FUNDAMENTAL ANALYSIS WITH NEURO-FUZZY TECHNOLOGY: AN EXPERIMENT IN ISTANBUL STOCK EXCHANGE

Birol YILDIZ
Eskişehir Osmangazi University
Faculty of Economic and Administrative Sciences

The purpose of this study is to perform fundamental analysis and cross-sectional prediction of stock return with neuro-fuzzy. This study also 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 is not any statistically significant difference, the neuro-fuzzy model provides slightly higher return than benchmark portfolios. This approach also exposes how investors select those firms which have low Price Earning (P/E) ratios but high gross and/or operating profit.

KEYWORDS
Neuro-Fuzzy, Fundamental Analysis, Financial Statement Analysis, Investment Decision Support System, Artificial Intelligence.

BULANIK-SİNİRSEL AĞ ILE TEMEL ANALIZ: İMKB'DE AMPRIK BIR ÇALIŞMA

Birol YILDIZ
Eskişehir Osmangazi Üniversitesi
İktisadi ve İdari Bilimler Fakültesi

Bu çalışmanın amacı bulanık-sinirsel ağ kullanarak hisse senedi getirisinin tahmin edilmesidir. Ayrıca bu çalışma yatırımcının finansal tabloları analiz etme sürecini, elde edilen bulanık-sinirsel ağ modelinin kurallarını yorumlayarak elde etmeyi amaçlamaktadır. İstanbul Menkul Kıymet Borsasında 1992-1999 döneminden işlem görmüş işletmelerden oluşan veri seti kullanılmıştır. Modelin portföy getirisi piyasanın üstünde olmasına karşın, bu fark istatistiksel olarak anlamlı değildir. Fakat çalışma yatırımcıların düşük Fiyat/Kazanç (F/K) ve yüksek brut satış karı ve/veya faaliyet karı olan işletmeleri seçtiğini ortaya çıkarmıştır.

ANAHTAR KELİMELER
Bulanık-Sinirsel, Temel Analiz, Finansal Tablolar Analizi, Karar Destek Sistemi, Yapay Zeka

1. 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 response 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; Siekman Kruse, Gebharddt, 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 system is 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.

2. 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) with 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.

3. **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. $\boldsymbol{A}$ is a fuzzy set defined as:

$$A=\{(x, \mu A(x)) | x \in X\}, \quad (1)$$

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:

$$\mu(x) = e^{-\frac{1}{2}(\frac{x-c}{\sigma})^2} \quad (2)$$

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: fuzzificaiton, 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.

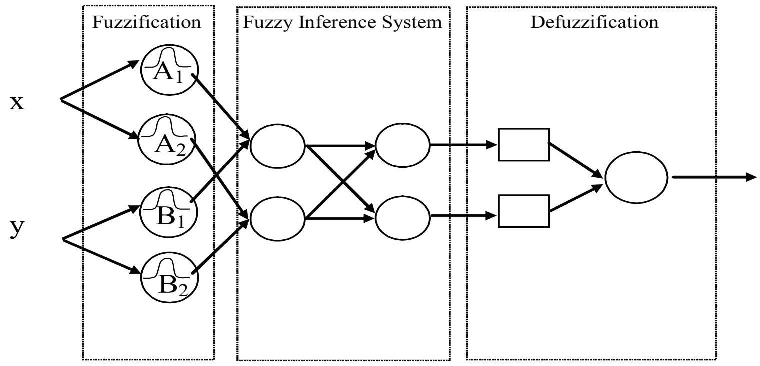


Figure 1: A typical neuro-fuzzy model; Jang, Sun, Mizutani, 1997, p.336 (simplified).

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 adaptive neuro-fuzzy inference system (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 fuzzifying inputs,

$O_{1,i}=\mu A_i(x)$, for i=1,2 and

$O_{1,i-2}=\mu B_i(y)$ 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,

$O_{2,i}=w_i=\mu A_i(x)\ \mu_{Bi}(y)$, i=1,2. (4)

3. This layer normalize firing strength of the node i,

$$O_{3,i}=\overline{w_i}=\frac{w_i}{w_1+w_2}, i=1,2. \quad (5)$$

4. This layer calculates the conclusions,

$$o_{4,i}=\overline{w}_i f_i=\overline{w}(p_i x+q_i y+r_i) \quad (6)$$

5. The last layer calculates the overall outputs of the ANFIS,

$$O_{5,i}=\sum_i \overline{w}_i f_i=\frac{\sum_i w_i f_i}{\sum_i w_i} \quad (7)$$

4. 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 1. Financial Ratios are as inputs and return is a output

