Forecasting TRY/USD Exchange Rate with Various Artificial Neural Network Models

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***Abstract* - Exchange rate forecasting is one of the most common subjects among the forecasting problem field. Researchers and academicians from many different disciplines proposed various approaches for better exchange rate forecasting. In recent years, for solving the stated forecasting problem artificial neural networks have become successful tool to obtain solutions. Many different artificial neural networks have been used, developed and still developing for even better and trustable forecasts. In this study, TRY/USD exchange rate forecasting is modeled with different learning algorithms, activations functions and performance measures. Various Artificial Neural Network (ANN) models for better forecasting were investigated, compared and the obtained forecasting results interpreted respectively. The results of the application show that Variable Learning Rate Backpropagation learning algorithm with tan-sigmoid activation function has the best performance for TRY/USD exchange rate forecasting.**

***Keywords* - Activations functions, artificial neural networks, Exchange rates, Forecasting, Learning algorithms, Performance measures, TRY/USD.**

1. Introduction

Forecasting future behavior of exchange rates is one of the most important tasks for economical decision makers. Due to intensive uncertainty of exchange rates, this important task becomes very difficult to perform.

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It's been pointed out in many studies in this field that discouragement after the studies [9],[10], where is stated that simple random walk is the best economic model for exchange rate. However, authors' investigation was relied on linear assumption thus the results naturally showed that simple random walk is superior. According to uncertain and nonlinear structures of exchange rates, parametric approaches are limited to perform satisfactory results.

By the development of ANN, researchers and investors are hoping that they can solve the mystery of exchange rate predictions. It has been proved that the ANN model, which is a type of non-linear model, is a strong alternative in the prediction of exchange rates. ANN is a very suitable method to find correct solutions especially in a situation which has complex, noisy, irrelevant or partial information [5].

Along with ANN there are many approaches such as heuristic algorithms, soft computing methods, fuzzy inference systems and others for modeling. Conventional nonlinear techniques, such as Markov switching models which have been used for modeling. However, generally the results suggest that conventional nonlinear modeling does not improve exchange rate forecasts [4].

The main purpose of this study is to compare different learning algorithms, activations functions and performance measures for forecasting models of the TRY/USD exchange rate time series. In the next section, we introduce the components of ANN and exchange rates. Section 3 gives the properties of the Feed Forward Neural Networks (FNNN). Section 4 reports the information for exchange rates data and the results of the application. Finally, conclusions are expressed in Section 5.

2. Components of ANN

As an exchange rate forecasting tool, ANN is one of the most popular approaches among similar research fields. Learning ability is the most important characteristic of ANN which allows learning from examples, experiences, patterns, functional relation mapping and so on. Learning algorithms make this process occur and the widely preferred popular algorithm called Back Propagation (BP) was introduced by Werbos [13]. There are many BP algorithms such as Levenberg-Marquadt, BFGS Quasi-Newton, Resilient Backpropagation, Scaled Conjugate Gradient and many more in literature.

Activation functions are major parameters of ANN which allows nonlinear mapping within data. Sigmoidal functions are the most common functions because of their shape. Also, there are some modified activation functions in the literature to conjugate different functions' advantages together such as SigHyper introduced by [1].

Architecture is another major parameter of ANN. Various types of architectures can be found in literature. For forecasting tasks, the Feed Forward Neural Networks (FFNN) with one hidden layer is sufficient and widely used by authors in this field. As one of the first important studies of ANN, [6],[7] are designed FFNN in their study for time series forecasting.

In paper [12] are compared forecasting performances for GBP, German mark and JPN. Authors in [15] and [16] evaluate British Pound/US Dollar exchange rate forecasting performance by the effects of different parameters of ANN. In paper [5] are employed ANN to TL/US Dollar exchange rate to find the best model for forecast accuracy. In paper [8] are searched efficient ANN models for prediction of exchange rates. In paper [14] authors utilized BP neural network for forecasting Chinese currency RMB. In work [2] are compared UK/US exchange rate forecasting performance of linear and nonlinear models. In work [4] are explored ANN performance of USD/EUR, JPN/USD, USD/GBP exchange rate series prediction.

