Emilian Dobrescu | Dumitru Iulian Nastac |
Elena Pelinescu

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Emilian Dobrescu

Professor, Romanian Academy, National Institute of Economic Research, Centre for Macroeconomic Modelling
050711 - Bucureşti, Casa Academiei Române, Calea 13 Septembrie nr. 13, Romania
Phone - +40722357057
E-mail - emiliand@clicknet.ro

Dumitru Iulian Nastac

Associate Professor, Polytechnic University of Bucharest
060042 - Bucureşti, Splaiul Independenţei nr. 313, sector 6, Romania
Phone - +40721485426
E-mail - nastac@ieee.org, iulian@nastac.ro

Elena Pelinescu

Researcher, Romanian Academy, National Institute of Economic Research, Institute for Economic Forecasting
050711 - Bucureşti, Casa Academiei Române, Calea 13 Septembrie nr. 13, Romania
Phone - +40722950607
E-mail - elena_pelinescu@yahoo.com

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Abstract

Our purpose is to verify the predictive performances of the artificial neural networks (ANNs) under volatile statistics and possibly misspecified system. Daily forecasts of exchange rate using exclusively primary available information for an emergent economy (such as the Romanian one) could be a proper experimental ground with such a goal. The present paper extends the previous authors' research (Dobrescu et al., 2006; Nastac et al., 2007) on the same issue to improve the accuracy of exchange rate forecasting by using a set of neural predictors in cascade, instead of a single one. The results show that the presented model, despite its proved advantages, could not avoid the translation into residuals of the high serial correlation present in the primary database.

Keywords: exchange rate, time series model, neural network, forecasting and prediction methods

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I. Introduction

As it is known, the artificial neural networks (ANNs) technique penetrated progressively into economics, with the last two decades offering a great number of methodological and empirical studies. Some bibliographical overviews in this field can be found in (Herbrich et al.,1999; Gonzalez, 2000; Heravi et al., 2003; Choudhary and Haider, 2008; Paliwal and Kumar, 2009). An extended thematic palette was searched, from purely cognitive problems to very narrow practical applications. Concerning gnoseological issues, we could notice inter alia: the recognition processes and classification (Herbrich et al., 1999; Razi and Athappilly, 2005), bounded rationality (Herbrich et al., 1999), revelation of changing patterns in the time series (Franses and Draisma, 1997), identification of explanatory variables in functional relationships (Kaastra et al., 1996), learning algorithms (Choudhary and Haider, 2008). Normally, all these issues have been investigated in the context of different micro- and macroeconomic phenomena.

To outline the increasing interest of ANNs researchers on important problems of the real economy, there were significant applications not only on the global output (Gonzalez, 2000; Heravi et al., 2003; Huang et al., 2007), but also on its sectoral structure with a special attention for industry (Portugal, 1995; Gonzalez, 2000; Heravi et al., 2003), agriculture (Kohzadi et al., 1995), construction (Kaastra et al., 1996; Razi and Athappilly, 2005) and energy consumption (Gonzalez, 2000). Although less frequent, the demand side issues were also examined. Among them, an example is the consumers' expenditures (Farhat, 2012).

Probably, the financial and monetary phenomena were the most often approached with the ANNs technique. This can be explained by taking into account the specificities of the corresponding databases (high frequency). From this point of view, the capital market was undoubtedly in top. The ANNs have been involved in testing some theoretical foundations (for instance, Fama hypothesis) and also in the analysis of many empirical research regarding stock exchange and risk rating (White, 1988; Beltratti et al., 1996; Donaldson and Kamstra, 1996; Haefke and Helmenstein, 1996; Hiemstra, 1996; Kaastra et al., 1996; Zekic, 1998; Zhang et al., 1998; Herbrich et al., 1999; Gonzalez, 2000; Virili and Freisleben, 2000; Hajto, 2002; Huang et al., 2007; Maciel and Ballini, 2008; Wong, 2009). The exchange rate was also one of the ANNs' preferred subjects (Verkooijen, 1996; Zhang et al., 1998; Herbrich et al., 1999; Gonzalez, 2000; White and Racine, 2001; Huang et al., 2007; Pacelli et al., 2011). Among other financial and monetary topics, we could include banking credit (Razi and Athappilly, 2005), bankruptcy and business (Zhang et al., 1998) and mainly inflation (Binner et al., 2006; Choudhary and Haider, 2008).

In general, the computational performances of ANNs have been continuously confronted with the standard econometric methods. Numerous papers have found ANNs results more accurate than those offered by statistical regressions (Moody, 1995; Portugal, 1995; Donaldson and Kamstra, 1996; Herbrich et al., 1999; Gonzalez, 2000; Moshiri and Cameron, 2000; Plummer, 2000; Razi and Athappilly, 2005; Abdel-Aal, 2008; Choudhary and Haider, 2008; Maciel and Ballini, 2008; Majhi and Sahoo, 2009; Paliwal and Kumar, 2009; Kolarik and Rudorfer, 2010; Pacelli et al., 2011). On the other hand, there is also no lack in the contrary statements (Portugal, 1995; Swanson and White, 1997; Gonzalez, 2000; Moshiri and Cameron, 2000; Plummer, 2000; Binner et al., 2006; Paliwal and Kumar, 2009; Pacelli, 2012). However, there are many ambiguous positions or, at least, those that consider the results provided until now by ANNs inconclusive, when compared with the traditional procedures (Zhang et al., 1998; Herbrich et al., 1999;, Gonzalez, 2000; , Moshiri and Cameron, 2000; Heravi et al., 2003; Huang et al., 2007; Paliwal and Kumar, 2009).

A dominant position seems to be the assertion that the dilemma "standard econometrics or ANNs" remains an open question. Besides, an extending preference for some hybrid solutions, combining the classical methods with ANNs, can be observed (Moody, 1995; Donaldson and Kamstra, 1996; Hansen and Nelson, 1997; Stock and Watson, 1998; Gonzalez, 2000; Razi and Athappilly, 2005; Huang et al., 2007; Choudhary and Haider, 2008; Maciel and Ballini, 2008; Paliwal and Kumar, 2009; Kolarik and Rudorfer, 2010; Yu and Huarng, 2010; Pacelli et al., 2011). Such an interdisciplinary approach could become a future mainstream of the quantitative analysis in economics.

Concerning this debate, several categories of problems are of special interest. The first relates to the properties of the involved statistical series. There is an increasing interest in favour of ANNs and their capability to involve large databases. Such a possibility really represents an important advantage of ANNs, first of all, for question requiring quick decisional reactions.

However, we can notice another face (less pleasant) of the medal. Long series can be available only for high frequency statistics. Unfortunately, at least nowadays and in the expectable future, such a frequency is not yet practicable for the most part of macroeconomic fundamentals. As a consequence, in many applications of ANNs, these essential variables cannot be implied as input neurons. Hereinafter, we shall come back to this problem in relation with our empirical research.

Among pluses of the ANNs, their so-called 'immunity' to non-linearities and, generally, their capacity to process non-stationary time series and misspecified systems are included (White, 1988, 1989; Hornik et al., 1990; Kuan and White, 1994; Moody, 1995; Portugal, 1995; Kaastra et al., 1996; Zhang et al., 1998; Marks,1999: Herbrich et al., 1999; Gonzalez, 2000; Plummer, 2000; Virili and Freisleben, 2000; Heravi et al., 2003; Razi and Athappilly, 2005; Choudhary and Haider, 2008; Maciel and Ballini, 2008; Paliwal and Kumar, 2009; Yu and Huarng, 2010; Pacelli et al., 2011). Obviously, such characteristics of ANNs are especially valuable for economics.

We have to remark that ANNs are associated with some reverse consequences. Hence, as long as the actual nature of the given relationships is not yet identified, we are not sure whether statistical 'noise' hides the influence of possibly stable causal factors. The absence of explicit functional dependencies, which operate among the searched variables affects, categorically, the predictive estimations themselves. In other words, the 'black box' advantages of ANNs have their (not quite low) informational cost.

Therefore, it would be risky to ignore the properties managed by ANNs data, at least in the case of economics. On the one hand, it is reasonable to choose the input variables of the neural networks taking into consideration the generally assumed theorems and statistical selection criteria. On the other hand, it seems necessary to submit the resulted ANNs residuals to usual tests of significance.

