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A Comparatıve Study On Credıt Rısk Assesment Of Enterprıses In Turkey

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Abstract
Credit risk prediction models attempt to predict whether a business will experience to be in a level of investment, speculative or below investment. The purpose of this paper is to propose an alternative model for predicting failure. The constructed credit rating model was on a sample data that consists of financial ratios from 356 enterprises that are listed on the Istanbul Stock Exchange. The data covers observations running from the first quarter of 2014 to the end of year. We have classified 356 enterprises into three levels using 18 parameters for each. The applied methods are discriminant analysis and Adaptive Neuro Fuzzy İnference Systems (ANFIS). The study supports building a balanced financial environment and help to determine the firms which are appropriate for credit loan.
Keywords: ANFIS, Credit Risk Assessment, Discriminant Analysis, Financial Ratios.

1. Introductıon

The motivation of Altman (1968) to assess credit risk of firms was to reduce the loses, he developed models for predicting risk levels on the financial reports of firms. Altman employed discriminant analysis to rank firms on the basis of five financial ratios. (Deakin, 1972). Ohlson (1980) applied the Logit model and became popular for prediction of financial problems of companies. Ohlson used the data of 105 bankrupt companiesand 2058 non bankrupt companies.
Pham and Liu (1993) used of recurrent neural networks for the identification of linear and nonlinear dynamic systems. The interest in the use of neural networks for modeling and

identification on the basis of the input-output data pairs was a new development. Hong and Xinkuo (2002) proposed a neural network approach by combining the equivalence between RBF and the Fuzzy inference system (FIS) for identification of a nonlinear system.
Lee & Chen (2005) explain the credit scoring using a two-stage hybrid modeling with artificial neural networks and multivariate adaptive regression splines (MARS).
Hsieh & Hung (2010) work on determining whether a credit applicant is good, bad or borderline. This task applied for credit scoring is performed by neural network, support vector machine, and Bayesian network.

Ensemble learning is a machine learning paradigm which has advantages in many applications. In the study of Wang, Hao, Ma, & Jiang (2011), a comparative assessment of three popular ensemble methods, Bagging, Boosting, and Stacking, based on models DT, ANN and SVM is carried out. All these ensemble methods have been applied to three real world credit datasets. Experimental results reveal that the application of ensemble learning has been brought improvements for risk assessment. Derelioğlu & Gürgen (2011) proposes a method that uses multilayer perceptron (MLP) for credit risk analysis (CRA) of real-life enterprises in Turkey.
Wang and Ma (2012) propose an ensemble approach, called RSB-SVM. The enterprise credit risk dataset is collected by the Industrial and Commercial Bank of China.
In our research we use the hybrid structure ANFIS (Adaptive Neuro-Fuzzy Inference System). Adaptive Neuro- Fuzzy Inference System (ANFIS) is a neuro fuzzy technique which is obtaining neural network and the fuzzy inference system (Jang & Sun, 1993). Using this hybrid method, an initial fuzzy model is derived with the help of the rules extracted from the input data of the system. Next the neural network is used to minimize the rules of the initial fuzzy model to shape the final version ANFIS model as ANN+ANFIS.

This study will make identification of factors of failure for enterprises and will make the measurement of credit risk for banks to establish risk precaution mechanism with their own characteristics so as to minimize the loss arises from defaults. This research develops models to accurately evaluate the credit risk on the data obtained from financial statement of enterprises.

The paper is organized as follows. Section 2 is about data collection and proposed methodologies to select the variables for credit risk modeling Section 3 describes the models applied. Section 4 explains the experimental results and Section 5 is a conclusion on the obtained results of DA and ANFIS model designs.

2. Methodology

The traditional models are models of linear discriminant analysis, models of linear regression and logit and probit model. The recent application of non-linear methods to credit risk analysis shows improvements on the traditional models. We propose first to investigate and compare the accuracy of DA and ANN+ANFIS models. For our experiments, we use financial data of enterprises functioning in İstanbul Stock Exchange.