Another important component of ANN modeling is performance measuring. Unlike parametric approaches and the same as all nonparametric approaches, ANN also has the disadvantage of giving the best model for every case. There is no certain way to obtain the best resulted ANN model. In literature, the most common and accepted way is trial and error method by out of sample performance of models. This method is data-aimed by the nature of approach and results cannot be generalized and also the applications must be utilized again for every different data.

3. Feed Forward Neural Networks

FFNN is a type of multi-layer perceptron which has interconnection between all neurons in a network and unlike different types of multi-layer perceptron such as recurrent networks, FFNN has no loops or circles within the architecture and signal flows through input layer to output layer in one direction. A FFNN structure can be seen in Figure 1.

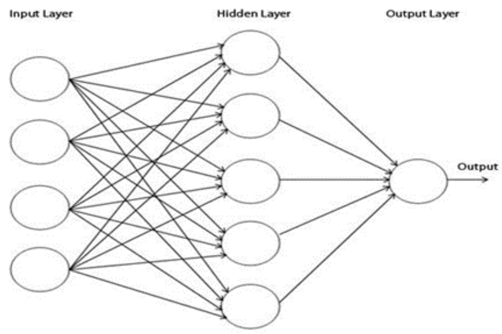

Fig. 1. A FFNN structure

In this study, the data contains univariate time series, thereby FFNN has only one neuron in output layer. Learning process can be described as finding the best weights between the layers. For this study, the training process was carried out with Levenberg-Marquardt Backpropagation, BFGS Quasi-Newton, Scaled Conjugate Gradient, Conjugate Gradient with Powell/Beale Restarts, Fletcher-Powell Conjugate Gradient, Polak-Ribiére Conjugate Gradient, One Step Secant, Variable Learning Rate Backpropagation learning algorithms.

Activation functions provide the non-linear mapping between input and output. The performance of networks depends on the proper choice of activation function. In general, the activation function introduces a degree of the non-linearity that is valuable in most of the artificial neural networks applications. In this study, tan-sigmoid and log-sigmoid transfer functions were used as activation functions in hidden layers and linear function in output layers for comparing ANN models.

Determining the best architecture of ANN is too important issue in the applications [3]. Every performance measure assesses forecasting error from different aspects and various model selection criteria have been used for determining the best architecture of ANN. All performance measures used in this study can be seen in six subsections as absolute, percentage, symmetric, relative, scaled and others due to high number of measurements. Each table of subsections is shown below.

Table 1. Model selection criteria based on absolute errors.

Name of Criteria	**Formula**
Mean Absolute Error	MAE = $mean_{i=1,n}\|e_i\|$
Median Absolute Error	MdAE = $median_{i=1,n}\|e_i\|$
Geometric Mean Absolute Error	GMAE = $gmean_{i=1,n}\|e_i\|$
Mean Square Error	MSE = $mean_{i=1,n}(e_i^2)$
Root Mean Square Error	RMSE = $\sqrt{mean_{i=1,n}(e_i^2)}$
Fourth Root Mean Quadrupled Error	R4MS4E = $\sqrt[4]{mean_{i=1,n}(e_i^4)}$

Table 2. Model selection criteria based on percentage errors.

Name of Criteria	**Formula**
Mean Absolute Percentage Error	MAPE = $mean_{i=1,n}\|p_i\|$
Median Absolute Percentage Error	MdAPE = $median_{i=1,n}\|p_i\|$
Root Mean Square Percentage Error	RMSPE = $\sqrt{mean_{i=1,n}(p_i^2)}$
Root Median Square Percentage Error	RMdSPE = $\sqrt{median_{i=1,n}(p_i^2)}$

Table 3. Model selection criteria based on symmetric errors.

Name of Criteria	**Formula**
Symmetric Mean Absolute Percentage Error	SMAPE = $mean_{i=1,n}(s_i)$
Symmetric Median Absolute Percentage Error	SMdAPE = $median_{i=1,n}(s_i)$

Table 4. Model selection criteria based on relative errors.

Name of Criteria	**Formula**
Mean Relative Absolute Error	MRAE = $mean_{i=1,n}\|r_i\|$
Median Relative Absolute Error	MdRAE = $median_{i=1,n}\|r_i\|$
Geometric Mean Relative Absolute Error	GMRAE = $gmean_{i=1,n}\|r_i\|$

Table 5. Model selection criteria based on scaled errors.

