ABSTRACT
The purpose of this study was to perform fundamental analysis and cross-sectional prediction of stock return with neuro-fuzzy. Also this study tries to understand the investors' process of financial statement analysis by interpreting the neuro-fuzzy model rules. The data set consisted of firms traded on the Istanbul Stock Exchange (ISE) in Turkey during the period of 1992-1999. Validation of the neuro-fuzzy model is conducted at the portfolio level. Even though there wasn’t any statistically significant difference, the neuro-fuzzy model provides slightly higher return than benchmark portfolios. Also this approach exposes how investors select those firms which have low P/E ratios but high gross profit and/or operating profit.

Keywords: Neuro-Fuzzy, Fundamental Analysis, Financial Statement Analysis, Investment Decision Support System, Artificial Intelligence.
I. Introduction

From both national and international perspective, there are bulk numbers of equities in the stock markets. Therefore; the analysis and selection of correct equities are crucial for investors to ensure a satisfactory return. Acceleration of the financial world also forces investors to respond more quickly. Consequently, decision support systems for investment activities are becoming increasingly important.

Soft computing techniques are used to develop decision support systems. The term “Soft Computing” involves expert systems, fuzzy logic, neural network and genetic algorithm (Jang, Sun, Mizutani, 1997: p. 1). Soft computing techniques are quite appropriate to develop decision support systems for the finance and investment field.

As it is well known, the financial world is complex and difficult to model by classical techniques. Decrease in computing cost in the last two decades is another factor encouraging soft computing researches in the finance and investment field with possibly the most popular soft computing technology being neural networks.

The neural network is widely used for financial prediction and classification purposes in the literature due to production of successful results when there is a non-linear problem. However, the majority of studies deal with technical analysis and/or stock index forecasting (Kimoto, Asakawa, Yoda, Takeoka, 1996; Wood, Dasgupta, 1996; Tsaih, Hsu, Lai, 1998; Quah and Srinivasan, 1999; Leigh, Paz, Purvis, 2002; with neuro-fuzzy Siekmann Kruse, Gebhardt, 2001). Fundamental analysis studies are very limited and existing studies were realized with neural networks (Kryzanowski, Galler, Wright, 1993; Kryzanowski, Galler, 1995), except Wong, Wang, Goh, Quek (1992) study include neuro-fuzzy technology. Nevertheless, neural networks models remain in black-box after training and the synaptic connections can not be interpreted by humans. This is an important drawback of neural networks if the decision maker wants to know “how”. In such situations, fuzzy logic is a viable alternative to neural networks.

A typical Fuzzy Inference System (FIS) uses IF-THEN rules such expert systems but evaluates each rule using the fuzzy set theory. One of the important advantages of FIS is the interpretability of its rules, but the adjusting of membership functions is difficult and very time consuming in the developing phase of a FIS. Neuro-fuzzy technology offers an accomplished solution to overcome the problems arising from both neural networks and fuzzy logic. Neuro-fuzzy is a hybrid technology that combines both the inferencing capabilities of FIS and the learning feature of neural networks. Thus, deficiency of the techniques is eliminated. In the association of two techniques, the Neural Networks technique is used to the adjust parameter of the membership function in a FIS. Neuro-fuzzy systems offer the advantage of both the fuzzy systems’ explanation feature and the neural network’s learning capabilities in a single structure (Nuck and Kruse, 1999).

Because of the advantages of neuro-fuzzy explained above, it is seen as the best alternative technology to develop investment decision support system for stock
selection. In this study, neuro-fuzzy systems are used to develop an investment
decision support system that helps investors to do fundamental analysis. The final
decision support system has slightly greater prediction performance that isn’t
statistically significant. But the decision support system provided interpretable rules
without lengthy and tedious rule extraction efforts. Moreover, these rules may help
us to understand how investors select stocks.
Main problem about relationship between fundamental analysis and return
represented in section two, neuro-fuzzy technology was briefly summarized in
section three. Data was described in section four. Section five and six include
methodology and results consecutively. Conclusion is the last section of the study.

