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Financial Distress Prediction Models for Wind Energy SMEs

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ABSTRACT

The purpose of this paper was to identify suitable variables for financial distress prediction models and to compare the accuracy of MDA and LA for early warning signals for wind energy companies in Korea. The research methods, discriminant analysis and logit analysis have been widely used. The data set consisted of 15 wind energy SMEs in KOSDAQ with financial statements in 2012 from KIS-Value. We found that five financial ratio variables were statistically significant and the accuracy of MDA was 86%, while that of LA is 100%. The importance of this study is that it demonstrates empirically that financial distress prediction models are applicable to the wind energy industry in Korea as an early warning signs of impending bankruptcy.

Key words: *Distress Prediction, Discriminant Analysis, Logit Analysis, SMEs, wind energy Sector.*

1. INTRODUCTION

1.1 Background

Wind energy industry has experienced great changes and challenges since the fall of 2008 when the collapse of the Lehman Brothers, one of the worst financial crisis struck almost all sectors of global markets, especially newly emerging NRE(new and renewable energy) depending on a variety of government subsidies. Both sharp reductions in subsidies for wind energy installations particularly in EU (European Union) and oversupply of wind energy turbines in china have resulted in a sharp drop in demand for wind energy systems. Some companies in the wind energy industry are rumored to be on the brink of financial distress. As a result of deteriorating market situation, there has been strong curiosity to find out objectively where SMEs in wind energy industry stand using proven statistical methods such as MDA and LA. In addition, according to the research of NIPA(National IT industry Promotion Agency), many companies in NRE are facing hard financial times and responds to the questionnaires asking what's the most urgent need in the management of each firm by answering the financial assistance is the most urgent one (Conglomerate 26%, SMEs 40%) [1]-[4].

1.2 Purpose

The purpose of this paper is to identify the suitable variables for the financial distress prediction models and compare the accuracy of both MDA and LA for the early warning signal of wind energy companies in Korea by raising and solving the following research questions:

1.2.1 Are there some financial ratios clearly better for distinguishing dangerous group from healthy group of wind energy companies in Korea?

1.2.2 Which financial ratios are the most significant for distress prediction of wind energy SMEs (Small and Medium Enterprises) in Korea?

1.2.3 Is MDA (Multivariate Discriminant Analysis) model much better than the LA (Logit Analysis) model in financial distress prediction of wind energy companies in Korea?

1.3 Structure

This thesis is organized as follows. Chapter 1 explains about research background, purpose and structure. Chapter 2 introduces prior studies. Chapter 3 describes research design and methodology (hypothesis, data set and research methodology). Chapter 4 describes empirical analysis. Chapter 5 describes results of the analysis, the conclusions and implications including the limitations of this study and further research directions.

2. PRIOR STUDIES

2.1 Overview

There have been a variety of researches on the causes of financial distress, the models to predict financial distress of companies, their applications and other related issues since in 1960s. Some of the major distress prediction models having been developed and applied widely so far are listed below in a row; univariate analysis, multivariate analysis, logit analysis, probit analysis, neural network analysis, artificial intelligence and others. Some of them are described further below:

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2.1.1 Univariate Analysis

In the beginning the univariate analysis was applied as the basic econometric method in financial studies. It was first employed by Beaver (1966) in order to predict the likelihood of firms' failure through financial ratios. Using this method, a financial ratio of the interested firm is compared to a perceived benchmark ratio to discriminate a failed firm from non-failed one [5]-[7].

2.1.2 Multivariate Discriminant Analysis

Altman (1968) was among the first to make additional changes to Beaver's (1966) univariate analysis. He introduced a multivariate approach in which two or more different variables included in the bankruptcy models are examined at the same time. The approach is known as the multivariate discriminant analysis. The objective of discriminant analysis is to obtain the linear combination of variables that best separate the bankrupt firms from the non-bankrupt ones. Then, Altman (1968) developed the discriminant model, known as the "Z-Score" model, by using manufacturing firms which went bankrupt during 1946 to 1965. He found out that out of twenty two potential ratios, five ratios are best used to classify the bankrupt & non-bankrupt firms. These five financial measurements are objectively weighted and then included in the ultimate model [8]-[11].

