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NEURAL NETWORK MODELLING FOR A SHORT-TERM FORECAST OF KEY MACROECONOMIC INDICATORS IN RUSSIA

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Abstract:
The study aims to evaluate the effectiveness of ruble floating exchange rate policy introduced by the Bank of Russia in late 2014, based on the relationships between the main macroeconomic indicators of the RF monetary system.
In this paper, a comprehensive econometric model is proposed for forecasting the dynamics of macroeconomic indicators of the monetary system and financial markets, taking into account the transformation of the monetary regime in the Russian Federation. The model is based on two blocks: autoregressive modelling (VAR) and neural network modelling (NARX). The VAR block can provide a qualitative forecast only in the form of a mathematical expectation and a standard deviation of future values of the time series, which is useful,but not enough concrete information. The neural network, on the other hand, provides an accurate prediction of the time series values, but does not provide an estimate of this forecast. Approbation of the model on the macroeconomic indicators of the monetary system and financial markets confirmed the continuation of the trend of a weak diversification of the Russian economy, focused primarily on energy exports. In addition, it revealed the strong nature of the currency value of bank deposits in the state of strong volatility in the commodity market. However, it is worth noting that the analysis of the impulse responses of the variable models to the oil shock showed that the Bank of Russia's move to a floating exchange rate had a positive effect on stabilizing the domestic economy. In particular, modelling shows that the volatility of the values of the macroeconomic indicators of the Russian Federation monetary system significantly decreases after the introduction of the floating exchange rate regime, while the return to stable values after the oil shock occurs more quickly. Using the neural network of the model, a short-term forecast of the main macroeconomic indicators of the Russian Federation monetary and credit system and oil prices was obtained. The forecast confirmed the stabilization for the next 6 months of oil prices and the ruble exchange rate against the US dollar.

Key words:
Forecasting (C53); Exchange Rates and Intervention (F 31); Neural Networks (C45).

JEL: C53; F31; C45.

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1. Introduction: Overview of models formacroeconomic research and forecasts

Modern economics makes extensive use of mathematical methods both at the stage of construction of theoretical propositions, and in the course of the practical economic research. To solve the problems encountered in assessment of risks derived from dependencies of the certain company to macroeconomic situation, it is required to build fairly complex models. Models used for macroeconomic analysis are vector autoregression (VAR), artificial neural network (ANN) (and other machine learning techniques) anddynamic stochastic general equilibrium (DSGE). We have to plunge into details concerned listed models, in order to choose basis methodology for the current research.

Vector autoregression (VAR). Vector autoregression model is a system of equations, in which the value of each variable is determined by the previous values of the other variables. For example, the VAR-model may include three variables: inflation, output and money supply. In the model of inflation depends on past values of the variables of inflation, output and money supply; output and money supply is determined by the past values of the same variables.

VAR model is used in the short-term forecasting and in detection statistically significant macroeconomic indicators. These models do not contain strict limitations depending on other variables, one imposed by economic theory and does not take into account future expectations. Methodology of VAR models was proposed by C. Sims (1980), as an alternative to address the complexities associated with the simultaneous equations models.

Dynamic Stochastic General Equilibrium models (DSGE). The theoretical foundation for the simulation of DSGE models are microeconomic studies, in which the overall dynamics of the economic system is the result of optimization of economic agents. DSGE-model at the micro level considering the preferences of economic agents and constraints under which they operate. This quality distinguishes the DSGE model from other macroeconomic models. Preferences and constraints are structural parameters and unchanged by changing economic policy.

First DSGE-model can be considered a general equilibrium model of Kydland and Prescott, which they used for the analysis of business cycles. In the model of the analysis of the real business cycle (RBC) economists have relied on the provisions of the new classical theory, in which it was assumed that markets are perfectly competitive, the price is completely flexible and economic agents have rational expectations (Kydland and Prescott, 1982).

The basic tenets of the theory of the business cycle is that fluctuations in the growth of real output only arise as a result of shocks that affect the level of technology. Later DSGE-models were modified taking into account the provisions of the new Keynesian theory based on the assumptions of monopolistic competition, rigid prices and nominal wages. An example of such a DSGE-model can be considered a model of J. Gali, T. Monacelli(2005).

Thus, modern DSGE-models are the result of the synthesis, on the one hand, the theory of rational expectations, proposed by Kydland and Prescott, and on the other hand, they are built taking into account the existence of monopolistic markets, nominal price and wage rigidity.

Structurally any DSGE-model consists of three mandatory components (Fagiolo and Roventini, 2012):

- The dynamic IS equations for modelling the national income;
- New Keynesian Phillips curve - for inflation;
- Taylor rule for modelling interest rates.

In addition to the key equations of the model, it requires the allocation of trend-cyclical component, calculation of short-term deviations from equilibrium and calculation of deflated variables.

DSGE models have been actively used since the late 1990s and owe their wide distribution through the use of the central banks of different countries to develop economic policies. Examples of such models can serve as models of the US Federal Reserve FRB / US (Brayton and Tinsley, 1969), the European Central Bank NAWM (Christoffel et al, 2008), the Bank of Canada ToTEM (Murchison

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et al, 2008), developed within the framework of individual countries, as well as models of GEM (Kumhof M. et al, 2010) and GIMF (Cogley and Sbordone, 2008) used by the IMF for the study of the global economy.

Artificial neural networks (ANNs). ANNs are mathematically-based models, including their hardware or software implementation, which is based on the principle of construction and operation of the biological neural networks, i.e. networks of nerve cells in the living body. The concept of artificial neural networks emerged in the study of brain processes, as well as attempts to model these processes. The first such attempt was a neural network of McCulloch and Pitts (1943). Further, when sophisticated learning algorithms were developed, models have been employed in practical applications, including control problems, forecasting and pattern recognition.

ANNs are not programmable in the usual sense of the word - they are trainable. One of the fundamental advantages of neural networks over conventional computing algorithms – training opportunity. From a technical point of view, training is to find the coefficients of connections between neurons. Identify complex relationship between inputs and outputs, as well as the fulfillment of generalizations - one of the objectives of the learning process of artificial neural networks. This means that in case of successful completion of the training process the neural network will be able to return the correct result, based on the data that may be missing in the training set, including the "noisy", incomplete data or data having a partial distortion.