CR: Current ratio = Current Assets / Short Term Liabilities
LR : Liquidity Ratio = (Current Assets - Inventories) / Short Term Liabilities
STSE : Short Term Liabilities / Shareholders Equity
TLSE : Total Liabilities / Shareholders Equity
TLTA : Total Liabilities / Total Assets
IC : Interest Coverage
LAT : Liquid Assets Turnover = Net Sales / Liquid Assets
CAT : Current Assets Turnover = Net Sales / Current Assets
TAT : Tangible Fixed Asset Turnover = Net Sales / Tangible Fixed Asset
ET : Equity Turnover = Net Sales / Shareholders Equity
AT : Asset Turnover = Net Sales / Total Assets
GP : Gross Profit Margin = Gross Profit / Net Sales
OP : Operating Profit Margin = Operating Profit / Net Sales
NP : Net Profit Margin = Net Profit / Net Sales
ROE : Return On Equity = Net Profit / Equity
PE : Price/Earning
BM : Book/Market
PS : Price/Sales
R: Return (Output)

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.

5. 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. Inputs variables are CR, LR, STSE, TLSE, TLTA, IC, LAT, CAT, TAT, ET, AT, GP, OP, NP, ROE, PE, BM, PS. Output variable is R. There is no information about which financial ratios are important and utilizing a statistical tool for dimension reduction is not disired. 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 output 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 in to 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.

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.

AR	A(Lowest)	B	C	D (highest)	Market Return
Return	0.071	0.0702	0.0718	0.0941	0.0766
Risk	0.1694	0.1732	0.1659	0.1774	
β	0.9856	1.0152	0.9719	1.0275	1
α	-0.0057	-0.0063	-0.005	0.0176	-
Sharpe	-0.155	0.0104	-0.0893	0.1182	-
Treynor	-0.0266	0.0018	-0.0152	0.0204	-
M^2	0.0712	0.0702	0.0716	0.093	-
R^2	0.962	0.9691	0.9719	0.9546	1
t †	-0.162154	-0.183989	-0.141583	0.493935	

† The deffference between the AR's and arket Rerurn

Table 2. The returns of AR and Market portfolios

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. Structure, the rules of the final neuro-fuzzy model are below (Figure 2 and 3). The membership functions of the inputs are also given in Figure 4-6. The RMS errors of train and test are 0.064786 and 0.10675 respectively (Figure 7). R^2 beetween original and predicted values is close to 0.

