An Application of Risk Management On Airline Industry Via Financial Ratios And Artificial Intelligence

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Abstract

The growing demand for airline transportation in recent years has increased the importance of airline passenger and cargo operations and aviation sector globally. Aviation sector is a sector that has unique properties like high fixed costs, cyclical demand, intense competition, and vulnerability to external shocks like terrorist attacks, disasters, global financial crises especially after deregulation in 1978. Air transport industry is responsible for connecting the global economy, providing a lot of jobs and making modern quality of life possible. Under high competition, it is crucial for airline companies to evaluate and analyze which core business areas are essential for them to prevent bankruptcy and to reach sustainable success. Initially developed in 1968 and evaluated by Altman in time, Altman's Z score model remains a commonly used tool for evaluating the financial health. Altman Z'' score has been well accepted, widely used models of predicting survivals and failures. This model is one of the most frequently used risk early warning models. As one of the biggest player of aviation sector, Turkish airline industry is affected by many different social, political, economic and legal factors on both national and international level as well as other airlines. It is very important to forecast the companies that may gone bankrupt and determine underlying causes. Therefore, this paper evaluates the Altman's Z'' score model for predicting the bankruptcy risk of Turkish Airlines inc. which is the Turkey's flag carrier via financial performance ratios taken from financial statements for the years between 2002 to 2016. Within the scope of the research, both the theoretical information and the applied method details are held. Also for next three years (2017-2019) Z'' score values are predicted using artificial intelligence neural network algorithms.

Keywords: Airline Transportation, Bankruptcy Forecasting Models, Artificial Intelligence

JEL Classification: G32,G33,C45

1 Introduction

The air transport industry is the global network of commercial aircraft operators, airports, service providers of air navigation and the manufacturers of aircraft and their components. Also, it is an integral part of the tourism industry. The airline industry is one of the fastest growing sectors in the world. It is also a sector that greatly affected by the social, political and legal developments nationally and internationally. Many airline companies in this industry are established for various reasons and they are also shut down or go bankrupt for a variety of reasons. Unfortunately, airline bankruptcy has become an everyday event in the year 2005 in the USA. In order to analyze the financial situation of aviation sector enterprises operating under intense competition, a number of indicators specific to these enterprises are used together with the commonly used financial ratios. Historically, analysts have computed different

types of financial ratios to assess different aspects of financial well-being. Comparisons of these ratios and indicators for previous periods and years, evaluation of risks, creation of appropriate reports, making estimations will guide especially airline finance managers, analysts and related stakeholders to make better vision, strategies, and decisions about the financial condition of enterprises.

Increasing demand for air transportation in the world has also brought the importance of passenger and cargo transportation services and brought intensive competition. The airline industry sector has intense competition that has high fixed costs, has cyclical demand and vulnerable to external shocks like terrorist attacks, disasters, global financial crises. Successful risk applications and models used and developed for other sectors may not be suitable for airline firms. For this reason, airline companies should establish their own models according to airline business dynamics. Airlines often seem to avoid taking too much risk, especially focusing on decreasing financial risks and trying to limit exposure to the risks associated with business activities. A set of indicators which are specific to the airline sector have been used along with the widely used financial ratios to analyze the financial situation of companies. Finance engineers, finance analysts, managers, and related business owners can make better decisions and make accurate planning through regularly calculating essential financial ratios and indicators, comparing them for past periods and years, making estimations for the future periods, developing simulations for future scenarios when necessary.

It is certain that methods which could predict insolvency or at least gauge companies' relative financial state are very crucial. It is obvious that airlines try to avoid taking too much risk and avoid risks associated with business processes in today's business environments. Since the structure of each industry is different; successful risk application and models used by other sectors may not be suitable for airline firms. Additionally, airlines should establish their own models according to their environments and their business dynamics. Even though there are financial ratios which are generally used for services, manufacturing and raw materials sectors widely, there are a lot of metrics and indicators specific to the airline industry used to assess the financial status of airlines. Traditional ratio analysis is frequently used for financial analysis and different ratios and metrics are used to match the type of analysis that needs to be done.

The aviation industry contributes to economic progress and social development by facilitating trade and tourism and connecting people. Moreover, it increases a country's connectivity, raises productivity, encourages investment and innovation and generates employment. Some major structural changes have been taking place in the air transport industry throughout the world recently. The regulatory framework which forms the air transport industry has been undergoing significant changes both in a global, regional and national scale. There are some evident reflections of these structural changes to Turkish Air Transport Industry (Gerede, 2010). In parallel with the rapid advances and changes regarding aviation in all over the world, Turkey has risen to a significant position in the international arena in civil aviation. Established in 1933, Turkish Airlines is the flag carrier airline of the Republic of Turkey. Headquartered in Istanbul, Turkish Airlines is a private Company and its main fields of activity are all types of domestic and international passenger and cargo air transportation.

