A Review of the History of Air Carrier Bankruptcy Forecasting and the Application of Various Models to the U.S. Airline Industry: 1980-2005*

by

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** The views expressed here do not represent the official position of the U.S. Dept. of Transportation and/or any division within DOT.

Introduction:

Airline bankruptcy has become an everyday event in the year 2005. The first major U.S. carrier, Braniff, failed way back in 1982, only three years after the de jure deregulation of the U.S. airline industry. It was followed shortly by the receivership of Continental the next year. Insolvency seems to have reached its peak this year with Delta and Northwest both filing for court protection in October of 2005, and with American threatening to file at any time. In addition, UAL still operates under court protection (having filed almost three years ago) and US Airways has just exited from its second court filing. The situation is abysmal. To date over 148 air carriers have sought court protection and many have ceased to exist, including famous names such as Braniff, Eastern, Pan-Am, and TWA. Several others, UAL and US Airways are still not out of danger and could follow their predecessors into oblivion.¹

Obviously, methods that could predict insolvency, or at least gauge relative financial condition, are important. Historically, financial analysts have measured financial strength by calculating ratios derived from various financial statements such as the balance sheet and income statement. It has only been since the mid-1960s, however, that attempts were made to sophisticate traditional financial ratio analysis by the use of newer statistical techniques. The purpose of this paper is to chronicle the history and to outline and briefly discuss many of the different models, both generic and industry specific, that have been used to assess the financial health of air transportation, such a vital industry in the U.S. economy. It should be stressed that models can be designed for international carriers as well, and have been, as will be explored below. A number of groups would be interested in such research. They include financial analysts, bondholders and other credits, stockholders, lessors, governmental agencies, and others.

Financial Ratios as Predictors of Stress:

Historically, analysts have computed different types of financial ratios to assess four separate aspects of financial well-being. These four types of ratios measure liquidity (the ability of a firm to pay its obligations as they come due), leverage (the extent to which a firm uses debt as a method of finance), activity or turnover (the efficiency of asset usage), and profitability. More recently financial researchers have begun to combine these financial ratios into models that produce an overall score that can be used to both assess financial stress and to predict bankruptcy well in advance of the event. What follows is a

¹ Thirteen major carriers now exist/or have existed since 1980. Those carriers include: Alaska, American, America West, Braniff, Continental, Delta, Eastern, Pan Am, Northwest, Southwest, TWA, United, and US Air. Ten have filed for bankruptcy/reorganization, in some cases multiple times (Eastern, Continental, TWA, US Airways), and several have disappeared forever (Braniff, Eastern, Pan Am and TWA). That’s a failure rate of almost 77%. That bankruptcy rate is appalling.
summary of some of the models that the authors, and others, have used over time, and in some cases designed, for this purpose. The models are:

1. The Altman Model, often referred to as the Z Score (and its variant, the Z” Score).
2. The Altman ZETA® Model
3. The AIRSCORE Model
4. The Pilarski or P-SCORE Model
5. Neural Networks (NN)
6. Genetic Algorithms (GA)
7. The Gudmunsson Model
8. A “Fuzzy” Logic Model

The first two models are generic; that is, they were specified using a wide sample of different firms in various industries. The latter six are industry specific; that is, they were designed using airline data only.

Generic Models: (1) The Altman Z Score Model

Edward Altman of NYU is truly the ‘father of financial bankruptcy forecasting.’ His early research in 1968 resulting in the design of what is perhaps the most famous bankruptcy-forecasting model, the Z Score [Altman, 1968]. Designing using a database of 33 failed and 33 non-failed manufacturing companies, Altman used a stepwise multiple discriminant regression to specify the following model from a group of 23 different financial ratios:

\[ Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \]

Where \( X_1 \) – \( X_5 \) are ratios that measured each of the aspects of strength.

\( X_1 = \) net working capital to total assets (a liquidity ratio)
\( X_2 = \) retained earnings to total assets (a profitability ratio)
\( X_3 = \) operating profit to total assets (a profitability ratio)
\( X_4 = \) market value of equity to book value of debt (a leverage ratio)
\( X_5 = \) operating revenues to total assets (a turnover ratio)

High ratios in each category increase the Z Score and thus lessen the danger of failure. Altman found that the critical values of Z were 1.81 and 2.99. Firms with scores of <1.81 fit a bankruptcy profile, while firms with Zs >2.99 fit the solvency profile. Score between the two values lie in what Altman called the ‘grey zone’ where profiling is more difficult. Altman argued for a 2.67 cutoff, if one barrier was desired. The model’s

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2 Altman has produced models for many different U.S industries (railroads, over-the-counter broker/dealers, etc.) and many of his doctoral students have modeled bankruptcy in countries such as Austria, New Zealand, Britain, Israel, etc.). One of the authors of this paper has also specified a model for the U.S. motor carrier industry.
success rate in forecasting insolvency was 76%. It should be noted that the model can also be used to assess overall relative financial strength.