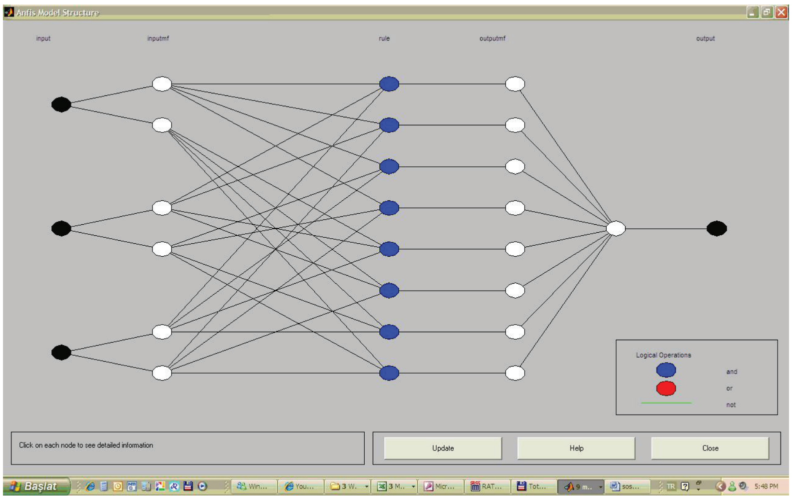


Figure: 2 The structure of neuro-fuzzy model

Figure: 3 . The rules of neuro-fuzzy model

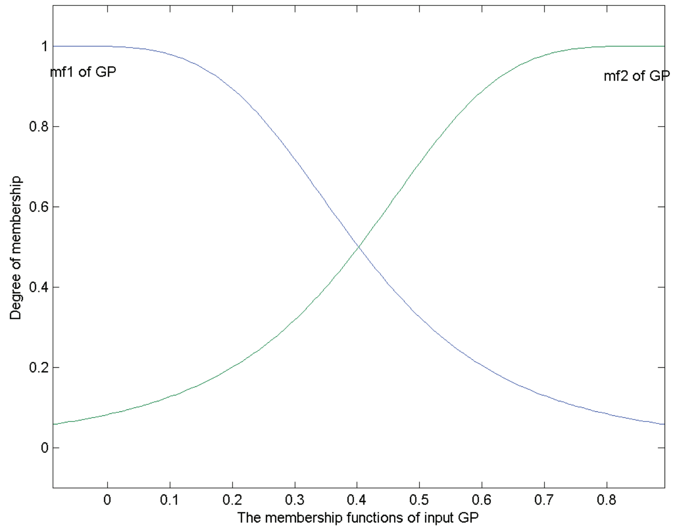


Figure:4 The membership functions of GP

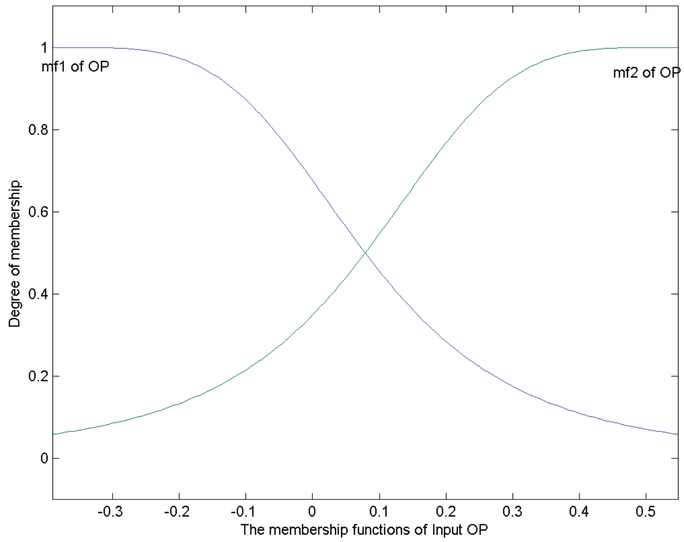


Figure:5 The membership functions of OP

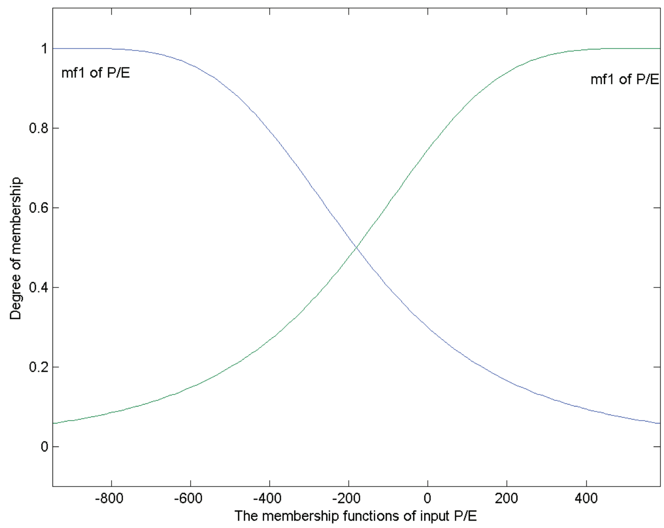


Figure:6 The membership functions of P/E

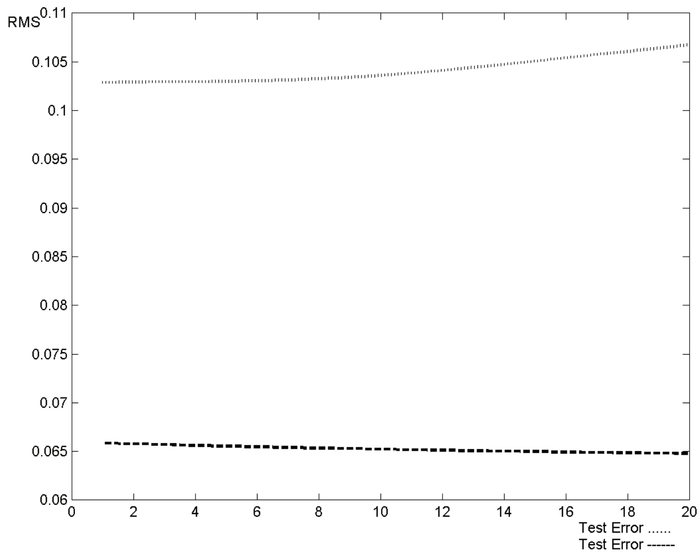


Figure: 7 The RMS graphs of train and test

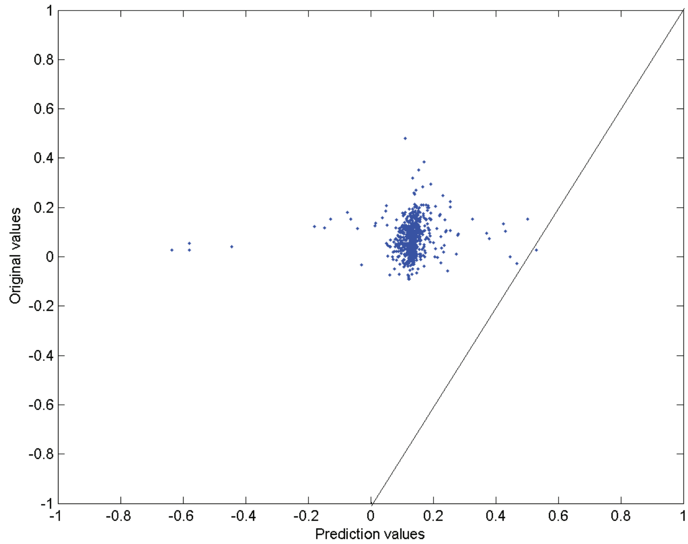
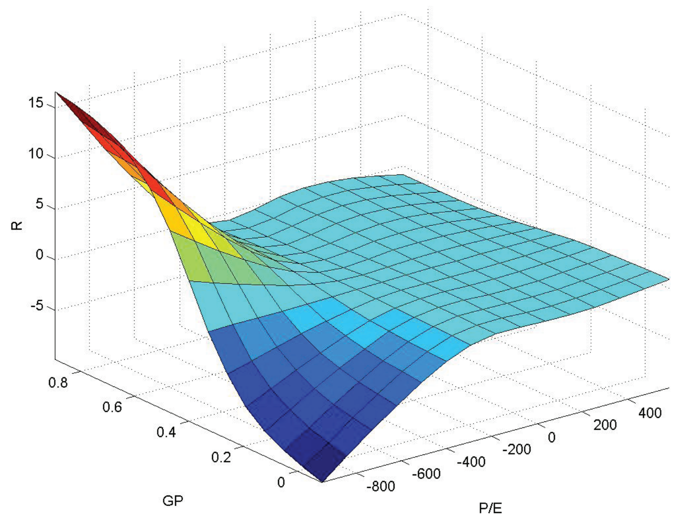
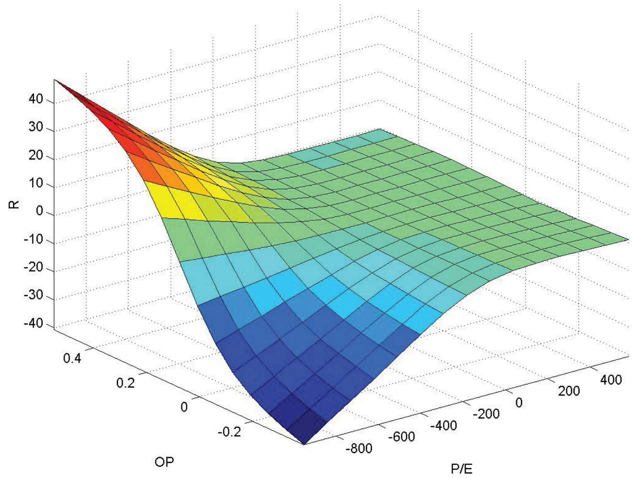


Figure:8 Prediction values versus Originals

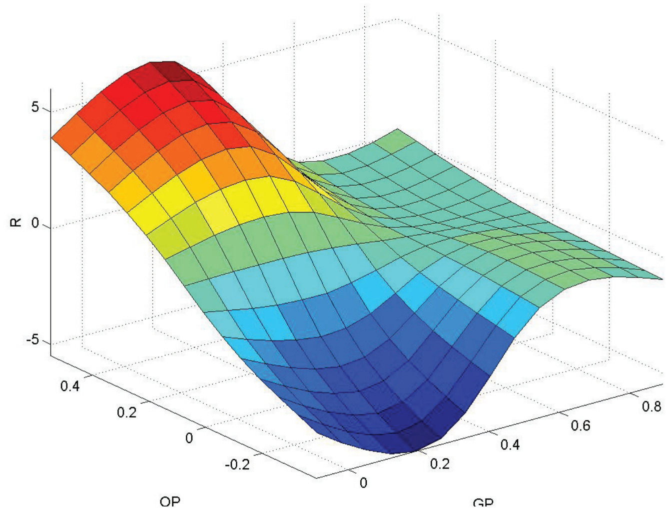
To this point of view, the neuro-fuzzy technique is used as a data-mining tool. When the rules are investigated, the relationships among financial ratios are seen as below (Figure 9 a,b,c).



(a) GP, P/E and Return Relation



(b) OP, P/E and Return Relation



(c) OP, GP and Return Relation

Figure: 9 The relations between financial ratios and return

The relation GP, P/E and return is shown in Figure 9 (a). 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 9 (b). The relation in Figure 9 (b) also supports the conclusion about the previous Figure 9 (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 9 (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 9 (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.

7. 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. The neuro-fuzzy model is expected 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. This study should be repeated with more data, new variables, better rules and fine tuned membership functions. 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.

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