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Comparative Study of Artificial Neural Network and ARIMA Models in Predicting Exchange Rate

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Abstract: Capital market as an organized market has an effective role in mobilizing financial resources due to have growth and economic development of countries and many countries now in the finance firms is responsible for the required credits. In the stock market, shareholders are always seeking the highest efficiency, so the stock price prediction is important for them. Since the stock market is a nonlinear system under conditions of political, economic and psychological, it is difficult to predict the correct stock price. Thus, in the present study artificial intelligence and ARIMA method has been used to predict stock prices. Multilayer Perceptron neural network and radial basis functions are two methods used in this research. Evaluation methods, selection methods and exponential smoothing methods are compared to random walk. The results showed that AI-based methods used in predicting stock performance are more accurate. Between two methods used in artificial intelligence, a method based on radial basis functions is capable to estimate stock prices in the future with higher accuracy.

Keywords: ARIMA, artificial neural network, intelligent systems, stock prices

INTRODUCTION

One of the main components comprising the capital market is stock market, which offenders and capital suppliers are confronted and investment will be possible for different people. Stock market is market that buying and selling stock or bonds of public or private institutions under agreement, the rules and regulations can be certain.

Estimates of future stock prices using existing data named predict. Different data are used to predict stock prices. The most important information that can be used in forecasting stock prices is stock price in the past.

For encouraging people to invest in the stock should have been accurate and certain method or methods to predict future stock price until people invest with more sure in the stock.

ARIMA has been one of the well-known technique (Box and Jenkins, 1976) that has been widely used for time series analysis to evaluate some new modeling approaches (Hwarng and Ang, 2002). This model is suitable to time series data for forecasting future points in the series. In addition, ANN has been applied in nonlinear system modeling in enormous applicability in time series analysis recently (Dunis and Williams, 2002). Due to possess some important and attractive characteristics ANN can be chosen or forecasting exchange rate. Firstly, ANN is a method which can be easily adapted to the types of data with few limiting hypotheses against classical method. Secondly, for ANN exists a general functional structure that can be generalized (Hornik *et al*., 1989). Furthermore, ANN is known as nonlinear models (Zhang *et al*., 1998).

In recent years, many studies have been carried out for forecasting exchange rates using time series models; for instance, (Dunis and Williams, 2002; Kadilar *et al*., 2009; Kamruzzaman and Sarker, 2003; Bissoondeeal *et al*., 2008; Ashok and Amit 2002; Dallah and Ismaila 2009) and many researchers carried out comparative studies between ANN and ARIMA that have shown ANN model is better than ARIMA model. Moreover, some researchers have shown examples for the studies using artificial neural network (Zhang and Hu, 1998; Hu *et al*., 1999; Franses and Griensven, 1998).

Due to the large volume of research in the field of stock prediction with using neural network and its omplexity, psychological and political affecting issues and nature of stock that is still in early stages of

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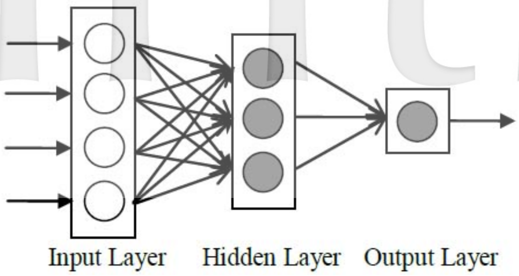

Fig. 1: ANN architecture

evolution more research is needed. This study is based on that the application of methods and new algorithms to predict the stock market must be examined and compare between them.

Thus, the objective of present study is to compare predicting of two models, ANN and ARIMA , applied for forecasting stock prices. Data has been chosen for year 2010 of Iran-Tehran stock price with training data for years 2008 and 2009. Results showed that ANN model is better than ARIMA model for forecasting stock prices with more accuracy.

Artificial neural network model: Artificial neural network is a network of interconnected elements which are inspired from studies of biological nervous systems. Producing an output pattern using an input pattern is the main function of an artificial neural network. Connectionist models, such as ANNs, are well suited for machine learning where connection weights are adjusted to improve the performance of a network. Figure 1 shows a general architecture of ANN.

Multi-Layered Perceptron (MLP) is most widely utilized in ANN paradigm that approximates nonlinear relationships existing between an input set of data (and the corresponding output data set. A three-layer MLP with a single intermediate layer housing a sufficiently large number of nodes can approximate any nonlinear computable function to an arbitrary degree of accuracy.