The literature comments some problems regarding the ANNs technique as such (Draisma et al., 1995; Portugal, 1995; Kaastra et al., 1996; Herbrich et al., 1999; Gonzalez, 2000; Moshiri and Cameron, 2000; Plummer, 2000; Huang et al., 2007; Abdel-Aal, 2008; Paliwal and Kumar, 2009). Almost unanimously, it is deplored that there is a lack of rigorous procedures for an efficient application of ANNs. The principle 'trial and error', currently practiced in this field, is highly time-consuming and never certain.

The rest of the paper is structured as follows. Section II describes the statistical framework for daily prediction of the exchange rate in the actual Romanian economy. The ANN algorithm is presented in Section III, together with results obtained by this technique. The last section is consecrated to the residuals analysis and several concluding remarks.

2. Statistical Framework

As already mentioned, our application operates with daily data, with the output variable of neural network being the nominal exchange rate of RON per Euro (symbol ex_ro). Introducing for holidays the previous available information, there were constituted continuous sets of 3364 data. The duration adopted for the experiment series (January 2000–December 2012) is long enough to be admitted as a suitable candidate for a neural networks algorithm.

Obviously, the option for daily frequency considerably narrowed the possibilities to involve classical model specifications for ANNs input variables. We can easily noticed the following issues:

• The famous Cassel's purchasing power parity (either in its absolute or relative approximations) needs obligatorily different price indices, which – as reliable information – have almost a monthly frequency.

• For the Harrod-Balassa-Samuelson theorem, additional information is necessary, at least about the sectoral structure of economy and the dynamics of labour productivity.

• Due to its construction, the Mundell-Fleming theory cannot be quantitatively described without the international capital flows, for which some daily data are accessible only accidentally.

• The monetary paradigm is not applicable in its standard version because of the absence of daily information about money equilibrium and its main determinants.

Therefore, the referential models, as such, are not quite helpful for our attempt. Nevertheless, some of their elements, combined with other hypotheses, could be taken into consideration. We can further notice that:

a) Indeed, in as early as the 1970s, the modern asset-market approach has outlined (Dornbush, 1976; Frankel, 1979) a significant connection of the exchange rate with the interest rate. This link (including in the form of Taylor rule) was frequently commented in the recent economic literature (Meredith and Chinn, 1998; Kasuya and Kozo, 2000; Chortareas and Driver, 2001; Chinn, 2003; Engel and West, 2005; Molodtsova and Papell, 2008, 2012; Sun et al., 2010; Hacker et al., 2010; Chen, 2011). This correlation has also been examined from the point of view of risk premium problem (Engel, 2011). On the other hand, daily official information concerning the interest rate and stock market indices are available. In the case of Romania, for instance, there are such series covering the entire interval for BET Indices (BET) and weekly interest rate ro-bid (Ro_BID1W) and ro-bor (Ro_BOR1W).

b) Our attempt could also be sustained by the modelling research dedicated to the regional and global economic integration, because the exchange rate is congenitally implied in the international economic relationships.

With special address to the last global financial crisis, Fratzscher (2009) revealed three factors that explain the cross-country exchange rate movements: “First, it is in particular the financial exposure vis-à-vis the United States that is statistically significant in the estimation…A second driver of cross-country exchange rate movements is the size of FX reserves, measured as a share of GDP. A third driving factor for currencies during the crisis appears to be the size of countries’ current account positions, with those countries having stronger positions suffering significantly less from currency depreciations” (p. 15-16).

The financial contagion effect has been initially associated with the so-called models of speculative attacks (Krugman, 1979), and later, the accent was put on national differences in monetary policy (Obstfeld, 1986). Commenting on these models (including their derivations exposed in the study by Eichengreen et al., 1995), Glick and Rose (1998) also insisted on commercial inter-flows among countries. This channel is again outlined by Pesenti and Tille (2000), who mentioned that its effect can be either direct or propagated. Contagion problem (related to financial markets) are also discussed by Mishkin (1999), Forbes and Rigobon (1999), Goldstein et al (2000), Edwards (2000), Dungey and Vance (2001) and many others.

According to this theoretical mainstream, our application involves the daily series for exchange rates of several countries with non-negligible impact on the Romanian international transactions, namely Czech crown (EX_CZK), Hungarian forint (EX_HUF), Polish zloty (EX_PLN), Swiss franc (EX_CHF), Russian ruble (EX_R) and US Dollar (EX_USD). As a global indicator, the ratio of US dollar to Euro quoted on the Romanian exchange market (UD_Euro_Rap) has also been introduced.

It is important to mention that we used information sources that cover a recent time interval, as long as possible. In the case of exchange rates for the involved countries, the Eurostat statistics was used because it provides information concerning the entire period from January 2000 to December 2012. The series for the ratio of US Dollar to Euro quoted on domestic exchange market and both the mentioned interest rates were obtained from the interactive database of the National Bank of Romania. The daily data for BET were obtained from Bucharest Stock Exchange (BVB) site. The main properties of statistical data retained for the ANNs application are presented hereinafter.

As expected, such a series is characterised by relatively pronounced volatility, which transpires even from their graphical representation (see the Figure 1).

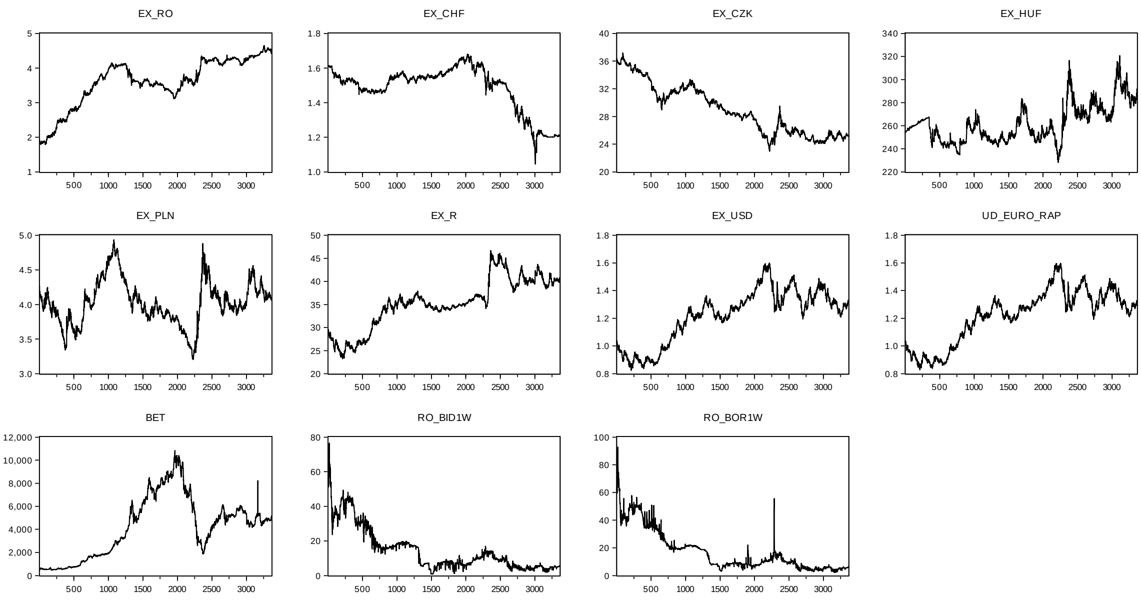

Figure 1: Series' Volatility

The descriptive statistics (Table 1) confirmed this feature as well as the absence of normality in data distributions.

Table 1: Descriptive statistics

	Mean	Median	Max.	Min.	Std. D.	Skew.	Kurt.	Jarque-Bera	Prob.
EX_RO	3.602	3.660	4.647	1.792	0.691	-0.930	3.155	487.933	0.0000
EX_CHF	1.483	1.526	1.680	1.045	0.131	-1.150	3.301	753.683	0.0000
EX_CZK	28.979	28.445	37.202	22.968	3.585	0.341	1.939	223.002	0.0000
EX_HUF	261.824	258.710	320.780	228.160	16.426	0.803	3.242	369.946	0.0000
EX_PLN	4.024	4.000	4.935	3.205	0.322	0.180	3.033	18.332	0.0001
EX_R	35.236	35.268	46.714	23.190	5.386	-0.321	2.490	94.306	0.0000
EX_USD	1.221	1.268	1.599	0.825	0.192	-0.473	2.249	204.781	0.0000
UD_EURO_RAP	1.220	1.266	1.598	0.828	0.192	-0.469	2.257	200.901	0.0000
BET	4197.560	4508.205	10813.590	460.670	2678.981	0.279	2.138	147.878	0.0000
RO_BID1W	14.541	9.490	76.630	0.840	12.420	1.462	4.716	1610.690	0.0000
RO_BOR1W	17.214	10.275	92.880	2.380	14.639	1.411	4.505	1432.876	0.0000

Estimated as the ratio of the standard deviation to mean, the coefficient of variation appeared as follows: EX_RO 0.192; EX_CHF 0.088; EX_CZK 0.1237; EX_HUF 0.0627; EX_PLN 0.08; EX_R 0.153; EX_USD 0.158; UD_EURO_RAP 0.16; BET 0.638; RO_BID1W 0.85 and RO_BOR1W 0.85.

