Bankruptcy Prediction Using Neuro Fuzzy: An Application in Turkish Banks

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ABSTRACT

With the global crisis, bankruptcies have increased and bankruptcy prediction models have become more important. The purpose of this study is to actualize the prediction of Turkish bank bankruptcies with Neuro Fuzzy (NF). NF does not have the problems, which come from the assumptions of statistical methods, and, as in Artificial Neural Network (ANN), it has learning ability. At the same time, the model does not stay in a black box. The proposed NF bank bankruptcy prediction model's performance was compared with Multivariate Discriminant Analysis (MDA) and ANN. Besides getting the best prediction of accuracy from Neuro Fuzzy, in this study, the addition of the forerunner indicators on the decision making process can also be interpreted.

I. INTRODUCTION

Monitoring and controlling the banking sector is important for maintaining confidence in a financial system. As a result, the banking sector is one of the most tightly regulated sectors in modern economies. This is especially important in transition economies, as a healthy banking sector is a prerequisite for increasing private savings and allocating loans to their most productive use (Lanine and Vennet, 2006). The banking sector is especially important for Turkey because banks constitute a major part of the finance sector, and companies such as asset investment funds, leasing companies, insurance companies, and factoring companies are generally subsidiaries of banks. The first major bankruptcies in Turkey appeared during the 1994 crisis. After that, as a result of reflecting upon the Asia crisis, which happened in 1997 and 1998, bankruptcies came into question. The biggest bankruptcies to date in Turkey occurred in 2000 and 2001. Bank bankruptcies have a greater effect on an economy than bankruptcies of any other type of company. One reason for this is because bank bankruptcies affect more than just the banks' shareholders: borrowers, depositors and other institutions that lend funds to the banks are also negatively affected. According to the bank size, the economy of the country can also be affected negatively in this case. Bank bankruptcies sometimes can prompt other bank bankruptcies successively.

When the studies on bankruptcy predictions are examined, firstly, it is seen that statistical models have been used in this area. However, the assumptions within the statistical models reveal some

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objections about the subject of generalizing the success of these models. ANN has been used since 1990s. But there is an important disadvantage of ANN. The coefficients regarding the ANN model cannot be interpreted. So, it cannot be known how the independent variables are used in the model.

Neuro Fuzzy (NF), which is one of the Artificial Intelligence (AI) technologies, is a hybrid technology obtained by using ANN and Fuzzy Logic (FL) simultaneously. NF has learning ability. Moreover the most important feature that separates NF models from ANN is the built model that does not stay in a black box. The purpose of this study is to investigate the bank bankruptcy prediction ability of the NF model by using the Turkish banks' data. The performance of the NF model is also compared with ANN and MDA. The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 gives a brief outline of NF in building bank bankruptcy prediction model. Section 4 presents the research design and methodology. Section 5 presents the empirical results of the bank bankruptcy prediction models. In the last section concluding remarks are given.

II. PREVIOUS RESEARCH

Bankruptcy prediction studies go back to 1960s. Beaver (1966) pointed out that early warning signals could be taken from the financial ratios. Altman (1968) used MDA successfully in predicting bankruptcies for the first time. In predicting bankruptcies, MDA was used by Sinkey (1975), Multivariate Regression Analysis (MRA) was used by Meyer and Pifer (1970), Logistic Regression Analysis (LRA) was used by Martin (1977) successfully. West (1985) pointed out that using Factor Analysis and LRA together in evaluating bankruptcies produced hopeful results.