ARIMA model: ARIMA Modeling ARIMA models are the most general class of models for a short time series forecasting. These series must be stationary, if not; it must be transformed into stationary time series, this transformation can be done by taking the difference or taking the log. ARIMA (p, d, q): ARIMA models are, in theory, the most general class of models for forecasting a time series which can be stationarized by transformations such as differencing and logging. In fact, the easiest way to think of ARIMA models is as fine-tuned versions of random-walk and random-trend models: the fine-tuning consists of adding lags of the differenced series and/or lags of the forecast errors to the prediction equation, as needed to remove any last traces of autocorrelation from the forecast errors.

The acronym ARIMA stands for "Auto-Regressive Integrated Moving Average." Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, lags of the forecast errors are called "moving average" terms and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. Random-walk and random-trend models, autoregressive models and exponential smoothing models (i.e., exponential weighted moving averages) are all special cases of ARIMA models.

A nonseasonal ARIMA model is classified as an "ARIMA (p, d, q)" model, where: p is the number of autoregressive terms, d is the number of nonseasonal differences and q is the number of lagged forecast errors in the prediction equation.

To identify the appropriate ARIMA model for a time series, you begin by identifying the order (s) of differencing needing to stationarize the series and remove the gross features of seasonality, perhaps in conjunction with a variance-stabilizing transformation such as logging or deflating. If you stop at this point and predict that the differenced series is constant, you have merely fitted a random walk or random trend model. (Recall that the random walk model predicts the first difference of the series to be constant, the seasonal random walk model predicts the seasonal difference to be constant and the seasonal random trend model predicts the first difference of the seasonal difference to be constant-usually zero). However, the best random walk or random trend model may still have autocorrelated errors, suggesting that additional factors of some kind are needed in the prediction equation.

METHODOLOGY

General models predict not only predict the demand for commercial and production systems but also can be used to forecast demand for goods and services, consumption and other economic and non economic flows used. Various methods of artificial intelligence have been used to predict stock. ANN method refers to techniques that use neural networks. RW method is based on random walk. The ARIMA method refers method that one model a time series model fitted and predict future observations will be done using the model. MLR relationship between one or more explanatory variables with the response variable with the data fitted a linear equation.

Table 1: Summary of types of used neural networks

Research	Type of network	Pre-processing	Layers	Transmission function
[BRO98]	RNN	N/P	49-10-1	N/P
[CHA99]	MLP	N/P	10-{3-10}-1	N/P
[DES98A]	MLP	N/P	11-15-15-1	Sig-Sin-Sig
[GEN98]	MLP	N/P	6-{1-10}-1	Sig-Sig
[HOC97]	MLP	N/P	3-8-1, 5-8-1, 12-9-1	N/P
[KIM98]	TNN	N/P	{5-8}-{2-15}-1	N/P
[KIM00]	MLP	yes	12-{4-10}-1	Sig-Sig
[KOH96]	MLP	0-1	{5,6}-{5,6}-1	Sig-Sig
[LAM00]	MLP	Differencing	6-5-1	Tan-Tan
[LEU00]	MLP	Differencing	5-{6,10}-1	N/P
[WOO96]	MLP	Yes	8-3-1	Sig-Sig

Table 2: Methods used in current research

Abbreviated name	Method
Random walk	RW
Exponential smoothing	EXA
Radial basis functions	RBF
Radial basis functions	MLP
Moving average model of mass distribution	ARIMA

Genetic algorithm is a special type of evolutionary algorithms that use techniques such as inheritance and mutation biology uses and there of approximate solution for optimization problems and search is used. Different Neural network models for time series prediction has been used. Table 1 MLP Multilayer Perceptron Neural Network, TNN and RNN neural networks based on time delay neural network and are repeatable (Brown *et al*., 1998; Chandra and Reeb, 1999; Darbellay and Slama, 2000; Kohara *et al*., 1999)

Table 2 summarizes the types of neural networks used for forecasting using artificial intelligence techniques, Multilayer Perceptron neural network and radial basis functions is used. These methods are compared with known methods. Methods used in this study are in Table 2.

Another new tool is predicted as the ARIMA. In this method, the statistical properties of time series analysis, probability and their impact on individual or simultaneous equations will be emphasized. Above models allow each variable are explained with past values by the same variable (or constant) and random error terms. Important points about the ARIMA model is found to be stationary time series And that the time series are stationary after differencing once or twice until they can be used.