2.1.3 Logit Analysis

Logit model is equivalent to two-group discriminant analysis. The logistic procedure fits linear logistic regression models for binary or ordinal response data using Maximum Likelihood estimations and compares the estimated samples using Wald chi-square. The Maximum Likelihood procedure is used in an iterative manner to identify the most likely estimates for the coefficients. The Wald statistic is used to test the hypothesis that a coefficient varies from zero [12].

2.2 Brief summary of past studies

According to the proportion of model categories employed by past studies, statistical models comes first with 64%, followed by AIES Models (25%) and theoretic models (11%) in 3 major categories of models. And proportion of model employed by past studies shows that MDA comes first with 30.3%, followed 2nd by Logit (21.3%) from 16 models employed previously for the distress prediction. Accordingly it can be clearly understood that statistical techniques (MDA and Logit models in particular) have been most frequently used overseas and in Korea as shown in the table 1, that the AIES approach is relatively new and that theoretical models are relatively uncommon [13].

Table 1. Prior Studies on Bankruptcy Prediction Models

Categories	Yrs	Researchers	Statistical Models
Overseas	1932	Fitzpatrick	Ratio Analysis
	1966	Beaver	UA*
	1968	Altman	MDA*
	1972	Deakin	MDA
	1980	Ohlson	Logit Model
	1997	Wilkins	UA, Logit
	2012	Wanida	MDA, Logit
	2013	Elena Makeeva	Logit, Probit
Korea	2000	Nam, J-H	Logit Model
	2001	Kyung-Shik, Shin	NN, GA
	2002	Tae-sung, Choi	MDA, Logit
	2004	Kim, Si-joong	MDA
	2006	Kim, H	Logit
	2007	Young-Sook Kim	Black scholes
	2008	Jeong-Sik, Yang	Logit
	2010	Huo, Yang-Hoe	Logit Model
	2011	Jun, Hyun-Woo	MDA
	2011	Shin, Taek-soo	ANN
	2014	Kim, Soo-Young	ANN

* Abbreviation listed up in the footnote[1] [14]-[32]references were arranged again in numerical order according to their order of appearance in the table1.

3. RESEARCH DESIGN AND METHODOLOGY

3.1 Hypothesis

Early models of predicting insolvency employ financial ratios using univariate and multivariate statistics. A univariate approach explores the relationship between individual financial ratios and insolvency. The multivariate approach employs pooled ratios for predicting insolvency (Zavgren 1985). Based on the past studies, I formulated two hypothesis statements. The 1st one is that there are some financial ratios clearly better than others in distinguishing dangerous group from healthy group of wind energy companies in Korea. And the 2nd one is that the accuracy of multivariate discriminant analysis is superior to that of logit analysis in distinguishing dangerous group from healthy group of wind energy companies in Korea: [23].

Hypothesis I:
(H_0): a healthy gr. = a dangerous gr.
(H a): a healthy gr. ≠ a dangerous gr.

(H_0) indicates that the mean of the healthy group is not different from that of the dangerous group which means that there is no statistical difference to distinguish healthy group from dangerous group.

Hypothesis II:
(H_0): a MDA is superior to a LA
(H a): a MDA is not superior to a LA
Where a MDA = the accuracy of Multivariate Discriminant Analysis and a LA = the accuracy of Logit Analysis.

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[1] * Abbreviation : UA : univariate analysis, MDA : multivariate discriminant analysis, NN : neural network, GA : genetic algorithms, SMEs.: small and medium enterprises, KOSDAQ ; Korean Securities Dealers Automated Quotations, AIES : artificial intelligence expert systems, LM : logit model, LA : logit analysis

For conducting hypothesis test, Independent samples t-test and wilcoxin test were used in this study to find out the difference between healthy group and dangerous group in the wind energy energy industry in Korea. The analysis was conducted using Statistical Package for Social Sciences (SPSS) Version 21.