The objective of this study is to evaluate the Altman's Z" score model for forecasting of the financial health of Turkish Airlines using financial ratios taken from financial statements for the years between 2001 to 2016. In the application part, the aim is to analyze and forecast the bankruptcy risk on the Turkish Airlines Inc. by four events that affect the aviation industry globally since 2000 by using Altman's Z" score model. These four important events including 9/11 terrorist attack to World Trade Center Network, the SARS outbreak in 2003, the global financial crisis in 2008 and the volcanic ash eruption in 2010 over Europe which caused cancellation of a lot of flights, re-routing and temporary closing of European airspace partially. Altman's Z" score model, which is a model is chosen among bankruptcy prediction models and evaluated using the Turkish Airlines' financial values and/or ratios are analyzed. The findings are for four majör events there was bankruptcy risk existed. And also next three years values forecasted by artificial intelligence neural network algorithms and found that Z" score values might be in the gray area.

2 Literature Review on Financial Crisis Early-Warning Model

To be able to predict the risks of failure of enterprises becomes a very critical task in today's very competitive market conditions. Analysts and scholars began to work on financial crisis pre-warning models, from single variable and multivariable discriminant analysis models to the artificial intelligence models and higher

discriminating rate pre-alarming models since 1932. Prediction of the financial crisis has become an important factor in the healthy development of trade, capital markets as well as airline companies and countries (Yim and Mitchell, 2005).

Practically, methods and models used by companies for financial risk analysis are largely based on ratio analysis (Göçen et al., 2011). Approximately more than 90 years, the literature on bankruptcy prediction with initial studies regarding with the help of ratio analysis techniques to predict bankruptcy studies up to the mid-1960s focusing on several univariate techniques are developed (Bellovary et al., 2007). Especially for the last four decades, research on predicting bankruptcy has been of significant interest in accounting, banking sector, and finance (Agarwal and Taffler, 2007). The decrease in the cash flows of the enterprise will put the business into financial distress depending on its debt obligations. Therefore, any event that adversely affects the cash flows of the company increases the risk of bankruptcy. In general speaking, bankruptcy models provide measures of financial distress and examined by scholars to examine the financial health of enterprises (Grice and Dugan, 2001).

Theoretically, Beaver (1966) initiated financial ratios that were basically univariate in nature. However, the univariate approach employed a single ratio, which had individual signs of impending problems that might lead to misinterpretations (Altman, 1968). There is a variety of analysis such as single variable model analysis and multivariable model analysis could be used by different purposes (Uysal, 2010).

There are plenty of models of financial risk assessment and estimation of bankruptcy status, eight of them which can be used for analysis for airlines are listed as follows (Gritta et al., 2008):

- Altman Model (Z-score)
- Altman Zeta Model
- Airscore Model
- Pilarski Model (P-score)
- Gudmunsson Model
- Artificial Intelligence Models:
  * Artificial neural networks (Nn)
  * Genetic Algorithms
  * Fuzzy Logic Model

Academician E. Altman was the first one who published the multivariable discriminant model (MDA) technique for failure prediction in 1968 which is called Z-Score. This technique is still one of the very popular models in the literature. Altman's Z score model could be applied to various domains such as merger and divestment activity, market efficiency and asset pricing, capital structure determination, the pricing of credit risk, and bond ratings and portfolios (Agarwal and Taffler, 2007). Since 50 years a variety of improvements have been made on the model for example linear discriminant analysis (Altman, 1973), principal component analysis (Altman et al., 1974), logarithm, stepwise analysis, linear and quadratic analysis (Altman et al., 1977), neural networks for classifications (Altman et al., 1994), aggregated and weighted rates for pricing (Altman et al., 2005) etc. In this study, Altman's model is applied to Turkey's flag Carrier airline Turkish Airlines via its financial ratios over the past 15 years and also for the next 3 years artificial intelligence models used for forecasting.