EVALUATION

In this study the average price index of 50 companies (SAX), index of Tehran Stock Exchange IDX, indicators relating to banks, credit institutions and other financial institutions BNK and the basic metals MTL is used. Only be compared to the data concerning the opening of the IBM Corporation has been used in this study. Iran's stock market data and data from the site http://www.irbourse.com IBM Corporation www.ibm.com company have been extracted from the site.

Used data from the beginning of the end of 84 to 85 and test data is about for year 86. For evaluation methods performance for time series prediction should be used as a criterion for evaluation. The following evaluation criteria have been used.

The mean square error is the quantity to evaluate and compare the predicted and is used the real value of the quantity and According to the mean square error is defined that yf and yi respectively represents predicted actual values and E represents the mathematical expectation:

$$MSE = E((y_i - f_i)^2) \tag{1}$$

normalized mean square error is quantity defined for predicted survey accurately the mean square error based on the actual amount of variance:

$$\text{NMSE} = E((y_i - f_i)^2)/Var(y_i) \tag{2}$$

Yf and yi which represent respectively the predicted and actual and vary represents the variance.

Before the evaluation of the data preprocessing is performed. Among the most basic functions on the data pre-processing, is normalization of them. This data will be changed so that the data range is between 0 and 1.

One of the major problems in predicting, the number of input data is used. Evaluations performed in the stock price in 10 and 30 days before and 50 days before it is used.

The Exponential Smoothing from the following equation is used:

$$f_{i+1} = \lambda\, f_i + (1-\lambda) y_i \tag{3}$$

Table 3: NMSE results related to exponential smoothing

	ALL	SAX	BNK	MTL	IBM
EXA0.9	0.1182910	0.1034610	0.1026731	0.1237640	0.1178090
EXA0.8	0.1178090	0.1034060	0.1024851	0.1210770	0.1111341
EXA0.7	0.1168650	0.1032130	0.1024930	0.1207210	0.1080820
EXA0.6	0.1151830	0.1031210	0.1023620	0.1206380	0.1078280
EXA0.5	0.1158060	0.1032060	0.1022170	0.1207930	0.1077340
EXA0.4	0.1166890	0.1034610	0.1024180	0.1212480	0.1078150
EXA0.3	0.1178480	0.1038650	0.1027110	0.1220620	0.1081320
EXA0.2	0.1192190	0.1044480	0.1031430	0.1231820	0.1086810
EXA0.1	0.1210683	0.1053719	0.1038213	0.1248718	0.1095470
EXA0 = RW	0.1238560	0.1070480	0.1050970	0.1280070	0.1107711

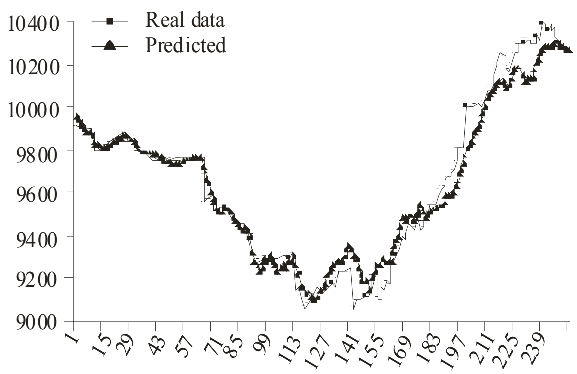

Fig. 2: Predicted data and real data, Tehran stock market index for year 2010 and training data are for years 2008 and 2009, respectively. Multilayer Perceptron neural network is used and each has 50 network inputs

where, yi stock amount in i day and fi predicted value of the stock is in the i. λ is the smoothing coefficient, which leads to higher levels of dependence that is predicted to previous values. Smoothing coefficient λ with λ EXA is shown in this study. Table 3 shows the NMSE of exponential smoothing (Desai and Bharati, 1998; Gencay, 1998; Han and Micheline, 2000).

The average of these results is shown in Table 3. It is seen superior results to the smoothing coefficient is about half.

Multilayer perceptron neural network: Network structure consists of one hidden layer. Hidden layer contains 20 nodes and output layer is a layer. Input layer to the number of inputs 10, 30 and 50 are input. Figure 2 shows data and the prediction of stock index for year 2010. As can be seen, prediction always is later main value. Also In most above cases the network is able to predict rapid changes.

