# FORECASTING THE CHANGE AND DIRECTION OF CHANGE IN ISE SECTOR INDICES: AN ARTIFICIAL NEURAL NETWORK APPLICATION

**Murat MAZIBAŞ**
Middle East Technical University, Institute of Applied Mathematics
METU, Institute of Applied Mathematics, Ankara, TURKEY
muratmazibas@yahoo.com

**Dr. C. Coşkun KÜÇÜKÖZMEN**
Middle East Technical University, Institute of Applied Mathematics
METU, Institute of Applied Mathematics, Ankara, TURKEY
kcoskun@metu.edu.tr

**Abstract**

*We employ neural network models to forecast the direction and the level of change in Istanbul Stock Exchange (ISE) Composite Index and 10 sector indices. We use 7 domestic and 15 international economic variables and stock indices. Three types of forecast methods were employed for each sector stock indices and composite index. Models were estimated and trained for the period of June 1992-December 2002. Trained network models were tested through out-of-sample forecast performance for the period of January 2003-December 2003. The out-of-sample period was specifically selected for testing ability of ANN models to forecast in high volatility conditions of stock indices. The results were then evaluated both on the basis of ability to forecast the direction of change in the stock index and on the basis of total gains in terms of index points. The results indicate that the models have some ability to forecast changes in ISE Composite Index and 10 sector indices.*

*Key words: forecasting, stock indices, neural networks, Istanbul Stock Exchange, ISE sector indices.*

*JEL Classification:C45, C53*

## 1. INTRODUCTION

There are numerous studies investigating the effects of economic variables on stock prices and stock indices. Many of them find that economic variables have effect on stock prices with varying influence. Despite the fact that there exist many studies employing the data of Istanbul Stock Exchange (ISE) index and stocks listed, best to authors' knowledge this study is the first one that employs ANN models to forecast direction of change in sector indices. Forecasting the direction of change in stocks and stock indices is very important for institutional investors who speculates and get profit from even minor movements in prices.

Main objective of this study is to evaluate whether composite index and sector indices of Istanbul Stock Exchange (ISE) could be forecasted using publicly available economic time series by employing Artificial Neural Network (ANN) models.

To serve this purpose, 22 publicly available economic variables were used to forecast the direction and magnitude of change in ISE sector indices. Economic variables were selected to reflect a well-known fact that domestic macroeconomic variables had an effect on indices. Besides, depending on the level of globalization in financial markets, cross-country factors also have effects on domestic markets. Since macroeconomic variables are available on a monthly basis, to preserve the consistency, we use monthly data for all variables.

Following the work of Stansell and Eakins (2004), three separate approaches were used in this study: First one is to separately model each sector index with lagged data by using 22 economic variables to forecast the direction of change in each of 10 sector indices on a monthly basis. The second one is, classification of economic variables into three groups (such as domestic macroeconomic, international macroeconomic and world stock markets) then construct the mode for each of these groups. The objective of adopting this approach was to separate the effects of domestic, international and world stock market variables from each other and to assess the performance of each group in forecasting ISE indices. The last one is to model each sector index by using lagged data on all 22 economic variables simultaneously to forecast and evaluate the forecasts based on each sector.

This paper is organized as follows: in the first section, ANNs were introduced and discussed in detail. In the second section, a comprehensive literature review on the application of ANNs in stock market analysis was provided. In the third section, data, models and time series used were introduced. Fourth section is about the methodology of the study about the forecasting and evaluating direction of change in sector indices. In the fifth section, empirical results were evaluated and a general overview and summary of the results presented in conclusion section.

## 2. ARTIFICIAL NEURAL NETWORKS (ANN)

History of ANN starts with the human interest on neurobiology and studies on computer modeling of neurons based on knowledge gathered in neurobiological studies. Early studies were conducted by McCulloch and Pitts (1943), Hebb (1949), Rosenblatt (1959) and Widrow and Hoff (1960). After a silence period due to XOR problem introduced by Minsky and Papert (1969), based on the works of Kohonen (1972), Anderson (1977) and

Grosberg (1973), innovations gathered pace again in 1980s and most of the models currently used were developed after 1980s. Works of Hopfield (1982 and 1984), Rummelhart *et al*., (1986a, 1986b, 1988), Broomhead and Lowe (1988), Specht (1988 and 1990) are cornerstone studies to be referred.

Today, developments on ANN models continue with parallel to the improvements in computer technology. ANNs are currently used as pattern classifiers, associative memories, feature extractors and dynamic networks in many areas from engineering applications, medicine, psychology, scientific computing to economics and finance.

ANN models are generally classified with respect to training and learning rules, network structure, features of nodes within the network, type of threshold function, application of analog/dual or continuous values to the nodes, timing of parameter update.

ANNs are structures inspired from the structure and working of brain cells (called neurons). ANNs, as its name suggests, imitate the operational framework of neurons in simple terms. Similar to human neurons, artificial neurons receives signals from other neurons as inputs, then convert these inputs into weights, then execute a number of transformations (summations etc), transmits these inputs into operators, then transfer numeric results as an output. Networks are collection of these neurons. Each neural network consists of at least three layers (input, hidden and output layers), in each layer a number of connected neurons, in each neuron dendrites, soma, snaps and axons, between neurons neurotransmitters. Therefore, a neural network could be characterized as a mathematical system with numerous interconnected neurons.

A typical ANN composed of an input layer, one or more hidden layers and one output layer. Similar to econometric models, input layer includes independent variable(s) and output layer includes dependent variable and bias term. Each connection from the input layer to the hidden layer or from the hidden layer to the output layer has a weight. These weights represent the coefficients or the parameters of the model. The size of each weight represents the relative strength of the connection.

In this study, to forecast ISE indices we employ Multilayer Perceptrons (MLPs) which are layered feed-forward networks typically trained with static back-propagation.

Let L be number of layer (L-1 hidden layer), $z^0 \in R^{r_0}$ is input vector and $\phi(z^0) = z^L \in R^{r_L}$ output vector. A recursive input-output relation in this network could be expressed as:

$$y^j = w^j z^{j-1} + v^j \tag{1}$$

$$z^j = \hat{\sigma}_j(y^j) = \left[\sigma_j\left(y_1^j\right), \sigma_j\left(y_2^j\right), \ldots, \sigma_j\left(y_{r_j}^j\right)\right]' \qquad (2)$$

In equation (1), weights are $w = \{w^j, u^j\}$ where $w^j \in R^{r_j x r_{j-1}}$ and $j = 1,2, \ldots, L$, bias is $v^j \in R^{r_j}$ and dimensions of $y^j$ and $z^j$ is shown by $r_j$. In equation (2), scalar activation functions $\sigma_j(.)$ in hidden layers are sigmoid functions and activation functions $\sigma_j(.)$ in output layer are linear functions such as $\sigma_j(.) = (.)$.

## 3. LITERATURE REVIEW

With the start of using neural networks in finance, application of this technique to stock market analysis became very popular. Studies on stock market application of ANN's can be classified as prediction, forecasting, forecast comparison with alternative models, technical analysis, trading, pattern recognition, effect analysis, discussing the limits and use in dividend analysis.

