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The Effects of Economic Variables on Exchange Rate, Modeling and Forecasting: Case of Iran

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Abstract

This paper investigates the model estimation and data forecasting of exchange rate using artificial neural network. Recent studies have shown the classification and prediction power of the neural networks. It has been demonstrated that a neural network can approximate any continuous function. In this research, ANN is employed in training and learning processes and after modeling, the forecast performance is measured by making use of a loss function (RMSE). By sensitivity analysis, the importance and the weight of each economic variable on exchange rate such as consumer price index, old price, oil price and total value of export and import have been determined. The results show that Iran consumer price index is the most effective factor on exchange rate trend. In addition to, it is possible to estimate a model to forecast the value of exchange rate even by having access to a limited subset of data.

Keywords: forecasting exchange rate, artificial neural networks, consumer price index, gold price, oil price, export, import, sensitivity analysis

1. Introduction

Forecasting is a very important activity and essential factor in the financial markets, which is useful for various players like investors, academia, practitioners, regulators and policy makers. Forecasting with very week tools has an adverse effect on the economic development due to its negative effect on international trade and investment. Using a weak model to forecast will lead to taking a wrong judgment. For this reason forecasting is very important to all categories listed above.

Exchange rate is one of the most valuable parameters on governmental financial and monetary policies. So an accurate forecasting model for this variable has drawn much academic and decision maker's interest.

It is an established fact that increased volatility of a variable and using weak forecasting technique in the financial markets is harmful to economic development due to their adverse impact on international trade and foreign investment (Chang & Foo, 2002). Hence, forecasting a variable in the financial markets is a matter of imperative importance, especially in a country like Iran.

Classical statistical and econometric models used for forecasting in the field of financial time series fails to efficiently handle uncertainty nature of foreign exchange data series. Neural networks have the advantage that can approximate nonlinear function. An artificial neural network (ANNs), as an emerging discipline emulates the information processing capabilities of neurons of the human brain. It uses a distributed representation of the information stored in the network, and thus resulting in robustness against damage and corresponding fault tolerance (Shadbolt & Taylor, 2002). To develop a feed forward artificial neural network for forecasting exchange rate purpose, the specification of its architecture in terms of number of inputs, number of hidden layer, number of neurons and output is very important. In the last four or five decades many different non-linear models have been proposed in the literature to model and forecast exchange rates. ANNs are nowadays used in a large variety of modeling and forecasting problems.

In empirical studies, Kamruzzan and Sarker (2003) use ANNs to predict six currencies against the Australian dollar and comparison it to ARIMA model. They show that the ANNs outperformed the ARIMA model in every case for each of the six currencies. Rudra P. Pradhan (2010) employs Artificial Neural Network (ANN) to forecast foreign exchange rate in India during 1992-2009. Empirical results confirm that ANN is an effective tool to forecast the exchange rate. The results of Adam Stokes (2011) show that ANNs are able to deal with daily and weekly data as well as the nonlinearities in exchange rate movements. But Vincenzo Pacelli (2012) by empirically comparing mathematical models developed in his research, investigate that the ARCH and GARCH models, especially in their static formulations, are better than the ANN for analyzing and forecasting the dynamics of the exchange rates. Georgios Sermpinis et al. (2012) in their research has introduced a hybrid Neural Network architecture of Particle Swarm Optimization and Adaptive Radial Basis Function (ARBF-PSO), a time varying leverage trading strategy based on Glosten, Jagannathan and Runkle (GJR) volatility forecasts and a Neural Network fitness function for financial forecasting purposes. They believe that the ARBF-PSO architecture outperforms all other models in terms of statistical accuracy and trading efficiency for the three exchange rates. Akintunde Mutairu Oyewale (2013) in his study investigates the modeling, describing and forecasting of exchange rates of four countries using Artificial Neural Network. Results show that the ANN is a very effective tool for exchange rate forecasting of financial time series due to non-linearity, non-stationarity and high degree of noise. Present paper uses Artificial Neural Network as an alternative model for forecasting exchange rate in Iran in both technical and fundamental approaches.

