appropriate coefficients:

$$X_{CAT} = \alpha_i s_{CAT}, \tag{3}$$

where X_{CAT} is final input vector, α_i appropriate calculated coefficient (where i is in the range 1 – 6), and s_{CAT} corresponding standard deviation value. Forming procedure for all input vectors is presented in **Table 4**.

Described optimization method is finished after calculating input vectors. Initial 140 input vectors for both economic systems are reduced to 12 new input vectors after applying complete optimization method. In the next section neural network will be formed and simulation results will be presented.

Table 4
Neural network input vectors forming procedure.

Country	Category	Input vector	Equation
RUS	Main Sector Indicators	X_{mei}	$X_{mei} = \alpha_1 s_{Rmei}$
RUS	Real Sector Indicators	X_{rsi}	$X_{rsi} = \alpha_2 s_{Rrsi}$
RUS	External Sector Indicators	X_{esi}	$X_{esi} = \alpha_3 s_{Resi}$
RUS	Financial Sector Indicators	X_{fsi}	$X_{fsi} = \alpha_4 s_{Rfsi}$
RUS	Government Sector Indicators	X_{gsi}	$X_{gsi} = \alpha_5 s_{Rgsi}$
RUS	Market Sector Indicators	X_{msi}	$X_{msi} = \alpha_6 s_{Rmsi}$
USA	Main Sector Indicators	y_{mei}	$Y_{mei} = \alpha_1 s_{Umei}$
USA	Real Sector Indicators	y_{rsi}	$Y_{rsi} = \alpha_2 s_{Umei}$
USA	External Sector Indicators	y_{esi}	$Y_{esi} = \alpha_3 s_{Uesi}$
USA	Financial Sector Indicators	y_{fsi}	$Y_{fsi} = \alpha_4 s_{Ufsi}$
USA	Government Sector Indicators	y_{gsi}	$Y_{gsi} = \alpha_5 s_{Ugsi}$
USA	Market Sector Indicators	y_{msi}	$Y_{msi} = \alpha_6 s_{Umsi}$

6 Neural Network Development and Simulation Results

Elemental feedforward multilayer neural network with 12 inputs and 1 output was used for simulation purposes. Feedforward network is commonly used for forecasting purposes so it will be also used in this paper. Standard hyperbolic tangent sigmoid transfer function (*tansig*) was integrated inside the network. Formed input vectors from Section 5 are applied to the network inputs. Vector formed from the actual exchange rate values RUB/DOLL (for the corresponding period of 2008-2012th) [14] is brought to the network output for the training purposes. Number of units inside network hidden layer is three. The network has undergone the procedure of batch training and optimization during the learning cycle was performed by the method of decreasing gradient. Relation graph between predicted and real output values for defined time period can be seen in Fig. 3, as well as error rates of predicted values compared to the actual values.

An error rate of predicted exchange rates occurs within a range of 0 to ±0.003 which presented in percentages is from 0 to 10%. It can be concluded from Fig. 3 that the predictive ability of the network is not completely satisfactory. It should be noted that the most of the predicted values occur with an error in the range 0 to 5%, which is a good starting point for further researches. Error computations based on the testing samples are presented in **Table 4**. From model summary can be observed that testing errors are smaller compared to training errors. That can be considered as a good result and it is proved that learning procedure was effective and input and output vectors were formed on satisfactory principles.

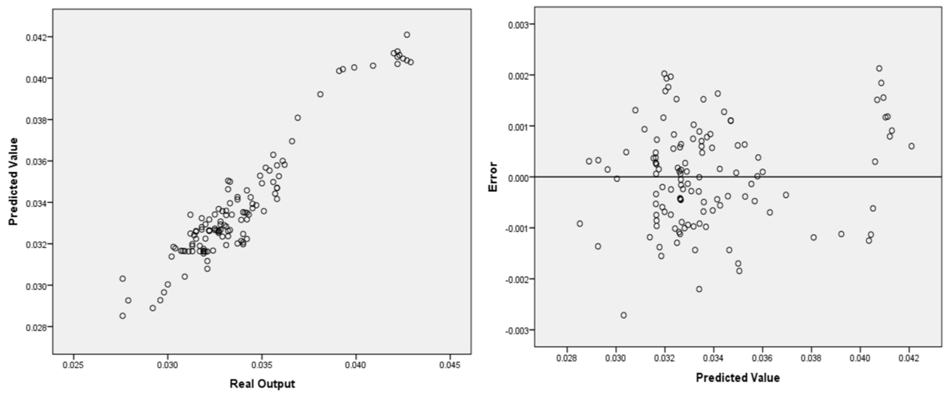

Fig. 3 – *Graphical display of neural network optimization procedure (predicted and real output values relations on the left side and errors of the predicted values on the right side.*