Concerning the efficiency of ANNs, there are researches showing benefits of neural models in comparison with classical linear autoregressive, for instance, in number of researches NARX – non-linear autoregressive neural network with exogenous inputs showed better results than ARIMA and GARCH (Diaconescu, 2008; Chaudhuri and Ghosh, 2016).

The majority of the modern large-scale econometric models, such as stochastic general equilibrium models (DSGE) or agent-based model (AB), are artificial in nature, which often results in the erroneous application in the framework of large-scale crisis economic phenomena, such as the Great Recession 2008. The issues of adequate specification and parameterization of the model are the key challenges for the further successful development and application of sophisticated mathematical techniques in economic modelling. In view of this, it is of particular importance to develop methods to detect modelling errors and features that are sensitive to the baseline parameters estimation errors. The attempts to create an integrated model for the resolution of these problems were made in a number of economic studies. In particular, so-called DSGE-VARs approach (VAR - vector autoregression), proposed by economists Del Negro and Schorfheide (Del Negro and Schorfheide, 2006), who suggests identifying DSGE model specification errors using VAR modelling, which allows easing restrictions imposed on the equation of DSGE models. Combining different econometric models enables not only to identify parameterization errors, but also to increase the flexibility in their use, to eliminate the disadvantages arising from the independent use of the models. In addition, such integrated modelling makes it possible not only to identify the mutual relationships between the model variables and explain the nature of its development, but also to forecast model parameters for different time horizons.

Interesting research by Eastern economies was done by Darvas Z. (Darvas, 2013), where he "studied the transmission of monetary policy to macroeconomic variables with structural time-varying coefficient vector autoregressions in the Czech Republic, Hungary and Poland, in comparison with that in the euro area. There were discussed various factors that can contribute to differences in monetary transmission, such as financial structure, labor market rigidities, industry composition, exchange rate regime, credibility of monetary policy and trade openness".

Another researchersD'Agostino A. (D'Agostino et al, 2013) "assessed whether modelling structural change can help improving the accuracy of macroeconomic forecasts. They conducted a simulated real-time out-of-sample exercise using a time-varying coefficients vector autoregression (VAR) with stochastic volatility to predict the inflation rate, unemployment rate and interest rate in the USA".

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Some researchers (Naser, 2015) "utilized simple regression estimates and factor-based models to produce forecasts gross domestic product growth".

Białowolski P. (Białowolski et al, 2014) "develop a methodology, based on the Bayesian averaging of classical estimates method, for forecasting key macroeconomic indicators, based on business survey data. They estimated a large set of models, using an autoregressive specification, with regresses selected from business and household survey data".

From recent research in the field of application of VAR neural network modelling we can mention Taylorand Yu (Taylor and Yu, 2016), who "applied auto-regressive logit models for forecasting the probability of a time series of financial asset returns exceeding a threshold". They"incorporate the exceedance probability forecasts within a new time varying extreme value approach to value at risk and expected shortfall estimation".

2. Methods: Vector autoregression block (VAR) and nonlinear autoregressive neural network block (NAR).

Considering the goal of the research, we propose time series forecasting model based on two blocks: vector autoregressions block (VAR) and nonlinear autoregressive neural network block (NAR).

We choose NAR block for a model because it forecasts punctual values of time series. However, NAR does not provide probability estimation for predictions, what arise the problem of results reliability enforcing decision maker to take not estimated risk. In order to face this problem, we decide to use VAR block, which provides predictions expressed in expected value and standard deviation. Moreover, employment of two blocks, which presents results independently, give a possibility for model estimation. For instance, if results of NAR and VAR coincide one may consider results as more reliable. Thus, decision maker obtains a reliable tool for decision making which allows him to forecast time series and estimate results of forecasting.

The selection of the analyzed time series, calibration and validation of the developed model was carried out in view of the transformation of exchange rate regimes established by the Bank of Russia.

In order to evaluate the effectiveness of the floating exchange rate policy of the Bank of Russia, five variables were selected. According to these variables, corresponding time series within three time frames were built: 2008-2016, 2012-2014, 2014-2016. The selection of time frames is preconditioned by the transition of the Bank of Russia from the managed floating exchange rate regime to a floating exchange rate regime. To calibrate and validate the model, 2008-2016 timeframe was selected.

We use the following time series for forecasting and analysis:

'Var1' (abbr. *variable*) – USD/RUB;

'Var2' –Brent oil (USD/bbl);

'Var3' – Demand foreign currency deposits of individuals (expressed in million rubles);

'Var4' – Term foreign currency deposits of individuals (expressed in million rubles);

'Var5' – Current foreign currency deposits of legal entities (expressed in billion US dollars)

Historical data is downloaded from: Thomson Reuters Eikon, Central Bank of Russia (www.cbr.ru)

We use MATLAB Econometrics Toolbox for mathematical modelling.

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2.1 Vector autoregression

VAR(p) has the following form:

$$y_t = a_0 + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + \varepsilon_t = a_0 + \sum_{n=1}^{p} A_n y_{t-n} + \varepsilon_t$$

where

a_0 – constant vector;

$A_1 \ldots A_p$ – matrices of model parameters (autoregression coefficients);

y_t – vector of time series;

y_{t-p} – vector of previous values of time series;

ε_t – vector of random errors.

Data preparation. VAR model requires stationary time series as input. Hence, we should examine whether input data comprise trend component. For this purpose, we employ Dickey-Fuller (DF) test. The test fails to reject the null hypothesis with raw data (see results in appendix A), therefore, input data are not stationary time series. In order to reduce given time series to trend stationary we calculate first differences. DF test rejects the null hypothesis for all series (see results in appendix B). Thus, we have integrated time series of the first order – *I* (1). Since we have prepared data for model, we may fit it.

Model fitting. Further we use Akaike Information Criterion (AIC)(Akaike., 1973)and Bayesian Information Criterion (BIC) (Pesaran et al,1998) to determine optimal lag order in terms of model accuracy. According to both criterions 1 lag is an optimal one (see appendix C).

We apply root mean squared error (RMSE) for estimation of the model (see appendix D).

After fitting VAR, we are able to forecast. For this purpose, we employ Monte-Carlo method, which generates 1000 sample path for each next period. With generated path, we calculate expected value and standard deviation. Results of VAR forecasting are presented at the fig. 1 in combination with results of NAR.