Z-score model which is a multivariable model adopts multi-variable linear function and selects those variables (ratios) with the biggest difference between the two sample groups and applies statistical techniques in order to convert them to categorical variables and obtains an equation (Altman and Haldeman, 1977). Also, it continues to be used in a variety of business situations involving the prediction of bankruptcy and other financial stress conditions. For example, commercial banks use the model as part of the periodic loan review process, and investment bankers use the model in security and portfolio analysis. Edward Altman's original model has been employed in recent research to evaluate the financial conditions of firms from a variety of industries and periods (e.g., Chen and Church, 1996; Chen and Wei, 1993; Carcello et al., 1995; Berger et al., 1996; Subramanyan and Wild, 1996; Grice and Ingram, 2001).

To develop the Z-score model, Altman (1968) compiled a list of 22 financial ratios and classified each into one of five categories (liquidity, profitability, leverage, solvency, and activity). The ratios were not selected on a

theoretical basis, but rather, on the basis of their popularity in the literature and Altman's belief about their potential relevancy to bankruptcy (Grice, Ingram, 2001). The lower Z score of a firm, the higher its probability of bankruptcy. The formula is given below:

$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.999X5$
X1: the working capital/total assets
X2: retained earnings/total assets
X3: earnings before interest and taxes/total assets
X4: the market value equity/book value of total debt
X5: the sales/total assets
Z: overall Z-score index.

Z-score range financial situation;
$Z \leq 1.81$ high bankruptcy probability
$1.81 \leq Z \leq 2.99$ unstable financial status (gray area)
$2.99 \leq Z$ Stable financial status

Z-score model theory is the research conclusion published by Altman in 50 years ago. Later, Altman got some critics and has to revised the original model, then finally established Z" score. The Z" Score, the model has no turnover ratio (Chu-tang, Zhi-qiang, 2009). So, the revised Z" model function of listed non-manufacturing companies is as follows:

$Z" = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$
X1 : operating asset/total asset
X2 : retain earnings/total asset
X3 : profit before interest and tax/total asset
X4 : owner's equity/total liability
Z" : overall Z-score index.

Z"-score range financial situation;
$Z" \leq 1.1$ high bankruptcy probability
$1.1 \leq Z" \leq 2.6$ unstable financial status (gray area)
$2.6 \leq Z"$ Stable financial status

It is noteworthy that there is a limited number of studies on airline business bankruptcy. As one of those studies, it is analyzed that the equities of the US airline companies in the bankruptcy protection program (Gong, 2007) and a similar study were conducted by Jayanti and Jayanti (Jayanti, Jayanti, 2011). It is found that when an airline company goes bankrupt, the competitor airline companies earn an abnormal amount of income from their securities. Davalos, Gritta, and Chow (1999) conducted a study analyzing the bankruptcy risks via financial variables of airline companies. Borenstein and Rose (1995) focused on the effects of Chapter 11 which is the United States Bankruptcy Code on airline bankruptcies and ticket pricing. Besides, Ciliberto and Schenone (2012) empirically studied the effects of Chapter 11 for the US airline companies regarding their filing bankruptcy and competition.

Models and methods that could predict insolvency are very important for evaluating financial well-being. Analysts have measured financial strength through calculating financial ratios taken from financial statements historically (Gritta et. all, 2006). In time, researches continue the search for more accurate methods for evaluating financial strength, some of them have pursued a newer approach and comes to the use of artificial neural networks. A Multivariable model Analysis-Artifical Neural Network Model is a neural network model that made up of numerous interconnected simple processing units. There are layers called the input layer, an output layer and hidden layer that obtains desired output through network study and data correction and then makes a prediction. Neural networks are being applied to identification problems in a variety of fields (Gritta et. all, 2006). Learning algorithms used in artificial neural networks differ from classical computer algorithms. Nowadays, science in many different disciplines deals with artificial neural networks and works. Research on artificial neural networks; modeling, classification, optimization,

learning, estimation and shape recognition, etc. are used in many areas. These networks can learn, forecast and generalize through test and experiment. The relationship between artificial neural networks and complex data is difficult to detect and difficult to detect. Neural Networks mirror the architecture of the brain and they derived from research on the neural architecture of the brain (Caudill, 1989).

3 Research Design and Application

The analyses in this study use data belonging to the period of 2002–2016 taken from Turkish Airlines' annual financial files. 2002 was the first year of the study because certain variables were unavailable prior to the 2002 year. The goal is to reveal and predict the bankruptcy risk on the Turkish Airlines over four global important events which affected global aviation industry since 2001 via Altman's Z" score model that is still one of the widely used models by financial analysts. These four important events are listed as 11 September 2001 terrorist attack to the World Trace Center in new York city; the far east SARS outbreak in 2003; 2008 the global financial crisis that was accepted as the worst economic disaster since the Great Depression 1930s and the European volcanic ash eruption in Iceland caused to cancellation of a lot of flights, re-routing of planes and temporary closing of partial European airspace in 2010. Altman's Z" score model is chosen and evaluated using the Turkish Airlines financial values and also Z" score values are forecasted by back propagated artificial neural network algorithms.