The unit root tests (Augmented Duickey-Fuller and Plillips-Perron) are presented in Table 2.

Table 2: Unit root tests
Null Hypothesis: Unit root (individual unit root process)

Exogenous variables	None	Individual effects	Individual effects, individual linear	None	Individual effects	Individual effects, individual linear
Intermediate ADF test results				Intermediate Phillips-Perron test results		
Series	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.
EX_RO	0.9933	0.1346	0.6303	0.9905	0.1842	0.6257
EX_CHF	0.1791	0.8958	0.9161	0.1572	0.918	0.9357
EX_CZK	0.0517	0.4037	0.2589	0.0409	0.4038	0.2997
EX_HUF	0.7553	0.095	0.0247	0.7771	0.1651	0.0481
EX_PLN	0.5712	0.1225	0.3231	0.5723	0.1466	0.3679
EX_R	0.8697	0.6218	0.4163	0.8828	0.634	0.4876
EX_USD	0.7937	0.6036	0.6629	0.791	0.5949	0.6335
UD_EURO_RAP	0.789	0.5898	0.6177	0.7909	0.5936	0.6161
BET	0.6762	0.5656	0.9264	0.6755	0.5621	0.9245
RO_BID1W	0.0042	0.0253	0.0246	0.0057	0.0481	0.0479
RO_BOR1W	0.0049	0.0276	0.0119	0.003	0.0465	0.0232

Therefore, with few exceptions (interest rates), the series included in ANNs application are non-stationary.

Table 3: z-Statistic for BDS test

Dimension	Fraction of pairs	Fixed value	Standard deviations	Fraction of range	Fraction of pairs	Fixed value	Standard deviations	Fraction of range
BDS Test for EX_RO					BDS Test for EX_CHF			
2	143.4139	183.3383	308.1678	171.1415	118.1161	NA	140.2576	237.7689
3	153.9026	225.9144	465.2264	157.8983	126.3838	NA	179.6376	216.9159
4	166.8821	285.7926	743.025	145.8749	136.633	NA	237.3946	197.1773
5	185.5002	376.0803	1263.791	136.8979	151.4481	NA	327.9099	181.5545
6	210.849	512.5406	2263.826	130.2018	171.6489	NA	470.7932	169.0962
BDS Test for EX_CZK					BDS Test for EX_HUF			
2	269.0433	923.3397	864.9612	217.6671	159.0545	1206.995	299.6426	218.5978
3	290.3093	3233.929	1420.759	200.2583	170.8249	9034.652	449.2343	200.2567
4	316.6614	13493.82	2502.098	184.3233	185.1162	97543.62	712.1253	181.9191
5	354.2528	63616.85	4734.941	172.282	205.5053	1359241	1201.752	167.9886
6	405.3521	324088.3	9489.545	163.151	233.2301	22801488	2136.428	156.7267
BDS Test for EX_PLN					BDS Test for EX_R			
2	155.2181	163.5032	220.1593	473.9019	170.3936	537.1452	300.4568	300.3794
3	166.7827	157.5043	333.4995	430.4972	183.2613	2155.386	470.4218	274.7926
4	180.8766	151.7797	534.9389	390.3775	199.0963	10453.01	783.781	251.3136
5	200.9576	148.6235	914.9875	358.9545	221.718	57442.92	1396.611	233.2625
6	228.2216	147.6023	1650.585	334.0672	252.4597	341463.1	2627.972	219.2989
BDS Test for EX_USD					BDS Test for UD_EURO_RAP			
2	184.4788	731.5529	275.9869	272.6953	183.5845	728.5944	273.6266	271.5945
3	198.2679	672.3906	408.6225	251.066	197.3531	666.0115	405.3508	250.3329
4	215.3028	613.0251	637.9294	230.9395	214.3334	607.4398	633.1103	230.3547
5	239.6474	566.3587	1058.344	215.5636	238.5959	561.1575	1050.974	215.0966
6	272.7297	528.7167	1847.418	203.8038	271.5688	523.6466	1835.597	203.4328
BDS Test for BET					BDS Test for RO_BID1W			
2	240.557	3808.518	756.3696	211.942	111.0134	790.9707	152.2311	90.72082
3	259.1557	1354124	1241.527	195.5962	118.6248	4318.55	203.6047	81.88197
4	282.2234	7.09E+08	2184.599	180.7309	128.0646	29977.91	283.049	74.32212
5	315.0658	4.15E+11	4129.102	169.6241	141.7313	240912.5	413.6961	68.54447
6	359.7467	2.52E+14	8264.134	161.2752	160.4623	2116093	631.4589	64.1015
BDS Test for RO_BOR1W								
2	114.1973	795.7175	154.9528	89.73666				
3	122.0252	4569.924	210.0465	81.07397				
4	131.8111	33363.64	296.3917	73.73952				
5	145.9056	280355.3	440.034	67.93832				
6	165.1082	2567647	682.6099	63.59047				

Regarding the serial correlation of data, the BDS is a powerful tool to identify it irrespective of its nature – linear, non-linear and chaos. Five embedding dimensions were adopted: 2, 3, 4, 5 and 6. As the available sample was large enough, the test was applied only for the primary data, without random repetitions (bootstrap probability). Regarding the distance, all options allowed by the recent software were applied: fraction of pairs, fixed value, standard deviations and the fraction of range. The z-Statistic estimated for all 220 resultant variants (11X5X4) are presented in Table 3.

The conclusion is clear: despite their volatility and non-stationarity, the examined series are characterised by undisputable serial correlations.

The correlation matrix revealed other significant characteristics of the statistical series submitted to ANNs exercise, which was determined in both most-used variants, namely Galtung-Pearson and Spearman Rank (Table 4).

Table 4: Galtung-Pearson (bellow the main diagonal) and Spearman-Rank (above the main diagonal) correlations

	EX_RO	EX_CHF	EX_CZK	EX_HUF	EX_PLN	EX_R	EX_USD	UD_EURO_ RAP	BET	RO_BID1W	RO_BOR1W
EX_RO	1	-0.5273	-0.6904	0.6058	0.5538	0.896	0.5806	0.5985	0.3102	-0.6168	-0.6707
EX_CHF	-0.5067	1	0.31524	-0.433	-0.298	-0.3499	0.0684	0.03128	0.28825	0.24114	0.27468
EX_CZK	-0.7703	0.45434	1	-0.426	0.0818	-0.7816	-0.8239	-0.8242	-0.6664	0.78793	0.81984
EX_HUF	0.4746	-0.6262	-0.4373	1	0.3565	0.5379	0.2937	0.31365	0.08593	-0.3828	-0.44
EX_PLN	0.4356	-0.2272	0.11393	0.3898	1	0.4044	-0.0033	0.00607	-0.2446	-0.034	-0.0638
EX_R	0.9076	-0.4088	-0.817	0.5413	0.3856	1	0.81	0.80121	0.43357	-0.6323	-0.6847
EX_USD	0.7263	-0.0979	-0.8327	0.2701	0.05	0.8418	1	0.9583	0.7247	-0.6328	-0.6676
UD_EURO_RAP	0.7322	-0.1177	-0.8358	0.2851	0.0528	0.836	0.9786	1	0.69436	-0.6254	-0.6603
BET	0.4087	0.09974	-0.6584	0.0656	-0.246	0.4712	0.7562	0.72869	1	-0.7834	-0.771
RO_BID1W	-0.806	0.30011	0.82716	-0.277	-0.111	-0.779	-0.7824	-0.7765	-0.7561	1	0.98636
RO_BOR1W	-0.8252	0.3025	0.83998	-0.307	-0.122	-0.8031	-0.8108	-0.8027	-0.7622	0.99105	1

A link between the output-variable (EX_RO) and the input-variables was identified, but such a connection was not very strong in some cases. On the other hand, relatively high inter-correlations among input variables themselves were frequently registered, which indicated a possible important impact of multicolinearity.

The properties described above seem to be a very challenging statistical framework for a neural networks algorithm. As a result, our application can be considered as relevant for testing the capabilities of ANNs to surpass the difficulties generated by high volatility, non-stationarity, serial correlation, multicollinearity and, in general, specification problems.