2. Methodology

In this section, some useful methods are collected which are used to forecast economic variables. In this regard there are usually two approaches to forecast the future values of an exchange rate. The first one is technical which is based on past behavior of the variable. In this way we assume—which is basically true—the past values of the variable, contain mostly all of the information that are needed to forecast. So we do not want to detect the causal relationships between this variable and the other ones. Technical analysts usually record the historical data in charts and try to determine the most probable future values based on that history. ARIMA is an example of this approach.

In Fundamental approach the forecast is based on an estimated model which contains the relations between the variable of interest and other economic variables. Purchasing power parity, Monetary and Portfolio balance models are some examples of it.

3. A Brief Note on Artificial Neural Networks

Basically artificial neural network is a tool for modeling unknown, complex or ambiguous process or systems. In such cases there is no full description of effective relationship between inputs and outputs or complexity of variables are so high that modeling is difficult via common approaches. Recently neural networks have been used for modeling non-linear economic relationship because of its ability to extract complex non-linear and interactive effects. Neural networks are a class of non-linear model that can approximate any non-linear function to an arbitrary degree of accuracy and have the potential to be used as forecasting tools in many different areas (Oyewale, 2013). The ability to process information and extract hidden knowledge from them and then generalize it to unsighted data, has turned the neural networks to powerful computational methods for modeling.

The inherently nonlinear structure of neural networks is useful for capturing the complexity underlying relationship in many real world problems It is a more reliable methods for forecasting applications because not only that they can find linear structure in a problem they can also model linear processes. However, the weakness or limitations of neural networks in any study includes: Black-box problem which is a situation where all information are contained in weight matrices for their output and hidden layers, and these do not make apparent identities of salient predictor variables. This is in contrast with parametric variables which do not only identify influential variables but also provides the degree of their contributions. To overcome this problem, sensitivity analysis can be used to determine the effect and contribution of each input variable in output variable.

Usually there are some steps on designing a neural network which can briefly reviewed as: neural network type selection, input variable selection, data collection, data processing, dividing data to training, testing and validation subsets, selection of the number of hidden layers, hidden neurons and output neurons, selection of transfer functions, choosing of evaluation criteria and setting the of number of training iteration and choosing training algorithm.

Obviously there are a lot of different network parameters, and the configurations must be chosen based on the application and conditions. So determination of a good configuration for a neural network is a very complex and time consuming job and need some degree of experience and knowledge. But the good news is after a proper network selection, it can be used in same problem but different data sets.

In very first and important step of every neural network, it should be trained. For this purpose usually the whole data set must be divided to training and testing subsets (or training, cross validation and testing subsets). Training subset is used for learning while test one is used for evaluation of network generalization ability in the end of training.

Cross validation test which usually is used in sophisticated and complex training methods, is a measure of network training accuracy in each iteration while network is being trained. Although it may add some more computational cost, it is able to find the correct direction of learning and lead the network training method to a better final point. Selection of good samples to add to cross validation and test subsets has a vital effect on learning accuracy of network. It’s a common mistake to use the last x percent of data as a test subset. This kind of mistake has a huge effect in long-term time series with high dynamic volatilities and the effect in short-term time series is not neglect able.

The testing subset´s size is ranging from 10% to 30% of the data set. From empirical results it can be said that as a rule of thumb one hidden layer is enough to approximate any continuous function and using more than 2 hidden layers will not add any improvement to the network results.

In non-linear and complex situations, the problem of trapping in local minimums of error arises. In these cases by adding some more computational cost -usually a lot more-, it’s possible to employ genetic search or optimization algorithms as a natural way of finding global minimum of error to reach the lowest possible amount of error.

Other parameters usually must be chosen via try and error or heuristically.

4. Modeling by Neural Network

In this section the neural network is used to estimate a model to forecast exchange rate variable based on other economic variables. It is obvious that this variable is influenced by many qualitative and quantitative economic variables. Input variables are monthly data values of gold price, oil price, consumer price index in Iran and America and total value of export and import over the period Jan 2003 to June 2013.

By comparing the historical data of Iran and USA CPIs, the maximum of Iran CPI is 6.5 times of its base value while it is 1.3 for USA one. Hence if the network had been trained just based on price index of two countries, the exchange rate would had been very greater than 3 times in the end while the real factor is about 3, so it means that other variables have been involved. Hence the addition of some other variables to network inputs is a logical decision. Here global gold price, Iran's crude oil price and total value of export and import are chosen to add to network. Of course there are many other probably effective variables such as monthly GDP, foreign borrowing, future expectations, economic policies, balance of payments, economic crises and sanctions which are necessary to add, but because of inaccessibility to historical monthly data, they excluded from the network.