In the application part of this study, Turkey's first and only full-service airline provider of Turkish Airline's Altman Z" score values for 15 years were calculated. The quarterly results of the Z" score model and artificial neural network predictions for the next 3 years, which is calculated by using the Turkish Airlines' financial data, are given in the below sections.

## 4 Z" Score and Prediction via Artificial Neural Networks

Altman's Z score model is updated to measure service sector companies' bankruptcy risk more accurately by him in 2000 and it is called as Z" score. Z" score formula is given below:

Z" Score = 6.56T1 + 3.26T2 + 6.72T3 + 1.05T4

Turkish Airlines Z" score values are calculated from companies' financial sheets and stock prices and listed as a table and graphics for the time period between 2002 and 2016 below.

Var.	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
T1	-0,037	0,049	-0,017	-0,106	-0,047	0,071	0,123	0,099	0,089	0,007	-0,034	-0,083	-0,061	-0,044	-0,049
T2	-0,321	-0,314	-0,285	-0,230	-0,108	-0,031	0,144	0,166	0,147	0,084	0,134	0,112	0,147	0,161	0,117
T3	0,129	0,097	0,037	0,052	0,043	0,082	0,166	0,086	0,034	0,009	0,086	0,038	0,071	0,082	0,000
T4	0,045	0,076	0,085	0,078	0,043	0,059	0,023	0,608	0,558	0,191	0,480	0,458	0,583	0,304	0,147
Z" Score	-0,372	0,033	-0,701	-1,016	-0,329	0,976	2,414	2,407	1,882	0,585	1,296	0,556	1,167	1,106	0,217

Table 1. Turkish Airlines Z" score values for years 2002-2016
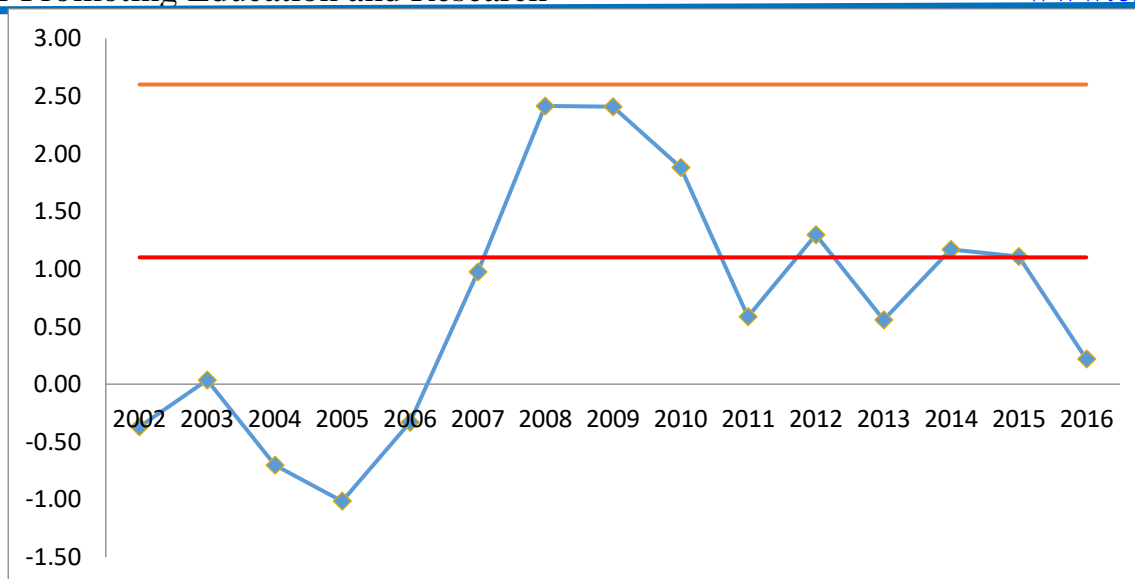
Graph 1. Turkish Airlines Z" score graphic for years 2002-2016

Besides calculating Altman's Z" score values, also preciton study was made via Artificial Intelligence Network algorithms through Matlab 2010 software program. Artificial neural networks are widely used in analysis because of their performance, they mostly get better results of traditional statistics based methods (Sevim et al, 2014). Firstly each years quarterly Z" score values calculates in order to get more data. Then all data are normalized to match them range between 0,1 and 0,9. Normalization formula is given below:

% i1 → first variable
i1_min = min(i1);
i1_max = max(i1);
i1n = 0.8*(i1 - i1_min) / (i1_max - i1_min) + 0.1;

$X' = 0.8 * (X_i - X_{min} / X_{max} - X_{min}) + 0.1$
X'= Normalized data,
X i= Input value,
X min= Min value in the input dataset
X max= Max value in the input dataset.