3. ANNs model

The basic model of the adaptive retraining technique (Nastac, 2004) has already been used for various data forecasting applications, such as industrial processes (Nastac, 2004, Cristea et al., 2012), bioinformatics (Nastac and Cristea, 2005; Cristea et al., 2008), environmental pollution prevention (Nastac, 2010) and the exchange rate of RON (Dobrescu et al., 2006; Nastac et al., 2007).

The predictive model that was previously used for various applications on data forecasting (see previously mentioned references) is showed in Figure 2.

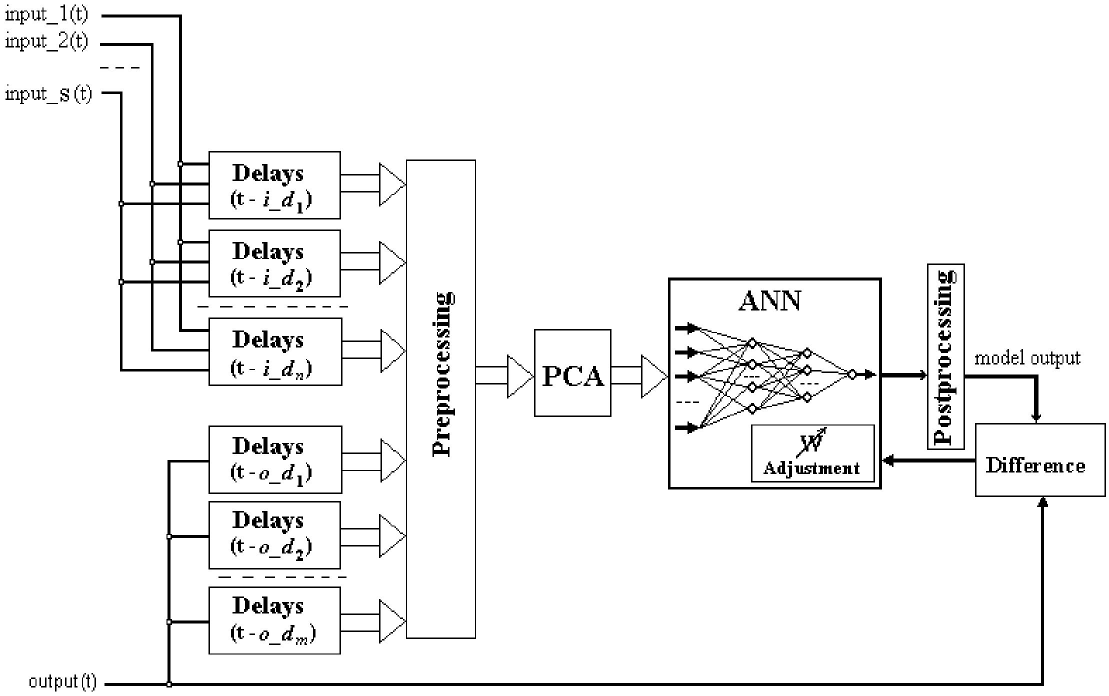

Figure 2: The general model architecture during training process

Source: Nastac I., An Adaptive Retraining Technique to Predict the Critical Process Variables, TUCS Technical Report, No. 616, June 2004, p.2

Briefly (Nastac, 2004), the output of the adaptive model at a moment t is related to the inputs at previous steps (t - i_d_1, …, t - i_d_n), as well as to the outputs at other set of steps (t - o_d_1, …, t - o_d_m). The forecasting model is thus determined by two delay vectors that involve several delays:

$$In\_Del = [i\_d_1, i\_d_2, ..., i\_d_n] \quad (1)$$

and

$$Out\_Del = [o\_d_1, o\_d_2, ..., o\_d_m] \quad (2)$$

where, usually, $n > m$ and i_d_n significantly exceeds o_d_m. The elements of delay vectors are in an ascending order and have to be carefully selected.

It is quite clear that the neural part of the model uses an important amount of inputs. However, this number can be drastically reduced by employing a step of Principal Component Analysis (PCA) (Jolliffe, 2002) before the input of the ANN. It is important to mention that the pre-processing part (Fig. 1) performs a normalisation of all the input data before the PCA block, whereas the post-processing part executes a denormalisation of the ANN output. After PCA, the model retains the essential part of the initial information (which means that the model usually preserves first eigenvectors that are able to reproduce the most valuable data). It is assumed that the PCA block acts as a filter for the outliers data. An intuitive recurrence formula (Nastac, 2004) performed by the general model that forecasts the output is:

$$y(t+1) = F(\ X(t+1-In\_Del(i)), y(t-Out\_Del(j))) \tag{3}$$

where X acts as the input vector and y is the output, with $i = 1,.., n$ and $j = 1,.., m$.

There are two main ways to make predictions using this computational technique (Nastac and Cristea, 2005):

• The first consists of an Iterative Simulation (IS) that allows forecasting the output in a sequential mode. Therefore, to produce one output at step t, the neural model uses as input the previously computed outputs (besides the real inputs) that had been obtained at former steps, by using other simulated outputs, and so on. By applying this iterative process, a prediction may be extended to as many steps as required, with the risk that each step increases the estimation error. In addition, with IS, we can establish different scenarios of the possible evolutions of the system, which we want to predict.

• Alternatively, we can resort to the Always Real Inputs (ARI) approach, which always employs the real outputs and not the previous estimated ones (in a recurrent manner). The main concern with the ARI mode is that we have to always wait for real data to feed the predictive system and can make predictions only over few steps, which are established by the minimum element of the delay vectors.

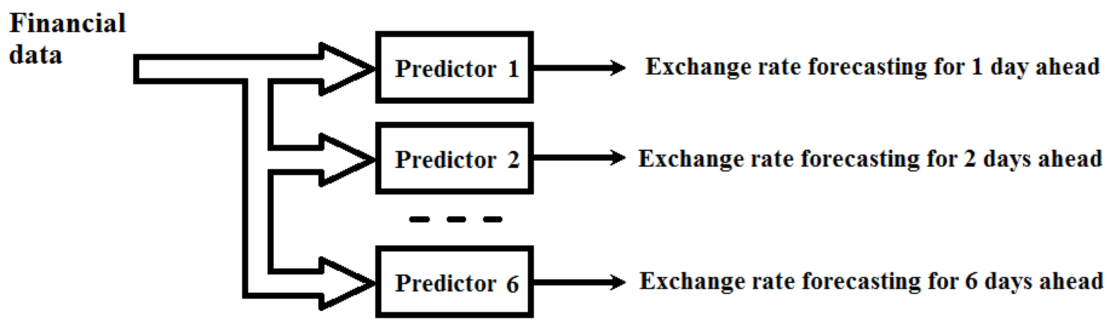

Figure 3: A set of predictors in cascade that forecast a number of 6 successive days.

In this study, we propose an intermediate form of predictions between these two approaches. A set of six predictors has been used to provide the evolution of the exchange rate in a forecasting horizon of the next 6 working days (i.e., more than a week). In this study, we attempt to obtain a compromise between the IS and ARI approaches by using a series of separate predictors. Each of them gives, in a successive way, a farther prediction point according to its delay vectors (see Figure 3).

The main idea is sustained by the simple observation that the first prediction is similar, both in IS and ARI approaches (then, the IS progressively uses the past computed values of the model). Intuitively, we focus on the fact that each of the predictors is a 'specialist' for a certain forecasting window, which implies a specified number of time steps.

In other words, if we intend to make a forecast for a week, at intervals of one day, then we can call seven such specialists: first, the specialist for tomorrow; second, the specialist for day after tomorrow and so on. Thus, with our data being updated for the current day and having seven fresh retrained predictors, we can simply obtain the graphic of a desired parameter during one week. Each of these systems has its own individual set of delay vectors, and it is obtained by using the method described in (Nastac et al., 2007). Therefore, it gives an effective mechanism for forecasting non-stationary environments where multiple predictors simultaneously collaborate.

As a financial week consists of a maximum of 5 working days, we decided to use six different predictors to have the best possible view of the evolution of the exchange rate for more than an average week. Each individual system had a specific ANN architecture that was established after an intensive searching procedure. Then, after all six predictive systems were determined, it was quite easy to apply the retraining procedure to accommodate the entire group to the newest evolution of non-stationary data, because there would be no modifications in the structures of neural networks, but only in their distribution of weights.