Name of Criteria	**Formula**
Mean Absolute Scaled Error	MASE = $mean_{i=1,n}\|sc_i\|$
Root Mean Square Scaled Error	RMSSE = $\sqrt{mean_{i=1,n}({sc_i}^2)}$

Table 6. Model selection criteria based on various errors.

Name of Criteria	**Formula**
Akaike Information Criteria	AIC = $log\left(\frac{\sum_{t=1}^{n}(y_t-\check{y}_t)^2}{n}\right)+\frac{2*m}{n}$
Bayesian Information Criteria	BIC = $log\left(\frac{\sum_{t=1}^{n}(y_t-\check{y}_t)^2}{n}\right)+\frac{m*\log(n)}{n}$
Nash Sutcliffe Efficiency	NS = $1-\frac{\sum_{t=1}^{n}(y_t-\check{y}_t)^2}{\sum_{t=1}^{n}(y_t-\bar{y})^2}$

In Table 6, parameter m is equal to the total number of weights in ANN. As seen above, each model selection criteria has advantages and disadvantages. It can be said that each measure based on mean has the same disadvantage as having high influences for outliers. In addition, it can be said that each measure based on median has the same disadvantages as longer time calculation if data set is large. AIC and BIC penalize the models with much parameters, so they may be over penalized because ANN consists of many parameters.

4. Application

The TRY/USD exchange rate data has been taken from the official website of the Central Bank of the Republic of Turkey, http://evds.tcmb.gov.tr/. Time series contains weekly data from January 2010 to April 2016 and consist of 331 observations. Graph of the data can be seen in Figure 2.

The first 281 observations of data were used for training and the last 50 observations as 15% of the data was used for testing. The training set was used for ANN model development and the test set was used to compare model selection criteria. Predicted values obtained from testing were compared with real values along the performance measures to find the best ANN model.

Obtained results consist of 8 different learning algorithms with 2 different activation functions and 21 different performance measures. Total number of 336 different ANN models has been achieved. It can be seen from all tables that because ANN has high number of parameters, AIC and BIC leads to over penalizing the model for almost every situation. This shows that these in-sample performance measures are not suitable for out-of-sample forecasting. In paper [11] is also stated the same conclusion.

Generally, all models give satisfying forecasts when comparing the actual value of 2.83596. However, in terms of consistency and overall results it shows that Variable Learning Rate Backpropagation learning algorithm with tan-sigmoid activation function gives the same architecture as the best models for all performance measures except AIC and BIC.

Fig. 2. Graph of TRY/USD exchange rate weekly

5. Conclusions

This paper aims to find the best model from the different ANN models obtained by using different major parameters for forecasting TRY/USD exchange rate time series. The results of the application showed that Variable Learning Rate Backpropagation learning algorithm with tan-sigmoid activation function has the best performance for forecasting TRY/USD exchange rate. However, there are still many things that have to be explored and investigated about the behaviors of different parameters in ANN.

Table 7. Best models selected by Levenberg-Marquadt BP and BFGS Quasi-Newton learning algorithms.