2.1 Selection of independent variables

The aim of the model building methodology is to find the significant variables that make the maximum contribution to the explanation of the dependent variable by using the financial information provided in balance sheets. Those are:

Current Assets
Fixed Assets
Short Term Liabilities
Long Term Liabilities
Net Profit
Sales
Equity
Total Assets
Financial Expenses

The independent variables formed from information we have obtained from balance sheets and income sheets are the following financial ratios:

Table 1 The independent variable

Attribute Information
Current Rate
Operating Profit Margin (OPM)
Earnings Before Interests and Taxes Margin(EBITM)
Equity Ratio
Debt to equity ratio
Net Profit Margin (NPM)
Fixed assets/ Long Term Debt (FALTD)
Equity Multiplier (EM)
Operating Profit
Sales
Total Debt/Sales
Short term debt/ Sales
Long Term Debt/Total debt
Net Profit/ Equity
Long Term Debt/ Equity
TFAE(Tangible Fixed assets-Equity ratio)
ICR(Interest Coverage Ratio)
STDA(Short term debt-assets ratio)

Some variables are removed because of deviations from normality and multicollinearity problem.

2.2 Selection of the dependent variable

Yüce (2011) developed a method for selecting the dependent variable for credit ratings. He has calculated an index of each company from correlation matrix of variables he has included in analysis. He saw that the current ratio depends on the other four independent variables. Than the current ratio is transformed to derive a 10-scale dependent variable that represents the ratings of the firms. In this study it is assumed that the debt ratio is sufficient to rate a company's credit worthiness. The debt ratio represents the dependent variable as an risk indicator and the other ratios constitute as the independent variable group.

The debt ratio indicates the proportion of a company's assets financed with debt. The ratio is used to determine the financial risk of a business. A ratio greater than 1 shows that assets are b funded with debt, a lower ratio indicates that it is funded from equity. A ratio greater than 1 means that the company is at risk of failure to pay its debt (http://www.accountingtools.com). A ratio less than 0.5 is acceptable in international financial institutions, in Turkey it is normal to have a ratio of 0.6 (www.bilgaz.net).
For the purpose of justification of selecting debt ratio the variables that can be graded to determine the credit risk are chosen as current ratio, debt ratio and the equity multiplier. Multiple linear regression analysis is performed to see the R^2 values that shows how many percent of the variance can be explained by the independent variables (Gıyarati, 2003). In the case of perfect relationship ($R^2=1$) independent variables explain all variation in dependent variable and we can predict without error (Healey, 2005). From the chosen variables the one with higher value of coefficient of determination (R^2) will be selected as the dependent variable. Mitruț & Simionescu (2014) propose a procedure for selecting the most suitable variable that explains the best the evolution of another variable and that generates the best predictions. They have performed linear regression analysis using different dependent variables and concluded that the variable with higher R^2 is more accurate in predictions. The following table shows that the dependent variable has R^2=0. 859.

The debt ratio has an $R^2 = 0.859$, which means that 85.9% of the total variation can be explained by the independent variables. The debt ratio depends on the other independent variables. The statistical evidence for the selection of the debt ratio as the dependent variable is shown in Appendix 1. Also we need to check the Durbin-Watson test result to see if there exists autocorrelation. Interval between the values 1.5-2.5 shows that there exist no autocorrelation (Kalaycı, 2009).

2.3 The dataset

Financial and qualitative information of the Istanbul Stock Exchange traded (ISE) companies are derived from the Public Disclosure Platform for the year 2014. Besides providing audited financial statements (solo and/or consolidated), this platform also provides notices, disclosures, balance sheet foot-notes, and qualitative information about the companies. Financial Risk Ratios are considered to be used as parameters of the dataset. The ratios chosen have an impact on the risk assessment of the enterprise and it is one of the most important element in analyzing financial statements.
Credit ratings of the enterprises in 2014 are retrieved from JCR Eurasia Rating (http://www.jcrer.com.tr). JCR Eurasia Rating, is an international credit rating which is a member of ACRAA. The other source of data is Corporate Governence Association of Turkey which broadcasts the credit ratings of companies which are evaluated by SAHA and KOBIRATE corporate rating agencies.