At the end of each complete retraining phase for all predictors, we could predict T = 6 values of the outputs, in a sequential mode. To estimate the efficiency of the forecasting model, we computed the error ERR (Nastac, 2004), which represents the accuracy of the approximation of the output data within the forecasting horizon of T days:

$$ERR = \frac{100}{T} \sum_{p=1}^{T} \frac{|O_{Rp} - O_{Fp}|}{|O_{Rp}|} \cdot \frac{T}{T+p} \tag{4}$$

where T is the number of time steps, O_{Rp} is the real output at step p and O_{Fp} is the forecasted output at the same step. Similar or related relations are known as the mean absolute percentage error (MAPE) and are frequently used (Senjyu et al., 2002; Wu and Shahidehpour, 2010) to evaluate the forecasted results.

We used feedforward neural networks with two hidden layers and the Scale Conjugate Gradient (SCG) algorithm (Moller, 1993) as training algorithm. As the adaptive retraining technique is flexible and independent of the training algorithm, it is quite easy to replace the SCG method with another one. We applied the validation stop method during the training process to avoid the overfitting phenomenon. The whole set of available data for the learning process was randomly split into approximately 90% for effective training and the rest for validation. Here, the validation set also acts as a test set, even if there is a separate test set.

The configurations of delay vectors, which were already proved to be beneficial (Nastac, 2013) for the model with predictive systems in cascade, are presented in Table 5.

Table 5: The configuration of delay vectors

Predictive system	Input vector (In_Del)	Output vector (Out_Del)
Predictor I	[1 2 3 4]	[0 1 2]
Predictor II	[2 3 4 5]	[1 2 3]
Predictor III	[3 4 5 6]	[2 3 4]
Predictor IV	[4 5 6 7]	[3 4 5]
Predictor V	[5 6 7 8}	[4 5 6]
Predictor VI	[6 7 8 9]	[5 6 7]

Source: Nastac DI (2013), Intelligent processing of multidisciplinary information for adaptive predictions in the context of globalisation, Editura Muzeul Naţional al Literaturii Române, Bucureşti, p. 171

We can see in Table 5 that each predictor has a similar number of elements for its delay vectors. The main differences consist of the shifted (incremented) values of these elements. In this way, the predicted time horizon will exceed the interval of one week that includes 2 days of the weekend (Saturday and Sunday), by successively using all individual outputs of the forecasting systems. As an exercise of imagination, it can be easily noted that, given the system parameters (incoming and outgoing data) available in Friday, the exchange rate for the next week plus Monday (on the following week) can be predicted. Therefore, in this situation, we can count a period of 10 days on the calendar. Moreover, if there are other days off on the predicted apparent projection, then the forecasting calendar automatically spans a longer period, although, essentially, only the following six successive values are estimated.

Searching by absolutely independent procedures, each neural network was individually selected to obtain minimum error during the training process. This error includes both training and validation sets. As all delay vectors have similar numbers of elements, the total number of inputs becomes $12 \times 4 + 3 = 51$ (where 12 is the number of inputs, 4 is the dimension of input vector and 3 is the dimension of output vector) for each predictive system. However, after the PCA block, such a system reduces this large number of inputs to only 30 principal components, without losing the basic information. Therefore, all ANNs have in fact 30 inputs and one output. Their pyramidal architectures include two hidden layers, as shown in Table 6.

Table 6: The characteristics of predictive systems

Predictive System	Number of inputs	The Dimension of PCA Transformation Matrix	The number of neurons on the first hidden layer	The number of neurons on the second hidden layer	The number of outputs
Predictor I	51	30×51	20	8	1
Predictor II	51	30×51	24	5	1
Predictor III	51	30×51	20	5	1
Predictor IV	51	30×51	12	10	1
Predictor V	51	30×51	21	5	1
Predictor VI	51	30×51	15	9	1

Source: Nastac DI (2013), Intelligent processing of multidisciplinary information for adaptive predictions in the context of globalisation, Editura Muzeul Naţional al Literaturii Române, Bucureşti, p. 171

For the PCA transformation matrix, we considered it useful to use the same number of eigenvectors that holds approximately 99.999% of the initial information. The remaining tiny loss was assessed to abnormal values, which were filtered in this way. Therefore, the process of decorrelation data also allowed the removal of the PCA dimensions, which were rather irrelevant among the global structure of the data.

The fact that all the systems in Table 5 have the same dimensions of delay vectors (number of elements) implicitly leads to the conclusion that some columns in Table 6 have identical values. Basically, one important difference between the predictive systems is the movement (sliding) values of these delay vectors by one unit from one system to another. Other decisive difference consists of the independent search of the best architecture for each predictive system, and this result is visible on the numbers of neurons on the hidden layers (as we can see in Table 6).

The length of the training set includes 1500 lines of data that represent a period that exceeds 5 years. This dimension of data volume, which was initially used to find an adequate neural network for each predictive system, was then successively employed with shifted data during many retraining phases. These retrainings were performed sequentially at intervals of one working day.

The whole evolution of the error ERR during 1844 retraining phases can be seen in Figure 4. Here, we have an extension of the previous results, which was published in

(Nastac 2013). In that study, the last retraining had the number 1653. In the present study, based on an extended data set, we continued the successive retrainings from 1654 to 1844.

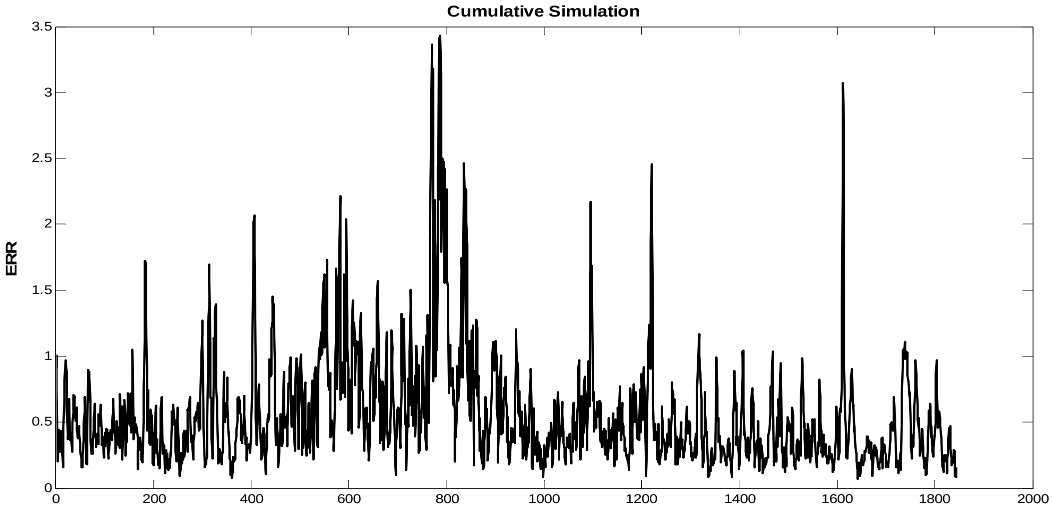

Figure 4: ERR trend of test sets (that consist of six predicted values) for the first training and L = 1844 successive retraining phases

We can observe a decreasing trend of ERR, which has in fact several jumps during the retraining phases. The abscissa from the ERR graph represents the number of the successive retraining phases and the initial value (0) is associated with the first training, used for predicting the interval from 2005/10/4 to 2005/10/12. A statistical descending trend of ERR can be observed when we successively calculate the mean values of the error for the whole interval (of 1844 values, which include first training), then for the second half, followed by the last quarter and, finally, for the last one-eighth of this interval. By following this idea, we obtained the values presented in Table 7.

Table 7: The mean values of ERR for different intervals

$m_{\text{ERR whole interval}}$	0.56369
$m_{\text{ERR for the second half}}$	0.43586
$m_{\text{ERR for last quarter}}$	0.40761
$m_{\text{ERR for the last 1/8 of the interval}}$	0.40423

The descending trend of the ERR is more visible in this way (Table 7) than that in Figure 4. The evolution of the ERR is quite complex and it is better to have the entire view as large as possible. For example, if we decide to separate only the interval of

1654–1844 from the whole successive retrainings (depicted in Figure 4), then we can obtain the image shown in Figure 5.