ANN models have been used for predicting firm bankruptcies since 1990s. In the studies, results showed that ANN models are more successful than the statistical models such as MDA, MRA, LRA and Probit Analysis (PA) (Davalos et al, 1999; Han and Lee 1997; Lee et al, 2005; Leshno and Spector 1996; Salchenberger et al, 1992; Sharda and Wilson 1993; Tan and Dihardjo 2001; Tsukuda and Baba 1994; Wilson and Sharda 1994; Yang et al, 1999; Zhang et al, 1999). ANN models have been also used in bank bankruptcy predictions. Tam (1991) and Tam and Kiang (1992) pointed out that in predicting Texas bank bankruptcies ANN was more successful than the statistical techniques. While Bell (1997) pointed out that ANN is more successful than LRA, Swicegood and Clark (2001) pointed out that ANN is more successful than MDA in prediction of bank bankruptcies. Alam et al, (2000) pointed out that in predicting bankruptcies, Fuzzy Clustering and Self-Organizing Maps would be able to be done successfully. Ravi and Pramodh (2008) have actualized prediction of the bankruptcies with the principal component of the ANN. Data Envelopment Analysis on bank bankruptcy prediction has been used successfully in the studies which were done by Cielen et al, (2004) and Kao and Liu (2004). Kolari et al, (2002) and Lanine and Vennet (2006) have found that the Trait Recognition model is more successful than LRA in bankruptcy predictions. With the significant nine variables, the prediction of bank bankruptcies was actualized in a 21-year-process in the USA between 1980-2000 by using the Generic Self-Organizing Fuzzy Neural Network (GenSoFNN) model by Tung et al (2004). According to the findings GenSoFNN has been found more successful than Cox's Proportional Hazards model on a total of 3,635 banks. However, Ng and Jiang (2008) found that Fuzzy Cerebellar Model Articulation Controller (FCMAC) model more successful than GenSoFNN and Cox's proportional hazards model with the same data set. Nguyen and Quek (2008) obtained prediction accuracy up to 95% by using the Ying-Yang FCMAC model. With wavelet ANN models, Chauhan et al, (2009) have obtained, 100%, 89.99%, 93.33% prediction accuracy on the data sets of Turkey, Spain and USA respectively.

Also in Turkey, some researchers have built various bankruptcy prediction models, in which bank bankruptcies that happened in the period between 1994 and 2003. Canbas et al (2005) got 90%, 87.5% and 87.5% prediction performance from MDA, LRA and PA, respectively. Doganay et al (2006) obtained prediction success which changed between 81% and 95% by using MRA, MDA, LRA and PA. Karacabey (2007) obtained 92.3% prediction accuracy from mathematical based MDA. In the study done by Boyacioglu et al (2009), the best bank bankruptcy prediction performance was obtained from Multilayer Perception and Learning Vector Quantization. Çelikyılmaz et al (2009) got 98%, 94% and 97% prediction performance from the Improved Fuzzy Classifier Functions model.

III. NEURO FUZZY

Zadeh (1965) introduced FL, a mathematical system which deals with modeling imprecise information in the form of linguistic terms. The point where FL emerges becomes the crisis about the classic set theory. One member definitely belongs to the set or does not belong to the set in the classic set theory. FL makes possible that one individual can be a member of more than one set in a certain degree by means of membership functions. A is defined as a fuzzy set below.

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

This equation $\mu A(x)$ shows membership function which gets value between 0 and 1, x shows a member of A set. FL represents models using if-then rules. For example;

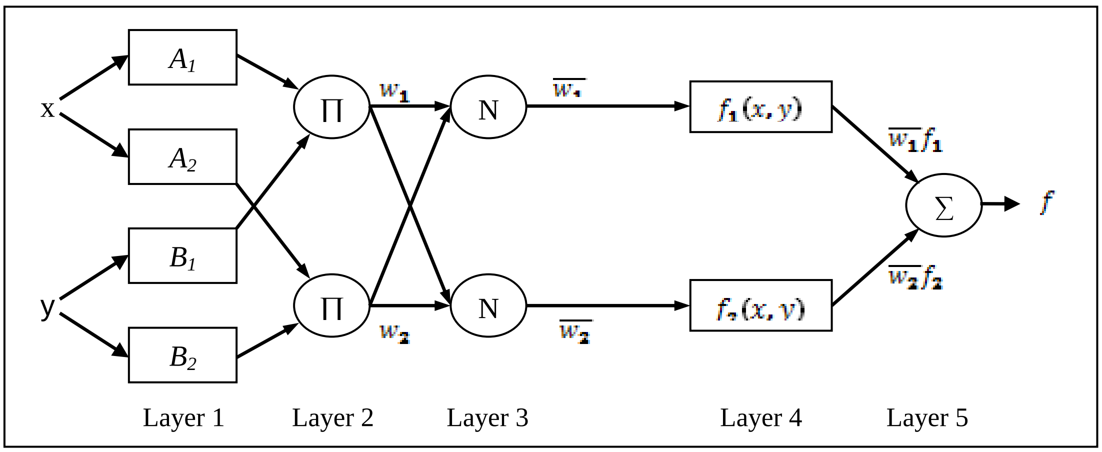
If *Liquidity* is **average** and *Capital Ratio* is **high,** then *Bankruptcy Risk* is **low,** where *Liquidity, Capital Ratio* and *Bankruptcy Risk* are linguistic variables; **low, average** and **high** are linguistic values that are identified by membership functions. Each AI technology has a unique ability. ANN carries out machine learning by stimulating the human being's neural system. However, FL is very similar to a human being's reasoning. But these technologies have some unique disadvantages. The information that stays in the black box is an important disadvantage for ANN. An important disadvantage of FL is not having the ability to learn. In parallel to AI technology development, combinations of these technologies have come into question. To take advantage of the learning capability of ANN and the modeling superiority of FL, these technologies are used simultaneously and that is called NF. NF systems have the ability to apply human experience on the problem area by means of fuzzy rules (Jang et al., 1997). Learning capability by using verbal variables is the most important advantage for NF models, compared to other non-linear AI technologies (Abonyi, 2003). Another advantage of NF is being able to make a comment on how the model produced the output value. NF has been applied to few researches for financial prediction (Akkoc, 2007; Chen et al., 2009; Malhotra and Malhotra, 2002; Piramuthu, 1999; Yildiz and Akkoc, 2009).

