Öneri.C.7.S.28.
Haziran 2007.301-307.

A COMPARISION OF NEURAL NETWORK AND LINEAR REGRESSION FORECASTS OF THE ISE-100 INDEX

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Abstract: In recent years the artificial neural network models have been successfully applied to solve many the real life problems. Especially for the last decade, the artificial neural network models have been applied to solve financial problems like bankruptcy prediction, portfolio construction, credit assessments and stock market forecasting.

This study examines the comparison of artificial neural network models and stepwise linear regression forecasting the daily and sessional returns of the ISE-100 index. By using stepwise regression inputs is selected then the same inputs is used in the neural network. Both methods are compared on the basis of mean squared error, normalized mean squared error and trend accuracy measures.

Relying the findings of this study, it is concluded that the artificial neural network model is better than stepwise linear regression.

Keywords: Artificial Neural Network Models, Stock Market Forecasting.

İMKB-100 ENDEKSİNİN YAPAY SİNİR AĞLARI VE DOĞRUSAL REGRESYON TAHMİN SONUÇLARININ KARŞILAŞTIRILMASI

Özet: Son yıllarda yapay sinir ağları modelleri gerçek hayatın pekçok problemlerini çözmede başarılı bir şekilde kullanılmaktadır. Özellikle son on yılda yapay sinir ağları modelleri iflas tahmini, portföy oluşturma, kredi analizleri ve hisse senedi piyasası tahminleri gibi finansal problemleri çözmede de uygulanmaktadır.

Bu çalışma İMKB 100 endeksinin günlük ve seanslık getirilerinin yapay sinir ağları ve regresyon modeli ile tahminlerinin karşılaştırmasını yapmaktadır. Çalışmada ilk olarak regresyon tekniği kullanılarak girdiler belirlenmiş ve aynı değişkenler kullanılarak yapay sinir ağı oluşturulmuştur. Bu iki yöntem ortalama hatalar karesi, Normalleştirilmiş ortalama hatalar karesi ve trend doğruluğu değerlerine bakılarak karşılaştırılmıştır.

Performans kriterleri İMKB-100 endeksinin getirilerini tahmin etmede yapay sinir ağları modelinin daha başarılı olduğunu göstermiştir.

Anahtar Kelimeler: Yapay Sinir Ağları Modelleri, Hisse Senedi Piyasası Tahminleri.

I. INTRODUCTION

Since the foundation of the financial markets, especially the stock markets, several studies have been devoted to explain the market behaviour. Among these studies, *The Efficient Capital Market Hypothesis* and *Random-Walk Theorem* tried to figure out the price determination process in the financial markets in order to explain the market behaviour. On the other hand, some theories tried to ease the understanding of the market behaviour by relating the expected returns with risk factors. The *Capital Asset Pricing Model* and *Arbitrage Pricing Theory* are well known examples for those theories.

Besides the financial theories that are dedicated to explain the fundamentals of market behaviour, some statistical forecasting techniques have been developed to forecast the future market behaviour in order to reduce the uncertainty about the market behaviour.

Among the alternative statistical forecasting techniques, the nonlinear forecasting techniques have been appealing interests of many researchers as the recent studies have presented some evidences on the nonlinear dependence in the stock market returns.

For the developed markets, several researches presented the existence of nonlinear relation in market returns for S&P 500, DAX, Nikkei 225, FTSE-100 indexes [1–4] and for the developing market case some evidence was found on the nonlinear relation for Korean, Hong Kong, Singapore and Taiwan stock markets [5].

In addition to evidences found on nonlinearity in the international financial markets, for the Turkish financial markets it was stated that the inefficiency in Istanbul Stock Exchange (ISE) could be explained by nonlinear market behaviour [6] and the portfolio losses could be reduced by exploiting the nonlinear dependence in ISE [7]. And also, some evidences for nonlinear dependence in ISE was reported for the period of 1989- and 2001 [8].