For the training set it is used 2/3 data, for test and simulation 1/6 number of data used in the dataset. For training of network, Levenberg-Marquardt (Lm) backward propogation network algorithm is used (TrainLm). "logsis activation function" is selected and used. Important parameters are given blow.
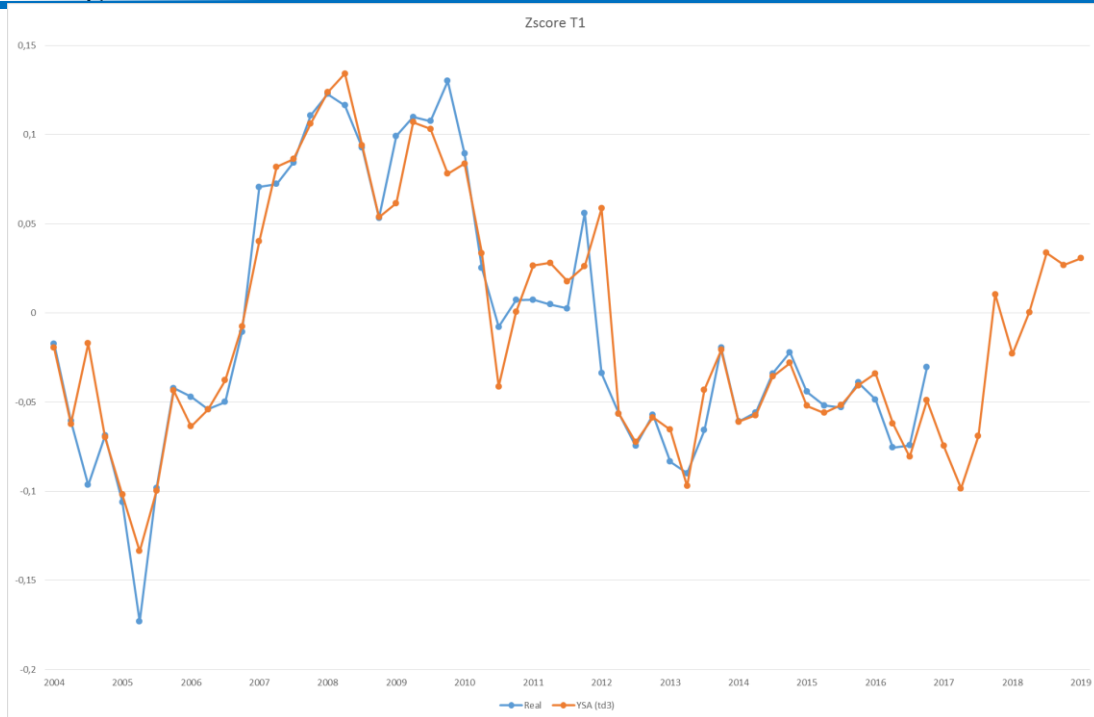
net. train Param. show = 1;
net. train Param. epochs = 100;
net. train Param. goal = 0;
net.trainParam.min_grad = 0;