The results related to the use of multilayer perceptron networks are listed in Table 4. This table has been reported in error based on MSE criteria.

As can be seen in most cases, results of the use of 50 inputs are better than 30 inputs. Also the use of 30 inputs has Better results than the use 10 inputs. For having a comparison between different stocks, the results of NMSE criterions in Table 5 and Fig. 3 are reported (Kim and Han, 2000; Kishikawa and Tokinaga, 2000).

The results in Fig. 2 correspond to an average of 10, 30 and 50 inputs. These results indicate a possible predictor of whether a stock. The results indicate that the rate be predicted Metal Exchange is less important than other exchanges (Egeli *et al*., 2003; Oh and Kim, 2002; Qiao *et al*., 2001)

Results of the method based on radial basis functions: NMSE error related to the method based on radial basis functions have been reported in Table 6.

The results show that the first stock index to 50 companies had the worst predictability.

Overhand, Tehran's stock index has had the best predictability. The results also indicated that increasing the number of inputs is predicted to perform better.

The prediction of indices based on ARIMA models: Predicted values for an index based on time series data in the first phase of stagnation for the data subject should be investigated. One of the tests used in this test is generalized Dicke Fuller Reacting. The following indices have been investigated using the above test.

Generalized testing of fuller dicke: This test is used for evaluating existence of unit root and collective variables in the model. The results of this test are shown in Table 7. As the results show the level of stock price index variable, in the surface is non identity but mentioned variable in difference surface the first order difference is stationary or static, this means that null hypothesis based on existence of unit root in surface and with the 5% level and the error can not be rejected. But the hypothesis is rejected for the first order difference. Therefore, based on test results Dicke, mentioned variable was a resident of the first order by means subtracting the variable mass is order 1. As can

Table 4: Results of multilayer perceptron and MSE error

	IDX	SAX	BNK	MTL	IBM
MLP10	306.3301	786.0184	2.996484	353.062	5.309322
MLP30	170.7745	478.0222	2.674050	527.860	1.690905
MLP50	94.52245	419.9447	1.867260	497.958	0.941373

Table 5: Results of multilayer perceptron and NMSE error

	IDX	SAX	BNK	MTL	IBM
MLP10	0.032148	0.039628	0.035265	0.061225	0.066902
MLP30	0.017853	0.024895	0.033052	0.193836	0.022515
MLP50	0.009815	0.028549	0.010285	0.176545	0.012302
Average	0.019939	0.031024	0.026201	0.143869	0.033906

Table 6: Results of error-based method for radial basis functions and NMSE error

	IDX	SAX	BNK	MTL	IBM
RBF10	0.006075	0.025571	0.008705	0.017395	0.008883
RBF30	0.003966	0.023029	0.007205	0.017042	0.007880
RBF50	0.00339	0.021075	0.005921	0.016837	0.006053
Average	0.004477	0.023225	0.007277	0.017092	0.007605

Table 7: Fuller generalized dicke test results on data

Description	Static status	Critical value	ADF	Variable
Variable in surface	Non-static	-3.45	-2.89	AU
First order difference of variable	Static	-3.45	-4.25	
Variable in surface	Non-static	-3.68	-2.91	SAX
First order difference of variable	Static	-3.68	-4.32	
Variable in surface	Non-static	-3.69	-2.97	BNK
First order difference of variable	Static	-3.69	-4.28	
Variable in surface	Non-static	-3.70	-2.99	MTL
First order difference of variable	Static	-3.70	-4.16	
Variable in surface	Non-static	-3.71	-3.10	IBM
First order difference of variable	Static	-3.71	-4.27	

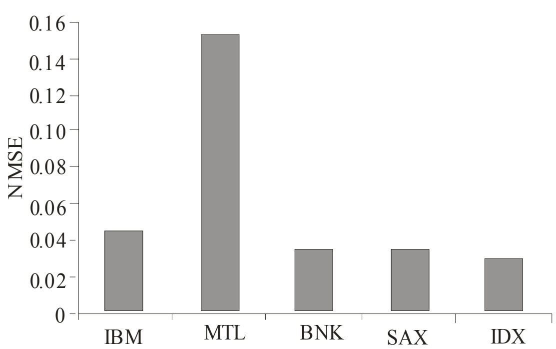

Fig. 3: NMSE error related to different shares. As can be seen errors are nearly all indicators except basic metals

be seen in all variables studied in the paper non-static but the first order differences are static (Zhang, 2004; Javier, 2003).