Realizing the nonlinear dependence in stock markets, several nonlinear statistical forecasting techniques have been devoted to forecast the market behaviour. Among the alternative nonlinear statistical forecasting techniques, the artificial neural network models (NNs) have attracted interest of many researchers as these models have comparative advantages over the other nonlinear forecasting techniques. The comparative advantages of the NNs could be summarised as being data driven model, which did not require a model specification [9], ability to deal with complex information even the functional form of the data was not known [10]. Moreover, if the stock markets have been linearly dependent in nature, even simple NNs could be used effectively in forecasting linear time series [11].

This study aims to investigate and compare the forecasting performances of one of the artificial neural network models, the multilayer perceptron model, and the linear regression for daily and sessional returns of the Istanbul Stock Exchange Composite Index (ISE-100). Performances of each model are determined by the use of statistical performance measures that are defined in the following pages.

II. LITERATURE REVIEW

Although the theoretical framework of the artificial neural network models was developed in early 1940s by McCulloch – Pitts [12], the stock market forecasting application of these models could be realised in 1988 by White's study [13].

Following White's study, several attempts have been made to utilise the neural network models in stock market forecasting. Wong, et.al. utilized the neural network models to forecast the returns of various US stocks [14]. Kryzanowski, et. al. utilized the neural network models to select stocks from the Canadian stock markets [15].

Numerous studies were conducted in order to measure the stock market forecasting power of artificial neural network models. While some studies were concentrated on measuring forecasting performance of one type of artificial neural network models [16-20], some other studies were conducted with the aim of comparing the forecasting performances of different artificial neural network models [21–23].

Besides the studies that only utilised the artificial neural network models, there were some other studies, which compared the forecasting performances different statistical forecasting methods.

Dropsy studied the predictability of risk premia in four stock markets (Germany, Japan, U.K. and U.S.) with macroeconomic variables and compared the predictive ability of neural networks with the linear regression and random walk model [24]. The forecasting accuracy of each model was analysed according to the root mean squared error (RMSE), maximum absolute errors (MxAE), directional correctness ratio (DCR) and Pesaran-Timmermann market timing test. For the forecasting horizon, linear regression and neural network model performed better than the random walk model. On the other hand, linear regression presented better forecasting accuracy than neural network model in terms of RMSE and MxAE. Directional and market timing tests presented that both of the models provide information on the directional changes in the stock markets.

In order to enhance predictive power of forecasting methods, Desai and Bharati used economic and financial variables for linear regression methods and neural networks [25]. They used five different neural network architectures. In-the-sample R^2 results presented that the simplest form of neural network outperformed other neural networks and linear regression. Also, out-of-sample correlation coefficient results showed that the tightest neural network model was best. Similar conclusion was stated according to mean squared errors. Conditional efficiency of the models was tested and the neural network forecasts were found to be conditionally efficient with respect to linear model. Moreover, the neural network models outperformed the linear regression in high volatility periods.

In another study, Desai and Bharati [26] investigated the forecasting effectiveness of neural networks on large stocks, corporate bonds, small stocks and intermediate-term government bonds with respect to linear regression and the GARCH model. According to mean squared error (MSE) and mean absolute error (MAE) performance measures the GARCH model found to be the best model over all assets. The neural network model was better for corporate bonds and small stocks according to the mean absolute percentage error (MAPE) performance measure and also it was better for large stocks and small stocks using the correlation coefficient performance measure. The GARCH model was found to be conditionally efficient with respect to neural network on all assets. The neural network models were found to be conditionally efficient with respect to linear regression models for large stocks and corporate bonds.

Lim and McNelis examined the effects of U.S. S&P index and Japanese Nikkei index on the Australian All-Ordinaries index and tested the daily predicability of the All-Ordinaries index returns [27]. By use of lagged index returns for each market, a linear autoregressive model, GARCH-M model and feedforward neural network models were constructed. Among the alternative models, partly connected feedforward neural network model with 15 input variables outperform other models. However, the results also presented that the forecast error generated by the neural network model was not statistically different from zero for the linear model.