To measure the performance of trained network, MSE (mean square error) values are used. The 4 variables composed Z" score formula are predicted for years 2017, 2018 and 2019 and also network prediction performance is depicted in below graphic.
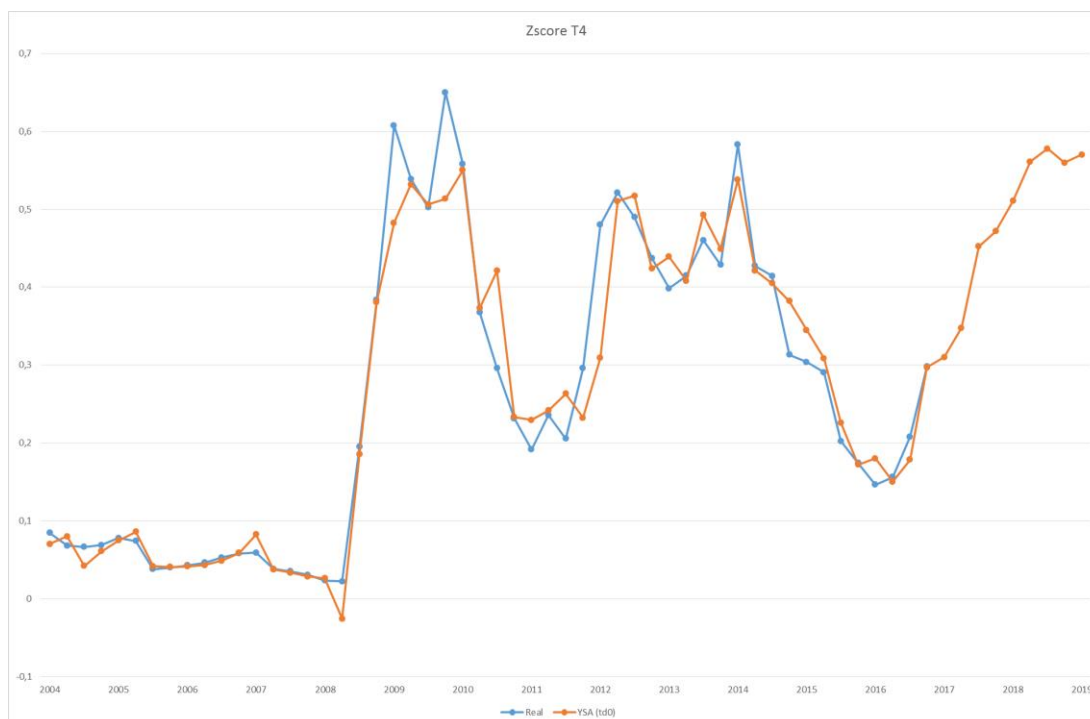
Graph 2. Z"score variable (T1) real and Artificial Neural Network predicted values