Gritta [1982] used the basic Altman Model and forecasted the insolvencies of both Braniff and Continental several years before their actual filings. Subsequently, Gritta used the model to assess the industry in several other published studies [for example, Gritta, Chow, Davalos, 2002]. The following chart summarizes Z Scores for different years over the past four decades. The carriers are grouped in two categories; those that failed over the period and those that have remained solvent for the entire study period. The figures for the year 2001 were computed for the January-August period, so as to exclude the effects of 9/11. Z Scores after that date fell significantly.

<table>
<thead>
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</tr>
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<tbody>
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<td>2.00</td>
<td>1.23</td>
<td>0.63</td>
<td>1.11</td>
<td>1.26</td>
<td>1.49</td>
<td>2.36</td>
<td>1.92</td>
<td>1.04</td>
<td></td>
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<td>2.17</td>
<td>2.00</td>
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<td>1.02</td>
<td>0.96</td>
<td>1.21</td>
<td>1.25</td>
<td>1.46</td>
<td>1.96</td>
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<td>0.59</td>
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<td>National 1</td>
<td>4.64</td>
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<td>1.80</td>
<td>1.79</td>
<td>2.33</td>
<td>3.07</td>
<td>2.71</td>
<td>2.85</td>
<td>3.61</td>
<td>3.82</td>
<td>3.83</td>
<td></td>
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<tr>
<td>Southwest 1</td>
<td>4.10</td>
<td>2.24</td>
<td>2.43</td>
<td>1.67</td>
<td>0.29</td>
<td>-.08</td>
<td>1.47</td>
<td>1.75</td>
<td>1.52</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
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<tr>
<td>Failed</td>
<td>1.67</td>
<td>1.47</td>
<td>2.36</td>
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<tr>
<td>America West 2</td>
<td>2.67</td>
<td>2.23</td>
<td>2.35</td>
<td>0.90</td>
<td>1.81</td>
<td>-3.8</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Braniff 2</td>
<td>3.64</td>
<td>1.08</td>
<td>2.05</td>
<td>1.57</td>
<td>0.93</td>
<td>-0.4</td>
<td>-0.2</td>
<td>0.50</td>
<td>0.99</td>
<td>1.61</td>
<td>1.83</td>
<td>1.46</td>
<td>0.90</td>
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<td>Continental 2</td>
<td>5.86</td>
<td>4.19</td>
<td>4.17</td>
<td>3.54</td>
<td>2.41</td>
<td>1.43</td>
<td>1.11</td>
<td>1.12</td>
<td>1.51</td>
<td>1.55</td>
<td>1.98</td>
<td>1.49</td>
<td>0.64</td>
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<td>Delta 2</td>
<td>2.16</td>
<td>1.10</td>
<td>2.21</td>
<td>2.19</td>
<td>-.14</td>
<td></td>
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<tr>
<td>Eastern 2</td>
<td>2.16</td>
<td>1.10</td>
<td>2.21</td>
<td>-2.19</td>
<td>-.14</td>
<td>0.65</td>
<td></td>
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<td></td>
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<tr>
<td>Pan Am 2</td>
<td>6.50</td>
<td>2.31</td>
<td>3.14</td>
<td>2.85</td>
<td>2.03</td>
<td>1.26</td>
<td>1.10</td>
<td>1.53</td>
<td>1.56</td>
<td>1.75</td>
<td>0.89</td>
<td>1.20</td>
<td>0.70</td>
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<tr>
<td>Northwest 2</td>
<td>2.34</td>
<td>1.67</td>
<td>2.57</td>
<td>2.08</td>
<td>1.92</td>
<td>1.28</td>
<td>0.94</td>
<td>1.16</td>
<td>1.39</td>
<td>1.50</td>
<td>1.24</td>
<td>1.17</td>
<td>-1.3</td>
</tr>
<tr>
<td>TWA 2</td>
<td>1.76</td>
<td>0.67</td>
<td>0.31</td>
<td>0.01</td>
<td>0.46</td>
<td>0.71</td>
<td>1.68</td>
<td>1.08</td>
<td>-0.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>United 2</td>
<td>2.00</td>
<td>1.10</td>
<td>2.21</td>
<td>-2.19</td>
<td>-.14</td>
<td>0.65</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>US Airways 2</td>
<td>1.76</td>
<td>0.67</td>
<td>0.31</td>
<td>0.01</td>
<td>0.46</td>
<td>0.71</td>
<td>1.68</td>
<td>1.08</td>
<td>-0.4</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Notes:
1. Alaska became a major carrier in the late 1980s; National was acquired by Pan Am in 1979; Southwest became a major in 1989 and Western was acquired by Delta in 1979.
3. United files in 2002 and now operates under Chapter 1; both Delta and Northwest file in October 2005.

Source: All scores calculated from data contained in the Handbook of Airline Financial Statistics and Air Carrier Financial Statistics Quarterly (various issues).

The chart clearly shows the usefulness of the Z Scores in both signaling an early warning and in assessing the relative financial strengths of the major carriers. It also shows the decline in the overall financial health of the U.S airline industry since the 1960s. The scores during that decade were all well above the barrier on solvent specified by Altman.
It is worthy to note that scores declined sharply after the deregulation of the industry in 1978.