Qi examined the predictability of the S&P500 index for recursive investment horizons during 1960-1992 based on the linear regression and neural network models [28]. For the whole forecasting period (1960-1992) the neural network model outperforms the linear regression on 5 statistical performance measures. However, if the forecasting performance was compared in three forecasting periods (1960-1969, 1970-1979,1980-1989), neural network model outperformed the linear regression for the first two sub-periods, and linear regression outperformed the neural network model for 1980-1989 by four out of five statistical performance measure. According to the result of the study, it was concluded that the investment horizon has an important effect on the forecasting accuracy, and furthermore the forecasting accuracy of various models could be measured different by different performance measures. Although, conflicting results were reported by different performance measures and the difference between the forecasting accuracy of the models under study was not statistically significant, profitability of a trading strategy guided by neural network model clearly outperformed the linear model.

Leung et.al. compared the forecasting performances of classification and level estimation models for three globally traded market indices (S&P500, FTSE100 and Nikkei225) [29]. The classification models (linear discriminant, Logit and Probit, probabilistic neural networks) were implemented to forecast the direction (up or down) of the indices. On the other hand, the level estimation models (adaptive exponential smoothing, vector autoregression and multivariate transfer function model and backpropagation neural network) were used to estimate the return of the indices. The comparison between models was based on the number of correct forecasts (HIT) of the direction of the index return and excess return from index trading. The results of HIT presented that for classification models probabilistic neural network model was best for S&P 500 and FTSE 100, and discriminant analysis was best for Nikkei 500. For level estimation models backpropagation neural network model, multivariate transfer function model and adaptive exponential smoothing was best for S&P500, FTSE100 and Nikkei225 respectively. In addition, return measures presented that probabilistic neural network was best for S&P500 and FTSE100, and discriminant analysis was best for Nikkei500. On the other hand, for level estimation models, backpropagation neural network was best in predicting three indices according to return measure.

Kanas & Yannopoulos studied predictive powers of the linear and nonlinear techniques in order to forecast monthly stock returns for Financial Times All Share Index (FT) and Dow Jones Industrial Average (DJIA) [30]. They utilized monthly aggregate stock returns, trading volumes (number of shares) and the dividends for Financial Times All Share Index and Dow Jones Industrial Average as inputs for both models. The period under examination was from January 1980 to December 2000, and the period from 1980 to 1995 was used as in-the-sample period for neural network model (Multilayer Perception-MLP) and estimation period for the linear model. The results of the study showed that the neural network model forecasts were significantly more accurate than the linear model in both indices. In order to validate the effectiveness of the neural network model, Diebold & Mariano test and forecast encompassing test was applied.

Maasoumi and Racine examined the predictability of the S&P500 index for recursive investment horizons during 1960-1992 based on the linear regression, neural network, nonparametric kernel regression models and unconditional mean of past returns [31]. According to the RMSE, MAE, and MAPE performance measures no model can significantly predict the market for the entire sample period. Furthermore, according to profitability of a trading strategy guided by those models, no model constantly dominated the others. Depending on the findings of the study it was concluded that linear and nonlinear predictability of the stock returns depends on the period of the analysis, frequency of data observations, conditioning variables, and predictability criteria.

By using 61 accounting ratios and 3 commonly used market ratios of Canadian companies, traded on Toronto Stock Exchange (TSE), Olson & Mossman [32] tired to capture the differences in the predictability powers of three forecasting techniques: neural network model (back propagation), ordinary least squares and logistic regression technique for stock returns. The date used in the study covered the periods from 1976 to 1993. In the analysis, most recent 6 years' data were used to predict the coming year's return. Such that the period from 1976 to 1982 was used to forecast the next year, 1983; and for each year between 1983 and 1993 returns were forecasted by using the prior 6 years accounting ratios. The results of the study showed that the neural network model out performs the other two models in both classification and estimation of the returns of the companies under examination. In addition, application of various trading rules was found to be more profitable under the neural network model.