II. Fundamental Analysis
Fundamental analysis assumes that the market is not efficient and some equities may
be mispriced. When the market value of a security differs from the intrinsic value on
the basis of fundamentals such earnings, dividends, debt and capital structure, they
are identified as mispriced. Therefore investors can identify under-priced or over-
priced equities using financial, industrial or economic data and it is possible to gain
abnormal return from these equities. Such assumption encourages investments and
analyst to attach too much importance to fundamental analysis. For example, Carter
and Van Auken (1990), Wong and Cheung (1999) studies indicated that
fundamental analysis was the most popular method amongst investment
professional. But there is no theoretical model for fundamental analysis. Some
researchers provided that future earnings and returns could be predicted from
financial statement information using statistical techniques (Ou and Penman, 1989;
Lev and Thiagarajan, 1993; Abarbanell and Bushee, 1997, 1998; Houltsen and
Lacker, 1992; Kothari, 2001). Similarly, the model developed in our study expects
to reveal the unspecified relationship between financial statement information and
stock return with neuro-fuzzy technology.

III. Neuro-Fuzzy Technology
Fuzzy Set Theory is a theory which can handle imprecise or linguistic information
that actually probability theory cannot do properly (Zadeh, 1965). Opposed to
classical logic, a fuzzy set object may belong to a set in a degree. A is a fuzzy set
defined as:
\[ A=\{(x, \mu A(x))| x \in X\}, \]  
where \(\mu A(x)\) is called the membership function and \(\mu A(x) \rightarrow [0,1]\). The
membership function determines the degree of an object, which belongs to a set and
the number of parameters shape the membership function. For example, typical
Gaussian membership functions controlled by two parameters and as follow:
\[ \mu(x) = e^{-\frac{1}{2}\left\{\frac{x-c}{\sigma}\right\}^2} \]  
A typical fuzzy inference system (FIS) consists of such rules:
R: if $x$ is $A$ and $y$ is $B$ then $z$ is $C$,
where $A$, $B$ and $C$ are fuzzy sets. The first part of this rule “if $x$ is $A$ and $y$ is $B$” is called the premise of the rule and the second part of this rule “then $z$ is $C$” is called the conclusion.

Typical FIS works in three steps: fuzzification, fuzzy inference and defuzzification outputs (Figure 1). In the fuzzification step, the crisp inputs are converted to fuzzy values based on the membership functions. In the fuzzy inference step, fuzzy operations such as OR, AND, NOT are performed on the fuzzy rules. Each rule contributes a different degree of fit to the final decision. At the last step, the fuzzy conclusions are converted to crisp values.
Figure 1: A typical neuro-fuzzy model
In most cases, specifying parameters of the membership functions in FIS is a difficult process. If there are enough data, the neural network technology can be used for extracting these parameters from data set. In this case, a neural network’s nodes are replaced with the premise and conclusion part of FIS as shown in Figure 1.

A neuro-fuzzy tool ANFIS has a five layer equivalent to general FIS and the functions of each layer are explained as below (Jang et al., 1997, pp. 336-337):

1. This layer fuzzyifying inputs,
   \[ O_{1,i} = \mu_{A_i}(x), \text{ for } i = 1,2 \]
   \[ O_{1,i-2} = \mu_{B_i}(y), \text{ for } i = 3,4, \]
   (3)
   where \( O \) is the output of the layer \( l \), node \( i \)

2. This layer calculates the firing strength of a rule,
   \[ O_{2,i} = \frac{\mu_{A_i}(x) \mu_{B_i}(y)}, i = 1,2. \]
   (4)

3. This layer normalize firing strength of the node \( i \),
   \[ O_{3,i} = \frac{\bar{w}_i}{w_1 + w_2}, i = 1,2. \]
   (5)

4. This layer calculates the conclusions,
   \[ O_{4,i} = \bar{w}_i f_i = \bar{w}(p_i x + q_i y + r_i), \]
   (6)

5. The last layer calculates the overall outputs of the ANFIS,
   \[ O_{5,i} = \sum_i \bar{w}_i f_i = \sum_i \frac{w_i f_i}{\sum w_i} \]
   (7)