3.2 Data Set

The data set utilized for this statistical test is composed of 15 wind energy SMEs*. All of them were or still are listed on the KOSDAQ (KOrea Securities Dealers Automated Quotation). And the financial ratios and other related data for the analysis were collected from the Kis-value DB, a variety of corporate financial statements and their respective websites or company brochures [20]-[21].

3.3 Research Methodology

Three steps of selecting predictive variables as independent inputs were conducted; the first step was to review distress prediction literatures and select a broad range of potential variables, the 2nd step was to check the availability of the data good enough for the analysis, the 3rd step was to narrow down the potential variables to the final variables which are given below in the Table 2. Considering the purpose of this research for financial distress prediction more weight was given to the solvency (7) than profitability (5) and growth (2) after reviewing prior studies and analyzing data.

Table 2. The Fourteen Ratios Selected in This Study

Measure	Descriptions	Count
Solvency	Current ratio, Debt ratio, Total Borrowings And Bonds Payable To Total Assets, Interest Coverage Ratio, Net Working Capital To Total Assets, Retained Earnings To Total Assets, Retained Earning To Paid-in Capital.	7
Profitability	Operating Income To Sales, Net Income To Sales, Net Income To Stockholders' equity, Operating Income To Total Assets, EBT To Sales	5
Growth/ Activity	Growth Rate of Operating Income, Growth Rate Of Total Assets	2
Total		14

Another step of selecting optimal variables as dependent outputs was conducted; As shown in the Table 3, Z-Score was determined using the Altman Z-Score model(1968)* described further in the footnote[2] and those companies with a score greater than 2.99 fell into the non-bankrupt group (Group A), while those companies having a Z-Score below 1.81 were in the bankrupt group (Group C). The area between 1.81 and 2.99 is defined as the zone of being watchful or the gray area (Group B).

Table 3. Debt Ratio and Altman Z-Scores of wind energy SMEs in KOSDAQ (Unit: Percent, Points)

Group A(Cos)	Debt Ratio	Z - Score	Group B(Cos)	Debt Ratio	Z - Score	Group C(Cos)	Debt Ratio	Z - Score
SH	10.25	6.58	TU	65.84	2.8	SG	503.05	1.04
UL	31.75	3.85	US	57.14	2.56	SP	199.15	0.89
			KM	52.19	2.53	MI	207.43	0.62
			DG	35.47	2.51	YH	247.79	0.44
			TE	52.4	2.34	UI	405.97	0.23
			HJ	123.21	1.9	PS	532	-2.4
			UY	189.68	1.82			
No. of Cos	2		No. of Cos	7		No. of Cos	6	
Max	31.75	6.58	Max	189.68	2.8	Max	532	1.04
Min	10.25	3.85	Min	35.47	1.82	Min	199.15	-2.4
Mean	21.00	5.22	Mean	82.28	2.35	Mean	349.26	0.14
StDev	15.20	1.93	StDev	54.93	0.36	StDev	150.43	1.28

For the sake of selecting dependent variables as an output data, I merged Group A and Group B to make another new group "healthy group" while defining the Group C as "dangerous group" based on the Altman Z-Scores of 15 wind energy companies. "healthy group" is equivalent to non-bankrupt group and "dangerous group" is like bankrupt group in the Altman Z-Scores (1968). This new dichotomous groups were necessary for finding discriminant financial ratios to develop financial distress prediction models by categorizing data into two groups for comparison as designed to conduct MDA and Logit Analysis.

In brief, generally speaking the stability related variables in financial ratios have been most widely used for the corporate distress prediction. However, the ratios related to the profitability, growth and activity in distress prediction have been also suggested to be important in prior studies. So in this study, the financial ratios in profitability and growth as well as solvency have been taken to perform discriminant analysis and logit analysis. And 14 financial ratios were selected as the independent variables and 2 dichotomous dependent groups (healthy and dangerous) for the validation test of statistical significance.