	Levenberg-Marquadt BP					
	Tan-sigmoid			**Log-sigmoid**		
	Model	**Error**	**Forecast**	**Model**	**Error**	**Forecast**
'AIC'	1-1-1	-7,40635	2,83614	2-1-1	-7,40465	2,82297
'BIC'	1-1-1	-7,32987	2,83614	1-1-1	-7,32795	2,82785
'GMAE'	5-1-1	0,00927	2,82927	4-1-1	0,00910	2,81940
'GMRAE'	5-1-1	0,00926	2,82927	4-1-1	0,00909	2,81940
'MAE'	3-1-1	0,01749	2,82415	3-1-1	0,01746	2,82549
'MAPE'	3-1-1	0,01981	2,82415	3-1-1	0,01979	2,82549
'MASE'	12-6-1	0,54007	3,02368	11-4-1	0,55213	2,78824
'MdAE'	1-3-1	0,01152	2,82502	10-1-1	0,01261	2,80303
'MdAPE'	1-3-1	0,01344	2,82502	12-2-1	0,01298	2,80714
'MdRAE'	1-3-1	0,01156	2,82502	11-1-1	0,01239	2,79277
'MRAE'	3-1-1	0,01732	2,82415	3-1-1	0,01731	2,82549
'MSE'	3-2-1	0,00053	2,82555	3-2-1	0,00052	2,83139
'MSMAPE'	3-1-1	0,01994	2,82415	3-1-1	0,01990	2,82549
'NS'	2-3-1	-99,89484	2,82725	2-3-1	-99,89372	2,83033
'R4MS4E'	1-1-1	0,03068	2,83614	1-3-1	0,03027	2,84545
'RMdSPE'	1-3-1	0,01345	2,82502	12-2-1	0,01298	2,80714
'RMSE'	3-2-1	0,02292	2,82555	3-2-1	0,02286	2,83139
'RMSPE'	3-2-1	0,02620	2,82555	3-2-1	0,02611	2,83139
'RMSSE'	8-9-1	0,82976	2,95317	5-11-1	0,80199	2,80253
'SMAPE'	3-1-1	0,01994	2,82415	3-1-1	0,01990	2,82549
'SMdAPE'	11-2-1	0,01339	2,80311	12-2-1	0,01290	2,80714
	BFGS Quasi-Newton					
	Tan-sigmoid			**Log-sigmoid**		
	Model	**Error**	**Forecast**	**Model**	**Error**	**Forecast**
'AIC'	2-1-1	-7,40460	2,82297	2-1-1	-7,40841	2,82331
'BIC'	1-1-1	-7,31178	2,83773	1-1-1	-7,32555	2,83658
'GMAE'	2-1-1	0,00946	2,82297	2-1-1	0,00951	2,82331
'GMRAE'	2-1-1	0,00945	2,82297	2-1-1	0,00949	2,82331
'MAE'	3-1-1	0,01746	2,82549	2-2-1	0,01755	2,82466
'MAPE'	3-1-1	0,01979	2,82549	2-2-1	0,01990	2,82466
'MASE'	9-3-1	0,56789	7,28046	2-2-1	0,62959	4,01557
'MdAE'	3-1-1	0,01281	2,82549	6-1-1	0,01337	2,81839
'MdAPE'	3-1-1	0,01417	2,82549	4-1-1	0,01479	2,82507
'MdRAE'	3-1-1	0,01294	2,82549	6-1-1	0,01341	2,81839
'MRAE'	3-1-1	0,01731	2,82549	2-2-1	0,01739	2,82466
'MSE'	3-1-1	0,00052	2,82549	5-1-1	0,00053	2,83087
'MSMAPE'	3-1-1	0,01990	2,82549	2-2-1	0,02002	2,82466
'NS'	3-1-1	-99,89553	2,82549	5-1-1	-99,89473	2,83087
'R4MS4E'	3-2-1	0,03055	2,83400	3-1-1	0,03062	2,83808
'RMdSPE'	3-1-1	0,01417	2,82549	4-1-1	0,01480	2,82507
'RMSE'	3-1-1	0,02291	2,82549	5-1-1	0,02300	2,83087
'RMSPE'	3-1-1	0,02619	2,82549	5-1-1	0,02631	2,83087
'RMSSE'	10-1-1	0,88328	2,80972	10-1-1	0,88339	2,81017
'SMAPE'	3-1-1	0,01990	2,82549	2-2-1	0,02002	2,82466
'SMdAPE'	3-1-1	0,01417	2,82549	4-1-1	0,01468	2,82507

Table 8. Best models selected by Scaled Conjugate and Fletcher-Powell Conjugate Gradient learning algorithms.