3. Research Models

3.1 Discriminant Analysis

One of the traditional models of credit risk analysis is linear discriminant analysis. It is simply the analysis of dependence of one dependent variable from several quantitative variables (Stankovičova & Vojtkova, 2007).

There exists some assumptions of Discriminant analysis:

- Normality
- Equality of covariance matrices
- Multicollinearity

The independent variables of the dataset were not normally distributed. To normalize all variables logarithmic transformation is applied with $\log_{10}$. Normalized data is used for analysis, six of the variables are excluded because they weren't normally distributed. The values for kurtosis between -2 and +2 are considered acceptable in order to prove normal univariate distribution (George & Mallery, 2010). According to Orhunbilge (2000) it is acceptable between -3 and +3. Hair et al. (1998) suggest that the researcher should always use both the statistical and graphical tests for normality.

Jarque Bera test is appllied to each factor for the analysis of normality. Skewness value around zero and Kurtosis value around three is required to have a normal distribution (Hair et al.,1998). Therefore we can conclude that we have an approximately normal distribution.

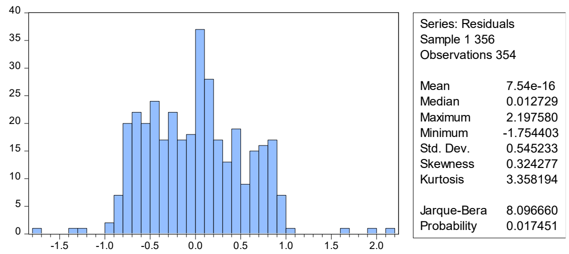

Figure 1 The result of Jarque Bera test

White's heteroskedasticity test shows that we don't have equality of covariance matrices. Tatsuoka (1971) mentions that even if the covariance matrices are not equal the results of discriminant function is approximately the same.

Table 2 White's Heteroskedasticity Test Results

Heteroskedasticity Test: White

F-statistic	18.66283	Prob. F(54,299)	0.0000
Obs*R-squared	273.0032	Prob. Chi-Square(54)	0.0000
Scaled explained SS	303.9679	Prob. Chi-Square(54)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 06/02/16 Time: 07:56
Sample: 1 356
Included observations: 354

In the correlation matrix there exists no high correlations that can be a problem in collinearity diagnostics, the matrix is given in Appendix 2.

Variance Inflation Factors (VIF) values indicate that there is no collinearity in the factors that still remain in analysis. VIF value of 3 is accepted, 5 means most probably there exists a collinearity and the value 10 shows an exact multicollinearity problem. In this case we have excluded variables which have a big deviation. The Table shows the variables which remains in analysis.

Table 3 Variance Inflation Factors (VIF) values of independent variables

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
F4	0.020733	66.19457	2.083218
F3	0.003712	7.939513	3.319892
F17	0.002910	21.38094	2.190931
F16	0.010140	48.18900	2.091034
F15	0.003714	5.364331	3.101176
F14	0.003637	5.622785	1.442012
F10	0.001117	80.89591	1.560431
F1	0.007637	1.938441	1.574869
F2	0.003226	5.901769	2.403901
C	0.176529	204.8514	NA

After we have shown that the requirements are met for discriminant analysis we have performed the analysis using SPSS Statistics 22 sofware.

3.2 ANN+ANFIS Model

An Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid system that is based on Takagi–Sugeno fuzzy inference system and artificial neural networks. The problem with ANFIS is its inability to process a large number of features (inputs) because of exponentially growing IF-THEN rule numbers. Hence, ANFIS needs to have reduced number of inputs and ANN can provide this (Hodzic and Karlı, 2015). A matlab code is written to build the model given in the Appendix 3. The approach of the 5-fold cross validation technique is used to select the optimal data set for training the ANN+ ANFIS system. The characteristics of the system is given in Table 5.