In order to estimate the dynamic of time series we employ impulse response function (IRF) analysis (Pesaran et al, 1998), we use 'Var2' variable as an oil shock (see fig. 2 and 3). The value of the shock is one sigma.

2.2 Nonlinear autoregressive neural network

NAR is defined by the following expression:

$$y_t = F(y_{t-1}, y_{t-2}, \ldots, y_{t-p}) + \varepsilon_t$$

where

y_t – vector of time series;

y_{t-p} – vector of previous values of time series;

ε_t – vector of random errors.

Model fitting. In order to train the neural network, we divide raw data into three groups: train (75%), validation (15%), test (10%). We choose mean squared error (MSE) as parameter for neural network performance estimation and levenberg-marquardt algorithm for training.

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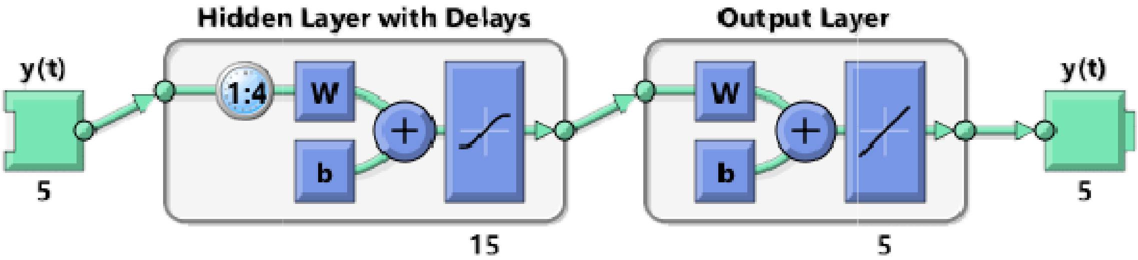
Fig. 1. Chosen architecture for the neural network



Indicators (MSE, error autocorrelation, regression) of model estimation are presented in appendix E.

3. Paper results

After the final stage of modelling the correlation analysis of the model's variables was carried out with the subsequent assessment of efficiency of the floating exchange rate policy.

As one can see from the visualization of the variables' reaction to the oil price shock,under the conditions of the exchange rate transition period of 2012-2014 (fig. 2) the increment of dynamic rates of the variables exceeds significantly the corresponding indicator of the floating exchange rate regime period of 2014-2016(fig. 3). It is also important to note that it takes a longer period in order for the values of the variables analyzed to return to the state of a sustainable trend. That can be explained by the fact that during the period of interim exchange rate regime the Bank of Russia carries out foreign exchange interventions in order to stabilize the exchange rate and maintain it within a certain exchange rate band. The sale and purchase of foreign currency in the framework of a foreign currency intervention allow stabilizing the exchange rate quite efficiently in case there are no powerful and long-term external shocks; however, in case they occur the fast and short-term changes in exchange rates cause destabilization of the foreign exchange market that is accompanied by inflation pressure and market members massively preferring foreign currency, which in its turn has a negative impact on long-term dynamics of macroeconomic indicators.

It is also worth mentioning that the decrease in oil prices is accompanied by a sharp increase in foreign exchange deposits of both natural persons and legal entities. Such a high level of foreign currency predominance creates excessive growth of foreign exchange indebtedness and contributes to the flight of capital which, in turn, might lead to destabilization of both banking system of Russia and whole economy at large.

The strong correlation detected between oil prices and sharp growth of the percentage of foreign currency denominated bank accounts confirms that the behaviour of economic agents in Russia is similar to that in countries where the transition from the managed float exchange rate regime to floating exchange rate regime was carried out, which is usually accompanied by a strong mistrust of the national currency in case sharp external shock occur that are related to the collapse of raw-material markets.

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Fig. 2. Responses to "Brent" oil prices shock (the model is estimated on the data from 2012 to 2014)

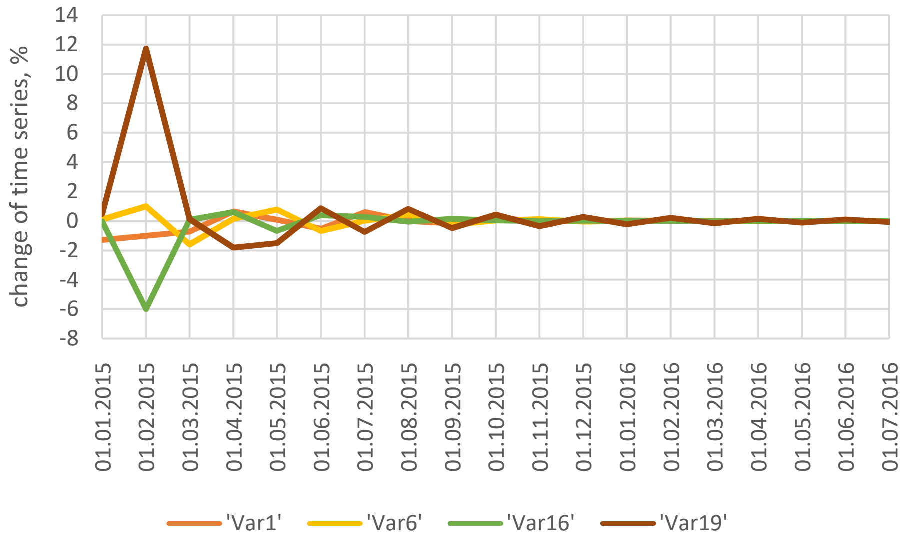
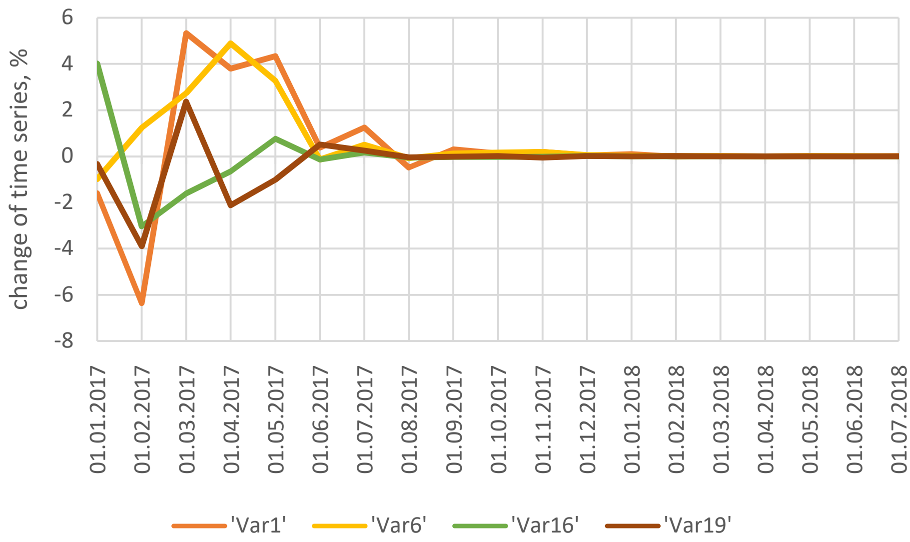