Scaled Conjugate Gradient						
	Tan-sigmoid			Log-sigmoid		
	Model	**Error**	**Forecast**	**Model**	**Error**	**Forecast**
'AIC'	1-1-1	-7,40463	2,82790	1-1-1	-7,32275	2,82288
'BIC'	1-1-1	-7,32814	2,82790	1-1-1	-7,24627	2,82288
'GMAE'	6-1-1	0,00865	2,81168	8-1-1	0,00927	2,80151
'GMRAE'	6-1-1	0,00864	2,81168	8-1-1	0,00926	2,80151
'MAE'	5-1-1	0,01765	2,82427	11-1-1	0,01831	2,78764
'MAPE'	5-1-1	0,01995	2,82427	11-1-1	0,02056	2,78764
'MASE'	10-1-1	0,67168	2,79985	11-1-1	0,69219	2,78764
'MdAE'	11-1-1	0,01241	2,78836	10-3-1	0,01054	2,83392
'MdAPE'	11-1-1	0,01300	2,78836	10-3-1	0,01210	2,83392
'MdRAE'	11-1-1	0,01273	2,78836	10-3-1	0,01056	2,83392
'MRAE'	5-1-1	0,01745	2,82427	11-1-1	0,01807	2,78764
'MSE'	5-1-1	0,00056	2,82427	1-1-1	0,00061	2,82288
'MSMAPE'	5-1-1	0,02012	2,82427	11-1-1	0,02080	2,78764
'NS'	5-1-1	-99,88868	2,82427	1-1-1	-99,87869	2,82288
'R4MS4E'	1-1-1	0,03189	2,82790	1-1-1	0,03349	2,82288
'RMdSPE'	11-1-1	0,01300	2,78836	10-3-1	0,01213	2,83392
'RMSE'	5-1-1	0,02365	2,82427	1-1-1	0,02469	2,82288
'RMSPE'	5-1-1	0,02682	2,82427	1-1-1	0,02794	2,82288
'RMSSE'	8-1-1	0,92701	2,80639	11-1-1	0,96544	2,78764
'SMAPE'	5-1-1	0,02012	2,82427	11-1-1	0,02080	2,78764
'SMdAPE'	11-1-1	0,01301	2,78836	10-3-1	0,01209	2,83392

Fletcher-Powell Conjugate Gradient						
	Tan-sigmoid			Log-sigmoid		
	Model	**Error**	**Forecast**	**Model**	**Error**	**Forecast**
'AIC'	2-3-1	-7,02413	2,82591	2-3-1	-6,93594	2,84547
'BIC'	2-3-1	-6,67996	2,82591	2-3-1	-6,59177	2,84547
'GMAE'	10-3-1	0,00926	2,81953	8-10-1	0,00966	2,83687
'GMRAE'	10-3-1	0,00924	2,81953	8-10-1	0,00965	2,83687
'MAE'	10-3-1	0,01804	2,81953	8-10-1	0,01708	2,83687
'MAPE'	10-3-1	0,02035	2,81953	8-10-1	0,01930	2,83687
'MASE'	3-8-1	0,63052	2,81447	4-3-1	0,68240	2,82342
'MdAE'	3-8-1	0,01187	2,81447	8-2-1	0,01016	2,80111
'MdAPE'	3-8-1	0,01360	2,81447	8-2-1	0,01164	2,80111
'MdRAE'	3-8-1	0,01196	2,81447	8-2-1	0,01000	2,80111
'MRAE'	10-3-1	0,01791	2,81953	8-10-1	0,01696	2,83687
'MSE'	3-8-1	0,00060	2,81447	8-10-1	0,00057	2,83687
'MSMAPE'	10-3-1	0,02041	2,81953	8-10-1	0,01933	2,83687
'NS'	3-8-1	-99,88083	2,81447	8-10-1	-99,88587	2,83687
'R4MS4E'	2-10-1	0,03159	2,87102	2-3-1	0,03186	2,84547
'RMdSPE'	3-8-1	0,01361	2,81447	8-2-1	0,01164	2,80111
'RMSE'	3-8-1	0,02447	2,81447	8-10-1	0,02395	2,83687
'RMSPE'	3-8-1	0,02747	2,81447	4-11-1	0,02750	2,82992
'RMSSE'	3-8-1	0,84620	2,81447	4-3-1	0,92796	2,82342
'SMAPE'	10-3-1	0,02041	2,81953	8-10-1	0,01933	2,83687
'SMdAPE'	3-8-1	0,01361	2,81447	8-2-1	0,01164	2,80111

Table 9. Best models selected by Conjugate Gradient with Powell/Beale Restarts and Polak-Ribiére Conjugate Gradient learning algorithms.