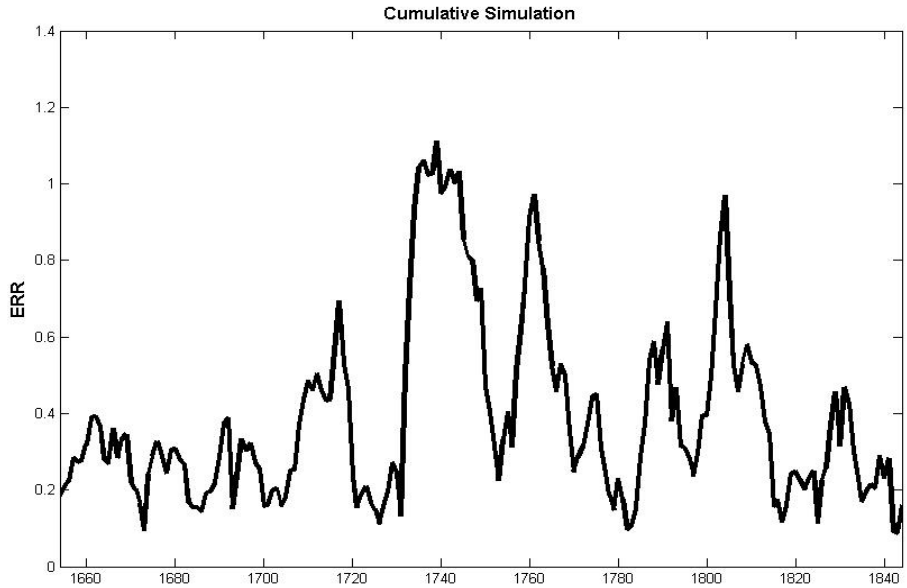

Figure 5: ERR trend between retrainings 1654 and 1844

There is a huge difference between Figure 4 and Figure 5. The statistic of the decreasing trend is not visible in Figure 5. If one tries to compute the mean values of ERR for different intervals, similar to that in Table 7, the result will be irrelevant. Although the graph of ERR (from Figure 5) presents some jumps during this interval, they are much smaller when compared with those observed before and around the retraining 800 (see Figure 4), where the behaviour of the economic crisis affected the predictions. It is important to mention that the returning to more accurate predictions occurs even during that time, because the entire system is daily retrained with new acquired data. In Figure 4, similar to a seismograph, we can perceive oscillations that portend financial crisis (which really is a global economic earthquake).

Better results of the model can be noticed after the retraining 805 (see Figure 4). However, the area between retrainings 830 and 840 still exhibits significant jumps of ERR. After the retraining 844, there are three major jumps. The first two are in the areas focused on retrainings 1095 and 1220, when two decreases of the exchange rate for the period from 4 to 11 January 2010 and from 30 June to 8 July 2010, respectively, are not correctly predicted. The third jump of ERR occurs close to the retraining 1612 when, seemingly oddly, an increasing rate between 3 and 11 January 2012 is not forecasted. A possible explanation for this latter aspect could be just the seasonality behaviour. Exactly in the same period a year earlier, in 2011, a decrease in the exchange rate was observed, as it happened in 2010 as well. Therefore, the system already learned, during the previous two years, that in the beginning of January, there is a decrease in the exchange rate, which was no longer considered in 2012. In a similar way, we might explain a jump of the ERR in the area of the retraining 1095 (predicting the onset of 2010), because the model had already been informed that at the beginning of the previous years, 2009 and 2008, there had been an increase in the exchange rate. One can infer that such a tool in the hands of a financial expert would provide more useful information than it was suggested here. Extended considerations are made in (Nastac 2013).

In the following, we shortly analyse the last retrainings (1654–1844) that were performed (with associate window forecasting) for each working day during March–December 2012. Each point in the graph from Figure 5 (or Figure 4) is in fact obtained from the predicted results that can be visible in another graph, such as in Figure 6, which particularly shows the test interval after the retraining 1654. This means that Figure 6 corresponds to the point of abscissa 1654 from the graph of ERR. This kind of figure is associated with the corresponding forecasting time horizon of 6 working days, in which ERR had been computed. The quality of the predictions can be graphically analysed by enforcing a tube of one per cent around the real outputs. If the predicted values fall inside the tube (represented with dotted lines in Figure 6), then the forecasting process proves to be very useful. In Figure 6, the real data are represented with thin lines, and the output values of the forecasting system (with several predictors in cascade) are denoted with thick lines. The abscissa of the graph shows the index number of the associated line in the database, which corresponds to computed prediction.

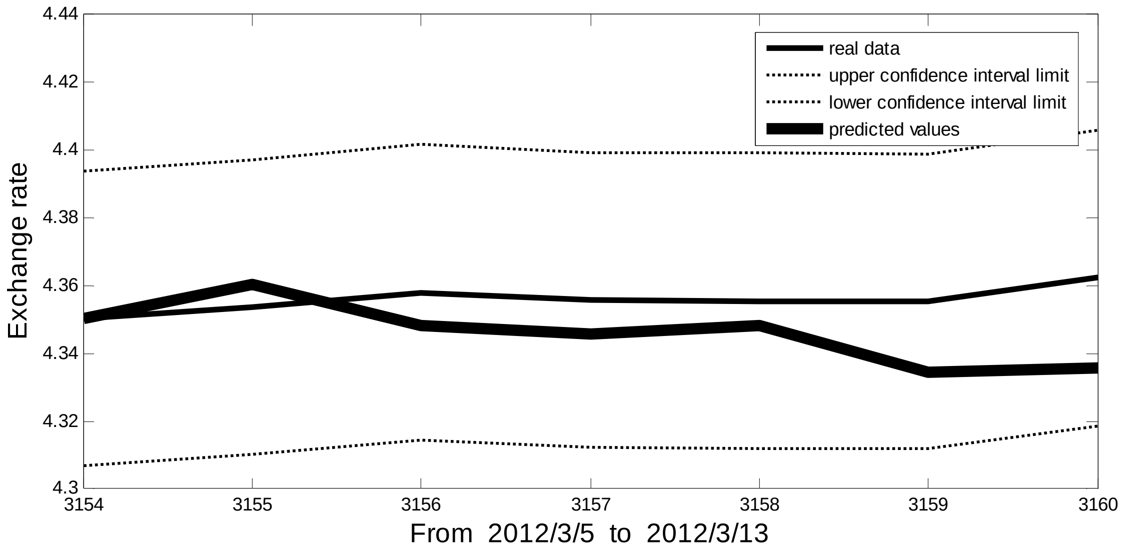

Figure 6: Data forecasting of the test interval after retraining 1654 (ERR=0.17377)

The first value (of abscissa 3154) is the day index when prediction is made; more precisely, the last value used for the effective retraining 3154, and therefore, the two graphs start from the same point. In fact, the first real predicted value has the abscissa 3155, provided by the first predictive system, followed by the points of abscissa 3156 produced by the second system and so on. As can be easily seen, the predicted values quickly slip outside the established confidence interval, right on the third day. Dates (below abscissa) are written in the order of year / month / day. Therefore, in GraphDF1, the first value of the abscissa (3154) corresponds to the date of 5 March 2012 (the current day when the prediction was made), and the last value (3160) corresponds to 13 March 2012. This is a good forecast, because all the predicted data fall inside the dotted tube. This suggests how close the system is adapted to the financial data. The value of ERR is quite small (0.17377).

In the analysed period (March–December 2012), there are four ERR significant jumps that occur after the following retrainings: 1717, 1739 (see Figure 7), 1761 and 1804. The biggest one is depicted in Figure 7, which represents the worst forecasting from the interval of Figure 5.

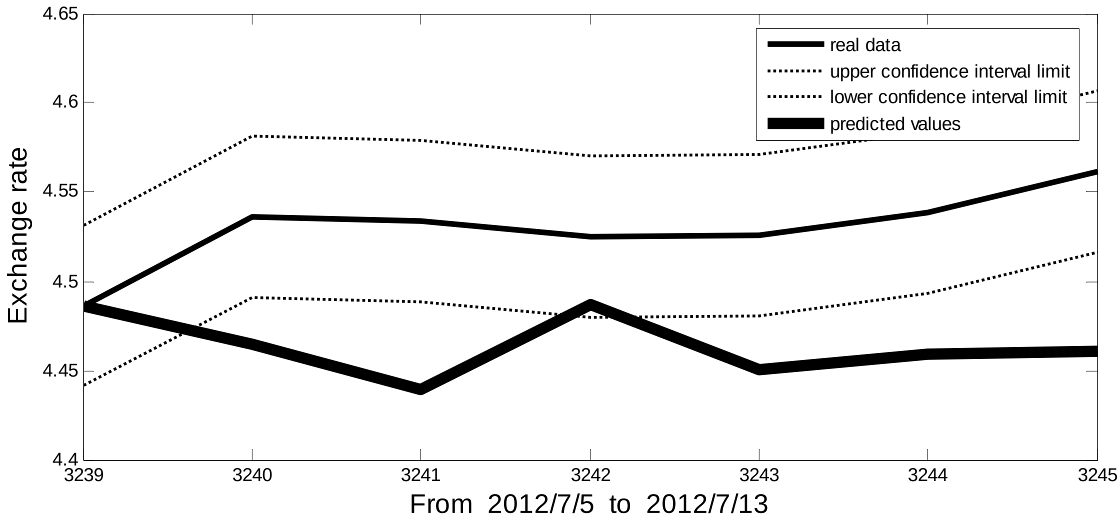

Figure 7: Data forecasting of the test interval after retraining 1739 (ERR=1.11144)

It can be noted that in all four above-mentioned cases (which are the worst in the period of March–December 2012), the prediction would still be within a 2% confidence interval. The forecasting system recovers very quickly; hence, after these jumps, all predictions fall within the confidence interval of 1%.