Fig. 3. Responses to "Brent" oil prices shock (the model is estimated on the data from 2014 to 2016)



However, it is worth adding that the transition to the floating exchange rate is a positive step made by the Bank of Russia to stabilize the national economy. This fact is confirmed by the results of the shock scenario analysis of the VAR model.

After modelling the vector autoregression and evaluating the responses of the model's variables to the impulse shock a neural network model (NAR) was elaborated and tested with the purpose of short-term forecasting of the indicators of time series of variables "Var1" (USD/RUB) and"Var2" (Brent oil)

The model was built basing on the statistic data through October 2016, three values of the forecast obtained (an 8-month forecast) were compared to the actual values of the time series. The results are shown in Table 1.

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Table 1. NAR forecast

Date	Indicators, name and code in the model						
	USD/RUB exchange rate (model forecast)	USD/RUB exchange rate (actual)	Brent oil (model forecast)	Brent oil (actual)	Demanddepositsofindividualsdenominatedinforeigncurrency (RUBbillion)	Fixed-term deposits of legal entities denominated in foreign currency (RUB billion)	Demand deposits of legal entities denominated in foreign currency (USD billion)
	Var1		*Var2*		*Var3*	*Var4*	*Var5*
1.11.2016	63,93	63,22	50,18	47,90	745	5337	44,79
1.12.2016	62,28	65,24	51,22	53,70	755	5207	45,06
1.01.2017	60,22	60,66	54,32	56,75	765	5213	45,74
1.02.2017	59,14	60,09	57,02	56,59	754	5207	46,21
1.03.2017	58,8	57,96	59,06	55,78	739	5200	44,76
1.04.2017	58,91	-	59,77	-	722	5215	43,95
1.05.2017	59,33	-	59,62	-	702	5197	43,37
1.06.2017	60,01	-	58,73	-	681	5174	42,72

Graphical visualization of the short-term forecasting dynamics of the variables' values in vector autoregression model (VAR) and neural network model (NAR) is shown in the figures 4-8.

Fig.4.'Var1' - USD/RUB Exchange rate

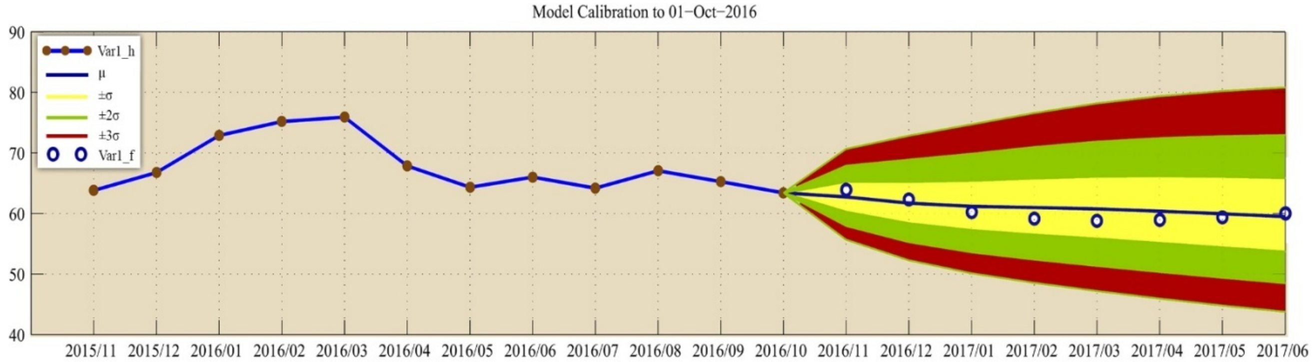

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Fig.5. 'Var2' – Oil Bret price (USD per a barrel)

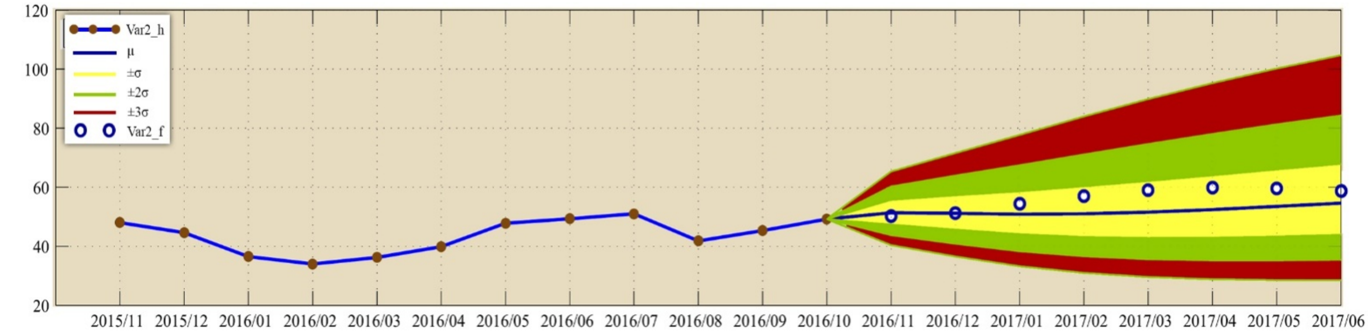


Fig.6. 'Var3' – Demand deposits of individuals in foreign currency (mln.Rub.)