III. METHODOLOGY

The data set used in the study is obtained from ISE between January 1996 and June 2005. Data set is composed of both daily and sessional closing price of ISE-100 and trading volume. This information is converted to 14 different inputs, which are given in the Table.1.

Table.1. Input Variables

1. Lagged index return for 1 day
2. Lagged index return for 3 days
3. Lagged index return for 5 days
4. Lagged change in volume for 1 day.
5. Lagged change in volume for 3 days.
6. Lagged change in volume for 5 day.
7. Moving average for index return for 3 days
8. Moving average for index return for 5 days
9. Moving average for change in volume for 3 days
10. Moving average for change in volume for 5 days
11. Moving average for index (raw data) for 3 days
12. Moving average for index (raw data) for 5 days
13. Moving average for volume (raw data) for 3 days
14. Moving average for volume (raw data) for 5 days

The analyses are done for eight data sets, which are 1996-2005, 1996-1999, 1997-2000, 1998-2001, 1999-2002, 2000-2003, 2001-2004, and 2002-2005. Each data is also divided into three part in order to establish the training, validation and test period. The training period is 70% of the observations, cross validation period is 20% of the observation and remaning part of 10% is utilized for testing the model for each eight sub period. The dependent variable, ISE 100 return, is calculated as logarithmic difference. Stepwise regression and feedforward neural network with backpropagation, which was trained by conjugate gradient algorithm, are used in the study. The neural network model had three layers: one input, one hidden and one-output layers. First of all stepwise regression is done to select the important variable from 14 inputs. Stepwise regression is done for all period and performance measures are calculated. Then with the same inputs neural networks are constructed and performance measures are calculated. By using stepwise regersssion irrelevant variables are excluded, the important variables from input list are given in the Table 2 for daily data. For the sessional data same procedure is done and relevant variables are given in the Table.3.

Table.2. Relevant Input for Daily Data

1996-2005	✓ Lagged change in volume for 1 day. ✓ Moving average for index (raw data) for 5 days
1996-1999	✓ Lagged index return for 5 days
1997-2000	✓ Lagged index return for 5 days
1998-2001	✓ Lagged index return for 5 days
1999-2002	✓ Moving average for index return for 5 days
2000-2003	✓ Moving average for index return for 3 days
2001-2004	✓ Lagged change in volume for 1 day
2002-2005	✓ Lagged change in volume for 1 day

Table.3. Relevant Input for Sessional Data

1996-2005	✓ Lagged index return for 1 session ✓ Lagged change in volume for 5 sessions. ✓ Lagged change in volume for 3 sessions. ✓ Lagged index return for 3 sessions. ✓ Moving average for index (raw data) for 3 sessions
1996-1999	✓ Lagged index return for 1 session ✓ Lagged index return for 3 session ✓ Moving average for volume (raw data) for 5 sessions
1997-2000	✓ Lagged index return for 1 session ✓ Lagged change in volume for 1 session.
1998-2001	✓ Lagged index return for 1 session ✓ Lagged change in volume for 5 sessions. ✓ Lagged change in volume for 1 session.
1999-2002	✓ Lagged index return for 1 session ✓ Lagged change in volume for 5 sessions. ✓ Moving average for index (raw data) for 5 sessions
2000-2003	✓ Lagged index return for 1 session ✓ Lagged change in volume for 5 sessions. ✓ Moving average for index (raw data) for 5 sessions
2001-2004	✓ Lagged index return for 1 session ✓ Lagged index return for 5 sessions ✓ Lagged change in volume for 3 sessions.
2002-2005	✓ Lagged index return for 1 session ✓ Lagged change in volume for 3 sessions.