Since ANN's are successful in modeling nonlinear structures, it is more likely to use them in forecasting nonlinear processes. Cogger *et al.* (1997) employs NN approach to forecast international equity markets, Bengoechea *et al.* (1996) to forecast stock market indices in Santiago de Chile. Grudnitski and Osburn (1993) forecast S&P and gold future prices, Hamid and Iqbal (2004) use ANN to forecast volatility of S&P 500 Index futures prices, Malliaris and Salchenberger (1996) to forecast the S&P 100 implied volatility. van Eyden and Caldwell (1996) utilizes ANN's in forecasting share prices, Wittkemper and Steiner (1996) in forecasting systematic risk of stocks and Lee and Chiu (2002) in forecasting of an opening cash price index. Kryzanowski *et al.* (1993) shows how to use ANN's to pick stocks. Kanas (2001) discuss ANN linear forecasts for stock returns.

There are studies compare the forecast performance of ANN's in comparison with other rival models. Leigh *et al.* (2002), compare NN with technical analysis, pattern recognizer and genetic algorithm in forecasting the NYSE composite index as a case study in decision support systems. Leung *et al.* (2000) compares with classification and level estimation models in forecasting stock indices. Ntungo and Boyd (1998) compares with time series models in forecasting turning points for trading commodity futures. Within the context of classifying trend movements in the MSCI U.S.A. capital market index, Wood and Dasgupta (1996) compares with regression and ARIMA models and Wu and Lu (1993) combines ANN's and statistics for stock market forecasting.

In predicting stock market trend and movements Brownstone (1996) uses percentage accuracy measures, Chenoweth and Obradovic (1996) employs a multi-component nonlinear prediction system, Saad *et al.* (1998) compares time delay, recurrent and probabilistic NN's, Wang and Leu (1996), use ARIMA-based neural networks, Yang and Liu (2001) applies multivariate time series prediction based on ANN's. In predicting stock market Hellström and Holmström (1998b), Phua *et al.* (2001), Schöneburg(1990) and, in economic and financial prediction Racine (2001) and White (1988) employs ANN's. Desai and Bharati (1998a) compares of linear regression and neural network methods for predicting excess returns on large stocks and Desai and Bharati (1998b) discuss the efficacy of neural networks in predicting returns on stock and bond indices. Hellström and Holmström (1998a) analyse the predictable patterns in stock return and Motiwalla and Wahab (2000) through a trading simulation searches predictable variation and profitable trading of US equities.

Qi and Maddala (1999) utilizes ANN's in analyzing economic patterns that influence stock markets. With employing a GARCH-NN approach, Meissner and Kawano (2001) tries to capture volatility smile of options on high-tech stocks and from an ANN perspective Miranda and Burgess models market volatilities.

In technical analysis of stocks and stock markets, Chenoweth *et al.* (2002) embeds technical analysis into NN based trading systems, Mendelsohn (1993) and Halquist and Schmoll (1989) discuss neural networks from a trading perspective.

Deboeck (1994) evaluates neural, genetic, and fuzzy systems for chaotic financial markets and Nevler (1993) discusses the limits of neural networks.

## 4. DATA ANALYSIS

Data collected for 10 sector indices covers the period of May 1991-December 2003 and obtained from DataStream.

The first step in data analysis is to determine (select) the economic variables to be used as independent or explanatory variables in the analysis. The selection criteria of Stansell and Eakins (2004) were adopted. First criteria in selecting economic variables is about the consistently publicly availability of data. We chose data publicized and available in public in a consistent basis. The second criterion is about the timely availability of data. And the third criterion is about the rationalization of data with economic theory and there should be rational to believe that it had an effect on stock market.

Table 1: Output Variables

| **ISE SECTOR INDICES** | |
|---|---|
| ISE-Composite | ISECOMP |
| 1-DS-Resources | ISEDS1 |
| 2-DS Basic Industries | ISEDS2 |
| 3-DS General Industrials | ISEDS3 |
| 4-DS Cyclical Consumption Goods | ISEDS4 |

| | |
|---|---|
| 5-DS Non Cyclical Consumption Goods | ISEDS5 |
| 6-DS Cyclical Services | ISEDS6 |
| 7-DS Non Cyclical Services | ISEDS7 |
| 8-DS Utilities | ISEDS8 |
| 9-DS Information Technology | ISEDS9 |
| 10-DS Financials | ISEDS10 |

Table 2: Input Variables

| **Domestic Macroeconomic Input Variables** | | **International Macroeconomic Input Variables** | | **Leading World Stock Market Indices** | |
|---|---|---|---|---|---|
| Leading Economic Indicators | TRLEAD | US Industrial Production Index 2002=100 | USIND-PRO | SP500 Comp. Index | SP500 |
| Producer Price Index | TRPPI | US Capacity Utilization: Total index | USCAP-UTIL | FTSE Comp. Index | FTSE |
| 3 months bank deposit rates | BDR | US Producer Price Index 1982=100 | USPPI | DAX Comp. Index | DAX |
| Total exports | EXP | Euro 12 Producer Price Index, 2000 = 100 | EUPPI | Nikkei225 Index | NKK |
| Total imports | IMP | JP yen; Libor interbank 3 months deposit rate | YDR | HSE Comp. Index | HSE |
| Reel effective exchange rate | REIR | US 3-month Libor interbank deposit rate | UDR | | |
| TR Capacity Utilization | TRCAP-UTIL | Euro area 10 year gov.bond yield | EUGBY | | |
| | | US 10 year gov.bond yield | USGBY | | |
| | | Japan 10 year gov.bond yield | JPGBY | | |
| | | W.Texas Intrm.Crude Oil | OIL | | |

With applying above-mentioned criteria, we selected a number of domestic and international economic variables to have possible effects on stock market. Variables were classified into three groups: domestic macroeconomic variables, international macroeconomic variables and leading world stock market indices (Table 2).

Historical data on ISE composite and sector indices data were collected from data provider DataStream while most of the domestic economic time series data were obtained from TCMB-EVDS system of Central Bank of Turkey and the DPT (State Planning Organization). International economic time series data were collected from REUTERS, Federal Reserve Systems (FED), European Central Bank (ECB) and a website called Economagic.

## 5. METHODOLOGY

Following preliminary data analysis, to make data to fit the network input needs, a set of lags for each input variable ranging from 1 to 12 months was constructed in order to include delayed effects of each variable. The aim of including lagged values of each input variable is based on the assumption that each macroeconomic variable could have an effect on sector index decreasing with the span of time. Therefore, lag structure is chosen ranging from 1 to 12 months.

Transformed versions of input variables were used in estimation and forecast of constructed models. Since aim of the study is to forecast direction and change in stock market indices, as a transformation percentage change in both dependent and independent variables were used in analysis. Rationale for this transformation is due investors' preference in stock markets is generally "percentage changes" in variables rather than "level" of each macroeconomic variable.

As mentioned earlier, three approaches to the neural network modeling was adopted:

In the *first approach*, each of 10 sector indices were separately modeled with lagged data, ranging from 1 month to 12 months, of each of 22 macroeconomic variables. For this purpose, we first constructed 11 x 22 = 231 separate neural network models in order to deal with each sector index separately. This could be expressed as:

$$ISE_t = X_{t-1} + X_{t-2} + ... + X_{t-12} \qquad (3)$$

where ISE is a sector index percentage change, and X is a lagged macroeconomic variable.