A variation of the model has been in use at the U.S. Bureau of Transportation Statistics to track airline financial health. That model is referred to as the **Z” Score Model.** Some analysts feel that the $X_3$ ratio can distort the results because of the significant use of operating leases by air carriers. Such leases do not appear on the balance sheet of the carrier, but the revenues resulting from these leases appear on the carrier’s income statement [Grita, Chou & Lippman, 1995]. The result is to inflate the ratio for one carrier using operating leases over the ratio of a comparable carrier that owns its aircraft. Altman suggested the use of a variant of the original **Z Score** to circumvent this problem [Altman 1983]. Called the **Z” Score**, the model gets around this problem by deleting the turnover ratio. The resulting model is:

\[
Z = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4
\]

This model utilizes four input variables; $X_1$ – $X_4$ as defined above.

A **Z-Score** of 1.1 or less indicates a high probability of bankruptcy in the near future. A **Z-Score** of 2.6 or above indicates a high probability that bankruptcy will not occur. A **Z-Score** between these two numbers indicates that there is insufficient statistical significance to make a prediction. As in the **Z Score** Model, Altman originally referred to scores in this range as the ‘zone of ignorance,’ now referred to as the ‘grey zone.’ This zone contains some firms that have failed and some that have remained solvent. The following table shows **Z” Scores** for the major carriers for the year end 2004.

<table>
<thead>
<tr>
<th>CARRIER</th>
<th>Z” Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>American</td>
<td>-1.209711065</td>
</tr>
<tr>
<td>Alaska</td>
<td>1.030260765</td>
</tr>
<tr>
<td>Continental</td>
<td>-0.680997649</td>
</tr>
<tr>
<td>Delta</td>
<td>-2.436372612</td>
</tr>
<tr>
<td>America West</td>
<td>-1.214482870</td>
</tr>
<tr>
<td>Northwest</td>
<td>-0.307042506</td>
</tr>
<tr>
<td>United</td>
<td>-4.113404597</td>
</tr>
<tr>
<td>US Airways</td>
<td>-2.455284490</td>
</tr>
<tr>
<td>Southwest</td>
<td>2.597307223</td>
</tr>
</tbody>
</table>

The very poor scores for all the carriers except Southwest, and to some extent Alaska, confirm the very shaky position of the major carriers despite the economic recovery now in progress.

**Generic Models: (2) The ZETA® Credit Score Model**

While the **Z Score** Model (and its variant, the **Z”)** was over 76% successful in predicting insolvency, Altman later added several variables to his original model, and
respecified the model in an effort to increase its predictive powers. Called the ZETA® credit score model [Altman, Haldeman and Narayanan, 1977], it takes the form:

$$ZETA^\circledast = a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 + a_6X_6 + a_7X_7$$

Where $X_1$-$X_7$ are:

- $X_1 =$ return on assets (the same ratio as $X_3$ in the Z Score Model)
- $X_2 =$ earnings stability (the deviation around a ten-year trend line of $X_1$)
- $X_3 =$ debt service
- $X_4 =$ cumulative profitability (the same as $X_2$ in Z Score)
- $X_5 =$ liquidity (measured by the current ratio)
- $X_6 =$ the ratio of equity to debt (using market values and a five year trend)
- $X_7 =$ firm size (measured by the log of the firm’s total assets).

The ZETA® credit score model is centered on 0. Scores less than 0 indicate stress. The model was applied to the airline industry in 1984 and was found to be reliable [Altman and Gritta, 1984]. The scores flashed advance warnings for several carriers that subsequently failed. These were US Airways (-0.06), TWA (-0.13), Eastern (-3.85), Pan Am (-4.17), Continental (-4.99), and Braniff (-15.42). Unfortunately, the model is proprietary and the intercept terms in the equation are not published. ZETA® credit scores are only available by subscription from ZETA® Services of Mountainside, New Jersey. This limits its availability, at least to academic researchers. The following are scores for the major airlines just prior to and after September 11, 2001. (The scores were provided courtesy of Bob Haldeman of ZETA® Services).

<table>
<thead>
<tr>
<th>Carrier</th>
<th>Dec.00</th>
<th>Aug.01</th>
<th>Dec.01</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alaska</td>
<td>-0.19</td>
<td>-0.56</td>
<td>-0.73</td>
</tr>
<tr>
<td>American West</td>
<td>-1.14</td>
<td>-1.84</td>
<td>-2.79</td>
</tr>
<tr>
<td>American</td>
<td>2.54</td>
<td>1.90</td>
<td>-0.99</td>
</tr>
<tr>
<td>Continental</td>
<td>1.02</td>
<td>0.37</td>
<td>-0.45</td>
</tr>
<tr>
<td>Delta</td>
<td>1.75</td>
<td>0.94</td>
<td>-1.06</td>
</tr>
<tr>
<td>Northwest</td>
<td>-1.62</td>
<td>-1.96</td>
<td>-2.15</td>
</tr>
<tr>
<td>Southwest</td>
<td>6.87</td>
<td>7.65</td>
<td>6.03</td>
</tr>
<tr>
<td>United</td>
<td>-0.10</td>
<td>-1.16</td>
<td>-2.02</td>
</tr>
<tr>
<td>US Airways</td>
<td>-2.72</td>
<td>-2.42</td>
<td>-6.21</td>
</tr>
</tbody>
</table>