Conjugate Gradient with Powell/Beale Restarts						
	Tan-sigmoid			Log-sigmoid		
	Model	**Error**	**Forecast**	**Model**	**Error**	**Forecast**
'AIC'	3-1-1	-7,27345	2,81928	1-3-1	-7,22747	2,83113
'BIC'	3-1-1	-7,12049	2,81928	1-3-1	-6,99803	2,83113
'GMAE'	2-2-1	0,00996	2,82241	11-3-1	0,01033	2,81120
'GMRAE'	2-2-1	0,00994	2,82241	11-3-1	0,01031	2,81120
'MAE'	2-2-1	0,01786	2,82241	1-3-1	0,01821	2,83113
'MAPE'	2-2-1	0,02018	2,82241	1-3-1	0,02061	2,83113
'MASE'	2-2-1	0,73604	2,82241	11-3-1	0,64970	2,81120
'MdAE'	7-2-1	0,01302	2,81727	8-3-1	0,01265	2,82654
'MdAPE'	9-5-1	0,01394	2,84491	8-2-1	0,01377	2,80046
'MdRAE'	7-2-1	0,01281	2,81727	11-3-1	0,01264	2,81120
'MRAE'	2-2-1	0,01766	2,82241	1-3-1	0,01814	2,83113
'MSE'	2-2-1	0,00056	2,82241	1-3-1	0,00057	2,83113
'MSMAPE'	2-2-1	0,02035	2,82241	1-3-1	0,02058	2,83113
'NS'	2-2-1	-99,88893	2,82241	1-3-1	-99,88628	2,83113
'R4MS4E'	2-2-1	0,03219	2,82241	12-5-1	0,03278	2,90570
'RMdSPE'	9-5-1	0,01394	2,84491	8-2-1	0,01377	2,80046
'RMSE'	2-2-1	0,02362	2,82241	1-3-1	0,02390	2,83113
'RMSPE'	2-2-1	0,02687	2,82241	12-7-1	0,02767	2,82443
'RMSSE'	8-3-1	0,96015	2,81801	11-3-1	0,90387	2,81120
'SMAPE'	2-2-1	0,02035	2,82241	1-3-1	0,02058	2,83113
'SMdAPE'	9-5-1	0,01395	2,84491	8-2-1	0,01387	2,80046

Polak-Ribiére Conjugate Gradient						
	Tan-sigmoid			Log-sigmoid		
	Model	**Error**	**Forecast**	**Model**	**Error**	**Forecast**
'AIC'	2-1-1	-6,72677	2,81513	1-2-1	-6,79917	2,86186
'BIC'	1-1-1	-6,64623	2,80289	1-2-1	-6,64621	2,86186
'GMAE'	12-4-1	0,00804	2,82893	6-3-1	0,00969	2,81828
'GMRAE'	12-4-1	0,00803	2,82893	6-3-1	0,00967	2,81828
'MAE'	11-10-1	0,01889	2,85997	11-3-1	0,01801	2,84375
'MAPE'	11-10-1	0,02120	2,85997	11-3-1	0,02019	2,84375
'MASE'	8-11-1	0,74773	2,82259	11-4-1	0,66225	2,82486
'MdAE'	12-4-1	0,01089	2,82893	11-3-1	0,00973	2,84375
'MdAPE'	12-4-1	0,01216	2,82893	11-3-1	0,01057	2,84375
'MdRAE'	12-4-1	0,01094	2,82893	11-3-1	0,00980	2,84375
'MRAE'	11-10-1	0,01874	2,85997	11-3-1	0,01787	2,84375
'MSE'	4-6-1	0,00070	2,81925	7-12-1	0,00062	2,85114
'MSMAPE'	12-4-1	0,02130	2,82893	11-3-1	0,02026	2,84375
'NS'	4-6-1	-99,85985	2,81925	7-12-1	-99,87576	2,85114
'R4MS4E'	3-5-1	0,03352	2,83901	7-12-1	0,03222	2,85114
'RMdSPE'	12-4-1	0,01216	2,82893	11-3-1	0,01059	2,84375
'RMSE'	4-6-1	0,02654	2,81925	7-12-1	0,02499	2,85114
'RMSPE'	4-6-1	0,02967	2,81925	6-6-1	0,02874	2,83239
'RMSSE'	2-8-1	0,99419	2,79248	8-7-1	0,89845	2,81549
'SMAPE'	12-4-1	0,02130	2,82893	11-3-1	0,02026	2,84375
'SMdAPE'	12-4-1	0,01209	2,82893	11-3-1	0,01058	2,84375

Table 10. Best models selected by Variable Learning Rate Backpropagation and One Step Secant learning algorithms.