Constructed 231 models were trained with using training datasets composed of t and t-i (i=1,…, 12) values of each variable. Trained networks were tested on out-of-sample data for 12 successive months. Forecasts were conducted on one-step-ahead basis. Therefore, each of 231 models was tested 12 times for out-of-sample forecast purposes. In total, 231 x 12 = 2772 point forecasts were conducted.

For the *second approach*, we classified 22 economic variables into three groups as domestic macroeconomic variables, international macroeconomic variables and leading world stock market indices. For each sector indices, 3 neural network models were constructed. In total, we constructed 11x3= 33 NN models for this approach. These models were trained with training datasets of each group of variables. Datasets were composed of variables in each group. Along with the value in t, lagged values of dependent and independent variables up to 12 months were included in each datasets. Therefore, for each sector indices, in NN models of domestic macroeconomic variables we utilized 102 variables, in NN models of international macroeconomic variables 181 variables and in NN models of world stock market indices 84 variables.

Constructed 33 NN models were trained with data for the period of the period June 1992-December 2002. Then, for out of sample forecast purposes, trained networks were tested for 12 successive months for the period of January 2003- December 2003. Forecasts were conducted on one-step-ahead basis. In total, 33 x 12=396 point forecasts were conducted.

For the *third approach*, each sector index was modeled using lagged data on all 22 economic variables simultaneously. The objective of adapting this approach was to forecast and evaluate the forecasts using the most comprehensive and near real life conditions on the basis of each sector. For this purpose, each of 11 network models were constructed and trained with using 343 variables. Trained networks were tested on out-of-sample data for 12 successive months. Forecasts were conducted on one-step-ahead basis. Therefore, each of 11 models was tested 12 times for out-of-sample forecast purposes. In total, 11 x 12 = 132 point forecasts were conducted.

Since our study is about to forecast the change and direction of change in each sector indices, we adapted the neural network models mostly used in prediction problems (*i.e.* multilayer perceptron neural network model). In selecting the number of hidden layer and nodes in each layer, through adapting genetic algorithms where each generation of model is tried subsequently, we tried a number of models and compared the results. Selected models were models, which provided the least error. Each model had 4 hidden layers and 60 PE's in each hidden layer.

For constructed ANN models, supervised learning strategy was adapted and QuickBackpropagation learning rules were employed. In training networks, a high number of simulations (5000 epoch) were considered.

Models were estimated with using data for the period of June 1992-December 2002 and forecast performances were tested for the 12 monthly period of January 2003-December 2003. Main reason for selecting January-December 2003 was to test out of sample performance of ANN models in a high volatile environment witnessed during the year 2003.

## 6. EMPIRICAL FINDINGS

### 6.1. Forecast Performance

As mentioned previously, the aim of this study is to search for suitability of ANN models in forecasting direction and magnitude of change in ISE composite index and 10 sector indices by using data from a number of domestic and international macroeconomic variables and leading international stock market indices.

As discussed in methodology section in detail, three modeling approaches were adopted[1].

For the *first approach*, for each sector indices we trained 22, in total 231 separate NN models. For training the NN models, we used the data for the period of June 1992-December 2002. Trained networks were then assessed in out of sample forecast performance for successive 12 months.

In all approaches, forecasts of each constructed model were estimated, but for presentation purposes only those of the model for variable TRLEAD were presented in Table 3. In this table, columns were grouped in terms of each month of forecast period. For each month, actual percentage changes in each index were compared with the forecast percentage changes. Since the one of the aims was to look for direction of change, we denoted "BothPos" for the positively signed actual and forecast values and "BothNeg" for the negatively signed actual and forecast values of the same index. Although forecasts of all months were estimated, In Table 3 for presentation purposes, only those of two months were provided. In the first column, name of indices, in the second column actual realized value of these indices and in the third column forecast values of these indices were given. 'BothPos' column took value '1' if the actual and forecast values (direction of change) were in the same direction and '0' if the either one was positive and the other was negative. Similarly, 'BothNeg' column took value '1' only if actual and forecast values were both negatively signed. At the end of 'BothPos' and 'BothNeg' columns, numbers of correct picks were given. In Table 3, for January 2003, numbers of 'BothPos' correct picks were 5 and 'BothNeg' correct picks were 1. That meant, our NN model correctly forecasted 5 increases and 1 decreases in sector indices. Percentage of correct picks gave the ratio of correct picks to the total forecasts for each of direction of change. Our TRLEAD model correctly forecasted 5 out of 10 increase and 1 out of 1 decrease in sector indices. This corresponded 50% and 100% success rates. At the end, percentage of correct forecasts to the number of forecasts was given. This indicated the success of our models in forecasting direction of changes in sector indices for the given month. From the Table 3, TRLEAD model correctly forecasted 55% of changes in January, 73% of changes in July 2003 and so on.

Table 3: Actual and forecast sector index percentage changes (approach 1) of TRALL variables

[1] In the *first approach*, single economic variable NN models were constructed for forecasting direction and magnitude of change in 10 sector indices and composite index. Aim of this approach was to analyze the capability of individual economic variables in forecasting direction and magnitude of change in ISE indices. In the *second approach*, 22 variables were classified into three groups as domestic macroeconomic, international macroeconomic and world leading stock market variables. Models were estimated and networks were trained with using these 3 groups of variables. Aim of adopting this approach was to search for capability of each group of variables in forecasting direction and magnitude of change in ISE indices. Since each group represents different parts of influence on ISE stock market, this analysis should make it possible to select the most influential factors. In the *third approach*, all 22 variables along with their lag values were used as an input to a global model. With taking all variables into analysis at the same time, as a near real-life framework, capability of ANN models as a forecasting tool was analyzed.

| | Model: | TRLEAD | | |
|---|---|---|---|---|
| | **Actual** | **Forecast** | | |
| | **Jan-03** | **Jan-03** | **BothPos** | **BothNeg** |
| **ISEDS1** | 9,0657% | -0,2669% | 0 | 0 |
| **ISEDS2** | 11,9882% | 5,3808% | 1 | 0 |
| **ISEDS3** | 4,6060% | 6,8099% | 1 | 0 |
| **ISEDS4** | 6,0928% | -7,0943% | 0 | 0 |
| **ISEDS5** | 3,5811% | 5,0768% | 1 | 0 |
| **ISEDS6** | 5,4650% | 3,6457% | 1 | 0 |
| **ISEDS7** | 14,7186% | -4,2464% | 0 | 0 |
| **ISEDS8** | 5,2977% | 1,8535% | 1 | 0 |
| **ISEDS9** | 6,5536% | -7,1510% | 0 | 0 |
| **ISEDS10** | 6,5622% | -10,4579% | 0 | 0 |
| **ISECOMP** | -10,7917% | -0,5762% | 0 | 1 |
| p | 10 | SUM | 5 | 1 |
| n | 1 | %Correct | 50% | 100% |
| | Total % | Correct | 55% | |

| Model: | TRLEAD | | |
|---|---|---|---|
| **Actual** | **Forecast** | | |
| **Jul-03** | **Jul-03** | **BothPos** | **BothNeg** |
| -3,3233% | -0,2669% | 0 | 1 |
| -2,0706% | 5,3808% | 0 | 0 |
| -2,8018% | 6,8099% | 0 | 0 |
| -4,6176% | -7,0943% | 0 | 1 |
| 5,2404% | 5,0768% | 1 | 0 |
| 3,5649% | 3,6457% | 1 | 0 |
| -1,3449% | -4,2464% | 0 | 1 |
| -14,5021% | 1,8535% | 0 | 0 |
| -1,2353% | -7,1510% | 0 | 1 |
| -3,6102% | -10,4579% | 0 | 1 |
| -3,0019% | -0,5762% | 0 | 1 |
| 2 | SUM | 2 | 6 |
| 9 | %Correct | 100% | 67% |
| Total % | Correct | 73% | |