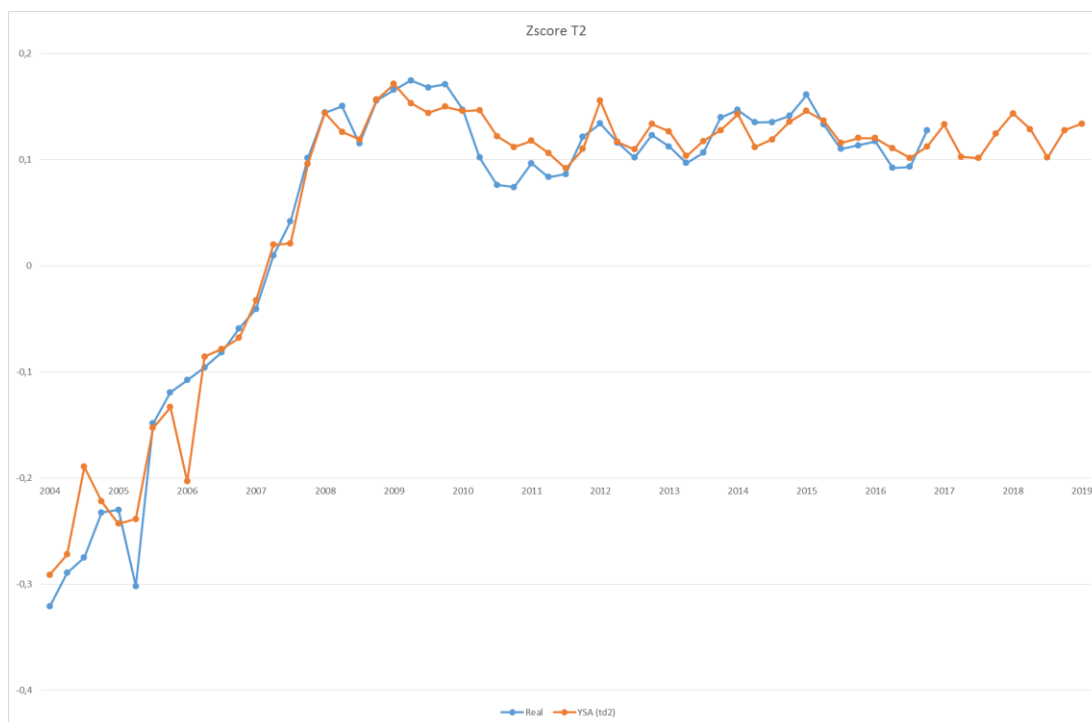
Graph 3. Z"score variable (T2) real and Artificial Neural Network predicted values
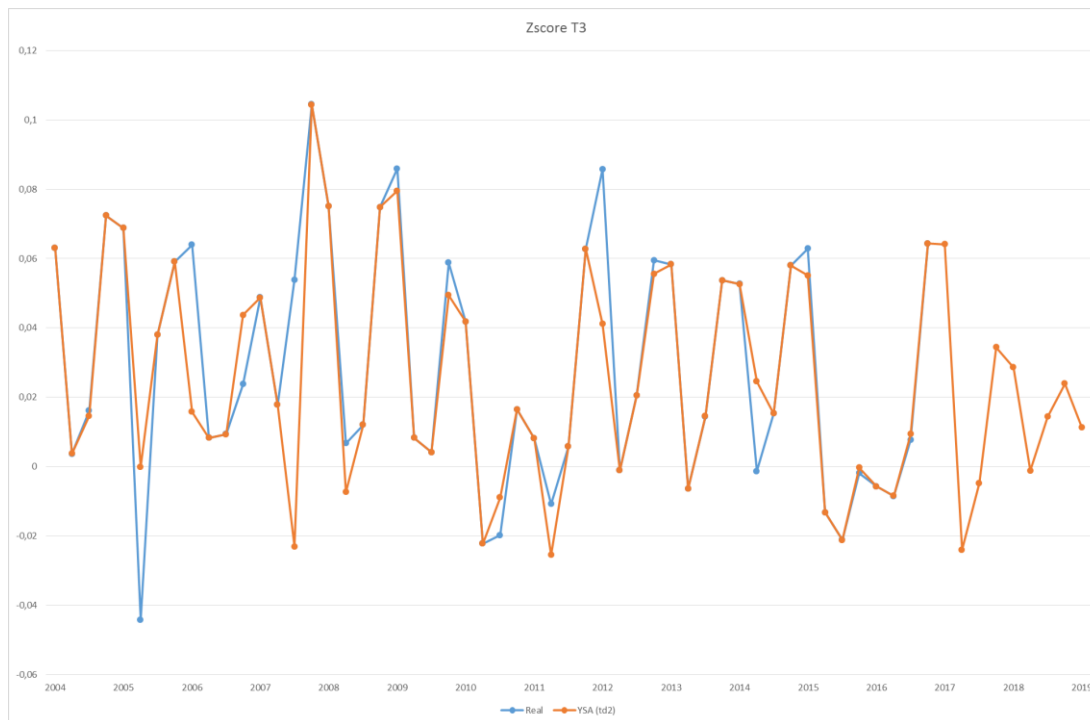
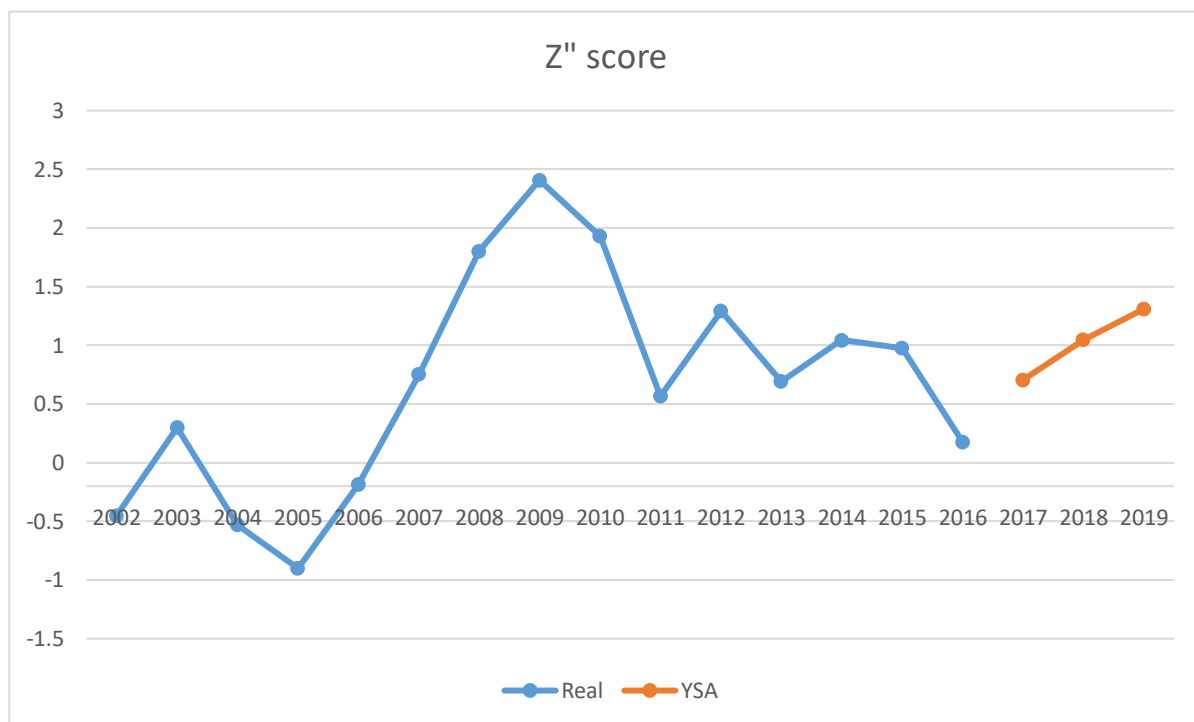Graph 4. Z" score variable (T3) real and Artificial Neural Network predicted values