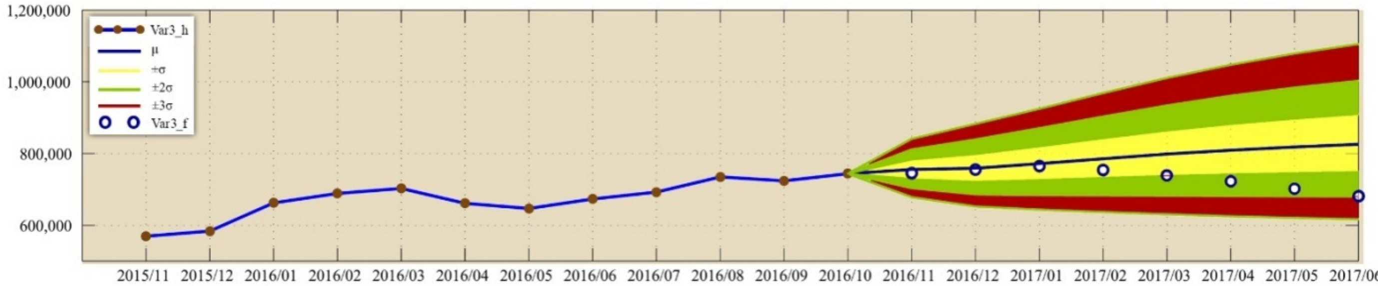


Fig.7. 'Var4' – Term deposits of individuals in foreign currency (in mln.Rub.)

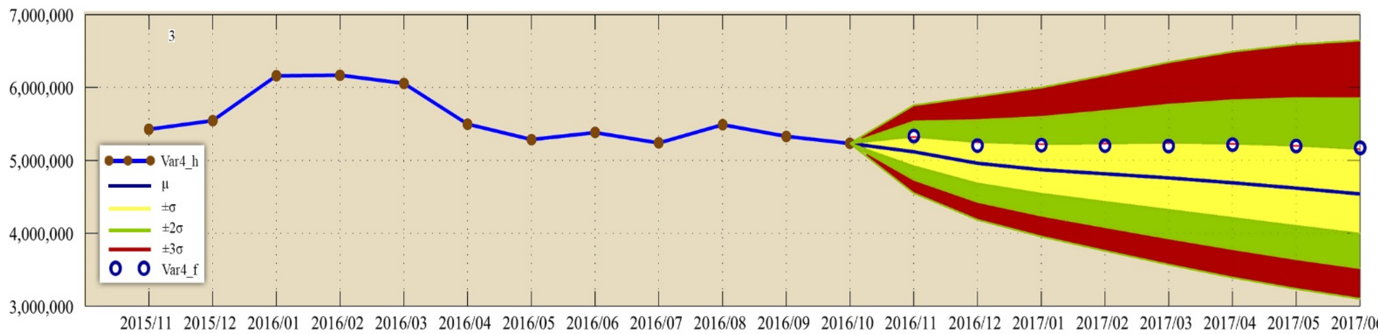
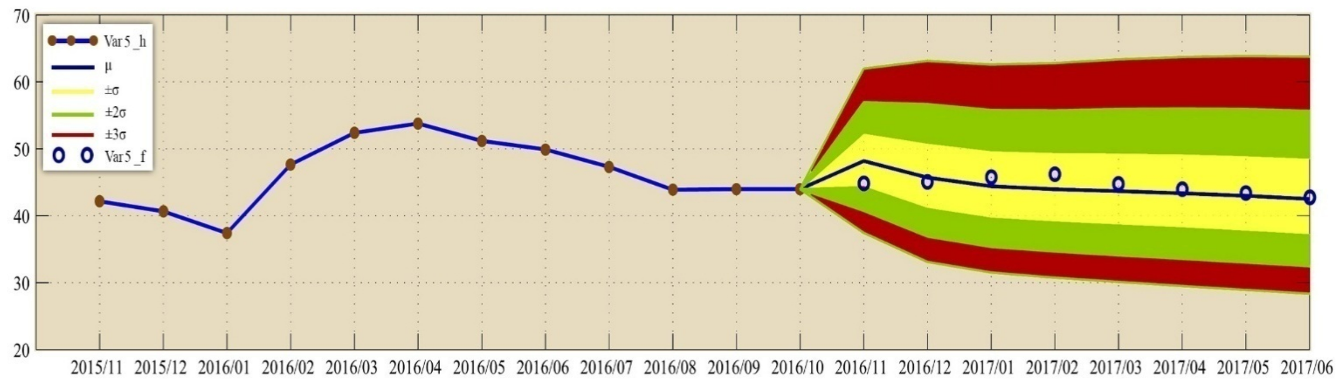


Fig.8. 'Var5' –Current deposits of legal entities in foreign currency (billion USD)



Figures 4-8 shows a short-term forecast of the main macroeconomic indicators of the Russian monetary system and oil prices. The forecast indicates stabilization of oil prices and the USD/RUB exchange rate in the next 6 months. As at 01.12.2016, the maximum discrepancy of the dynamics of the actual ruble exchange rate and the forecasted values obtained during the implementation of an

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integrated model amounted to 4.7%. As at 01.12.2017, the discrepancy between the actual ruble rate and the forecasted values amounted to 0.7%.

It should be mentioned that the model shows reliable results according to three sigma rule and the fact that two blocks functioned separately and provided codirected results in terms of closeness of NAR predictions to expected value provided by VAR and the majority of predicted values by NAR fell in the area of one sigma.

4. Discussions

The comprehensive econometric model was provided, including the vector autoregressive model, estimated on the dynamics of the domestic exchange rate, the macroeconomic indicators of banking sector activity and oil prices. Also, model includes neural network block for short-term forecasting of macroeconomic indicators. The result of VAR modelling have been identified and analyzed the main regularities between the dynamics of oil prices, the ruble exchange rate, as well as the dynamics of the level of the value of deposits of individuals and legal entities and other indicators of the banking sector.

In the analysis of impulse responses to oil shock in the framework of VAR-modelling, the influence of various currency regimes used by the Bank of Russia in the framework of the monetary policy in the period from 2012-2016 was revealed.

Also, a neural network model of exchange rate dependence on the dynamics of oil prices was developed and tested. As a result of neural network modelling, a short-term forecast of the exchange rate, Brent oil prices, and the main macroeconomic indicators of the banking sector activity was given.