Table 4 Properties of ANN+ANFIS system

Characteristics of the model	
Learning algorithm	trainlm
Learning rate	0.3
Input neurons	9
Hidden neurons	10,40,1
Transfer functions	logsig, tansig, purelin
Number of MF	3(gbellmf)

3.3 ANN Structure

The results of the credit risk evaluation neural network models were obtained using MATLAB software. The network is asked to predict the risk level of firms thus we have three output neurons. The number of inputs is the number of factors that consists of financial ratios of each company. The following steps should be followed in ordered sequence to classify the firms.

1) First the normalized data set is to be developed for all the data points so that the data set contains the records for 356 firms.

2) The entire data set is divided into two data subsets, one of which to be used as the training data and the other would be for testing the data.
3) We define a metric to calculate the actual classification error level.
4) Then we define a boundary value b-value for classification of firms and an acceptable classification error level.
5) We use the training data set for the neural network and compare it to a particular value as mentioned earlier (Kar, 2009).

Multi Layer perceptron (MLP) is a feedforward neural network which is commonly used in forecasting problems. A MLP consists of an input layer and an output layer, with one or more hidden layers in between. The feed-forward networks were applied to training set. Afterwards, the simulation was made based on the inputs. In the testing set, 20% of our dataset was used. To test the data, the same procedure was implemented as in the training partwhich is %80 of the dataset.

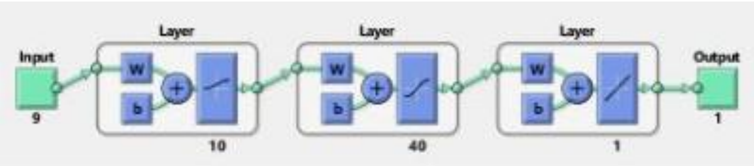

Figure 2 The ANN Structure MATLAB output

4. Experimental Results

We have performed Discriminant Analysis and a new hybrid algorithm(ANN+ANFIS) on the dataset. The new model will be presented with the comparision of applied models. Comparision of proposed CRA Model results with actual risk level of companies is given by Appendix 4, where the categories ‘AAA’ to ‘BBB’ denote investment level and ‘BB’ to ‘C’ speculative level and 'C' or 'D' are counted as below investment level. The table shows the companies whose credit ratings are obtained from JCR Eurasia Rating, SAHA and KOBIRATE corporate rating agencies. Table 5 shows the output of Discriminant Analysis Results.

Table 5 Discriminant Analysis Results

Classification Results[a]

RATING			Predicted Group Membership 1.0	2.0	3.0	Total
Original	Count	1.0	169	4	0	173
		2.0	34	11	2	47
		3.0	8	4	123	135
	%	1.0	97.7	2.3	0.0	100.0
		2.0	72.3	23.4	4.3	100.0
		3.0	5.9	3.0	91.1	100.0

a. 85.4% of original grouped cases correctly classified.

The application of non-linear methods to credit risk analysis shows improvements on the traditional models. Table 6 shows the accuracy of DA and ANFIS+ANN systems.Figure 3 illustrates ANFIS+ANN system best performance.

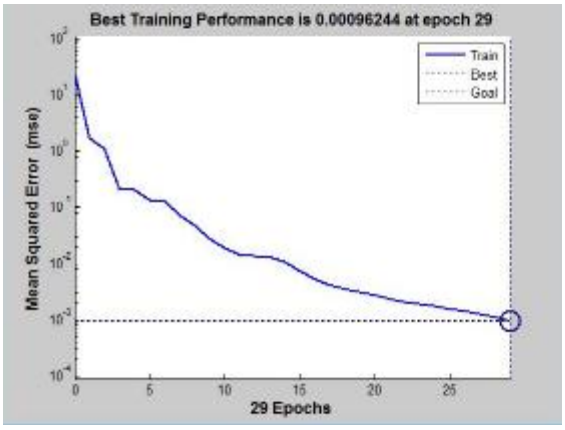

Figure 3 ANFIS+ANN system best performance MATLAB output.