The network is multilayer perceptron with one hidden layer again but without memory elements. Because in this approach the focus is on the relation between different variables, in order to simplify the situation and have a time independent series, arrangement of data is changed in a random basis. As the time based information is loosed, there is no need to have memory element here.

Training is unsupervised and the method of training is back-propagation of errors based on gradient decent algorithm again. Basically because of the nature of gradient descent method, the probability of being trapped in a local minimum is very high. While the purpose of training is to find the global minimum. In order to have a more optimized network, avoiding of entrapment in local minimums and achieving the lowest error, a genetic search algorithm is used. Genetic algorithms act based on natural selection rule which means strong options will be transferred to next generation and the weak ones be eliminated. There are different genetics search methods in neural networks; here Generational G.A method is used. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. In a genetic algorithm, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible.

Here, the population parameter value is set to 25 and the number of generation's parameter is set to100. The results are shown in the following table.

Table 1. The comparison of the network's result to real value

	Network inputs						Real value	Network output		Network output without USA price index	
Date	Iran price index	USA price index	Oil price ($)	Gold price ($)	Total import ($)	Total export ($)	Exchange rate (Rial)	Exchange rate (Rial)	Absolute error	Exchange rate (Rial)	Absolute error
8804	255.12	117.59	64.79	930.73	3,984,748,191	1,420,765,403	9941.19	9621.53	319.66	10162.38197	221.19
8910	305.30	121.07	91.64	1375.74	5,991,737,036	2,258,161,829	10835.50	10431.72	403.78	10126.96982	708.53
8601	172.44	112.76	62.29	680.01	3,507,928,974	1,097,680,714	9243.81	9256.41	12.60	9138.16408	105.64
8512	169.61	112.42	56.97	655.89	3,476,887,172	1,083,076,009	9240.31	9276.24	35.93	9070.085592	170.22
9112	550.88	127.24	108.24	1588.93	4,840,747,634	3,119,326,204	35985.00	36845.70	860.70	36041.43023	56.43
9204	606.71	127.78	103.06	1263.21	3,869,885,559	2,560,819,813	33030.65	30165.66	2864.98	37783.17079	4752.53
8302	121.91	103.07	34.98	383.95	2,327,655,654	505,024,175	8561.13	8464.35	96.78	8610.27944	49.15
8203	107.77	100.27	26.77	356.91	1,916,885,934	419,241,427	8149.77	8204.76	54.99	8539.858046	390.08
9010	367.84	124.65	110.61	1616.72	5,628,482,538	2,604,408,651	16266.33	13814.52	2451.82	14502.24683	1764.09
8303	123.67	103.45	35.49	391.78	2,388,874,911	507,789,121	8590.74	8501.54	89.20	8621.816552	31.07
9009	363.25	124.39	107.80	1680.50	5,080,372,504	2,879,528,007	13784.33	13765.02	19.31	14588.22763	803.89
8510	165.72	111.41	52.32	630.35	3,424,484,264	1,054,087,975	9224.17	9301.17	77.00	8999.368492	224.80
8710	244.52	116.07	39.73	839.96	4,604,535,194	1,481,828,270	9890.20	9960.54	70.34	9918.731996	28.53
9107	462.19	126.85	109.16	1764.36	5,264,642,851	3,047,826,864	30963.67	28765.18	2198.49	28206.42318	2757.24
8206	108.83	101.37	26.83	378.86	1,989,279,254	451,729,283	8340.65	8254.48	86.17	8547.583553	206.94
8508	158.66	110.62	54.89	626.83	3,382,926,184	1,024,386,844	9218.13	9289.66	71.53	8972.779705	245.35
8712	244.52	116.39	42.94	937.81	4,670,167,270	1,527,798,102	9791.97	10006.32	214.36	10050.82669	258.86
8807	259.01	118.56	69.63	1030.61	4,159,638,390	1,847,500,855	9888.57	10030.03	141.47	9733.490926	155.08
8803	254.77	117.63	66.14	953.55	4,729,787,670	1,643,414,249	9732.39	10009.80	277.42	10176.02411	443.64
8802	250.53	116.65	53.40	909.77	4,293,162,530	1,662,759,597	9860.19	9993.66	133.46	9883.278962	23.09
8112	103.18	100.71	31.44	341.56	1,856,265,789	384,035,734	8047.83	8114.23	66.40	8539.938415	492.11
9102	408.13	125.22	112.51	1614.65	5,090,648,209	2,521,433,743	17162.58	20318.98	3156.40	19684.41738	2521.84
8610	197.53	116.20	89.81	887.78	3,918,780,510	1,240,309,816	9292.20	9105.04	187.16	9358.041644	65.84
8408	140.64	108.49	52.06	476.67	3,208,129,084	765,616,528	9067.03	9154.79	87.75	8810.57625	256.46
9203	598.23	127.57	100.88	1380.31	3,428,365,046	2,639,506,181	35929.03	34358.96	1570.07	37403.09444	1474.06
Based on research's result											