From the forecast accuracy of each single economic variable NN models, overall success rate of each model ranged from 36 percent to 91 percent. That means models correctly forecasted direction of change from 4 to 10 out of 11 sector indices in each month. Since, single economic variable should be unable to choose a correct pick from the direction of change in stock indices, overall performance of these models was found satisfactory.

Another way of evaluating forecast performance of the models was to summarize total forecast success and failure rates of NN models in terms of each individual variable. Along with model forecast, success rates for positive and negative movements in indices, aggregate success and failure performance of the models for individual variables were calculated and presented in Table 7.

From estimation results, it was found that ANN models of each individual economic variables generally had higher success rates in forecasting negative change in indices than positive change. In addition, average success rate was about 50 percent. That meant, models were able to correctly forecast 1 change in sector indices in every 2 changes. Another important finding was the success of DAX model. The model correctly picked 71% of all positive changes, 41% of all negative changes and in aggregate 58% of all changes. This was the highest rate for an individual variable in forecasting changes in ISE indices.

For the *second approach*, we constructed 3 NN models for group of domestic macroeconomic, international macroeconomic and world leading stock market variables. Constructed models were trained with training datasets. Then, trained network models were tested for out of sample forecast performance for the period of January 2003-December 2003.

Table 4: Total forecast S/F rates for all group variables (approach 2)

| TRALL | BOTHPOS | % CORRECT | BOTHNEG | %CORRECT | AGGREGATE SUCCESS RATES | |
|---|---|---|---|---|---|---|
| TOTAL CORRECT | 53 | 71,62% | 20 | 34,48% | SUCCESS | 55,30% |
| TOTAL INCORRECT | 21 | 28,38% | 38 | 65,52% | FAILURE | 44,70% |
| NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| **INTMACROECON** | | | | | | |
| TOTAL CORRECT | 65 | 87,84% | 17 | 29,31% | SUCCESS | 62,12% |
| TOTAL INCORRECT | 9 | 12,16% | 41 | 70,69% | FAILURE | 37,88% |
| NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| **WRLDSTCKMRKTS** | | | | | | |
| TOTAL CORRECT | 45 | 60,81% | 26 | 44,83% | SUCCESS | 53,79% |
| TOTAL INCORRECT | 29 | 39,19% | 32 | 55,17% | FAILURE | 46,21% |
| NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| **ALLVARIABLES** | | | | | | |
| TOTAL CORRECT | 46 | 62,16% | 23 | 39,66% | SUCCESS | 52,27% |
| TOTAL INCORRECT | 28 | 37,84% | 35 | 60,34% | FAILURE | 47,73% |
| NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |

For the purpose of saving space, forecast details in terms of forecast month and market indices were not provided here. Summary forecast results for second approach were given in Tables 4. Forecast success of TRALL models ranged from 27% to 100%. In April 2003, all models successfully forecasted direction of changes in all indices. However, performance of models in March and July were poorer. TRALL models were especially more successful in forecasting positive changes rather than negative changes in sector indices. In general, performance of NN models, which used all domestic macroeconomic variables, were found satisfactory in forecasting direction of change in ISE indices. TRALL models were especially more successful in forecasting positive changes in sector indices. TRALL models successfully forecast 53 out of 74 positive changes, with a 72 percent success rate. The performance of TRALL models was rather poorer (only 35 percent) in forecasting negative changes in sector indices. In aggregate, TRALL models were able to correctly forecast 55 percent of all changes in ISE indices.

Similar to TRALL models, forecasting accuracy of international macroeconomic variables (INTMACROECON) models ranged from 27% to 100%. In February, models were able to correctly forecast 10 out of 11 indices with an overall correct rate of 91%. As in the case of TRALL models, INTMACROECON models were more successful in forecasting positive changes rather than negative changes in sector indices. Success rate of the models in forecasting positive changes were ever-high rate of 88 percent. However, their performance in forecasting negative changes was only 29.3 percent, poorer than TRALL models. In general, performance of NN models, which used all international macroeconomic variables, were found satisfactorily high (62 percent) in forecasting direction of change in ISE indices.

Forecasting accuracy of world leading stock market variables (WRLDSTCKMRKTS) models was similar to those of TRALL and INTMACROECON models. Changes in leading international stock market indices were able to forecast 61 percent of positive and 45 percent of negative changes in ISE indices. In total, they were able to forecast correctly 54 percent of changes in indices.

Forecast performance of TRALL, INTMACROECON and WRLDSTCKMRKTS models proved that ANN models using group of variables had an ability of forecasting direction of change in ISE composite and sector indices.

For the *third approach*, ALLVARIABLES model was constructed to include 343 variables along with lag values of dependent variables (ISE indices). This model was the most comprehensive model, which included all variables used in analysis. Summary forecast performance of the model was presented in Table 4. Although it included all the variables, its forecast performance was not better than more parsimonious models. Similar to models of approach 2, this model was found more successful in forecasting positive changes in ISE indices than in forecasting negative changes. Aggregate success rate was calculated as 52 percent. Although it could explain 100 percent change in ISE indices, their forecast performance, especially of negative changes, were lower. This finding could be explained by effect of non-economic (especially political factors) on ISE indices.

Since, ISE is not a mature market and market depth in comparison with mature markets is rather shallow, effects of non-economic factors on indices are higher than mature markets. This characteristic of emerging market countries stock markets makes the forecast job more difficult than other markets.

## 6.2. Investing with Model Forecasts

In stock markets, to take profitable positions and make money from these positions, institutional investors are generally interested in direction of the market and market indices. Having an insight about the direction of change in stock indices is a vital part of investment strategies and decisions. This insight could be achieved by close monitoring of factors, which have an effect on stock prices.

Main advantage of ANN models is their ability in modeling nonlinear structures and ability to work with a large number of variables without any constraint. ANN models have a potential to use in determining characteristic features of stock markets and forecasting stock prices and indices.

In this section, availability of forecast results as a guiding tool in investment decision was searched. For this purpose, first of all we defined two investment strategies: active and passive investment strategy. In active investment strategy, forecast results were actually used in investment decisions. In passive strategy, nothing done and changes in sector indices were just monitored.