Adaptive Neuro Fuzzy Inference System (ANFIS), which has been developed by Jang (1993) and used in the application part of this study, is a kind of NF systems. ANFIS utilizes human expertise in the form of fuzzy if-then rules. ANFIS has the ability to construct models only with target sample data and exhibits fault tolerance. ANFIS determines itself appropriate parameters to provide the best learning by describing membership functions (Jang et al., 1997). The most important feature that separates ANFIS from ANN is the obtained model that can be presented with rules like "If…then…" To give two fuzzy if-then rules example, for a first order Sugeno model the two rules will be below:

Rule-1: If $x = A_1$ and $y = B_1$ then $f_1 = p_1 x + q_1 y + r_1$

Rule-2: If $x = A_2$ and $y = B_2$ then $f_2 = p_2 x + q_2 y + r_2$ (2)

where x and y are independent variables, A_i and B_i are fuzzy sets (linguistic labels like; low and high), p_i, q_i, r_i are the parameters of dependent variable. The corresponding equivalent ANFIS architecture which consists of five layers is shown in Figure 1.



Layer 1: Every node i in this layer, is an adaptive node with a node function described by;

$O_{1,i} = \mu A_i(x)$, for i=1,2 and $O_{1,i-2} = \mu B_i(y)$, for i=3,4, (3)

where x is the input node i, A_i and B_i are the linguistic label (low, medium, high, etc.) associated with this node function $O_{1,i}$ and $O_{1,i-2}$ are the membership function of A_i and B_i respectively. This research utilized $\mu A_i(x)$ and $\mu B_i(y)$ to be bell-shaped membership function with maximum and minimum equal to 1 and 0 respectively, such as: $\mu A_i(x) = 1 / 1 + [(x\text{-}c_i / a_i)^{2}]^{bi}$, where a_i, b_i and c_i are the premise parameters of the membership function.

Layer 2: Every node in this layer is a fixed node labeled Π which multiplies the incoming signals and sends the product out. The outputs of this layer which represents firing strength of the rules can be represents as: $O_{2,i} = w_i = \mu A_i(x) \times \mu_{Bi}(y)$, i = 1,2. (4)

Layer 3: Every node in this layer is a fixed node. Every node is labeled N. The ith node calculates the ratio of the ith rules firing strength to the sum of all rule's firing strength. In other words, this layer normalizes firing strength of the node i.

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

Layer 4: This layer calculates the consequent. Every node in this layer is an adaptive node, with a node function, where $\overline{w_i}$ is the output of layer 3 and p_i, q_i and r_i are the parameter set.

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

Layer 5: The single node in this layer is a fixed node labeled Σ that computes the overall output as the summation of all incoming signals.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

IV. RESEARCH DESİGN AND METHODOLOGY

Data

In the sample of the study, there are 55 banks and 19 of these banks were bankrupt on different dates. As the bankruptcy prediction was actualized one year before, the data set has been constituted by taking into consideration the financial ratios of the previous year. Because 2001 was the year of crisis, in which most of the bankruptcies occurred, the financial ratios of the non-bankrupt banks in 2000, have taken place on the data set, too. The data set, constituted of 55 banks, has been divided into two groups as training and validation. The training set consisted of 11 bankrupt banks and 22 non-bankrupt banks, whereas the validation set consisted of 8 bankrupt banks and 14 non-bankrupt banks. The data have been taken from the Bank Associations of Turkey (BAT) (http://www.tbb.org.tr). Table 1 shows the descriptive statistics regarding financial ratios. On the data set, there are 36 financial ratios under 6 titles of Capital Ratios, Assets Quality, Liquidity, Profitability, Income-Expenditure Structure and Activity Ratios. As a result of the "t test" on bankrupt and non-bankrupt banks, the differences among 24 financial ratios have been found significant at the 5% level and stated in italics.