Using 14 financial variables the following hypothesis has been set and tested for the statistical validation to discriminate dangerous group from healthy group.

4. ANALYSIS

4.1 Descriptive Statistics and Correlation Analysis of Statistics

4.1.1 Descriptive Statistics

Prior to verify the effect of financial ratios on distress prediction of the wind energy in order to examine the

[2] **Z (Altman Z-Score model) = $1.2 X_1 + 1.4 X_2 + 3.3 X_3 + 0.6X_4 + 1X_5$**

X1 = working Capital / Total Assets, X2 = Retained Earnings / Total Assets

X3 = EBIT / Total Assets, X4 = Market Value of Equity / Total Liabilities, X5 = Sales / Total Assets characteristics of the variables used in distress prediction models, the analysis of the statistical values of each variable such as the average, the standard deviation, the median, minimum and maximum was done. The results are given in the Table 4 below.

Table 4. Descriptive Statistics of Variables

Classification		A	B	C	D	E	F	G	H	I	J	K	L	M	N
Mean	Dangerous	64.3	259.5	11.4.4	-44.2	1.2	72.8	.3	.4	.2	-22.4	-7.8	153.9	-5.1	-21.6
	Healthy	310.0	58.2	-8.7.8	26.0	63.3	19.2	3.6	1.8	3.2	2.5	1.3	1735.9	-5.5	2.9
	Total	211.7	130.1	-.7	-2.06	38.5	40.6	2.2	1.2	2.0	-7.5	-2.0	1175.1	-5.4	-6.9
StDev		236.2	119.0	28.6	54.7	49.7	42.7	4.5	3.3	5.6	31.3	13.6	12.1	12.1	31.6
Median		131.1	79.9	-3.0	12.1	48.8	38.4	.9	1.5	2.0	1.5	1.7	776.7	-5.9	1.5
Min		18.7	9.1	-55.6	-172.2	-118.8	0.00	-1.9	-8.3	-14.1	-117.6	-46.2	-1698.	-38.3	-117.6
Max		869.0	357.9	68.7	59.0	90.6	172.9	16.5	5.6	10.2	9.7	12.8	5485.	19.4	11.9

* For the tabulation of the data in a condensed form, long letters of each variable are denoted as A, B, C and others in a shortened fashion like in the footnote. This denotation is continuously applied in the following tables.

4.1.2 Correlation Analysis

The pearson correlation analysis was conducted to identify and measure the associations among two sets of variables. Whose results appear as follows: As shown in the Table 5, there are statistically significant correlations between two sets of variables.

EBT (Earnings before Taxes) to Sales and Net Income to Sales showed a significant correlation each other while Interest Coverage Ratio had no significant correlation with Total Borrowings and Bonds Payable to Total Assets. Net Working Capital to Total Assets and Current ratio showed a significant positive correlation each other while Net Working Capital to Total Assets had some significant negative correlation with Total Borrowings and Bonds Payable to Total Assets. Net Working Capital to Total Assets had almost no significant correlation with Growth Rate of Operating Income. Other parameters also appeared to be in a statistically significant correlation between variables.