Researchers recommend the use of nonlinear models for predicting the future risks, because of the failure of linear models (Lendasse, De Bodt, Wertz, & Verleysen, 2000). To compare the predictive performance of the models we can remark that ANFIS system has capability to handle the data without any requirements like normality, multicollinearity and achieves a great performance with 90.46% classification accuracy. Table 6 gives the accuracy of each model.

Table 6 Comparision of analysis results

MODEL	Discriminant Analysis	ANN+ANFIS
Samples	356	356
Parameters	9	9
Accuracy	85.40%	90.46%

5. Conclusion

An easy to apply CRA model to assess the creditworthiness of firms was developed in this study. We present and discuss the ANFIS and DA models for credit risk assessment and to compare the accuracy of these employed models on the performed analysis. Empirical results revealed that ensemble methods consistently outperform to statistical models in terms of accuracy rate. We conclude that in predicting risk levels ANFIS+ANN methodology is superior to discriminant analysis.

Our proposal has some limitations and directions for further research. Number of samples could be increased for higher accuracy and as a further work in the application of the selected methods , each firm can be evaluated in its own sector to claim that there might be differences among the sectors. Performing analysis on sector, scale and city relations would contribute to analysis. Also The use of machine-learning methodologies such as SVM, kNN, Decision trees that can provide more efficient results in terms of time and produce appropriate predictions in the credit risk analysis.

References

Accounting CPE & Books - AccountingTools. (2016). *Accountingtools.com*. Retrieved 14 July 2016, from http://www.accountingtools.com

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609.

Deakin, E. (1972). A Discriminant Analysis of Predictors of Business Failure. *Journal Of Accounting Research*, *10*(1), 167. http://dx.doi.org/10.2307/2490225

George, D., & Mallery, M. (2010). SPSS for Windows Step by Step: A Simple Guide and Reference, 17.0 update (10a ed.) Boston: Pearson.

Gıyarati, D. (2003). *Basic Econometrics*, 212-213.

Hair, J. (1998). *Multivariate data analysis*. Upper Saddle River, N.J.: Prentice Hall.

Hong, B., Yun, X., & Xinkuo, C. (2002). Generalized fuzzy RBF networks and nonlinear system identifications. In *4th World Congress on Intelligent Control and Automation*, 2508–2512. Shanghai.

Hsieh, N.-C., & Hung, L.-P. (2010). A data driven ensemble classifier for credit scoring analysis. *Expert Systems with Applications*, *37*(1), 534–545. doi:10.1016/j.eswa.2009.05.059

Hodzic, A. & Karlı, G. (2015). A Novel Approach for Face Recognition based on ANN and ANFIS. *International Journal Of Engineering Research And Management (IJERM)*, *2*(9), 2349- 2058.

Jang, J., & Sun, C. (1993). Functional equivalence between radial basis function networks and fuzzy inference systems. *IEEE Trans. Neural Netw.*, *4*(1), 156-159. http://dx.doi.org/10.1109/72.182710

Şeref, K. (2009). *SPSS Uygulamalı Cok Değişkenli İstatistik Teknikleri* (4th ed.). Ankara.

Kar, A. K. (2009). Using Fuzzy Neural Networks and Analytic Hierarchy Process for supplier classification in e-procurement. *Working Papers on Information Systems*, 9–23

Lee, T., & Chen, I. (2005). A two-stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines. *Expert Systems with Applications*, *28*(4), 743–752.

Lendasse, A., De Bodt, E., Wertz, V., & Verleysen, M. (2000). Non-linear financial time series forecasting-Application to the Bel 20 stock market index. *European Journal of Economic and Social Systems*, *14*(1), 81–92.