Selection of variables and factor analysis

In this study, some data reduction techniques have been used to increase prediction performance. The ratios which do not show a significant difference are taken out of the first data set and a second data set is generated. The second data set has 24 financial ratios. The third data set is taken out by applying the Factor Analysis method on the second data set. Firstly, factor analysis is taken out after the financial ratios, which affect KMO negatively, are extracted from the data set, and reliability analyses are done. As an extraction method, the Principal Component Analysis is applied to the data set. KMO value of 0.63, given at Table 2, shows that data set is suitable for factor analysis. As a result of the Factor Analysis, there are 4 factors which are above the Eigenvalue 1. All these 4 factors explain 78.7% of total variance. The first factor explains 45.7% of total variance. This factor includes P1, P4, C2, C4, C5, IE4 and C3 ratios. So, it can be said that this factor represents profit and capital ratios. The second factor explains 16% of total variance. This factor includes L1, A3, A2 and L2 ratios. This factor is a mixed factor which is constituted with liquidity and activity ratios. The third factor explains 8.9% of total variance. This factor includes IE11, IE2 and C1 ratios. It can be said that this factor reflects the form of income and expense ratios. The fourth factor explains 8% of total variance. The fourth factor includes only IE3. The fourth data set is generated with the variables that are used in discriminant function. ANN and MDA are applied on all data sets, but NF is applied on the third and the fourth data sets because it is capable of building models with a few variables. The best classification results, obtained from the models we used, are presented.

Table 1: Statistical Information about Financial Ratios

Financial Ratios	Non-Bankrupt		Bankrupt		Test Values	
1. Capital Ratios	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**t**	**P**
(C1) Standard Capital Ratio	*34*	*38.4*	*5.84*	*11.09*	*-3.116*	*0.003*
(C2) (Shareholders' Equity+T.Income)/Total Assets	*16.25*	*10.01*	*-1.94*	*30.72*	*-3.263*	*0.002*
(C3) (Shareholders' Equity+T.Income)/(Deposits+Non-depodit Funds)	*28.96*	*27.9*	*2.81*	*18.5*	*-3.674*	*0.001*
(C4) Net Working Capital/Total Assets	*10.53*	*9.49*	*-12*	*36.79*	*-3.487*	*0.001*
(C5) (Shareholders' Equity+ T.Income)/(T.Assets+Contin.and Com.)	*7.53*	*7*	*0.17*	*10.25*	*-3.149*	*0.003*
(C6) Fx Position/Shareholders' Equity	226.93	270.39	205.21	293.47	-0.275	0.784
2. Assets Quality						
(AQ1) Total Loans/Total Assets	*24.43*	*15.72*	*33.54*	*12.24*	*2.197*	*0.032*
(AQ2) Non Performing Loans/Total Loans	*4.55*	*6.59*	*42.24*	*102.97*	*2.206*	*0.032*
(AQ3) Permanent Assets/Total Assets	13.31	13.42	15.5	14.35	0.561	0.577
(AQ4) Fx Assets/Fx Liabilities	70.6	24.75	62.97	22.77	-1.117	0.269
3. Liquidity						
(L1) Liquid Assets/Total Assets	*55.53*	*22.97*	*32.7*	*16.25*	*-3.846*	*0.000*
(L2) Liquity Assets/(Deposits + Non-deposit Funds)	*96.46*	*91.85*	*37.36*	*19.32*	*-2.761*	*0.008*
(L3) Fx Liquid Assets/Fx Liabilities	45.68	26.48	33	16.23	-1.903	0.062
4. Profitability						
(P1) Net Income(Loss)/Average T.Assets	*3.32*	*3.24*	*-11.44*	*29.68*	*-2.977*	*0.004*
(P2) Net Income(Loss)/Average Equity	42	46.82	-221.67	932.43	-1.707	0.094
(P3) Net Income(Loss)/Average Share-in Capital	*74.7*	*118.15*	*-216.81*	*698.46*	*-2.458*	*0.017*
(P4) Income Before Tax / Average Total Assets	*5.18*	*5.21*	*-10.9*	*30.02*	*-3.151*	*0.003*
(P5) Provision for Loan Losses/Total Loans	*1.52*	*2.58*	*21.17*	*58.43*	*2.031*	*0.047*
(P6) Provision for Loan Losses/Total Assets	0.36	0.6	5.35	15.3	1.972	0.054
5. Income-Expenditure Structure						
(IE1) Net Interest Income After Provision/Average T. Assets	12.28	7.88	5.43	21.29	-1.729	0.090
(IE2) Interest Income/Interest Expenses	*221.42*	*81.6*	*146.23*	*43.2*	*-3.738*	*0.000*
(IE3) Non-Interest Income/Non-Interest Expenses	*16.18*	*79.9*	*-42.61*	*87.62*	*-2.51*	*0.015*
(IE4) Total Income/Total Expenditure	*130.09*	*29.11*	*92.3*	*31.82*	*-4.434*	*0.000*
(IE5) Interest Income/Average Profitable Assets	*33.72*	*12.7*	*62.37*	*36.78*	*4.247*	*0.000*
(IE6) Interest Expenses/Average Non-Profitable Assets	*18.46*	*10.88*	*30.34*	*13.89*	*3.496*	*0.001*
(IE7) Interest Expenses/Average Profitable Assets	*16.74*	*7.67*	*45.7*	*30.85*	*5.368*	*0.000*
(IE8) Interest Income/Total Income	96.22	23.72	32.07	338.02	-1.143	0.258
(IE9) Non-Interest Income/Total Income	3.78	23.72	67.93	338.02	1.143	0.258
(IE10) Interest Expenses/Total Expenses	*59.29*	*13.87*	*69.56*	*11.22*	*2.779*	*0.008*
(IE11) Non-Interest Expenses/Total Expenses	*40.71*	*13.87*	*30.44*	*11.22*	*-2.779*	*0.008*
6. Activity Ratios						
(A1) (Salaries and Emp'ee Benefits+Reserve for Retirement)/T.Assets	2.73	1.83	2.97	1.42	0.494	0.623
(A2) (Salary and Emp'ee Bene.+Res. for Retire.)/No.of Pers.(Billion TL)	*25.63*	*15.64*	*10.61*	*5.88*	*-4.023*	*0.000*
(A3) Reserve for Seniority Pay/No.of Personnel (Billion TL)	*0.62*	*0.58*	*0.21*	*0.22*	*-2.915*	*0.005*
(A4) Operational Expenses/Total Assets	3.5	2.53	3.93	1.79	0.668	0.507
(A5) Provisions except Provisons for Income Tax/Total Income	*1.84*	*1.64*	*6.39*	*13.33*	*2.038*	*0.047*
(A6) Provisions including Provisons for Income Tax/Total Income	5.13	5.6	7.34	13.11	0.876	0.385