The used data in this network are Iran pride index is taken from central bank of Iran, USA price index and gold price from Bureau of labor statistics, price of crude oil from Opec site, total export and import from custom site. It should be noted that because of inaccessibility to monthly data of total export and import from 1381 to 1387, annual data has turned monthly by Eviews software and Cubin spline curves.

According to above table, the amount of estimated exchange rate is very close to real ones, so the result of network is highly accurate. Although the differences in some cases are due to not access to all of effective variables, the results are satisfying and it is one of the neural networks advantages.

5. Sensitivity Analysis in the Fundamental Network

Sensitivity analysis is the study of how the uncertainty in the output of a mathematical model or system can be apportioned to different sources of uncertainty in its inputs (Saltelli et al., 2008). Quite often, some or all of the model inputs are subject to sources of uncertainty, including errors of measurement, absence of information and poor or partial understanding of the driving forces and mechanisms. This uncertainty imposes a limit on our confidence in the response or output of the model. Further, models may have to cope with the natural intrinsic variability of the system, such as the occurrence of stochastic events (Der Kiureghian et al., 2009).

There are many different methods of sensitivity computations which usually be chosen by application, here a neural network adapted method is used.

Sensitivity of exchange rate to corresponding network inputs is computed. The results are given in the following table. It should be noted that the changes applied to standardized variables and the sensitivity values are in percent such that the sum of the values of each column is 100.

Here, sensitivity is computed than to 0.01, 0.05, 0.1 and 0.5 changes.

Table 2. The result of exchange rate sensitivity to input variables changes

	0.01	0.05	0.1	0.5
Iran price index	14.94	15.00	15.08	15.67
USA price index	32.12	32.00	31.84	30.58
Oil price	3.03	2.99	2.94	2.63
Gold price	17.93	17.96	18.00	18.28
Total import	11.47	11.50	11.54	11.83
Total export	20.51	20.55	20.60	21.00
Based on research results				

According to the high sensitivity of network to the USA price index, it sounds that it's a fake mathematic sensitivity because of small range of its changes. In other words according to 30 percent changes in whole data, the network hasn't trained by the out of this range data and so is very sensitive to its changes. In this regard other statistics seem illogical. To study more, USA's CPI variable has deleted, the network trained again and the sensitivity computed. The result is shown in the table 3.

Table 3. The result of exchange rate sensitivity to input variables after omitting USA price index

	0.01	0.05	0.1	0.5
Iran price index	58.51	58.69	58.81	59.84
Oil price	9.63	9.58	9.49	9.04
Gold price	13.65	13.79	14.08	15.55
Total import	6.95	6.87	6.76	6.28
Total export	11.25	11.07	10.85	9.29
Based on research results				

Due to the results, it is obvious that after omitting USA price index absolute value of error has increased. RMSE has risen from 1144.38 to 1326.41. Hence despite it was sounded that this variable is fake, the presence of it is necessary because of reducing the error.

Based on these statistics, Iran price index, gold price, total export, oil price and total import are effective in order on exchange rate trend in Iran.

Also the model is sensitive to gold price more than oil price which is unimaginable in first sight. It may be due to the lack of their weights in the network. It seems if the monthly sells of oil and the import and export of gold historical data were accessible to apply to the network, more accurate and understandable results would be obtained. In other hand, gold price may really have more contribution on exchange rate than crude oil. It may be due to some indirect effects.