As a result of modelling, we came to the following issues:

1. The dynamics of the Rub. exchange rate in the studied time frames is strongly inversely related to the dynamics of oil prices. This confirms the continuing weak diversification of the Russian economy, which continues to focus on energy exports.

2. The fall in oil prices was accompanied by a sharp increase in foreign currency deposits of both individuals and legal entities (in the currency corridor regime). Strong foreign currency predominance created excessive growth of foreign currency debt, which contributed to capital outflow and destabilization of the banking system.

3. The transition to a floating exchange rate of the Bank of Russia turned out to be a positive step for the stabilization of the majority of monetary system indicators. This fact is confirmed by the results of the shock scenario analysis of VAR-model. In particular, the modelling showed that the volatility of macroeconomic indicators of the Russian monetary system declined significantly after the introduction of floating exchange rate regime. Return to the stable volatility values of majority of the monetary system indicators after the oil shock of 2014-2015 was more rapid than that observed in 2009-2010.

4. A short-term forecast of the main macroeconomic indicators of the Russian monetarysystem was received with help of the model including two blocks: VAR and NAR.

The novelty of the work lies in the integrated econometric model for the analysis of the main macroeconomic indicators during the regime of the floating exchange rate of the Russian ruble.

The practical significance:

- statistically sound results showing the positive role of the floating exchange rate regime in stabilizing the Russian economy in the context of the crisis in commodity markets;

- results of econometric modelling showing the dependence of the exchange rate and the main macroeconomic indicators of the banking sector on oil prices;

- the short-term forecast of the dynamics of oil prices, the exchange rate and the main macroeconomic indicators of the banking sector from the price of oil.

The results of the research can be used by the Bank of Russia to improve monetary policy, the banking sector to optimize foreign exchange positions, as well as professional participants in the financial market to carry out risk management in the foreign exchange market and build trading strategies.

5. Bibliography

[1] Adkison, M. D., Peterman, R. M., Lapointe, M. F., Gillis, D. M., Korman, J. (1996). Alternative models of climatic effects on sockeye salmon, Oncorhynchusnerka, productivity in Bristol Bay, Alaska, and the Fraser River, British Columbia. Fisheries Oceanography, 5(3-4), 137-152.

[2] Akaike, H. (1973). Maximum likelihood identification of Gaussian autoregressive moving average models. Biometrika, 255-265.

[3] Antonello D'Agostino, Luca Gambetti and Domenico Giannone (2013). Journal of applied econometrics. 28 (1): 82–101. DOI: 10.1002/jae.1257.

[4] Białowolski, P., Kuszewski, T. &Witkowski, B. (2014) Bayesian averaging of classical estimates in forecasting macroeconomic indicators with application of business survey data. Empirica. 41 (1): 53-68. Doi:10.1007/s10663-013-9227-x.

[5] Brayton F., Tinsley P. A. A guide to FRB/US: a macroeconomic model of the United States. – 1996.

[6] Chaudhuri, T.D. and Ghosh, I. (2016). Artificial Neural Network and Time Series Modeling Based Approach to Forecasting the Exchange Rate in a Multivariate Framework. Journal of Insurance and Financial Management, 1 (5), pp. 92-123.

[7] Chen, YF.,Funke, M. &Glanemann, N. (2014) The Signalling Channel of Central Bank Interventions: Modelling the Yen/US Dollar Exchange Rate Open Economies Review. 25 (2): 311-336. doi:10.1007/s11079-013-9280-x.

[8] Christoffel K. P., Coenen G., Warne A. The new area-wide model of the euro area: a micro-founded open-economy model for forecasting and policy analysis. – 2008.

[9] Cogley T., Sbordone A. M. Trend inflation, indexation, and inflation persistence in the New Keynesian Phillips curve //The American Economic Review. – 2008. – Т. 98. – №. 5. – С. 2101-2126.

[10] Cunha, A.B.(2013). On the relevance of floating exchange rate policies. Economic Theory. 53: 357-382. doi:10.1007/s00199-012-0694-2.

[11] Darvas, Z. (2013) Monetary transmission in three central European economies: evidence from time-varying coefficient vector autoregressions. Empirica (2013) 40: 363-390. doi:10.1007/s10663-012-9197-4.

[12] Del Negro, M. and Schorfheide, F. (2006) How Good Is What You've Got? DSGE-VAR as a Toolkit for Evaluating DSGE Models. Federal Reserve Bank of Atlanta Economic Review. 91: 21–37.

[13] Diaconescu, E. (2008). The use of NARX neural networks to predict chaotic time series. Wseas transactions on computer research, 3(3), pp.182-191. Available at: URL http://www.wseas.us/e-library/transactions/research/2008/27-464.pdf [Accessed 2 April 2017].

[14] Edwards, S. (2011) Exchange-Rate Policies in Emerging Countries: Eleven Empirical Regularities From Latin America and East Asia. Open Economies Review. 22: 533. doi:10.1007/s11079-011-9206-4.

[15] Fagiolo G., Roventini A. On the scientific status of economic policy: a tale of alternative paradigms //The Knowledge Engineering Review. – 2012. – Т. 27. – №. 2. – С. 163-185.

[16] Gali J., Monacelli T. Monetary policy and exchange rate volatility in a small open economy //The Review of Economic Studies. – 2005. – Т. 72. – №. 3. – С. 707-734.

[17] James W. Taylor, Keming Yu (2016) Using auto-regressive logit models to forecast the exceedance probability for financial risk management. Journal of the Royal Statistical Society: Series A (Statistics in Society). 179 (4): 1069–1092. Doi: 10.1111/rssa.12176.

[18] Kydland F. E., Prescott E. C. Time to build and aggregate fluctuations //Econometrica: Journal of the Econometric Society. – 1982. – С. 1345-1370.

[19] Kumhof M. et al. The Global Integrated Monetary and Fiscal Model (GIMF)–Theoretical Structure. – 2010.