Table 2. KMO and Bartlett's Test

KMO		0.63
Bartlett's Test	Approx. Chi-Square	1135.949
	Df	105
	Sig.	0.000

The multivariate discriminant analysis

MDA, one of the frequently used statistical techniques on bankruptcy prediction studies, puts forward whether there is an explicit difference or not among two or more groups depending on a group of variables. The model that MDA has is like stated below.

$$Z_i = B_0 + B_1 X_{i1} + B_2 X_{i2} + \dots\dots\dots + B_m X_{im},$$

where Z_i is a discriminant score, B_0 is the intercept term, B_m are the estimated coefficient and X_{im} are the independent variables. MDA has been actualized on the training data and the prediction performance of the model has been evaluated by applying the obtained function on the validation data.

Artificial neural network model

This study uses the feedforward multilayer perceptrons with the BPN training algorithm. In this study, forming optimal ANN model comes with the development of many unsuccessful models in the process of trial and error. It has been observed that some of the developed unsuccessful ANN models cannot develop learning and cannot minimize error. This trial and error process has been kept on until finding an optimum architecture. Finally, it has reached an optimum architecture when it learns the training data and provides high prediction success on the validation data. The optimum architecture's learning rate, momentum, hidden nodes and training epochs are 0.4, 0.6, 6, and 2,650, respectively.

Neuro fuzzy model

This process starts with entering variables to ANFIS and assigning membership functions. Hereby, ANFIS has determined each parameter about membership functions by considering the inputs and the outputs. ANFIS has set up rules in order to make the best learning by considering independent variables and membership functions. When the training of the network is completed in the frame of developed rules, decisions on the banks are made. Table 3 shows the parameter of the optimum NF model.