Graph 5. Z" score variable (T4) real and Artificial Neural Network predicted values

After predicting all Z" score variable values, for years 2017, 2018 and 2019 Z" score are predicted in given table and graphic.

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Z" score / Year	2017 prediction	2018 prediction	2019 prediction
t1 variable	-0,0745	-0,0229	0,0306
t2 variable	0,1329	0,1435	0,1336
t3 variable	0,0641	0,0286	0,0113
t4 variable	0,31	0,5105	0,5699
Z" score	0,704511	1,046948	1,309073

Table 2. Turkish Airlines Z" score values for years 2017-2019 (predictions)

Graph 6. Z" score real and Artificial Neural Network predicted values (2002-2019)

Additionally, after all calculations, we also calculated Z" score value for year 2017 as former years are not available at the time we did the research. It can be easily seen that the values for real and predicted one are so close to each other. So real Altman's Z" score and our model's Artificial Neural Network (Ann) estimated values belong to year 2017 are given below Table 3.

Altman Z" score value – Real - 2017	Altman Z" score value – Ann Prediction - 2017
0,710	0,705

Table 3. Turkish Airlines Z" score real and Ann prediction values for year 2017

Conclusion

It is certain that, airline industry plays a vital role in tourism and global economy. Tourism is important especially

for many developing countries, where it is a key part of economic development strategies. Disruptions in the world in 21th century, both economic and political, negatively affected the tourism and aviation sectors. This paper aims to held four dramatic events on the aviation industry in terms of bankruptcy risk. These events consist of the September 11, 2001 World Trade Center terrorist attack in NYC, the far east SARS disease epidemic in 2003, financial crisis in 2008 and the volcanic ash explosion in 2010 on bankruptcy risk of Turkish Airlines with the help of Altman Z" Score model and Artificial Neural Network algorithms. To accomplish this, the financial statements of Turkish Airlines for period 2002 and 2016 including the crisis periods and the post-crisis periods, financial ratios regarding the liquidity, financial structure, activity efficiency, profitability and growth rates and flown traffic data were considered as research variables. In the application part, Altman Z" score is examined for period 2001-2016 and additionally next three years' forecasts were made by artificial neural networks model.

According to application results, after year 2000, global events that effect most of airlines and its effect to Turkish Airlines according to Altman Z" score values are summarized below.

Global Event	Altman Z" Score
2001 September,11 Terror Attack	Bankruptcy Risk
2003 SARS Epidemic	Bankruptcy Risk
2008 Global Financial Crisis	Bankruptcy Risk
2010 Volcanic Ash Explosion	Bankruptcy Risk

Table 4. Turkish Airlines Z" score interpretions for years 2002-2016

For the period after 2000, according to Z" score values, none of the years can be defined in "safe area". Because all values calculated are above 2,6 bar. Only for years 2008, 2009, 2010, 2012, 2014 and 2015 Z" score values are located between 1,1 ile 2,6 (gray area). Other years values are below 1,1 which is described as risk (red) area.

Moreover, researchers also calculated Z" score value for year 2017 as former years are not available and released by Turkish Airlines investor relations team at the time we did the research. The calculated Z" score value for year 2017 is 0,710 and the artificial neural network model estimation which is 0,705 are so close to each other. The accuracy percentage is 0,99. So it can be stated that our model prediction will be similar for years 2018 and 2019.

It is obvious that financial variables are very important to the prediction process. Unfortunately especially for over the last decade the airline industry has experienced financial adversity. So airline performance and distress prediction becomes hot topics. For this reason, this study can give ideas and enlighten other researchers for airline bankruptcy predictions.

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