Table 5: Change in indices, actions could be taken and result of each action

| **Actual Change** | **Forecast Change** | **Action taken** | **Result** |
|---|---|---|---|
| Positive | Positive | Invest | Gain |
| Positive | Negative | Not invest | Gain foregone |
| Negative | Positive | Invest | Loss |
| Negative | Negative | Not invest | Loss avoided |

As a starting point, an investment matrix was defined (Table 5). In this matrix, depending on the actual and forecast change, each action and its more probable result was defined. For example, if the investor decides to invest in a view of an appreciation (based on the forecast result) in ISE indices and this increase was realized, the result of this action would be a gain amount of forecast percentage change. If the forecast result gave a decrease in indices then investor did not make an investment but this decrease did not happened, investor would foregone a gain amount of actual percentage change. Similarly, if model predicted a positive change in indices and investor decided to make investment, but this increase was not realized, investor had to bear loss in an amount of forecast change. Finally, if model predicted a negative change in indices and investor did not make any investment, investor avoided a loss amount of actual percentage decrease in indices.

This investment analysis was conducted only for the models of approach 2 and 3. Although analysis was conducted for each forecast month and market indices, in all models, for presentation purposes only gains and losses from forecasts vs. passive strategy for ISECOMP index in TRALL models were provided in Table 6.

Table 6: TRALL: Gains and losses from forecasts vs. passive strategy

| | **% Change in sector indices** | | **Investment Strategy** | | | | **Passive Strategy** | |
|---|---|---|---|---|---|---|---|---|
| **Sector Indices** | **Actual** | **Forecast** | **Investment Decision** | | **Gain/Loss from Investment** | **Sector Points from Forecast** | **Position** | **Sector Points from Passive Strategy** |
| **ISECOMP** | | | | | | **0,432** | | **0,432** |
| *Jan.2003* | -10,79% | 5,00% | INVEST | LOSS | -10,79% | | -10,79% | |
| *Febr.2003* | 7,36% | 5,03% | INVEST | GAIN | 7,36% | | 7,36% | |
| *Marc.2003* | -10,65% | 4,70% | INVEST | LOSS | -10,65% | | -10,65% | |
| *Apr.2003* | 8,11% | 4,89% | INVEST | GAIN | 8,11% | | 8,11% | |
| *May.2003* | -0,39% | 4,74% | INVEST | LOSS | -0,39% | | -0,39% | |
| *June.2003* | 0,48% | 5,02% | INVEST | GAIN | 0,48% | | 0,48% | |
| *July.2003* | -3,00% | 4,91% | INVEST | LOSS | -3,00% | | -3,00% | |
| *Aug.2003* | 9,60% | 4,99% | INVEST | GAIN | 9,60% | | 9,60% | |
| *Sept.2003* | 9,86% | 4,73% | INVEST | GAIN | 9,86% | | 9,86% | |
| *Oct.2003* | 17,92% | 4,82% | INVEST | GAIN | 17,92% | | 17,92% | |
| *Nov.2003* | 4,82% | 5,03% | INVEST | GAIN | 4,82% | | 4,82% | |
| *Dec.2003* | 9,88% | 4,42% | INVEST | GAIN | 9,88% | | 9,88% | |
| | | | | | | | | |

In Table 6, two strategies were analyzed. In investment strategy, it was assumed that investors made investment decisions by using model forecasts. Model forecasts were compared with actual changes in sector indices and in the guidance of Table 5, investment decision, resulting gain or loss from investment and total sector points from all forecasts for each ISE indices were calculated. For comparison, loss or gains and sector points from passive strategy were also provided.

Another way of evaluating forecast results in investment decision was also used. Results were provided for TRALL, INTMACROECON, WRLDSTCKMRKTS and ALLVARIABLES models in Table 8. For this purpose, gain or loss from a passive strategy was taken as a benchmark. In the table results of actions were summarized for each point of forecast and sector indices.

With using TRALL models for forecast purposes, an investor could gain 716.84 sector points, forego 218.56 point, bear 242.17 point and avoid 157.82 point losses. In total, he could get net 413.93 points from using these forecast results in his investment decisions.

If he used INTMACROECON model forecasts in his investment decisions, he could get 784.90 point as a gain, forego 150.50 point, bear 235.44 point loss, avoid 164.55 point loss and in total could get 563.50 point from forecasting.

If this investor used WORLDSTOCKMRKT models for forecast purposes, he could get 580.18-point, forego 355.22-point gain, bear 224.85-point loss, avoid 175.13-point loss and in total could get 175.24 point from forecast with these models.

If the investor preferred to use the greatest model, which comprised all variables, he could get 556.86 point as a gain, forego 378.54 point, bear 234.78 point loss and avoid 165.20 point loss. In total, he could get only 108.74 point.

Comparison of model results yielded that INTMACROECON models outperformed other models in terms of highest gains achieved, least gains avoided and net gain to forecasts. In terms of least loss born and loss avoided WORLDSTCK models outperformed other models.

Overall, model results indicated that although some models outperformed others in some areas, all models had capability to be used in forecasting ISE indices.

## 7. CONCLUSION

In stock markets, to take profitable positions and make money from these positions, institutional investors are generally interested in direction of the market and market indices. Having insight about the direction of change in stock indices is a vital part of their investment decisions. This insight could be achieved by close monitoring of factors, which have an effect on stock prices.

In this study, we worked with a number of economic variables. Time series used in this study included four crisis data (e.g. April 1994 monetary crisis, 1996 Asian Crisis, 2000 and 2001 banking crisis). Since one of the main aims of this study was to test the forecast ability of ANN models, we preferred to include these extreme data points rather than excluding them (as many researchers do). Moreover, we preferred to test out-of-sample performance of our models in a high volatility environment of year 2003 rather than lower volatility of the years 2004-2006. Even though these factors which negatively affected the forecast performance of out models, models performed satisfactorily well in these extreme conditions.

Main findings of this study could be summarized as follows:

- ANN models of each individual economic variable generally had higher success rates in forecasting negative change in indices than positive change. In addition, average success rate was about 50 percent.
- Among the single economic variable models the model DAX model correctly picked 71% of all positive changes, 41% of all negative changes and in aggregate 58% of all changes. This was the highest rate for an individual variable in forecasting changes in ISE indices.
- For the second approach, in April 2003, all models successfully forecasted direction of changes in all indices. Whereas, performance of models in March and July were poor
- TRALL models were especially more successful in forecasting positive changes rather than negative changes in sector indices. In aggregate, TRALL models were able to correctly forecast 55 percent of all changes in ISE indices.
- Performance of NN models, which used all domestic macroeconomic variables, was found satisfactory in forecasting direction of change in ISE indices. These models were more successful in forecasting positive changes rather than negative changes in sector indices. Success rate of the models in forecasting positive changes were ever-high rate of 88 percent. However, their performance in forecasting negative changes were only 29.3 percent, poorer than TRALL models
- Forecasting accuracy of world leading stock market variables (WRLDSTCKMRKTS) models was similar to those of TRALL and INTMACROECON models.