These observations are retrospectively more concluding when we look at the evolution of ERR. The graph of each weekly prediction (or rather 6 consecutive working days for the presented model) must be somehow correlated with the general one, of errors, from Figure 4 (or Figure 5). Together, this combination is more suggestive than individual forecasts.

The final predictions are not bad, as we can estimate from Figure 4. An illustrative example is the penultimate prediction, after the retraining 1843, which is depicted in Figure 8.

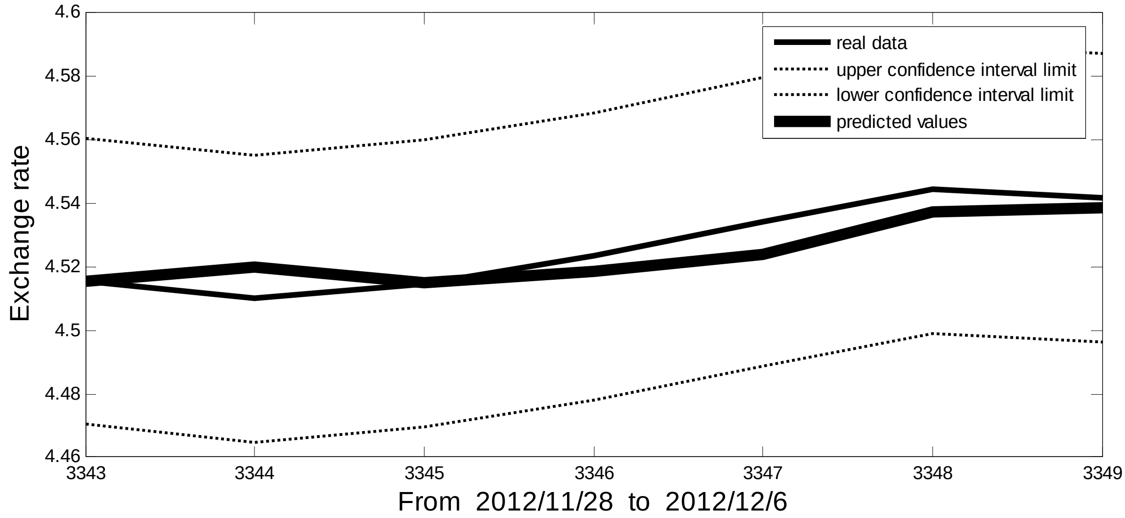

Figure 8: Data forecasting of the test interval after retraining 1843 (ERR= 0.08754)

4. Residual Analysis

In summary, the ANNs algorithm has provided forecasts concerning EX_RO for 6 successive days, each set containing 1845 positions (1499 observations were retained for the training process and 20 as post-sample checking data). The residuals of respective estimations (as algebraic differences against statistics) also appear in six variants: res1 for one-day ahead prediction, res2 for two-day ahead prediction,…, res6 for 6-day ahead prediction. As a global outlook, these can be observed in the Figure 9.

In all six series, the mean is actually situated in the proximity of zero (see Table 8), which is encouraging for ANNs applications.

Table 8: Descriptive statistics RES

	RES1	RES2	RES3	RES4	RES5	RES6
Mean	-0.00099	-0.00234	-0.00523	-0.00172	-0.00539	-0.00804
Median	-0.00025	-0.00067	-0.00395	0.00174	-0.0009	-0.00146
Maximum	0.32801	0.20228	0.52905	0.3832	0.34624	0.25255
Minimum	-0.10949	-0.19658	-0.36517	-0.35358	-0.42679	-0.54118
Std. Dev.	0.022981	0.035475	0.051334	0.058319	0.065914	0.070084
Skewness	1.459222	-0.45536	0.185154	-0.48228	-0.82522	-0.94139
Kurtosis	27.49339	6.678122	18.06372	8.455821	7.735071	8.207157
Jarque-Bera	46774.11	1103.77	17454.68	2359.781	1933.008	2356.939
Probability	0	0	0	0	0	0
Sum	-1.82074	-4.3251	-9.65615	-3.17597	-9.94667	-14.8407
Sum Sq. Dev.	0.973892	2.320571	4.859277	6.271611	8.011567	9.057254

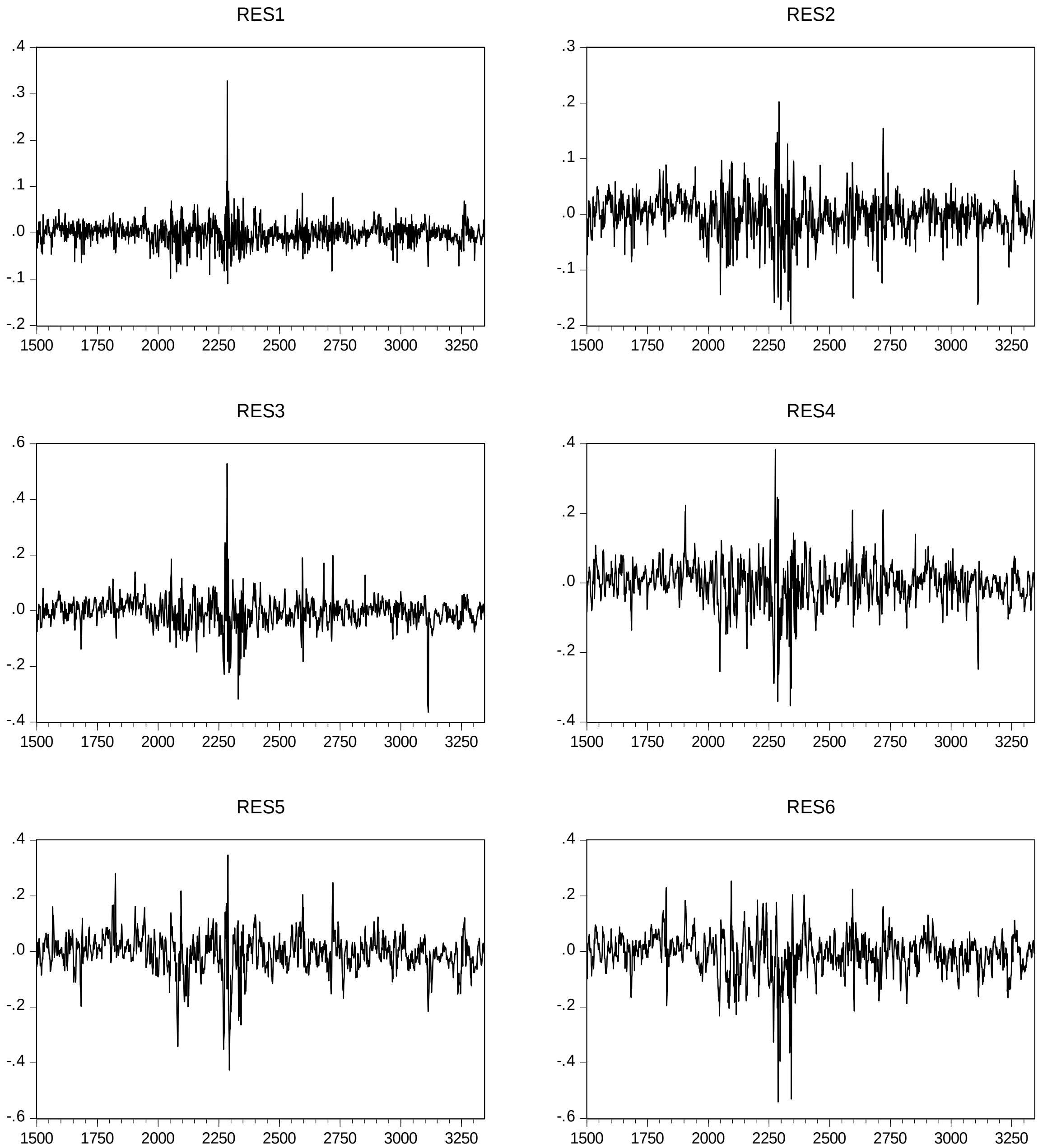

Figure 9: ANNs residuals

Nevertheless, in all the cases, the mean is negative, which can be interpreted as a systematic downwards bias (small, but is true).