Again, the poor scores for many of the airlines indicate the industry’s problems well in advance of the events of September 11, 2001. They also signaled the filings United (2002), and of Delta and Northwest in 2005.
Industry Specific Models: (3) The AIRSCORE Model:

It can be argued that a model derived from a sample of the same industry would be even more accurate than a generalized model such as the Altman Z Score or ZETA® credit scores. With that in mind, an industry specific model, AIRSCORE, was specified using a sample restricted to the airline industry [Chow, Gritta and Leung, 1991]. It included a significant sample of the large and smaller carriers (the latter referred to as regional airlines). Using an MDA approached similar to that utilized by Altman, the model derived was:

\[
\text{AIRSCORE} = -0.34140X_1 + 0.00003X_2 + 0.36134X_3
\]

The three ratios that were predictive of insolvency or stress were:

\[
X_1 = \text{interest/total liabilities (the imputed interest rate on debt)} \\
X_2 = \text{operating revenues per air mile} \\
X_3 = \text{shareholders’ equity/total liabilities}
\]

Because the distribution of the scores made the application of a single cut-off point difficult and inappropriate, several “gray zones” were defined and the model yielded results similar to the Altman Z Score and to ZETA® credit scores. It was able to achieve accuracy rates of between 76% and 83%, depending on the zone used. While the model was somewhat accurate, it did seem to be a bit biased toward the larger carriers in the sample. The interested reader is referred to the article for different cutoffs and the results.

Industry Specific Models: (4) The Pilarski Score Model

Logistics regression analysis has also been used to forecast financial stress and has become widely accepted [Ohlson, 1980]. Logit models estimate the probability of bankruptcy and are also useful in ranking firms in terms of financial strength. A logit model has been used to specify a model for airline financial stress [Pilarski and Dinh, 1999]. Called P-Score, the model takes the form:

\[
W = -1.98X_1 - 4.95X_2 - 1.96X_3 - 0.14X_4 - 2.38X_5
\]

Where:

\[
X_1 = \text{operating revenues/total assets} \\
X_2 = \text{retained earnings/total assets} \\
X_3 = \text{equity/total debt obligations} \\
X_4 = \text{liquid assets/current maturities of total debt obligations} \\
X_5 = \text{earnings before interest and taxes/operating revenues}
\]

The number P is determined by: \[ P = \frac{1}{1 + e^{-w}} \]
Notice that several of the input ratios \((X_1, X_2, X_3)\) are borrowed from the Altman \(Z\) score model. Rather than producing a score that must be compared to a scale, as is the case with the previous models, this model produces the \textit{probability of bankruptcy}. \(P\) is that probability. The higher the \(P\) value, the greater is the financial stress and the more likely is the chance of failure. \textbf{P-Score} is used by the U.S. Department of Transportation to track financial strength. The authors used the P-Score to assess the financial condition of the major carriers and found the model to be correlated to the Altman \(Z\) [Goodfriend, Gritta, Adrangi & Davalos, 2005]. The following charts from that article present \textbf{P-Scores} for two groups of carriers; the high risk and the intermediate risk carriers. The scores for the other majors are not shown since they are so low (that is, probabilities of default are near zero).
The following chart presents more recent results, the **P-Scores** for the 4th quarter of 2004.

<table>
<thead>
<tr>
<th>CARRIER</th>
<th>P_Score</th>
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<tbody>
<tr>
<td>American</td>
<td>0.15270469</td>
</tr>
<tr>
<td>Alaska</td>
<td>0.003763529</td>
</tr>
<tr>
<td>Continental</td>
<td>0.095027839</td>
</tr>
<tr>
<td>Delta</td>
<td>0.390392591</td>
</tr>
<tr>
<td>America West</td>
<td>0.048881060</td>
</tr>
<tr>
<td>Northwest</td>
<td>0.085842447</td>
</tr>
<tr>
<td>United</td>
<td>0.686357381</td>
</tr>
<tr>
<td>US Airways</td>
<td>0.257064338</td>
</tr>
<tr>
<td>Southwest</td>
<td>0.000616504</td>
</tr>
</tbody>
</table>

The score for Alaska indicates, for example, that the carrier’s likelihood of insolvency is only 0.3%, while that of Delta is 39.0%. Overall, they do show the continued weaken condition of the major airlines after the events of 9/11. The **P Scores** are flashing a warning for American, Delta and Northwest. The latter two carriers did file in October 2005, and American is still threatening to file.