IV. Data
In this study, the data set consisted of manufacturing, commercial and service firms traded on the Istanbul Stock Exchange (ISE) in Turkey during the period of 1992-1999. Financial institutions, holdings, and transportation companies were excluded, as these industries have quite different financial characteristics. Those firms with
different financial reporting periods were also deleted from the data set. Monthly returns (including the capital increases and dividend payments adjustments) were used in the study and drawn from a CD provided by ISE.
<table>
<thead>
<tr>
<th>CR: Current ratio</th>
<th>Current Assets / Short Term Liabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR: Liquidity Ratio</td>
<td>(Current Assets - Inventories) / Short Term Liabilities</td>
</tr>
<tr>
<td>STSE: Short Term Liabilities / Shareholders Equity</td>
<td></td>
</tr>
<tr>
<td>TLSE: Total Liabilities / Shareholders Equity</td>
<td></td>
</tr>
<tr>
<td>TLTA: Total Liabilities / Total Assets</td>
<td></td>
</tr>
<tr>
<td>IC: Interest Coverage</td>
<td></td>
</tr>
<tr>
<td>LAT: Liquid Assets Turnover</td>
<td>Net Sales / Liquid Assets</td>
</tr>
<tr>
<td>CAT: Current Assets Turnover</td>
<td>Net Sales / Current Assets</td>
</tr>
<tr>
<td>TAT: Tangible Fixed Asset Turnover</td>
<td>Net Sales / Tangible Fixed Asset</td>
</tr>
<tr>
<td>ET: Equity Turnover</td>
<td>Net Sales / Shareholders Equity</td>
</tr>
<tr>
<td>AT: Asset Turnover</td>
<td>Net Sales / Total Assets</td>
</tr>
<tr>
<td>GP: Gross Profit Margin</td>
<td>Gross Profit / Net Sales</td>
</tr>
<tr>
<td>OP: Operating Profit Margin</td>
<td>Operating Profit / Net Sales</td>
</tr>
<tr>
<td>NP: Net Profit Margin</td>
<td>Net Profit / Net Sales</td>
</tr>
<tr>
<td>ROE: Return On Equity</td>
<td>Net Profit / Equity</td>
</tr>
<tr>
<td>PE: Price/Earning</td>
<td></td>
</tr>
<tr>
<td>BM: Book/Market</td>
<td></td>
</tr>
<tr>
<td>PS: Price/Sales</td>
<td></td>
</tr>
</tbody>
</table>

Table 1. Financial Ratios
Eighteen these ratios (Table 1) were calculated from financial statements as of December 31 and price information as of the next year March 31 for each period. The return values were calculated for 1 April-31 March period for each year. For example, the financial ratios of a firm in the first year calculated using financial statement numbers as of 31 December 1992 and price information as of 31 March 1993. The return values were calculated for this firm using monthly return covers the period from 1 April 1993 to 31 March 1994. The entire data included 958 cases. The data set were divided into three parts: training, check and test. The training and check data sets were used for developing the neuro-fuzzy model and the test data set was used for validation of the neuro-fuzzy model. The data set covering the period 1992 to 1996 consists of 313 cases. The first 250 cases were used for training and 63 cases were used for the check. The remaining data set was used for test and consists off 645 cases and covers the period 1996 -2000.Eighteen financial ratios were calculated for each firm.

V. Methodology
This study intends to predict future stock returns from current fundamentals with the neuro-fuzzy model. The financial ratios of a firm were used as input vector and twelve months average return of this firm was used as output vector for developing neuro-fuzzy models. There was no information about which financial ratios are important and we didn’t want to utilize a statistical tool for dimension reduction. Then one, two, three and four variable combinations were constituted and all of these financial ratios combinations were used as input for model development process. The model generation process is very time consuming when the numbers of inputs increase. Therefore, the number of inputs was limited to four.

To find the best financial ratio combination that provided the highest return, the process below is repeated for each input combination. Total 4029 experiments were done. For each experiment, financial ratios were entered in to ANFIS (Adaptive Neuro Fuzzy Inference Systems), that is a neuro-fuzzy modeling tool in the Matlab. Primarily ANFIS generated a number of rules for Fuzzy Inference Systems (FIS), depending on the number of inputs and membership functions employed in the input and output layer. However, the initial parameters of membership functions in the rules do not reflect input output relations. The parameters of membership functions were adjusted using the relationship between inputs and outputs in the data set. The most important aspect of a training process is validation of the neuro-fuzzy model. In the training process, checking data set used to whether the neuro-fuzzy model overfitting training data or not. ANFIS uses checking data set for minimize the checking error. Also checking error is used as an indicator of the point where overfitting begins in the training process. If overfitting is occurring, the training process has to stop.
After the training process, the outputs of the neuro-fuzzy model (AR) are used as a rating measure and it is assumed that these rating scores are predictors of the firms’ future returns. Validation of the neuro-fuzzy model was conducted at the portfolio level and examined, whether or not high AR portfolio outperforms the portfolios of low AR. Also a high AR is portfolio compared with the market portfolios and the portfolios that constituted based on solely financial ratios. For each year, the stocks are sorted according to AR and divided into four portfolios (A, B, C, D). The return, risk and performance characteristics of the portfolios are calculated and listed for the test period. The procedure explained above is repeated for every financial variables combination. The best model that consisted GP, OP and PE provide the highest return and selected end of this procedure.