[20] McCulloch W. S., Pitts W. A logical calculus of the ideas immanent in nervous activity //The bulletin of mathematical biophysics. – 1943. – T. 5. – №. 4. – C. 115-133.
[21] Murchison S. et al. ToTEM: The Bank of Canada's new quarterly projection model. – Bank of Canada, 2006.Pesenti P. The Global Economy Model: Theoretical Framework: IMF Staff Papers. 2008. №55 (2). P. 243-284.
[22] Naser, H. (2015) Estimating and forecasting Bahrain quarterly GDP growth using simple regression and factor-based methods. Empirical Economics. 49: 449-479. Doi:10.1007/s00181-014-0892-9.
[23] Pesaran, H. Hashem, and Yongcheol Shin. (1998) "Generalized impulse response analysis in linear multivariate models." Economics letters 58.1: 17-29.
[24] Qifa Xu, Xi Liu, Cuixia Jiang and Keming Yu. (2016) Nonparametric conditional autoregressive expectile model via neural network with applications to estimating financial risk. Applied stochastic models in business and industry. 32 (6): 882–908. Doi: 10.1002/asmb.2212.
[25] Sun, W. and An, L. (2011) Dynamics of floating exchange rate: how important are capital flows relative to macroeconomic fundamentals? Journal of Economics and Finance. 35: 456-472. doi:10.1007/s12197-009-9103-5.
[26] Sims, C. A. (1980, January). Macroeconomics and reality. Econometrica: Journal of the Econometric Society, 48 (1), pp. 1-48 Available at URL: http://www.jstor.org/stable/1912017 [Accessed 12 March 2017].

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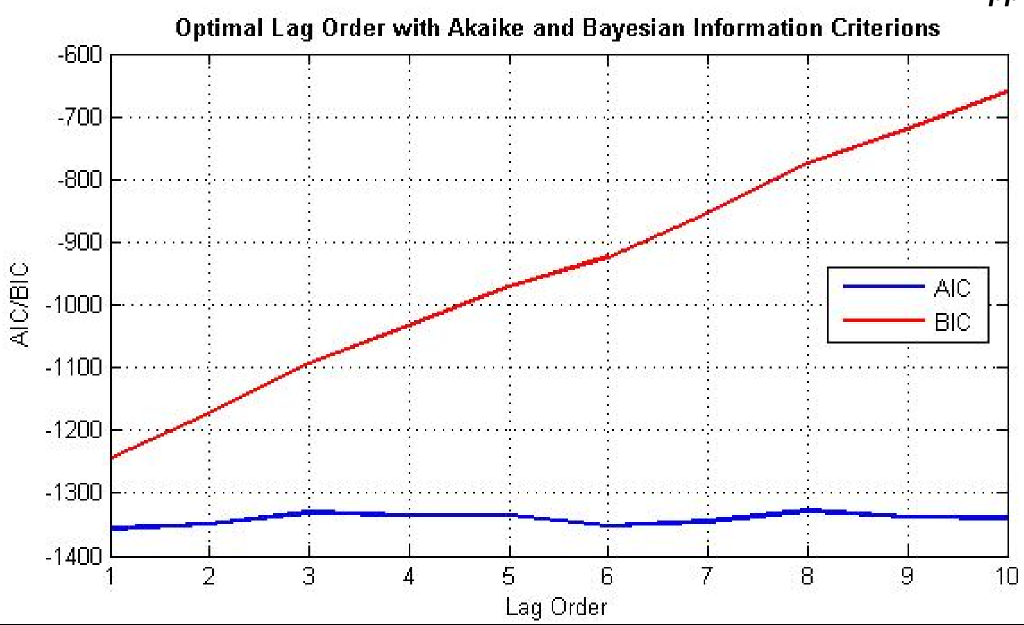
Appendix A

Time series №	h	pValue	stat	cValue
1	0	0.95	1.32	-1.94
2	0	0.35	-0.83	-1.94
3	0	0.99	3.08	-1.94
4	0	0.99	2.06	-1.94
5	0	0.72	0.19	-1.94

Appendix B

Time series №	h	pValue	stat	cValue
1	1	0.001	-20.57	-1.94
2	1	0.001	-21.87	-1.94
3	1	0.001	-18.44	-1.94
4	1	0.001	-17.67	-1.94
5	1	0.001	-23.22	-1.94

Appendix C



c r.\lag	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**1 0**
A IC	- 1356.9	- 1350.1	- 1331.5	- 1335.4	- 1335.8	- 1352.1	- 1344.6	- 1327.9	- 1337.5	- 1340.1
B IC	- 1243.4	- 1173.6	- 1091.9	- 1032.7	- 970.1	- 923.4	- 852.8	- 773.1	- 719.7	- 659.2