After finding the relevant variable, both for daily and sessional data set, forecasting process is done by stepwise regression and neural network model by using the inputs. Although, there are several performance criteria in the literature three of them are going to be used in the study: mean square error (MSE), normalized mean square error (NMSE) and trend accuracy (TA).

Mean Squared Error is calculated as

$$MSE = \frac{\sum_{j=0}^{P} \sum_{i=0}^{N} (d_{ij} - y_{ij})^2}{NP}$$

where P: number of output processing elements

N: number of exemplars in the data set

y_{ij} : network output for exemplar i at processing elements j

d_{ij} : desired output for exemplar i at processing elements j

Normalized Mean Squared Error is calculated as

$$NMSE = \frac{P \quad N \quad MSE}{\sum_{j=0}^{P} \frac{N \sum_{i=0}^{N} d_{ij}^{2} - (\sum_{i=0}^{N} d_{ij})^{2}}{N}}$$

where P: number of output processing elements

N: number of exemplars in the data set

MSE: mean Squared Error

d_{ij}: desired output for exemplar i at processing elements j

Trend Accuracy measures gives the percentage for which the actual output changed in the direction relative to the previous desired value.

Table.4. Performance Measures for Stepwise Regression and Neural Network for Daily Data

	MSE		NMSE		TA (%)	
	SR	NN	SR	NN	SR	NN
1996-2005	0,000270	0,000250	4,03	1,00	43	75
1996-1999	0,001360	0,001330	3,63	1,03	53	73
1997-2000	0,001860	0,001980	4,24	1,03	47	72
1998-2001	0,000892	0,000926	2,91	1,05	49	76
1999-2002	0,000895	0,000922	2,9	0,98	51	75
2000-2003	0,000530	0,000820	2,44	1,79	42	69
2001-2004	0,000242	0,000247	1,57	1,07	46	74
2002-2005	0,000290	0,000310	1,49	1,00	57	77

In Table.4 performance measure for daily data are given. NMSE and TA show that neural network model has a better result than stepwise regression. Although, according to MSE the regression is better than neural network for all the periods, except 1996-2005 and 1996-1999, the difference between the two methods under MSE is negligible.

In Table 5 performance measures for sessional data are given and by looking at the normalized mean square error and trend accuracy percentage neural network model has a better result than stepwise regression. Although there is a difference for MSE between regression and neural network analysis, it is also negligible.

Table.5. Performance Measures for Stepwise Regression and Neural Network for Sessional Data.

	MSE		NMSE		TA (%)	
	SR	NN	SR	NN	SR	NN
1996-2005	0,000100	0,000400	4,97	0,99	50	76
1996-1999	0,000400	0,000100	4,14	1,19	52	67
1997-2000	0,000800	0,000810	5,54	0,99	53	76
1998-2001	0,000490	0,000480	4,35	0,98	56	73
1999-2002	0,000393	0,000399	3,82	0,98	48	71
2000-2003	0,000250	0,000260	3,29	1,09	51	68
2001-2004	0,000105	0,000106	2,02	1,01	52	72
2002-2005	0,000120	0,000130	1,94	1,04	57	72

IV. CONCLUSION

Linear and nonlinear forecasting techniques are compared in the study by using MSE, NMSE and TA measures. Results show that neural network models are superior to stepwise regression on the bases of NMSE and TA but it is the other way on the basis of MSE criteria. The reason for the smaller MSE of the regression method is estimation of the coefficient by using the minimizing MSE. However, in the finance literature nonlinearity is a implicitly accepted fact for a decade. Neural network models can be used as tool to predict the ISE-100 index. When sessional and daily results of neural networks models are compared on the basis of MSE only 1996-2005 period is better predicted by using daily data. When the comparison is done on the basis of NMSE 1996-1999 and 2002-2005 sub periods are better predicted by using the sessional data. If the model selection criterion is chosen as Trend accuracy then 1999-2005 and 1997-2000 sub periods are predicted well by using sessional data. In order to beat the market any investor should use nonlinear models instead of linear one.

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