- Forecast performance of TRALL, INTMACROECON and WRLDSTCKMRKTS models proved that ANN models using group of variables had an ability of forecasting direction of change in ISE composite and sector indices.
- Although the most comprehensive model (ALL VARIABLES) included all the variables, their forecast performance was not better than more parsimonious models of approach 2. Although they could explain 100 percent change in ISE indices, their forecast performance, especially of negative changes, were lower. This finding could be explained by effect of non-economic (especially political factors) on ISE indices.
- In the search for suitability of ANN models as an investment decision support tool, comparison of model results yielded that INTMACROECON models outperformed other models in terms of highest gains achieved, least gains avoided and net gain to forecasts. In terms of least loss born and loss avoided WORLDSTCK models outperformed other models. As a conclusion, model results indicated that although some models outperformed others in some areas, all models had capability to be used in forecasting ISE indices.

As a general conclusion, we found that ANN models had a great potential in using as a forecast tool in support of investment decisions and in determining characteristic features of stock markets and forecasting stock prices and indices. Their main advantage is their ability in modeling nonlinear structures and ability to work with a large number of variables without any constraint.

## BIBLIOGRAPHY


[1] Anderson, J.A. (1977), "Brain modeling and memory", (in: X.J.R. Avula-Ed., *Proceedings of the First International Conference on Mathematical Modeling*. (Invited paper). Rolla, Missouri: University of Missouri.

[2] Bengoechea Glaria, A., Ordonez Uretaz, C., Marchant Saavedra, M., & Opazo Medina, N. (1996), "Stock market indices in Santiago de Chile: Forecasting using neural networks". Paper presented at the *1996 IEEE International Conference on Neural Networks*, Washington, DC.

[3] Broomhead, D. and D. Lowe (1988), "Multivariate functional interpolation and adaptive Networks", *Computer Systems*, 2:321-355.

[4] Brownstone, D. (1996), "Using percentage accuracy to measure neural network predictions in stock market movements", *Neurocomputing*, 10(3), 237-250.

[5] Chenoweth, T., & Obradovic, Z. (1996), "A multi-component nonlinear prediction system for the S&P 500 Index", *Neurocomputing*, 10(3), 275-290.

[6] Chenoweth, T., Obradovic, Z., & Lee, S. S. (2002), *Embedding technical analysis into neural networks based trading systems,* http://citeseer.nj.nec.com/143022.html, retrieved April 28, 2002.

[7] Cogger, K. O., Koch, P. D., & Lander, D. M. (1997), "A neural network approach to forecasting volatile international equity markets", (in M. Hirschey & M. W. Marr-Eds., *Advances in financial economics,* Vol.3, pp.117-157). Greenwich, CT:JAI Press.

[8] Deboeck, G. J. (Ed.). (1994), Trading on the edge: Neural, genetic, and fuzzy systems for chaotic financial markets. New York, NY: John Wiley & Sons, Inc.

[9] Desai, V. S., & Bharati, R. (1998a), "A comparison of linear regression and neural network methods for predicting excess returns on large stocks", *Annals of Operations Research,* 78, 127-163.

[10] Desai, V. S., & Bharati, R. (1998b), "The efficacy of neural networks in predicting returns on stock and bond indices", *Decision Sciences*, 29(2), 405-425.

[11] Grosberg, S. A. (1973), "Contour enhancement, short term memory, and constancies in reverbrating neural networks" *Studies in Applied Mathematics*, 52(3), 213-257.

[12] Grudnitski, G., & Osburn, L. (1993), "Forecasting S&P and gold futures prices: An application of neural networks", *Journal of Futures Markets*, 13(3), 631-643.

[13] Halquist, C. H., & Schmoll, G. F. (1989), "Neural networks: A trading perspective", *Technical Analysis of Stocks & Commodities*, 7(11), 48-54.

[14] Hamid, S. A., & Iqbal, Z. (2004), "Using neural networks for forecasting volatility of S&P 500 Index futures prices", *Journal of Business Research*, 57(10), 1116-1125.

[15] Hebb, D.O. (1949), The Organization of Behavior, John Wiley & Sons, New York.

[16] Hellström, T., & Holmström, K. (1998a), "Predictable patterns in stock returns" *Technical report No. ISRN HEV-BIB-OP-30-SE,* Vasteras, Sweden: Malardalen University.

[17] Hellström, T., & Holmström, K. (1998b), "Predicting the stock market" *Technical report No. IMa-TOM-199707,* Vasteras, Sweden: Malardalen University.

[18] Hopfield, J.J. (1982), "Neural networks and physical systems with emergent collective computational abilities", *Proceedings of the National Academy of Science,* vol. 79:2554-2558.

[19] Hopfield, J.J. (1984), “Neural Networks with graded response have collective computational properties like those of two-state neurons”, *Proceedings of the National Academy of Science*, vol. 81:3088-3092.
[20] Kanas, A. (2001), “Neural network linear forecasts for stock returns”, *International Journal of Finance & Economics*, 6(3), 245-254
[21] Kohonen, T. (1972), “Correlation matrix memories”, *IEEE. Transactions on Computers* C, 21, 353-359.
[22] Kryzanowski, L., Galler, M., & Wright, D. W. (1993), “Using artificial neural networks to pick stocks”, *Financial Analysts Journal*, 49(4), 21-28.
[23] Lee, T. S., & Chiu, C. C. (2002), “Neural network forecasting of an opening cash price index”, *International Journal of Systems Science*, 33(3), 229-237.
[24] Leigh, W., Purvis, R., & Ragusa, J. M. (2002), “Forecasting the NYSE composite index with technical analysis, pattern recognizer, neural network, and genetic algorithm: A case study in romantic decision support”, *Decision Support Systems*, 32(4), 361-377.
[25] Leung, M. T., Daouk, H., & Chen, A. S. (2000), “Forecasting stock indices: A comparison of classification and level estimation models”, *International Journal of Forecasting*, 16(2), 173-190.
[26] McCulloch, W.S., and Pitts, W. (1943), A Logical Calculus of the Ideas Immanent in Nervous Activity, *Bulletin of Mathematical Biophysics*, 5, 115-133.
[27] Malliaris, M., & Salchenberger, L. (1996), Using neural networks to forecast the S & P 100 implied volatility”, *Neurocomputing*, 10(2), 183-195.
[28] Meissner, G., & Kawano, N. (2001), “Capturing the volatility smile of options on high-tech stocks: A combined GARCH-Neural Network approach”, *Journal of Economics and Finance*, 25(3), 276.
[29] Mendelsohn, L. (1993), “Training neural networks”, *Technical Analysis of Stocks and Commodities*, 11(11), 457-460.
[30] Miranda, F. G., & Burgess, N. (1997), “Modelling market volatilities: The neural network perspective”, *European Journal of Finance*, 3(2), 137-157.
[31] Minsky, M., and Papert, S. (1969), Perceptrons, Cambridge, MA: MIT Press.
[32] Motiwalla, L., & Wahab, M. (2000), “Predictable variation and profitable trading of US equities: a trading simulation using neural networks”, *Computers & Operations Research*, 27(11-12), 1111-1129.
[33] Nevler, J. (1993), “Hitting the limits of neural networks”, *Wall Street & Technology*, 11(7), 34-38.
[34] Ntungo, C., & Boyd, M. (1998), “Commodity futures trading performance using neural network models versus ARIMA models”, *Journal of Futures Markets*, 18(8), 965-983.
[35] Phua, P. K. H., Ming, D., & Lin, W. (2001), “Neural network with genetically evolved algorithms for stocks prediction”, *Asia-Pacific Journal of Operational Research*, 18(1), 103-107.
[36] Qi, M., & Maddala, G. S. (1999), “Economic factors and the stock market: A new perspective”, *Journal of Forecasting*, 18(3), 151.
[37] Racine, J. (2001), “On the nonlinear predictability of stock returns using financial and economic variables”, *Journal of Business & Economic Statistics*, 19(3), 380-382.
[38] Rosenblatt, F. (1959), “The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain”, *Psychological Review* 65:386-408.