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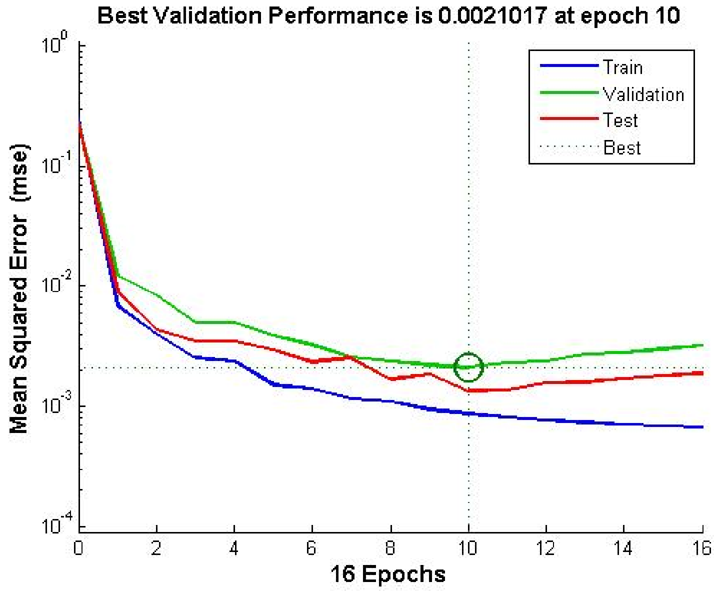
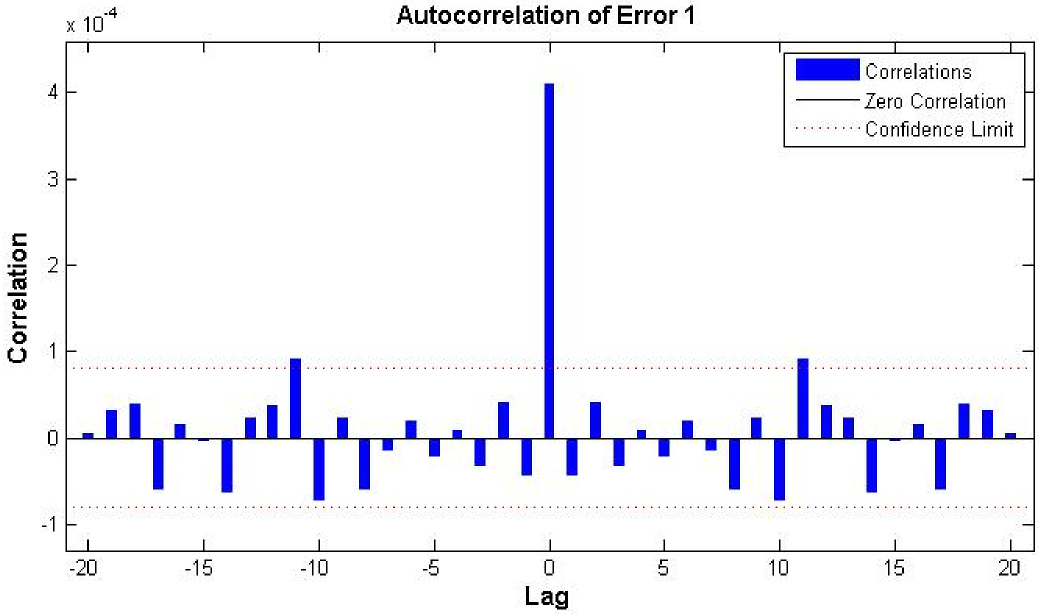
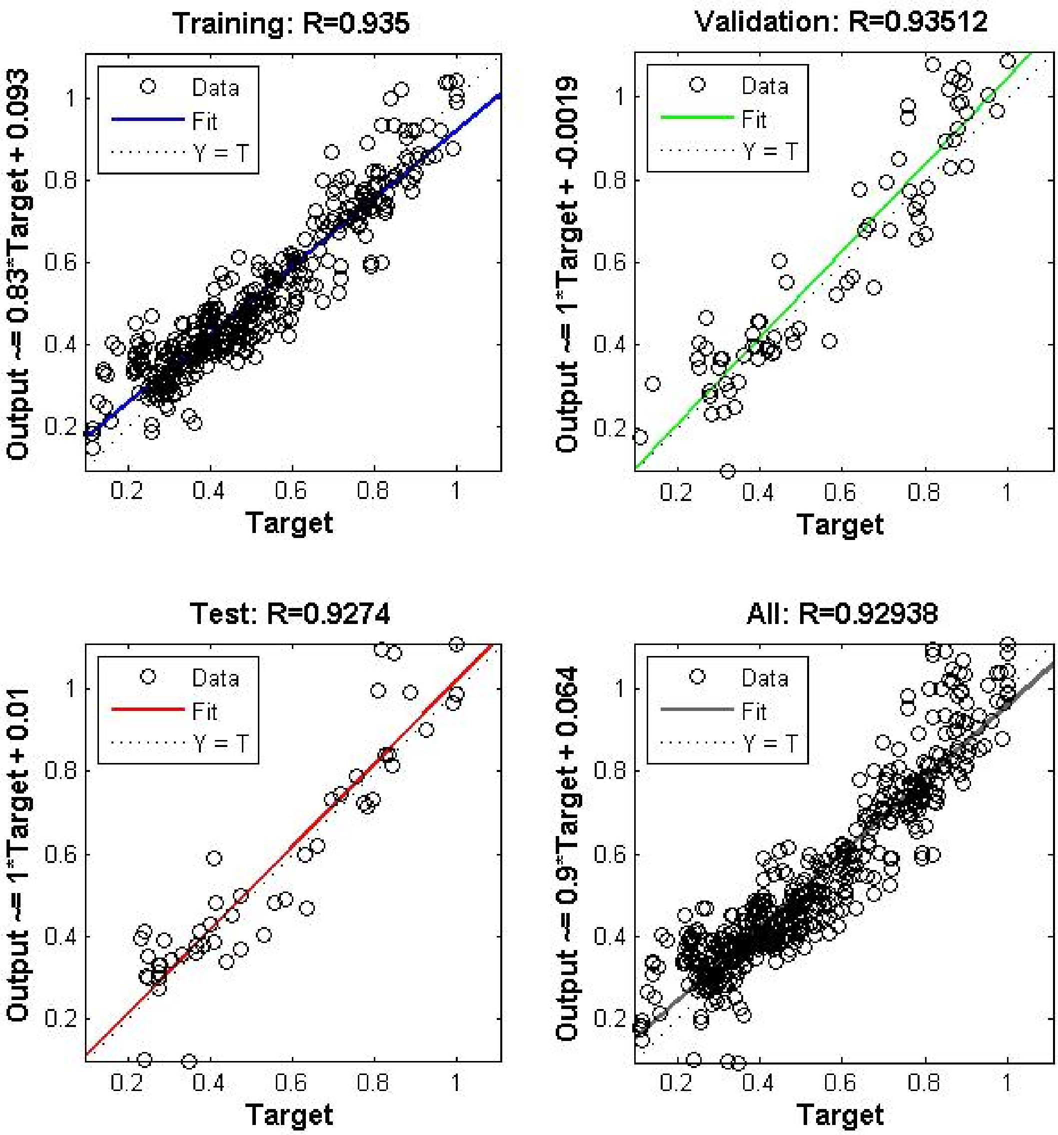
Appendix D

	Var1	Var2	Var3	Var4	Var5
31/01/2012	0.015	0.065	0.040	0.031	0.225
31/01/2013	0.089	0.019	0.201	0.107	0.386
31/01/2014	0.121	0.166	0.158	0.102	0.142
31/01/2015	0.096	0.170	0.043	0.136	0.282

Appendix E






Training: R=0.935
Output ~= 0.83*Target + 0.093
Data
Fit
Y = T
Target
Validation: R=0.93512
Output ~= 1*Target + -0.0019
Test: R=0.9274
Output ~= 1*Target + 0.01
All: R=0.92938
Output ~= 0.9*Target + 0.064