VI. Results
The 48 months return, risk and performance characteristics of the AR, market and PE portfolios that were used as the benchmark portfolio are given below.
### Table 2. The returns of AR and Market portfolios

<table>
<thead>
<tr>
<th>AR</th>
<th>A (Lowest)</th>
<th>B</th>
<th>C</th>
<th>D (highest)</th>
<th>Market Return</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Return</strong></td>
<td>0.071</td>
<td>0.0702</td>
<td>0.0718</td>
<td>0.0941</td>
<td>0.0766</td>
</tr>
<tr>
<td><strong>Risk</strong></td>
<td>0.1694</td>
<td>0.1732</td>
<td>0.1659</td>
<td>0.1774</td>
<td></td>
</tr>
<tr>
<td><strong>β</strong></td>
<td>0.9856</td>
<td>1.0152</td>
<td>0.9719</td>
<td>1.0275</td>
<td>1</td>
</tr>
<tr>
<td><strong>α</strong></td>
<td>-0.0057</td>
<td>-0.0063</td>
<td>-0.005</td>
<td>0.0176</td>
<td></td>
</tr>
<tr>
<td><strong>Sharpe</strong></td>
<td>-0.155</td>
<td>0.0104</td>
<td>-0.0893</td>
<td>0.1182</td>
<td></td>
</tr>
<tr>
<td><strong>Treynor</strong></td>
<td>-0.0266</td>
<td>0.0018</td>
<td>-0.0152</td>
<td>0.0204</td>
<td></td>
</tr>
<tr>
<td><strong>M²</strong></td>
<td>0.0712</td>
<td>0.0702</td>
<td>0.0716</td>
<td>0.093</td>
<td></td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td>0.962</td>
<td>0.9691</td>
<td>0.9719</td>
<td>0.9546</td>
<td>1</td>
</tr>
<tr>
<td><strong>t</strong></td>
<td>-0.162154</td>
<td>-0.183989</td>
<td>-0.141583</td>
<td>0.493935</td>
<td></td>
</tr>
</tbody>
</table>

† The difference between the AR’s and market return.
The table 2 presents the highest AR portfolio D, which yields the highest return value. In the portfolio D, to test the difference between return D and market portfolio, the t test is conducted. Nevertheless, the t test result didn’t support the superior return of the portfolio D. This means there is need for more improvement on the current model, such more data, better rules and fine tuned membership functions. However, the initial results encourage us to conduct further researches. The other important result of the study was the recognition of the rules lying in the stock market data by neuro-fuzzy. There is said to be final rules in the neuro-fuzzy which give us the relations between financial ratios and returns. To this point of view, the neuro-fuzzy technique is used as a data-mining tool. When we looked at the rules, the relationships among financial ratios are seen as below (Figure 2a,b,c).
(a) GP, P/E and Return Relation

(b) OP, P/E and Return Relation
The relation GP, P/E and return is shown in Figure 2. Those firms having negative P/E and low GP ratios provide negative return at the end of the period. However, the firms having negative P/E and high GP ratio can be identified as mispriced firms and yield high return next year. Due to the firms having high GP there is high potential for current year profit and if that year ended with loss, that situation would be transitory. The OP, P/E and return relations can be seen in the figure 2 (b). The relation in figure 2 (b) also supports the conclusion about the previous figure 2(a). The firms have negative P/E and low OP returns negative returns next year. If the firms have negative P/E and high OP, the firms stock can yield high return the following year. Then those firms having current period operating loss can be interpreted as transitory and this stock has a potential for yield high return. The figure 2(c) shows the relation between GP, OP and return. Neuro-fuzzy tools interpolate all possible input-output relations with their membership functions. Then a relationship in the figure 2 (c) is not meaningful. For example, the station that GP is 0.3 and OP 0.4 is impossible, as OP can’t be higher than GP.

VII. Conclusion

The neuro-fuzzy is a soft computing technique that combines the advantages of both neural networks’ learning power and fuzzy logic’s inference capability. Then it’s the most convenient computing technique for developing investment decision support system. The potential of neuro-fuzzy in the fundamental analysis field is investigated in this study. We expected the neuro-fuzzy model to discover relations between financial ratios and future stock return. After that, the neuro-fuzzy model can be used as a stock selection tool. Nevertheless, the neuro-fuzzy model provides slightly higher return than benchmark portfolios and there is not a statistically
significant difference. However, this study uncovered the relationship between financial ratios and future stock returns. The final neuro-fuzzy model indicated that those firms having negative P/E ratios and low GP ratios provide a negative return at the end of the period. However, those firms having negative P/E and high GP ratio yield high returns at the same time.
References