6. Summary and Conclusions

Modelling and forecasting of exchange rate are usually carried out by the regression techniques in economic researches. One shortcome of these techniques is data analyzed often exhibit some degrees of non-linearity that cannot be captured by a linear model. In this sense, Artificial Neural Network (ANN) which is highly flexible in estimation of non-linear models is a good candidate as an alternative.

The trend of variables has been shown in observation time.

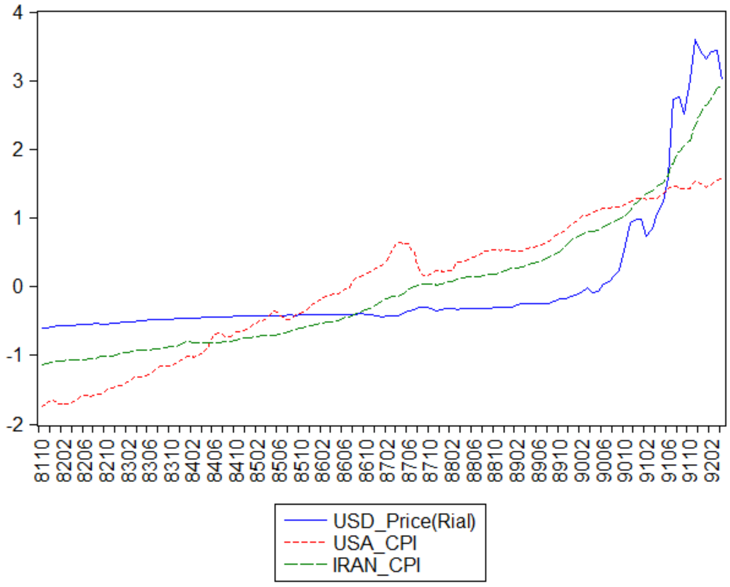

Figure 1. The trend of exchange rate, CPI in Iran & America

Based on the findings of the research Iran price index in the end of this period of time, is more than 650 percent than beginning while this index has increased just about 30 percent in USA. Given the fact exchange rate has become triple, in addition to these two variables, other economic variables are effective and their existence is necessary.