Table 3. Parameters about developed NF

The number of the processing elements in the input layer	3
Membership Function Number	C4 2; IE 2; A5 3
MF Type	Gaussmf
Epochs Number	3,322
Rule Number	12

V. EMPIRICAL RESULTS

The empirical results of the models

Whether or not the prediction performance of MDA is found as successful can be understood from Canonical Correlation, Eigen value and Wilk's Lambda values given in Table 4. Because the value of Eigen value is higher than 0.40, the discrimination power of the model can be considered as pretty good. Canonical Correlation (0.798) measures the discriminant score and the relationship among the groups, and the square of this value shows the explained total variance. As for Wilk's Lambda statistic, it shows the part of the total variance that is not explained by the discrimination among the groups. Discrimination functions developed on training data will be used in predicting financial situations of the banks on the validation data. Developed discrimination function is as stated below.

$$Z36 = 1.303 + 0.038 * C4 – 0.097 * IE7 + 0.232 * A5$$

Table 4. Statistics relating to MDA

Function	Eigen value	Can. Cor.	Wilks' Lambda	Sig.
36 financial ratios*	1.751	0.798	0.364	0.000

* Same results have been obtained on the second data set which has 24 financial ratios.

Prediction performance of the developed models on training and validation data sets is given in Table 5. MDA has predicted correctly 29 of 33 banks on training set and 18 of 22 banks on validation set. ANN has predicted correctly 32 of 33 banks on training set and 19 of 22 banks on validation set. NF has predicted correctly 30 of 33 banks on training set and 20 of 22 banks on validation set. It can be said that the high prediction success has been provided from each methods. But it is seen that the best result has been obtained with the NF model, when the validation set is taken into consideration.

Table 5. The Empirical Results of Training and Validation Data Set

Prediction Model	Variables	Training performance %	Validation performance %
MDA	36 financial ratios	87.9	81.82
ANN	3 financial ratios	96.97	86.36
NF	3 financial ratios	90.91	90.91

The 3D graphics of NF model

The most important feature that separates NF from ANN is the built model that does not stay in a black box. Non-Linear functions, which NF produces, take place in Figure 2a, 2b, and 2c. Non-Linear functions reflect just two dimensions of mixed relationships. So, significant relations should not be expected at each point of the functions. In Figure 2a, functions, which are developed relating to ratios of C4 and IE7, take place. Figure 2a indicates that the probability of going bankrupt increases dramatically when C4 is lower than -0.2 and IE7 higher than 50. On the Figure 2a, this point is shown in relatively dark places. Non-Linear functions developed relating to C4 and A5 ratios take place in Figure 2b. Figure 2b indicates that the probability of going bankrupt increases dramatically when C4 is lower than -0.2 and A5 is between 5 and 30. Non-Linear functions developed relating to IE7 and A5 ratios take place in Figure 2c. Figure 2c indicates that the probability of going bankrupt increases dramatically when IE7 higher than 50 and A5 is between 5 and 30. As for the positive values of C4 and the low values of IE7 and A5, banks were evaluated as non-bankrupt.

Figure 2a: The 3D graph for C4 and IE7

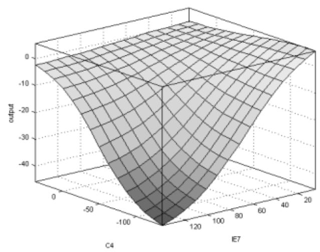


Figure 2b: The 3D graph for C4 and A5

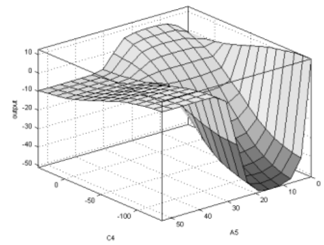
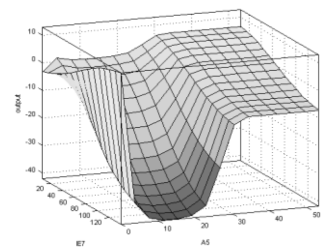


Figure 2c: The 3D graph for IE7 and A5



VI. CONCLUSİON

In this study, bank bankruptcies prediction was actualized with NF, with the aim of being an early warning system. Prediction accuracy of NF, ANN and MDA models were found at 90.91%, 86.36% and 81.82% respectively. Although there were not great differences between the performances of the models, it can be said that NF was slightly more successful. Models, which are built in the studies of bankruptcy prediction, generally focus on high prediction success. In addition to this success, how variables are used in the decision process by the models is also important. This study affirmed that in bank bankruptcy predictions, high prediction accuracy can be taken with NF. In addition to this, NF model presented how it makes its prediction. So, it is also possible for people to understand the nature of the bankruptcy model. This is NF's important superiority in comparison with ANN.

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