**Industry Specific Models: (5) Neural Networks**

In the continuing search for even more accurate methods of gauging financial strength, some researchers have pursued a newer approach—the use of artificial neural networks.
The use of artificial intelligence has gained widespread support for a variety of uses in finance, forecasting solvency being one major area of application. NNs mirror the architecture of the brain and are derived from research on the neural architecture of the brain [Caudill, 1989]. NNs are composed of inter-connected neurons linked together through a network of layers. Inputs of data are provided to the network along with desired outputs. The network then trains itself to classify new information based on the abilities it derives to separate the groups input into the model. The standard back-propagation network has several elements. They are an input layer, an output layer, and at least one hidden layer. Each layer is fully connected to each succeeding layer and each layer can contain any number of neurons or interconnections. The figure below depicts the feed forward of node values and the back propagation of error information.

An error function (it can be any error function) is used to evaluate the difference between the neural network output node values to the expected output. This error is back propagated to adjust the weights associated with each node. Since each node contributes to the global error, the adjustment made to its weights is directly proportional to the magnitude of the weight. Thus, the larger node weights get the most adjustment. The amount of the error of each node is based on the partial derivative of the error with respect to the node’s output. This will have the effect of adjusting the weights between the individual nodes locally based on the global error E of the system. The change (delta) in the weight is further adjusted by the use of a factor called the learning coefficient. The

\[^3\] NNs have several advantages over the MDA technique [Udo, 1993]. They can be run on smaller samples than MDA models, they can tolerate “noise” or missing data, they can self-organize and learn by changing the network connections, and they can find and establish complex relationships among input variables.
learning coefficient affects the rate at which the BP method converges on the configuration of network weights that is the optimum for minimizing the global error. In summary, the gradient descent method is based on making adjustments in each dimension (determined by the number of input variables) in a direction (partial derivative) that will minimize the global error. The size of the adjustment is based on the learning coefficient. In three dimensions, it is analogous to being on a terrain and moving in the x, y, and z directions that moves to the global minimum point. The learning coefficient is the size of the steps taken. Note that if the size of the steps is too large, the global minimum may be overstepped. The actual construction of NN is, as the case with the MDA technique, quite complex. The interested reader should consult references provided at the end of the paper for the mathematical model itself.

Several of the authors trained a neural network using only airline data. Two separate studies were conducted on the air carriers using the NN. Inputting 21 pieces of financial information from carrier balance sheets and income statements, a NN was specified for the major U.S. airlines [Davalos, Gritta and Chow, 1999]. In a second study, a NN was trained to identify bankrupt/stressed smaller carriers, known as large and medium regional airlines [Gritta, Davalos, Chow, and Huang, 2002]. The first study successfully classified all the major carriers that filed for receivership. The second study achieved an overall success rate of 88% in predicting stress for the smaller airlines. The network classified 77% of the total sample accurately. Two types of errors are present: Type I and Type II. A Type I error occurs when a bankrupt carrier is incorrectly classified as solvent. A Type II error results when a non-bankrupt carrier is classified as failed. Of the total 15 errors, 7 were Type I and 8 were Type II. Thus the successful classification rate for each group of carriers was:

<table>
<thead>
<tr>
<th>Number Correct</th>
<th>50</th>
<th>77%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Type I Errors</td>
<td>7</td>
<td>11%</td>
</tr>
<tr>
<td>Number of Type II Errors</td>
<td>8</td>
<td>12%</td>
</tr>
<tr>
<td>Total in Sample</td>
<td>65</td>
<td>100%</td>
</tr>
</tbody>
</table>

As indicated the overall success rate of the model was 77% (50/65). More importantly, the success rate of predicting bankruptcy or distress was 89% (or 100% – 11%, the failure rate) and that of solvency 88%. The use of neural networks thus provides an interesting supplement to the analyst in appraising financial health.

**Industry Specific Models: (6) Genetic Algorithms**

While Neural Networks (NN) have been used successfully to classify organizations in terms of solvency, they are limited in degree of generalization either by requiring linearly separable variables, lack of knowledge of how a conclusion is reached, or lack of a consistent approach for dealing with local optimal solution whether maximum or minimum. Because of this, the authors decided to try an even newer approach to the problem—a genetic algorithm (GA). A GA has the ability of the NN method to deal with
linearly inseparable variables and incomplete, noisy data; but at the same time, it resolves the problem of falling into a local optimum in searching the problems space.

The concept behind the GA is not new. It is based on the survival of the fittest and evolution. Starting with members of a candidate population of solutions, this population is evolved to the best set of solutions in an evolutionary manner. GAs are stochastic, global search techniques that can search large, complicated spaces [Goldberg, 1989]. It was thus decided to apply a GA to airline data, focusing on ratios that assess liquidity, leverage, activity and profitability [Davalos, Gritta, Goodfriend and Adrangi, 2005]. The steps in the design of the genetic algorithm are as follows:

1. A population of candidate solutions is randomly generated.
2. Members of this population are then evaluated for fitness based on a fitness function. The fitness function is used to determine how well the solution performs. The fitness function cannot be derived automatically but must be developed based on the judgment of the developer.
3. Once all members of the current population have been evaluated the next step is to remove members from the population and introduce new members. The weakest performing members are removed. The number removed depends on how many are in the population, but this number removed must be consistent.
4. New members of the population are generated on the basis of reproduction and mutation. Through reproduction a potentially better performing offspring is produced. Through mutation new members are introduced which have the potential of introducing a solution that would not have been derived through the reproduction method since mutations are random.
5. The new population then goes through steps 2-4 until a predetermined level of fitness is reached or enough iterations have been conducted without any improvement.