[39] Rummelhart, G. Hinton, and R.Williams (1986a), “Learning internal representations by error propagation”, (in: D. Rummelhart and J. McClelland, editors, *Parallel Distributed Processing*, pages 318–362), Cambridge, 1986. MIT Press.

[40] Rummelhart, D., Hinton, G., ve Williams, R. (1986b), “Learning internal representations by error propagation”, (in: D. Rummelhart ve J. McClelland-Eds, *Parallel Data Processing),* Cambridge, , The MIT press edition, pp. 318-362.

[41] Rumelhart, D. E., & Zipser, D. (1988), “Chapter 8 - Feature discovery by competitive learning”, (in: D. Waltz & J. A. Feldman-Eds., *Connectionist models and their implications: Readings from cognitive science,* pp. 205-242). Norwood, NJ: Ablex Publishing Corporation.

[42] Saad, E. W., Prokhorov, D. V., & Wunsch, D. C., II. (1998), “Comparative study of stock trend prediction using time delay, recurrent and probabilistic neural networks”, *IEEE Transactions on Neural Networks,* 9(6), 1456-1470.

[43] Schöneburg, E. (1990), “Stock price prediction using neural networks: A project report”, *Neurocomputing,* 2(1), 17-27.

[44] Specht, D.F. (1988), “Probabilistic Neural Networks for Classification, Mapping, or Associative Memory”, *Proceedings of the IEEE International Conference on Neural Networks*, Vol. 1, San Diego, CA. July 24-27, pp. 525-532.

[45] Specht, D.F. (1990), “Probabilistic Neural Networks”, *Neural Networks,* 3, 110-118.

[46] Stansell & Eakins (2004). Forecasting the direction of change in sector stock indexes: An application of neural networks, *Journal of Asset Management,* Vol 5, 1, 37-38.

[47] van Eyden, R. J., & Caldwell, R. B. (Eds.). (1996), The application of neural networks in the forecasting of share prices, Finance & Technology Publishing.

[48] Yang, Y., & Liu, G. (2001), “Multivariate time series prediction based on neural networks applied to stock market”, Paper presented at the 2001 *IEEE International Conference on Systems*, Man, and Cybernetics, Tucson, AZ.

[49] Wang, J.-H., & Leu, J.-Y. (1996), “Stock market trend prediction using ARIMA-based neural networks”, Paper presented at the *IEEE International Conference on Neural Networks*, Washington, DC.

[50] White, H. (1988), “Economic prediction using neural networks: The case of IBM daily stock returns”, Paper presented at the *IEEE International Conference on Neural Networks,* San Diego, CA.

[51] Widrow, B. and Hoff (1960), “Adaptive switching circuits”, (in: *1960 IRE WESCON Convention Record*, pp 96 – 104). IRE. Reprinted in *Neurocomputing - Foundations of Research* eds. Anderson and Rosenfeld.

[52] Wittkemper, H.-G., & Steiner, M. (1996), “Using neural networks to forecast the systematic risk of stocks”. *European Journal of Operational Research,* 90(3), 577-588.

[53] Wood, D., & Dasgupta, B. (1996), “Classifying trend movements in the MSCI U.S.A. capital market index - A comparison of regression, ARIMA and neural network methods”, *Computers & Operations Research,* 23(6), 611-622.

[54] Wu, S. I., & Lu, R.P. (1993), “Combining artificial neural networks and statistics for stock-market forecasting”, Paper presented at the *1993 ACM conference on 1993 ACM computer science,* Indianapolis, IN.

## Annex:

Table 7: Total forecast success and failure (S/F) rates for individual variables (approach 1)

| | | BOTHPOS | % CORRECT | BOTHNEG | % CORRECT | AGGREGATE SUCCESS RATES | |
|---|---|---|---|---|---|---|---|
| **Domestic Variables** | | | | | | | |
| | TOTAL CORRECT | 34 | 45,95% | 32 | 55,17% | SUCCESS | 50,00% |
| | TOTAL INCORRECT | 40 | 54,05% | 26 | 44,83% | FAILURE | 50,00% |
| **TRLEAD** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 34 | 45,95% | 32 | 55,17% | SUCCESS | 50,00% |
| | TOTAL INCORRECT | 40 | 54,05% | 26 | 44,83% | FAILURE | 50,00% |
| **TRPPI** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 34 | 45,95% | 32 | 55,17% | SUCCESS | 50,00% |
| | TOTAL INCORRECT | 40 | 54,05% | 26 | 44,83% | FAILURE | 50,00% |
| **TRBDR** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 33 | 44,59% | 32 | 55,17% | SUCCESS | 49,24% |
| | TOTAL INCORRECT | 41 | 55,41% | 26 | 44,83% | FAILURE | 50,76% |
| **TRIMP** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 29 | 39,19% | 38 | 65,52% | SUCCESS | 50,76% |
| | TOTAL INCORRECT | 45 | 60,81% | 20 | 34,48% | FAILURE | 49,24% |
| **TREXP** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 33 | 44,59% | 31 | 53,45% | SUCCESS | 48,48% |
| | TOTAL INCORRECT | 41 | 55,41% | 27 | 46,55% | FAILURE | 51,52% |
| **TRCAPUTIL** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| **Internatinal Macroeconomic Variables** | | | | | | | |
| | TOTAL CORRECT | 40 | 54,05% | 27 | 46,55% | SUCCESS | 50,76% |
| | TOTAL INCORRECT | 34 | 45,95% | 31 | 53,45% | FAILURE | 49,24% |
| **USINDPRO** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 33 | 44,59% | 31 | 53,45% | SUCCESS | 48,48% |
| | TOTAL INCORRECT | 41 | 55,41% | 27 | 46,55% | FAILURE | 51,52% |
| **USCAPUTIL** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 33 | 44,59% | 31 | 53,45% | SUCCESS | 48,48% |
| | TOTAL INCORRECT | 41 | 55,41% | 27 | 46,55% | FAILURE | 51,52% |
| **USPPI** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 41 | 55,41% | 28 | 48,28% | SUCCESS | 52,27% |
| | TOTAL INCORRECT | 33 | 44,59% | 30 | 51,72% | FAILURE | 47,73% |
| **EUPPI** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 33 | 44,59% | 31 | 53,45% | SUCCESS | 48,48% |
| | TOTAL INCORRECT | 41 | 55,41% | 27 | 46,55% | FAILURE | 51,52% |
| **YDR** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 41 | 55,41% | 27 | 46,55% | SUCCESS | 51,52% |
| | TOTAL INCORRECT | 33 | 44,59% | 31 | 53,45% | FAILURE | 48,48% |
| **UDR** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 32 | 43,24% | 35 | 60,34% | SUCCESS | 50,76% |
| | TOTAL INCORRECT | 42 | 56,76% | 23 | 39,66% | FAILURE | 49,24% |
| **EUGBY** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 30 | 40,54% | 35 | 60,34% | SUCCESS | 49,24% |
| | TOTAL INCORRECT | 44 | 59,46% | 23 | 39,66% | FAILURE | 50,76% |
| **USGBY** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 33 | 44,59% | 31 | 53,45% | SUCCESS | 48,48% |
| | TOTAL INCORRECT | 41 | 55,41% | 27 | 46,55% | FAILURE | 51,52% |
| **JPGBY** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 35 | 47,30% | 31 | 53,45% | SUCCESS | 50,00% |
| | TOTAL INCORRECT | 39 | 52,70% | 27 | 46,55% | FAILURE | 50,00% |
| **OIL** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| **International Stock Exchanges** | | | | | | | |
| | TOTAL CORRECT | 34 | 45,95% | 31 | 53,45% | SUCCESS | 49,24% |
| | TOTAL INCORRECT | 40 | 54,05% | 27 | 46,55% | FAILURE | 50,76% |
| **SP500** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 42 | 56,76% | 27 | 46,55% | SUCCESS | 52,27% |
| | TOTAL INCORRECT | 32 | 43,24% | 31 | 53,45% | FAILURE | 47,73% |
| **FTSE** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 53 | 71,62% | 24 | 41,38% | SUCCESS | 58,33% |
| | TOTAL INCORRECT | 21 | 28,38% | 34 | 58,62% | FAILURE | 41,67% |
| **DAX** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 49 | 66,22% | 23 | 39,66% | SUCCESS | 54,55% |
| | TOTAL INCORRECT | 25 | 33,78% | 35 | 60,34% | FAILURE | 45,45% |
| **NKK** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |
| | TOTAL CORRECT | 33 | 44,59% | 31 | 53,45% | SUCCESS | 48,48% |
| | TOTAL INCORRECT | 41 | 55,41% | 27 | 46,55% | FAILURE | 51,52% |
| **HSE** | NUMBER of FORECAST | 74 | 100,00% | 58 | 100,00% | AGGREGATE | 100,00% |