Predicted values of indices: As in the previous section was determined and the data stored in the first order differences are settled, the model is presented as follows:

$$P_1 = \alpha_0 + \alpha_1 P1_{t-1} + u_t \tag{4}$$

$$P_2 = \alpha_0 + \alpha_1 P1(-1) + u_t \tag{5}$$

In the above formula:

$$P1_{t-1} = P1(-1) \tag{6}$$

$$P1 = P - P(-1) \tag{7}$$

Model for estimating Eq. (5) from that used software Eviews3 estimating equation is derived as follows:

$$P_1 = 0.04 + 0.526\, P_1(-1) \tag{8}$$

To ensure that the Eq. (8) is a suitable model for the data an equation of residues Eq. (8) determined and correlation journalist has been judged based on the correlation problem. Result showed that none of their correlation or partial correlation is not statistically significant. Solidarity's words indicated that the estimated residual from Eq. (8) are completely random and therefore another ARIMA model is not required.

The first order difference time series forecasting model to predict mass consumption is obtained. Action to achieve such a goal is as follows:

Table 8: Comparison of NMSE error for different methods

	IDX	SAX	BNK	MTL	IBM	Average
MLP10	0.032148	0.039628	0.035265	0.061225	0.0669020	0.047034
MLP30	0.017853	0.024895	0.033052	0.193836	0.0225150	0.058430
MLP50	0.009815	0.028549	0.010285	0.176545	0.0123020	0.047499
RBF10	0.006075	0.025571	0.008705	0.017395	0.0088830	0.013326
RBF30	0.003966	0.023029	0.007205	0.017042	0.0078800	0.011824
RBF50	0.003390	0.021075	0.005921	0.016837	0.0060530	0.010655
EXA0 = RW	0.123856	0.107048	0.105097	0.128007	0.1107711	0.114956
EXA0.5	0.115806	0.103206	0.102217	0.120793	0.1077340	0.109951
EXA0.6	0.115183	0.103121	0.102362	0.120638	0.1078280	0.109826
ARIMA	0.415200	0.372800	0.295100	0.318500	0.3842000	0.216620

$$P_1 = P - P(-1) \tag{9}$$

The placement of the Eq. (9) in Eq. (5) the following equation is obtained:

$$P_t = \alpha_0 + (1+\alpha_1)p(-1) - \alpha_1 p(-2) + u_t \tag{10}$$

Values of Eq. (8) and the resulting zero is considered based on the following equation is obtained:

$$P_t = 0.04 + 1.526P(-1) - 0.226P(-2) \tag{11}$$

Using Eq. (11) can predict the values obtained for the period studied.

And then using real values and compared with predicted values based on Eq. (11) values of the deviation can be calculated. Estimate equations for other variables like stock price index variable were estimated using software Eviwes These equations are as follows:

$$\begin{aligned} All &= 0.154 + 0.742\ ALL\,(-1) \\ BNK &= 0.167 + 0.824\ BNK\,(-1) \\ MTA &= 0.267 + 0.749\ MTA\,(-1) \\ IBM &= 0.216 + 0.695\ IBM\,(-1) \end{aligned} \tag{12}$$

Given the above equations and using existing data from the deviation of actual rate variables determined that the study has been cited in Table 8 (Zhang, 2004; Javier, 2003; Weiss, 2000; Corradi *et al*., 2001).

Comparison of methods: The methods were all together in order to be seen, different results are shown in 0 Table 8. The results indicate that the minimum error in the use of methods based on radial basis functions is obtained.

CONCLUSION

In this study, the report shares the results of different prediction methods and results were compared. The results indicate the superiority of methods based on radial basis functions than other methods.

As the results of neural network and ARIMA model shows neural network performance was better than the ARIMA model.

For all variables studied in this study, the prediction error of the ARIMA method is more than neural network approach. This indicates a weaker predictive power of ARIMA rather than neural network approach. Therefore, the use of neural networks to predict future values of these variables is preferable. The stock market prediction using ARIMA-based and artificial intelligence techniques were studied. All chosen methods in this study and multilayer perceptron neural network and the method selected are based on radial functions. Among the traditional methods, exponential smoothing method and random walk was selected. Finally, results showed that using method predicate on radial basic function as an artificial intelligence technique is capable estimate stock price in the next day with a higher accuracy than other proposed methods.

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