Table 5. Correlation Coefficients of Variables

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
A	1													
B	-.627* (.017)	1												
C	-.220 (.430)	.235 (.419)	1											
D	.573** (.026)	-.868** (.000)	.272 (.326)	1										
E	.557* (.031)	-.899** (.000)	.137 (.627)	.951** (.000)	1									
F	-.570* (.026)	.919** (.000)	-.182 (.517)	-.952** (.000)	-.985** (.000)	1								
G	.380 (.180)	-.471 (.104)	-.214 (.462)	.240 (.409)	.399 (.158)	-.403 (.153)	1							
H	-.005 (.985)	-.287 (.320)	-.155 (.582)	.023 (.936)	.126 (.656)	-.198 (.480)	.554* (.040)	1						
I	.032 (.910)	-.387 (.072)	-.292 (.292)	.015 (.908)	.162 (.563)	-.227 (.415)	.590* (.026)	.966** (.000)	1					
J	.294 (.287)	-.601* (.023)	.285 (.304)	.881** (.000)	.909** (.000)	-.912** (.000)	.265 (.361)	.228 (.414)	.206 (.461)	1				
K	.215 (.423)	-.528 (.053)	.050 (.867)	.323 (.260)	.386 (.173)	-.562* (.036)	.415 (.159)	.894** (.000)	.874** (.000)	.970** (.000)	1			
L	.235 (.400)	-.352 (.218)	.097 (.730)	.597* (.019)	.632* (.011)	-.581* (.023)	.201 (.491)	.115 (.682)	.143 (.612)	.535* (.040)	.151 (.605)	1		
M	.140 (.620)	.411 (.145)	.477 (.072)	.557* (.031)	.578* (.024)	-.602* (.018)	.131 (.655)	.192 (.494)	.123 (.662)	.756** (.001)	.199 (.496)	.203 (.467)	1	
N	.294 (.287)	-.581* (.029)	.296 (.284)	.879** (.000)	.907** (.000)	-.911* (.000)	.277 (.158)	.235 (.399)	.214 (.445)	1.00** (.000)	.954** (.000)	.536* (.039)	.753* (.001)	1

* Notes: refer to the footnote on the page 5 for the meaning of A, B, C and others (denoting each independent variable)

**. Pearson Correlation Coefficient is significant at the 0.01 level (two-tailed).

*. Pearson Correlation Coefficient is significant at the 0.05 level (two-tailed).

* p<.05, ** p<.01, ( ): p value

4.2 Results of Hypothesis Test

4.2.1 Test of Hypothesis I

To select the variables that will discriminate the dangerous group of wind energy companies, parametric test of significance tests (t-test) and nonparametric Wilcoxon rank-sum test were conducted. Discriminant analysis and logit analysis were performed by employing the selected five variables which are statistically significant at the t-test and Wilcoxon rank-sum test alike. After examining variability in the ratio means as shown in the Table 6, many variables were found to be significant at the 0.05 level, indicating substantial differences in variables between groups. This shows there is significant variety in the ratios of healthy and dangerous groups. These findings indicate that Hypothesis I: financial ratios do have significantly different predictive abilities for detecting failures of wind energy companies in Korea. [(H a): a healthy gr. ≠ a dangerous gr.] should be accepted as the means across healthy and dangerous groups are different. So there is strong evidence to support the judgment that financial ratios have different predictive abilities for detecting financial failures among wind energy companies

Table 6. Outcome of T-Tests and Wilcoxon Tests

Classification	Mean		T-test values			Wilcoxon test values		
	Healthy	Dangerous	t-values	CI	Accept Reject	z-values	CI	Accept Reject
A	310.02	64.27	-2.73	.023	○	-2.83	.005	○
B	58.15	259.54	5.40	.000	○	-2.87	.004	○
C	-8.75	11.44	1.38	.190	X	-1.06	.289	X
D	26.01	-44.17	-3.09	.009	○	-2.71	.007	○
E	63.30	1.20	-2.96	.011	○	-2.83	.005	○
F	19.19	72.81	2.98	.011	○	-2.83	.005	○
G	3.58	.25	-1.41	.185	X	-1.81	.071	X
H	1.81	.40	-.806	.435	X	-.471	.637	X
I	3.18	.19	-1.02	.327	X	0.00	1.00	X
J	2.45	-22.40	-1.28	.258	X	-1.30	.195	X
K	1.28	-7.89	-.901	.417	X	-.715	.463	X
L	1735.91	153.89	-1.88	.083	X	-1.77	.077	X
M	-5.50	-5.13	.45	.965	X	-.354	.723	X
N	2.90	-21.63	-1.24	.268	X	-1.18	.239	X