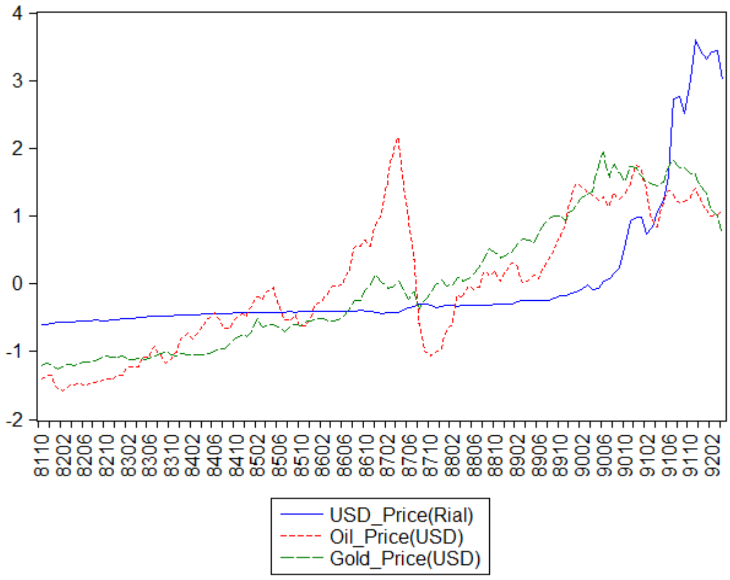

Figure 2. The trend of USD, oil and gold prices

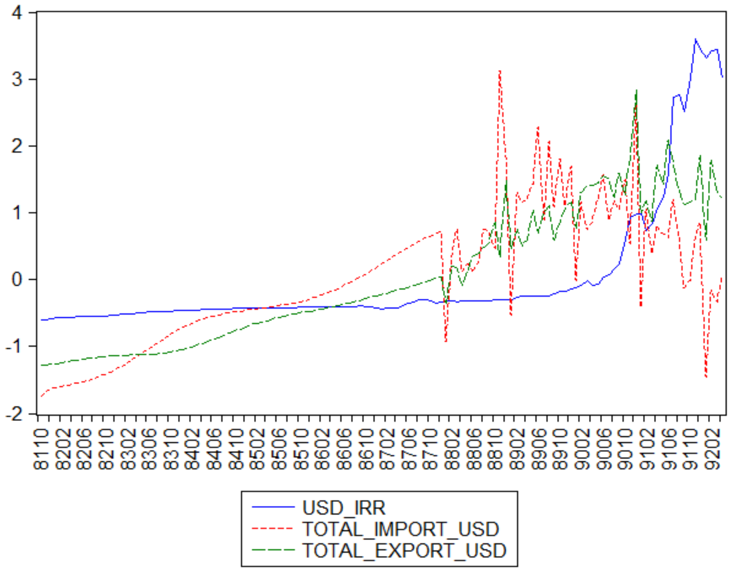

Figure 3. The trend of USD, total import and export

So adding input variables of gold and oil price, total export and import has been logical. Of course in case of access to monthly data of some other variables like GDP, balance of payment, stock index and liquidity, the result would be closer.

The results of network shows that while the overall error is very low and in most of the dates the network output is very close to real values, in some other ones it's obvious that the error quantity is high, which can be explained mostly by data limitation. However overall network performance indicates the ability of estimation of complex models even by access to a limited subset of data.

It should be noted that because of data limitation, reaching to a global minimum of error is very hard and in this kind of situations genetic based search algorithms are very effective.

And the last point is the importance of sensitivity analysis of the trained network to the input variables. While it's obvious if the play range of an input variable is small, the sensitivity to that variable is so high, in this situation, sensitivity analysis can help to make a quantitative big number for that which will be a fake high mathematical sensitivity. In contrary, when there's a very low sensitivity to an input variable, which means the given variable has a low contribution to model, this analysis produce a very small number, and it can be interpreted as a noise or error in computation. Finally in a situation that a variable really has an important effect on model, this analysis will make a relatively acceptable number. Based on the resulted number any network designer is able to decide to include such variable to network or exclude it or to guess if he needs to add another missing variable to network. Of course in selection of input data, it's necessary to note to the value of error, too. So USA price index is an important variable in this model.

So this approach can help to find and delete none significant parameters from the model and purify it. In the end, the weight and importance of each input variable is found. Based on the result, Iran price index, gold price, total export, oil price and total import are effective in order on exchange rate trend in Iran.

So policy makers are able to manage and control variables effective on exchange rate according to the contribution of them.

References

Chang, C. W., & Foo, C. (2002). Forecasting the Volatility of Stock Indices: Using Neural Networks. *Proceedings of Asia Pacific Economics and Business Conference, 2*, 919-928.

Der Kiureghian, A., & Ditlevsen, O. (2009). Aleatory or epistemic? Does it matter? *Structural Safety*, *31*(2), 105-112. http://dx.doi.org/10.1016/j.strusafe.2008.06.020

Kamruzzaman, J., & Sarker, R. (2003). Comparing ANN based on models with ARIMA for prediction of exchange rates. *ASBOR Bulletin*, *22*(2).

MutairuOyewale, A. (2013). Evaluation of artificial neural networks in foreign exchange forcasting. *American Journal of Theoretical and Applied Statistics*, *2*(4), 94-101. http://dx.doi.org/10.11648/j.ajtas.20130204.11

Pacelli, V. (2012). Forecasting Exchange Rates: A comparative analysis. *International Journal of Business and Social Science*, *3*(10), 145-156.

Pradhan, R. (2010). Forecasting exchange rate in India: An application of artificial neural network model. *Journal of Mathematics Research*, *2*(4), 111-117. http://dx.doi.org/10.5539/jmr.v2n4p111

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., … Tarantola, S. (2008). *Global Sensitivity Analysis. The Primer*. John Wiley & Sons.

Sermpinis, G. (2012). Forecasting foreign exchange rates with daptive neural networks using radial-basis functions and particle swarm optimization. *Innovative Applications of O.R.*, *12*.

Shadboth, J., & Taylor, J. (2002). *Neural networks and the financial markets*. Springer publishing company Limited.

Stokes, A. (2011). *Forecasting exchange rates using neural networks: a traders approach.* Student Theses & Publication.

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