Mitruţ, C., & Simionescu, M. S. (2014). A Procedure for Selecting the Best Proxy Variable Used in Predicting the Consumer Prices Index in Romania. *Procedia Economics and Finance*, *10*, 178–184.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research, 18(1), 109–131.

Orhunbilge A.N. (2000) Tanımsal İstatistik Olasılık Ve Olasılık Dağılımları, Avcıol Basım Yayın, İSTANBUL

Pham, D., & Liu, X. (1993). Identification of linear and nonlinear dynamic systems using recurrent neural networks. *Artificial Intelligence In Engineering*, *8*(1), 67-75. http://dx.doi.org/10.1016/0954-1810(93)90032-b

SMMM Barıs Ilgaz. (2016). *Bilgaz.net*. Retrieved 14 July 2016, from http://www.bilgaz.net

Stankovičová, I., & Vojtková, M. (2007). Viacrozmerné štatistické metódy s aplikáciami, Bratislava, Iura Edition

Tatsuoka, M. (1971). Multivariate Analysis: Techniques for Educational and Psychological Research , New York: John Wiley & Sons, 232-233.

Wang, G., Hao, J., Ma, J., & Jiang, H. (2011). A comparative assessment of ensemble learninfor credit scoring. *Expert Systems with Applications*, *38*(1), 223–230. doi:10.1016/j.eswa.2010.06.048

Wang, G. & Ma, J. (2012). A hybrid ensemble approach for enterprise credit risk assessment based on Support Vector Machine. *Expert Systems With Applications*, *39*(5), 5325-5331. http://dx.doi.org/10.1016/j.eswa.2011.11.003

Yüce, M. (2016). *Modellıng Internal Credıt Ratıngs Of Turkısh Companıes Lısted On The Ise* (Phd). Yeditepe Unıversıty Graduate Instıtute Of Socıal Scıences.

APPENDICES

Appendix 1

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.929[a]	.864	.859	.88727	.864	180.009	12	341	.000	1.973

a. Predictors: (Constant), F15, F3, F9, F14, F1, F17, F8, F16, F2, F18, F6, F13

b. Dependent Variable: DEBTR

ANOVAa

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1700.523	12	141.710	180.009	.000[b]
	Residual	268.449	341	.787		
	Total	1968.972	353			

a. Dependent Variable: DEBTR

b. Predictors: (Constant), F15, F3, F9, F14, F1, F17, F8, F16, F2, F18, F6, F13

Appendix 2

	F1	*F2*	*F3*	*F4*	*F10*	*F14*	*F15*	*F16*	*F17*
F1	1.00								
F2	0.03	1.00							
F3	0.00	0.72	1.00						
F4	0.44	0.14	0.11	1.00					
F10	-0.07	-0.45	-0.53	-0.15	1.00				
F14	-0.11	0.33	0.27	-0.29	-0.06	1.00			
F15	-0.51	-0.10	-0.04	-0.66	0.20	0.14	1.00		
F16	-0.50	0.07	0.18	-0.50	-0.01	0.17	0.66	1.00	
F17	0.38	0.27	0.45	0.35	-0.18	0.22	-0.48	-0.21	1.00