Variable Learning Rate Backpropagation						
	Tan-sigmoid			Log-sigmoid		
	Model	Error	Forecast	Model	Error	Forecast
'AIC'	1-2-1	-6,88510	2,81552	1-2-1	-6,96978	2,81342
'BIC'	1-2-1	-6,73214	2,81552	1-2-1	-6,81681	2,81342
'GMAE'	8-4-1	0,01169	2,82921	10-11-1	0,01105	2,85151
'GMRAE'	8-4-1	0,01167	2,82921	10-11-1	0,01103	2,85151
'MAE'	8-4-1	0,01805	2,82921	3-7-1	0,01865	2,83396
'MAPE'	8-4-1	0,02056	2,82921	3-7-1	0,02101	2,83396
'MASE'	8-4-1	0,63372	2,82921	7-11-1	0,84224	2,85998
'MdAE'	8-4-1	0,01310	2,82921	3-7-1	0,01331	2,83396
'MdAPE'	8-4-1	0,01448	2,82921	3-7-1	0,01614	2,83396
'MdRAE'	8-4-1	0,01337	2,82921	3-7-1	0,01329	2,83396
'MRAE'	8-4-1	0,01798	2,82921	3-7-1	0,01849	2,83396
'MSE'	8-4-1	0,00052	2,82921	3-7-1	0,00059	2,83396
'MSMAPE'	8-4-1	0,02053	2,82921	3-7-1	0,02110	2,83396
'NS'	8-4-1	-99,89726	2,82921	3-7-1	-99,88293	2,83396
'R4MS4E'	8-4-1	0,02970	2,82921	3-7-1	0,03344	2,83396
'RMdSPE'	8-4-1	0,01448	2,82921	3-7-1	0,01615	2,83396
'RMSE'	8-4-1	0,02272	2,82921	3-7-1	0,02425	2,83396
'RMSPE'	8-4-1	0,02587	2,82921	3-7-1	0,02767	2,83396
'RMSSE'	8-4-1	0,79773	2,82921	7-11-1	1,04679	2,85998
'SMAPE'	8-4-1	0,02053	2,82921	3-7-1	0,02110	2,83396
'SMdAPE'	8-4-1	0,01448	2,82921	3-7-1	0,01601	2,83396
One Step Secant						
	Tan-sigmoid			Log-sigmoid		
	Model	Error	Forecast	Model	Error	Forecast
'AIC'	1-1-1	-7,42395	2,83035	1-1-1	-7,20888	2,81819
'BIC'	1-1-1	-7,34747	2,83035	1-1-1	-7,13240	2,81819
'GMAE'	11-7-1	0,01009	2,80108	11-11-1	0,00961	2,80640
'GMRAE'	11-7-1	0,01007	2,80108	11-11-1	0,00959	2,80640
'MAE'	4-1-1	0,01818	2,81605	2-4-1	0,01813	2,82987
'MAPE'	4-1-1	0,02049	2,81605	2-4-1	0,02053	2,82987
'MASE'	7-12-1	0,70756	2,82435	11-11-1	0,71728	2,80640
'MdAE'	9-2-1	0,01145	2,80144	10-2-1	0,01067	2,83305
'MdAPE'	9-2-1	0,01274	2,80144	10-2-1	0,01123	2,83305
'MdRAE'	9-2-1	0,01133	2,80144	10-2-1	0,01079	2,83305
'MRAE'	4-1-1	0,01793	2,81605	2-4-1	0,01795	2,82987
'MSE'	1-1-1	0,00055	2,83035	3-5-1	0,00055	2,83561
'MSMAPE'	4-1-1	0,02071	2,81605	2-4-1	0,02065	2,82987
'NS'	1-1-1	-99,89036	2,83035	3-5-1	-99,89059	2,83561
'R4MS4E'	1-1-1	0,03132	2,83035	3-5-1	0,03068	2,83561
'RMdSPE'	9-2-1	0,01274	2,80144	10-2-1	0,01123	2,83305
'RMSE'	1-1-1	0,02347	2,83035	3-5-1	0,02345	2,83561
'RMSPE'	1-1-1	0,02691	2,83035	2-4-1	0,02694	2,82987
'RMSSE'	2-2-1	0,95741	2,83584	7-2-1	0,98852	2,82985
'SMAPE'	4-1-1	0,02071	2,81605	2-4-1	0,02065	2,82987
'SMdAPE'	9-2-1	0,01274	2,80144	10-2-1	0,01129	2,83305

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