The fitness function evaluates the quality of each rule (individual). The fitness function is based on the following four different types of results that can occur for a prediction:

- true positive (tp) - the rule predicts that the firm is financially insolvent and it is.
- false positive (fp) – the rule predicts that the firm is financially insolvent and it is not.
- true negative (tn) - the rule predicts that the firm is financially solvent and it is;
- false negative (fn) - the rule predicts that that the firm is financially solvent and it is not.

The fitness function utilized combines two indicators commonly used in statistical analysis, namely the sensitivity ($Se$) and the specificity ($Sp$), defined as follows:

$$Se = \frac{tp}{tp + fn} \quad (1)$$

$$Sp = \frac{tn}{tn + fp} \quad (2)$$
Finally, the fitness function used by our system is defined as the product of these two indicators, i.e.:

\[ \text{fitness} = Se \times Sp \]  

(3)

The goal is to maximize both the \( Se \) and the \( Sp \) at the same time, and the product shown in equation (3) provides a good gradient for the function.

Twenty-one financial variables from the carrier income statements and balance sheets were first collected for the data set. Seven ratios were used based on the three types of financial ratios that measure liquidity, profitability, operating efficiency and financial leverage. The seven were: A liquidity measure- current liabilities to total assets (CLIAB/TA); a profitability measure- retained earnings to total assets (REARN/TA); an efficiency ratio-operating expenses to revenue (OE/REV); another profitability ratio-profit to operating expenses (PROFIT/OE); a financial leverage measure-total liabilities to total assets (TLIAB/TA); another liquidity measure- current assets to total assets (CA/TA); and lastly, another liquidity measure-current assets to operating revenue (CA/REV). These ratios where then calculated for each data point. A string of the following form was used:

\[ \text{String(Var1, Var2, … VarN, Op1, Op2, …, OpN, X1, X2, …, XN).} \]

This string represented a rule that compared each of selected variable given by Var1 using the relational operator Op against the variable value, X. The particular variable used could be randomly selected. Rules were limited to only four of the seven ratios. Rules could take on the following form:

\[ \text{If Var1 > X1, And Var2 < X2, … And VarN > XN} \]

then the prediction would be Solvency. (Specific operators were used to better illustrate the format).

A training set was used to train the \( \text{GA} \) and then a test set was used to evaluate the outcome. Several iterations were conducted to examine variations in performance. The average prediction accuracy was 91%. The result of the most successful \( \text{GA} \) is a rule that can then is applied to the ratios in order to determine a firm’s solvency. The table below depicts the results of a run with 94% accuracy. All seven ratios were used in this run: CLIAB/TA, REARN/TA, OE/REV, PROFIT/OE, TLIAB/TASSET, CA/TA, CA/REV. The data row references the ratio used. The operators are either 1 or 2 with a 1 for “<” and a 2 for “>=”

In the example below there are five rules.
Rule 1 is as follows: If CA/TA < 0.22 THEN TRUE; IF NOT THEN FALSE
Rule 2 is If CA/TA < 0.189 THEN TRUE ELSE FALSE.
Rule 3 is If CA/REV < 0.239 THEN TRUE ELSE FALSE
Rule 4 is If EXP/SALES < 0.996 THEN TRUE ELSE FALSE
Rule 5 is If TLIAB/TA < 0.603 THEN TRUE ELSE FALSE
For a company to be predicted as financially solvent, all five rules have to be true.

**Industry Specific Models:** (7) The Gudmundsson Model (An International Model)

While financial variables are obviously important to the prediction process, Gudmundsson argued that other non-financial variables may also play a role, especially when forecasting multi-country failure [Gudmundsson, 2002]. Like Pilarski, he also felt that logistic regression analysis (LRA) provides a better forecast than MDA. Gudmundsson specified the following model:

\[
Z = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + \ldots \ldots \ldots B_nX_n
\]

and:

\[
P = \frac{1}{1+e^{-z}}
\]

As in the case the Pilarski Model, \( P \) is the probability of bankruptcy. The independent variables in the regression are as follows:

- \( X_1 \) = load factor (that is, the percent of the aircraft filled)
- \( X_2 \) = number of passengers per departure
- \( X_3 \) = number of hours flown per pilot
- \( X_4 \) = number of departures per aircraft
- \( X_5 \) = number of pilots per aircraft
- \( X_6 \) = number of employees per aircraft
- \( X_7 \) = average age of aircraft fleet
- \( X_8 \) = annual inflation rate in the carrier’s home economy
- \( X_9 \) = number of different brands of aircraft operated
- \( X_{10} \) = political influence (a dummy variable: yes=1; no=0)

The dataset used by Gudmundsson consisted of ratios, as well as continuous and nominal variables collected over a three year period (1996-1998) for 41 commercial airlines worldwide. (Data was collected from the Air Transport World’s Airline Report, IATA World Airline Statistics and ICAO Annual Digest of Statistics.). While all the
variables allowed to enter the model were not statistically significant, the overall accuracy rate of his model was 90.2%.