Appendix 3

```
clc
clear
% Read input, target and test data from excel.
```

```
fileName='Normalized-reduced-dataset.xls';
trainInput=xlsread(fileName, 'train');
trainInput=trainInput';
target=xlsread(fileName, 'trainTarget');
target=target';
test=xlsread(fileName, 'test');
test = test';
% Build MLP network
net1=newff(minmax(trainInput), [10, 40, 1], {'logsig' 'tansig' 'purelin'}, 'trainlm');
net2=newff(minmax(trainInput), [10, 40, 1], {'logsig' 'tansig' 'purelin'}, 'trainlm');
% Setup  training parameters.
net1.trainParam.epochs=10000;
net1.trainParam.goal=0.001;
net1.trainParam.lr = 0.3;
net1.trainParam.mc = 0.9;
net1.trainParam.min_grad = 1e-16;
net2.trainParam.epochs=10000;
net2.trainParam.goal=0.001;
net2.trainParam.lr = 0.3;
net2.trainParam.mc = 0.9;
net2.trainParam.min_grad = 1e-16;
% Train the nework
net1=train(net1, trainInput, target);
net2=train(net2, trainInput, target);

% Simulate or test the network with test data.
a1=sim(net1, trainInput);
a2=sim(net2, trainInput);
% Write the result to excel.
 xlswrite(fileName,a1', 'anfisTrainInput', 'A');
 xlswrite(fileName,a2', 'anfisTrainInput', 'B');
% Read input, target and test data from excel.
trainAnfis=xlsread(fileName, 'anfisTrainInput');
trainTargetAnfis=xlsread(fileName, 'trainTarget');
trainInputAnfis=[trainAnfis trainTargetAnfis];
% Build anfis network
numMFs = 3;
mfType = 'gbellmf';
epoch_n = 30;
initFIS = genfis1(trainInputAnfis,numMFs,mfType);
tempFIS = anfis(trainInputAnfis,initFIS,epoch_n);
a1Test=sim(net1, test);
a2Test=sim(net2, test);
% Write the result to excel.
 xlswrite(fileName,a1Test', 'testInputAnfis', 'A');
 xlswrite(fileName,a2Test', 'testInputAnfis', 'B');
 testInputAnfis = xlsread(fileName, 'testInputAnfis');
```

```
FISOutput = evalfis(testInputAnfis, tempFIS);
% Write the result to excel.
xlswrite(fileName,FISOutput', 'anfisNetworkOutput');
```

Appendix 4

Company	Risk Level Output	Target	Company	Risk Level Output	Target
MT_AKPAZ	2	2	MT_KARSN	1	1
MT_AKSA	1	1	MT_KATMR	1	1
MT_AKSGY	1	1	MT_KCHOL	3	1
MT_ALYAG	1	1	MT_KENT	1	1
MT_ARCLK	1	1	MT_KORTS	1	1
MT_ASELS	1	1	MT_LATEK	1	1
MT_AYGAZ	1	1	MT_LOGO	1	1
MT_AYNES	1	1	MT_MARTI	2	1
MT_BDOGA	1	1	MT_OTKAR	1	1
MT_BEYAZ	2	2	MT_PETKM	1	1
MT_BMEKS	1	1	MT_PETUN	1	1
MT_BOSSA	1	1	MT_PGSUS	1	1
MT_BOYP	1	1	MT_PINSU	1	1
MT_CCOLA	1	1	MT_PLASP	1	1
MT_CEMAS	1	1	MT_PNSUT	1	1
MT_CLKEN	1	1	MT_PRKME	1	1
MT_DENRJ	1	1	MT_SARTN	1	1
MT_DERIM	1	1	MT_SISE	1	1
MT_DITAS	2	2	MT_TAVHL	1	1
MT_DNYGZ	2	2	MT_TMPOL	1	1
MT_DOAS	3	1	MT_TOASO	1	1
MT_DOHOL	1	1	MT_TRCAS	1	1
MT_EGLYO	1	1	MT_TTKOM	1	1
MT_ENKAI	1	1	MT_TTRAK	1	1
MT_ERGLI	1	1	MT_TUPRS	1	1
MT_GLBMD	1	1	MT_USAK	1	1
MT_GLYHO	1	1	MT_VARYP	2	2
MT_HURGZ	1	1	MT_VESTL	1	1
MT_IHEVA	1	1	MT_YAZIC	1	1
MT_INANI	1	1	MT_YDATH	1	1
MT_ISGYO	1	1	MT_YGGYO	1	1
MT_ISMEN	2	1	MT_ZOREN	1	1
MT_IZOCM	1	1			