Table 8: Comparison of results from ANN forecasts

| MODELS | INDICES | GAIN | GAIN FOREGONE | LOSS | LOSS AVOIDED | NET |
|---|---|---|---|---|---|---|
| **TRALL** | | **716,84%** | **-218,56%** | **-242,17%** | **157,82%** | **413,93%** |
| | ISED1 | 46,90% | -19,07% | -24,78% | 19,63% | 22,68% |
| | ISED2 | 71,24% | -19,20% | -25,85% | 0,00% | 26,19% |
| | ISED3 | 95,54% | -4,61% | -23,60% | 10,62% | 77,96% |
| | ISED4 | 95,01% | -7,62% | -28,06% | 11,42% | 70,76% |
| | ISED5 | 76,56% | 0,00% | -20,20% | 0,00% | 56,36% |
| | ISED6 | 22,64% | -70,92% | -0,17% | 28,76% | -19,69% |
| | ISED7 | 52,09% | -25,39% | -22,31% | 9,39% | 13,78% |
| | ISED8 | 76,00% | 0,00% | -34,24% | 2,86% | 44,62% |
| | ISED9 | 0,00% | -59,45% | 0,00% | 75,14% | 15,69% |
| | ISED10 | 112,84% | -12,31% | -38,14% | 0,00% | 62,40% |
| | ISEDCOMP | 68,01% | 0,00% | -24,83% | 0,00% | 43,18% |
| **INTMACROECON** | | **784,90%** | **-150,50%** | **-235,44%** | **164,55%** | **563,50%** |
| | ISED1 | 65,97% | 0,00% | -15,63% | 28,78% | 79,12% |
| | ISED2 | 51,51% | -38,92% | -8,89% | 16,96% | 20,65% |
| | ISED3 | 100,15% | 0,00% | -27,74% | 6,47% | 78,88% |
| | ISED4 | 95,01% | -7,62% | -39,48% | 0,00% | 47,92% |
| | ISED5 | 76,56% | 0,00% | -20,20% | 0,00% | 56,36% |
| | ISED6 | 47,95% | -45,62% | -4,81% | 24,12% | 21,63% |
| | ISED7 | 77,48% | 0,00% | -12,73% | 18,96% | 83,71% |
| | ISED8 | 76,00% | 0,00% | -37,10% | 0,00% | 38,90% |
| | ISED9 | 10,70% | -48,75% | -41,27% | 33,88% | -45,44% |
| | ISED10 | 125,15% | 0,00% | -5,76% | 32,38% | 151,78% |
| | ISEDCOMP | 58,41% | -9,60% | -21,83% | 3,00% | 29,99% |
| **WORLDSTOCK** | | **580,18%** | **-355,22%** | **-224,85%** | **175,13%** | **175,24%** |
| | ISED1 | 62,32% | -3,65% | -0,75% | 43,66% | 101,57% |
| | ISED2 | 68,54% | -21,90% | -16,83% | 9,02% | 38,84% |
| | ISED3 | 54,82% | -45,33% | -6,47% | 27,74% | 30,76% |
| | ISED4 | 96,54% | -6,09% | -29,94% | 9,53% | 70,03% |
| | ISED5 | 35,77% | -40,79% | -8,06% | 12,14% | -0,94% |
| | ISED6 | 15,22% | -78,34% | -4,99% | 23,94% | -44,16% |
| | ISED7 | 75,26% | -2,23% | -7,65% | 24,04% | 89,42% |
| | ISED8 | 8,54% | -67,46% | -26,12% | 10,98% | -74,05% |
| | ISED9 | 48,75% | -10,70% | -63,22% | 11,93% | -13,24% |
| | ISED10 | 56,02% | -69,14% | -35,99% | 2,15% | -46,96% |
| | ISEDCOMP | 58,41% | -9,60% | -24,83% | 0,00% | 23,98% |
| **ALLVARIABLES** | | **556,86%** | **-378,54%** | **-234,78%** | **165,20%** | **108,74%** |
| | ISED1 | 65,97% | 0,00% | -44,41% | 0,00% | 21,56% |
| | ISED2 | 68,54% | -21,90% | -16,83% | 9,02% | 38,84% |
| | ISED3 | 100,15% | 0,00% | -34,21% | 0,00% | 65,94% |
| | ISED4 | 102,63% | 0,00% | -39,48% | 0,00% | 63,16% |
| | ISED5 | 36,18% | -40,37% | -12,37% | 7,82% | -8,74% |
| | ISED6 | 81,58% | -11,98% | -28,93% | 0,00% | 40,66% |
| | ISED7 | 0,00% | -77,48% | 0,00% | 31,70% | -45,79% |
| | ISED8 | 41,42% | -34,58% | -30,11% | 6,99% | -16,29% |
| | ISED9 | 0,00% | -59,45% | 0,00% | 75,14% | 15,69% |
| | ISED10 | 2,25% | -122,90% | -3,61% | 34,53% | -89,73% |
| | ISEDCOMP | 58,13% | -9,88% | -24,83% | 0,00% | 23,42% |