**Industry Specific Models: (8) Fuzzy Logic Model (An International Model)**

Several researchers have utilized yet another approach to forecasting air carrier insolvency. Silva, A. Espirito Santo, and Portugal (2005) employed a multivariate technique called Hybrid Financial Statement Analysis (**HFSAT**) to test several American and Brazilian carriers’ financial conditions and to profile the risk of bankruptcy. **HFSAT** is the result of a discriminant analysis multiple-variable model and the application of Fuzzy Logic to a firm’s financial data.\(^4\)

Discriminate analysis, as noted above, is a statistical tool used to classify a certain element in a determining group over the existent groups (\(G_1, G_2... G_n\)). This requires that the element to be classified really belongs to one of the groups and also that the characteristics of the elements of the two groups are known, so that comparisons among the characteristics of the elements of the several groups can be made. Those characteristics are specified starting from a group of aleatory variables \(\{X_1, ...X_n\}\) [Silva, 1983]. According to Hair et. Al. (1995), the discriminant method is particularly useful in those situations where the total sample can be divided in groups based on the dependent variable, characterizing well-known classes. Those classes can be represented by dicotomic or multicotomics variables (e.g. male/female, high-medium-low, etc.). The discriminant model can then be combined with Fuzzy Logic as a base. Fuzzy Logic consists of modeling the human thought structure for the problems resolution and decision making by means of mathematical instruments. Those instruments derive of the set theory, algebra and so on, and they can be represented by discrete models or even by means of integrals (integral-fuzzy). Zadeh (1975) argues that one of the great advantages of Fuzzy Logic is to obtain, by means of the fuzzy set properties, the translation of linguistic terms used in the daily communications (natural language) in mathematical expressions. According to Ross (1995),

\[\text{‘in classical, or crisp, sets the transition for an element in the universe between membership and non-membership in a given set is abrupt and well-defined (said to be ‘crisp’).’}\]

For an element in a universe that contains fuzzy sets, this transition can be gradual. Its transition among various degrees of membership can be thought of conforming to the fact that the boundaries of the fuzzy sets are vague and ambiguous. Hence, membership of an element from the universe in this set is measured by a function that attempts to describe vagueness and ambiguity. The fuzzy set representation can be given by means of discrete or continuous expressions as in the figure below.

\(^4\)The Silva, A. Spirito Santo and Portugal argue that the **HFSAT** application has the following advantages: It can classify a firm’s financial condition using a consistent theoretical base; it frees the analyst from the slow process of investigating a company’s financial structure by means of a large set of indexes; it is a functional and easily implemented algorithm; its quantitative and qualitative measures are intuitive to the analyst; and it can be used to compare companies in different markets, since the source data includes all the same classification criteria.
Expression of Fuzzy Sets

Discrete expression (when the universe is finite): Let the universe \( X \) be

\[ X = \{ x_1, x_2, \ldots, x_n \} \]

Then, a fuzzy set \( A \) on \( X \) can be represented as follows:

\[ A = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \cdots + \frac{\mu_A(x_n)}{x_n} \]

Continuous expression (when the universe is infinite): When the universe \( X \) is not infinite set, a fuzzy set \( A \) on \( X \) can be represented as follows:

\[ A = \int \frac{\mu_A(x_i)}{x_i} \]

Source: An Introduction to Fuzzy Logic for Practical Applications (Tanaka, 1997).

The steps required to specify the model include database structuring together with the calculation of an economic and financial index and the use of Fuzzy Logic. Silva, A. Espirito Santo, and Portugal structured the database dividing the air carriers into 3 categories (healthy, high risk and insolvent). Twenty-nine ratios (measuring profitability, liquidity, etc.) were then selected and a "stepwise regression" with a "forward and backward" method was used to specify the discriminant function.\(^5\) The inputs were from the financial statements of airlines on file with the Brazilian Department of Civil Aviation and from carrier websites. The output of the multiple regression was Equation 1.

\[
Z = 2.637 - 0.879X_1 + 0.466X_2 - 0.268X_3 - 0.28X_4 \tag{1}
\]

Where:

\[
X_1 = \text{Shareholder Funds by Total Assets (Equity ÷ Total Asset)}
\]

\[
X_2 = \text{Liquidity ((Current Liabilities + Long Term Liabilities) ÷ Total Asset)}
\]

\[
X_3 = \text{Net Operating Revenue by Total Assets (Net Op. Revenue ÷ Total Asset)}
\]

\[
X_4 = \text{Fixed Assets by Total Assets (Fixed Assets ÷ Total Asset)}
\]