The residuals have been defined relative to the statistical data, in module, resulting in the series rRES(i), again in six variants (i=1, 2,…, 6). In this form, the residuals become comparable (Table 9).

Table 9: Descriptive statistics rRES

	rRES1	rRES2	rRES3	rRES4	rRES5	rRES6
Mean	0.004072	0.006562	0.008795	0.010581	0.011995	0.013022
Median	0.002947	0.004807	0.006202	0.007451	0.008732	0.009246
Maximum	0.090386	0.05561	0.147779	0.10178	0.114329	0.147068
Minimum	2.34E-06	0	2.25E-06	9.35E-06	4.48E-06	0
Std. Dev.	0.004415	0.006403	0.009986	0.010857	0.012311	0.01279
Skewness	5.589806	2.318376	4.416204	2.814309	2.764273	2.573421
Kurtosis	85.83528	11.10436	39.86528	15.38116	14.58494	16.26725
Jarque-Bera	537100	6701.972	110474	14219.91	12667.14	15567.95
Probability	0	0	0	0	0	0
Sum	7.512293	12.10633	16.22754	19.5228	22.13102	24.02525
Sum Sq. Dev.	0.035944	0.075592	0.183885	0.217353	0.279476	0.30166

Therefore, the mean of the relative residuals increases, together with the length of the forecasting interval (from 0.004 for one-day ahead prediction to 0.013 in the case of 6-day ahead prediction). This can be considered as a normal behaviour of the computational algorithm. Furthermore, this variation takes place between adequate narrow limits.

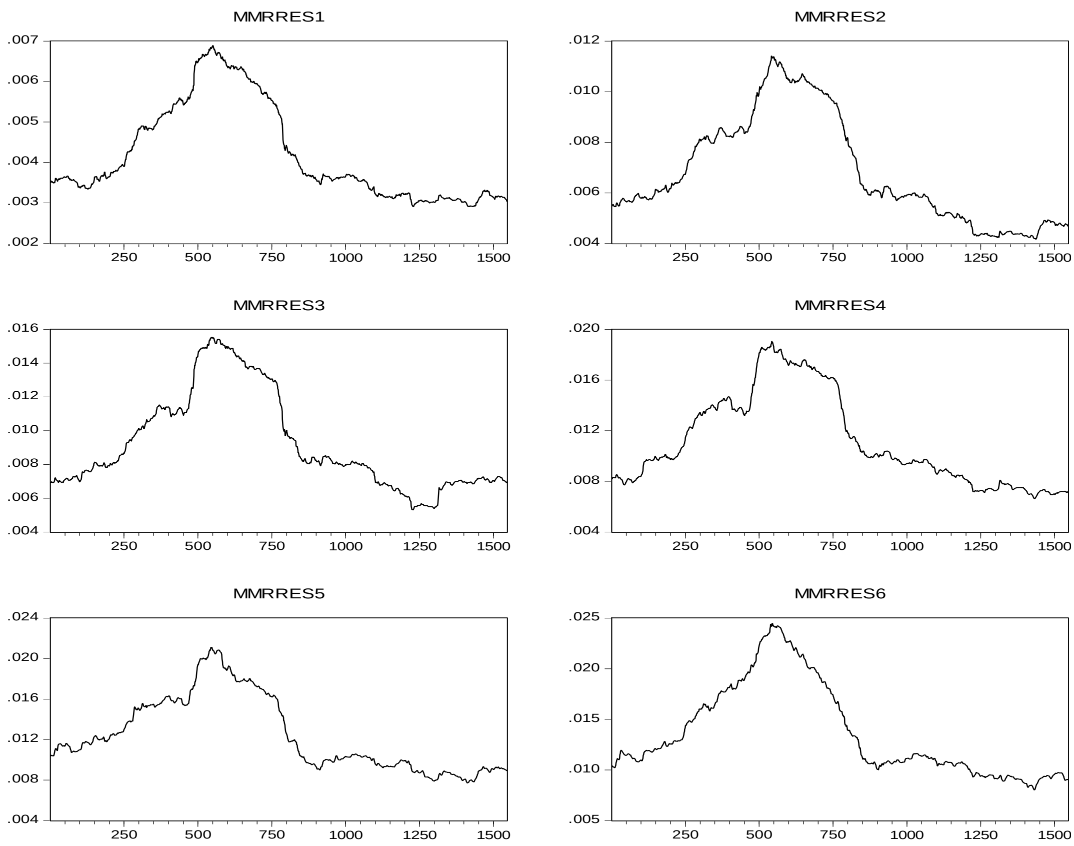

Figure 10: Mobile means of rRES (for 300 terms)

Taking into account the learning process, we should expect a decreasing temporal trend of rRES, which would be difficult to be deduced from the corresponding series as such. Consequently, these are transformed into mobile means of consecutive 300 terms (MMrRES). The Figure 10 describes them for all six variants.

Table 10: z-Statistic of BDS test for residuals

Dimension	Fraction of pairs	Fixed value	Standard deviations	Fraction of range
BDS Test for RES1				
2	22.55299	NA	26.12868	-0.04672
3	24.51712	NA	29.5683	-0.04987
4	25.65233	NA	33.08248	-0.05968
5	26.58106	NA	37.80618	-0.04876
6	28.17001	NA	44.75405	-0.05993
BDS Test for RES2				
2	41.60389	NA	55.20485	92.18502
3	43.83955	NA	63.87214	90.72842
4	45.16179	NA	74.79861	88.73167
5	46.82461	NA	89.36594	84.20693
6	49.04214	NA	109.7858	79.62752
BDS Test for RES3				
2	49.13069	583.5438	62.25767	275.048
3	50.42279	509.1095	70.43621	245.9386
4	51.48516	473.9656	80.52313	220.7317
5	53.50392	423.4376	95.00378	201.2854
6	56.26483	395.5743	115.0307	185.8641
BDS Test for RES4				
2	54.77547	NA	71.23487	297.6255
3	56.23451	NA	82.96674	266.1975
4	57.568	NA	99.41854	246.9494
5	60.15673	NA	124.2726	228.63
6	63.6482	-0.00616	159.9682	213.2487
BDS Test for RES5				
2	56.99519	NA	79.04328	175.1839
3	59.25116	NA	93.7597	156.7203
4	60.92699	NA	113.236	140.5381
5	63.54588	NA	142.0432	128.0749
6	67.31744	-0.00616	184.4871	118.3021
BDS Test for RES6				
2	59.60392	-0.08224	78.24798	-0.09652
3	61.68635	-0.10991	94.42745	-0.1298
4	64.00381	-0.13408	118.2112	-0.15551
5	67.6359	-0.15251	152.5637	-0.17748
6	72.45405	-0.16897	204.0329	-0.23889

Now, the picture seems conclusive, being concordant with the analysis developed in the previous section. Thus, during the most turbulent period of the global financial crisis, the predictive estimations of ANNs algorithm significantly worsened, after which, its performance visibly improved again.

It is interesting to mention that the effects of non-stationarity were absorbed by ANNs algorithm. The null hypothesis of unit root was rejected in all variants in which either ADF or PP tests were computed for all the residuals series. On the other hand, the situation is different in the case of serial correlation. Applied under the same conditions as those given in Table 3, the BDS test for residuals revealed the results presented in Table 10. Therefore, the presence of serial correlation in residuals cannot be rejected.

5. Concluding Remarks

Our application re-attests the opportunity to involve the ANNs in predictive estimations of exchange rate in an emergent economy, at least as a complementary algorithm. We outline 'complementary', because such a technique – despite its proven advantages – cannot completely surpass the computational problems induced by the noise in the data and the misspecified systems. The ANN procedure could not avoid the translation into residuals of the high serial correlation present in the primary database. Possible sources of this (at least partial failure) have to be hereinafter investigated.

The specification of input variables must be improved, searching adequate modalities to involve standard fundamentals in a model based preponderantly on high-frequency data. The modalities in which the technique as such is applied should also be taken into consideration. A special attention should be further paid to the ANN's topology, training/retraining processes and the sizes of training, testing and validation sets.

Certainly, further research in these fields could ameliorate the computational performances of ANNs in relatively 'cloudy' statistical environment as that of the economics.

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University of Turku
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