This method showed to be a good starting point for proposing complete data pre-processing phase for neural network usage. More effort will be made at future researches on testing proposed method and making modifications. Better results could be achieved with neural network modifications: by changing a type of the network, a number of hidden layers and the number of neurons, changing training process type, learning rate, by introducing input parameter delays etc. The results of optimization method have been applied to the elemental multilayer neural network, and it is proved that such a simple network is adequate for obtaining satisfactory output values if input data is properly processed.

Table 4
Model summary.

Training	Sum of Squares Error	3.879
	Relative Error	0.090
Testing	Sum of Squares Error	3.008
	Relative Error	0.086

7 Conclusion

The paper describes the optimization method for relevant input parameter selection for the purpose of exchange rate prediction. The PCA reduction method is applied to initial 140 economic indicators in the two economic systems, by which the number of parameters is reduced to 21 in total. Furthermore, importance degrees of each of the six analysed economic categories are found and weight coefficients of those categories are determined from importance degrees. Relations among dominant parameters (parameters separated after reduction) are established, and standard deviation method was applied for each of reduced economic category. Finally, 12 input vectors are formed after finishing optimization method described in this paper. A simple feedforward multi-layer neural network is further designed, with 12 newly created vectors applied to the network inputs. A vector with real values of exchange rates (for 4 months' time interval) is applied to the network output and experimental results of trained neural network are presented. It has been shown that the selection method has satisfactory results. In a following article type of neural network that would enable maximizing predictive performances for optimization method presented in this paper will be proposed, also as further researches on proposed method.

8 Acknowledgment

This paper was realized as a part of the projects TR 35005, III 43007 and III 44006 financed by the Ministry of Education, Science and Technological Development of the Republic of Serbia within the framework of technological development, integrated and interdisciplinary research for the period 2011-2015.

9 References

[1] [1] A. Sakalas, R. Virbickaite: Construct of the Model of Crisis Situation Diagnosis in a Company, Engineering Economics, Vol. 22, No. 3, 2011, pp. 255–261.

[2] R. Mileris, V. Boguslauskas: Credit Risk Estimation Model Development Process: Main Steps and Model Improvement, Engineering Economics, Vol. 22, No. 2, 2011, pp. 126–133.

[3] E. Tyree, J. A. Long: Forecasting Currency Exchange Rates: Neural Networks and the Random Walk Model, Third International Conference on Artificial Intelligence Applications on Wall Street, 1995, New York.

[4] E. Palombizio, I. Morris: Forecasting Exchange Rates Using Leading Economic Indicators, Open Access Scientific Reports, Vol. 1, No. 8, 2012, pp. 1–6.

[5] L. Yu, S. Wang, K. K. Lai: Adaptive Smoothing Neural Networks in Foreign Exchange Rate Forecasting, Computational Science – ICCS 2005, Springer, LNCS Vol. 3516, 2005, pp.523–530.

[6] E. Dobrescu, I. Nastac, E. Pelinescu: An Adaptive Retraining Method for the Exchange Rate Forecasting, Romanian Journal of Economic Forecasting, Vol. 7, No. 1, 2006, pp. 5–23.

[7] P. Tenti: Forecasting Foreign Exchange Rates Using Recurrent Neural Networks, Applied Artificial Intelligence, Vol. 10, No. 6, 1996, pp. 567–582.

[8] A. A. Philip, A. A. Taofiki, A. A. Bidemi: Artificial Neural Network Model for Forecasting Foreign Exchange Rate, World of Computer Science and Information Technology Journal, Vol. 1, No. 3, 2011, pp. 110–118.

[9] Principal Global Indicator, http:// principalglobalindicators.org.

[10] eLibrary – Data, http://elibrary-data.imf.org.

[11] Eurostat, http://epp.eurostat.ec.europa.eu.

[12] D. H. Jeong, C. Ziemkiewicz, W. Ribarsky, R. Chang: Understanding principal component analysis using a visual analytics tool, Charlotte Visualization Center, UNC Charlotte, CVC-UNCC–09–16, 2009.

[13] H. Abdi, L. J. Williams: Principal Components Analysis,Wiley Interdisciplinary Reviews: Computational Statistics, Vol. 2, No.4, pp. 433–459, 2010.

[14] Historical Exchange Rates, http://www.oanda.com/currency/historical-rates/.