Using the regression results, Silva, Espirito Santo, and Portugal argued that there were five groups evident (based on \( Z \) values). Firms were groups as follows; healthy, low risk, moderate risk, high risk and insolvent.\(^6\) Employing Tanaka’s approach (1997), the authors then applied a fuzzy logic model using the following equations.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Limit of ( Z )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>( Z \leq 1.862 )</td>
</tr>
<tr>
<td>Low Risk</td>
<td>( 1.862 \leq Z \leq 2.2 )</td>
</tr>
<tr>
<td>Moderate Risk</td>
<td>( 2.2 \leq Z \leq 2.515 )</td>
</tr>
<tr>
<td>High Risk</td>
<td>( 2.515 \leq Z \leq 2.73 )</td>
</tr>
<tr>
<td>Insolvent</td>
<td>( Z \geq 2.73 )</td>
</tr>
</tbody>
</table>

\(^5\) This method removes and adds variables to the regression model in order of identifying the best set of predictor’s variables.

\(^6\) The categories were determined by the \( Z \) values.
The output of these equations indicates the percentage identification with each category. If $\mu(G_1) = 1.0$ or $100\%$, then that carrier is clearly in the healthy range. A $\mu(G_2)$ in the midrange indicates moderate to high risk, and a $\mu(G_3)$ at $1.0$ or $100\%$ indicates an insolvency profile. As a case study, Silva et al. applied the above approach to eight carriers: American, United, Southwest, LanChile, Varig, Vasp, TAM, and Gol. The study encompassed three year of data, 2002-2004. The following chart shows most of the results for these carriers.

<table>
<thead>
<tr>
<th>Carrier</th>
<th>Year</th>
<th>Z</th>
<th>$\mu(G_1)$</th>
<th>$\mu(G_2)$</th>
<th>$\mu(G_3)$</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>American</td>
<td>2004</td>
<td>2.60</td>
<td>2%</td>
<td>91%</td>
<td>42%</td>
<td>High Risk</td>
</tr>
<tr>
<td></td>
<td>2003</td>
<td>2.62</td>
<td>2%</td>
<td>89%</td>
<td>43%</td>
<td>High Risk</td>
</tr>
<tr>
<td>Southwest</td>
<td>2004</td>
<td>1.84</td>
<td>100%</td>
<td>1%</td>
<td>0%</td>
<td>Healthy</td>
</tr>
<tr>
<td></td>
<td>2003</td>
<td>1.81</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>Healthy</td>
</tr>
<tr>
<td>United</td>
<td>2004</td>
<td>3.08</td>
<td>0%</td>
<td>2%</td>
<td>99%</td>
<td>Insolvent</td>
</tr>
<tr>
<td></td>
<td>2003</td>
<td>2.93</td>
<td>0%</td>
<td>13%</td>
<td>89%</td>
<td>Insolvent</td>
</tr>
<tr>
<td>LanChile</td>
<td>2004</td>
<td>2.34</td>
<td>20%</td>
<td>69%</td>
<td>13%</td>
<td>Moderate Risk</td>
</tr>
<tr>
<td></td>
<td>2003</td>
<td>2.39</td>
<td>13%</td>
<td>84%</td>
<td>18%</td>
<td>Moderate Risk</td>
</tr>
<tr>
<td>GOL</td>
<td>2003</td>
<td>1.83</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>Healthy</td>
</tr>
<tr>
<td>Varig</td>
<td>2003</td>
<td>5.80</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>Insolvent</td>
</tr>
<tr>
<td></td>
<td>2002</td>
<td>4.93</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>Insolvent</td>
</tr>
<tr>
<td>Vasp</td>
<td>2003</td>
<td>2.69</td>
<td>1%</td>
<td>75%</td>
<td>55%</td>
<td>High Risk</td>
</tr>
<tr>
<td></td>
<td>2002</td>
<td>2.69</td>
<td>1%</td>
<td>76%</td>
<td>55%</td>
<td>High Risk</td>
</tr>
<tr>
<td>TAM</td>
<td>2003</td>
<td>2.58</td>
<td>2%</td>
<td>98%</td>
<td>38%</td>
<td>High Risk</td>
</tr>
<tr>
<td></td>
<td>2002</td>
<td>2.58</td>
<td>2%</td>
<td>97%</td>
<td>39%</td>
<td>High Risk</td>
</tr>
</tbody>
</table>

Source: Silva, A. Spirito Santo, Portugal
The authors’ results of the preliminary test were interesting and show promise for future research. The intent of several authors of this paper is to collaborate on a study involving a much larger sample and an extended time horizon.

**Conclusion:**

The purpose of this paper was to detail the history of bankruptcy forecasting in the airline industry and to outline various models that can be of use to different interested groups, ranging from creditors, to stockholders, to governmental regulators, etc.. With that goal in mind, the paper has examined a range of different statistical techniques useful in forecast airline bankruptcy and/or financial stress. Two of the models are generic or non-industry specific. The others are all industry specific, having been designed using only airline data. In addition, two of the models involved international carriers. Finally, it bears mentioning that the non-generic models can be used for many different industries, and researchers in different countries can design models using many or all of the above techniques to better understand the factors behind financial stress and the forecasting of the event in different country environments.

**References**