* ○: Accept, X: Reject

4.3 Results of MDA

4.3.1 Results and Interpretations of MDA

The following discriminant function consists of a statistically significant coefficient.

$$Z = -1.421 - .002 * A - .013 * B + .023 * D + .039 * E + .041 * F$$

The denotation for A, B, D, E and F is explained below in the footnote[3]. And the cut-off score is 0.0000. The value of classification function is higher than 0 and then is classified as healthy group while lower than 0 and then is classified as dangerous group. The central value of discriminating score for the healthy group is 1.180 and that of discriminating score for the dangerous group is -2.213. Parameter Estimates in Discriminant Analysis Model Coefficients are given in the Table 7

Table 7. Parameter Estimates in Discriminant Analysis Model Coefficients

Varibles	Healthy	Dangerous
A	-.024	-.018
B	.090	.131
D	.155	.258
E	1.326	1.196
F	.985	.851
(Constant)	-55.156	-52.202

The discriminant function in this research was derived from the raw financial ratios as variables. And it is possible to determine whether a company in the wind energy industry in Korea is healthy or dangerous. The determination can be made by placing financial ratios as variables based on the discriminant coefficients in the Table 7 and judging the company which scored above the cut-off score as healthy and the company which scored below the cut-off score as dangerous.

[3] *Notes : A: Current ratio, B: Debt ratio, C: Growth Rate of Operating Income, D: Net Working Capital To Total Assets, E: Retained Earnings To Total Assets, F: Total Borrowings And Bonds Payable To Total Assets, G: Interest Coverage Ratio, H: Operating Income To Total Assets, I: Operating Income To Sales, J: Net Income To Sales, K: Net Income To Stockholders' equity, L: Retained Earning To Paid-in Capital, M: Growth Rate Of Total Assets, N: EBT To Sales

The value in the statistical discriminant function is important for assessing model fit of the discriminant function. Once discriminant function has been derived from a variety of variables,

Table 8. The Value of a Statistical Discriminant Function

Function	Wilks' Lambda				Eigenvalue		
	Wilks' Lambda	Chi-square	df	Sig.	Eigenvalue	% of Variance	Canonical Correlation
Z	.255	12.982	5	.024	2.922	100	.863

There are a number of ways to test its efficiency. One is by checking the statistic called wilks' Lambda. As shown in the Table 8, " Canonical correlation " relationships representing the degree of association between group canonical correlation is .863 and the eigenvalue of the discriminant function is 2.922 which is good enough to explain the 100% of the total variance. Eigenvalue serves as goodness of fit indicator. Higher values indicate a better discrimination between groups. Wilks Lambda is a high explanatory power and the chi-square value of 12.982 is statistically significant since the probability is 0.024 < a = 0.05.

Even if it is statistically significant, the discriminant function cannot be called effective function until the real predictive power is proven. To increase the accuracy of the distress prediction model, classifications in discriminant analysis, discriminant functions can be used to make predictions of the group to which a case most likely belongs.

According to the results of the discriminant analysis model as shown in Table 9, the value of a statistical discriminant function is as follows;

Sensitivity which measures the proportion of actual positives being correctly identified as such and is complementary to the false negative rate is 88.9% and specificity which measures the proportion of negatives being correctly identified as such and is complementary to the false positive rate is 80.0%. The level of prediction accuracy for both of the sensitivity and specificity was turned out to be good with sensitivity being a little higher than sensitivity.

Table 9. Prediction Accuracy of Discriminant Analysis Model

Categories		Predicted		
		Healthy	Dangerous	Accuracy (%)
Observed	Healthy	8 (88.9%)	1 (11.1%)	9(100.0%)
	Dangerous	1 (20.0%)	4 (80.0%)	5(100.0%)

* Notes : 85.7% of original grouped cases correctly classified.

4.4 Results of Logit Analysis

4.4.1 Results and Interpretations of Logit Analysis

Even though MDA is useful in determining whether a set of variables is effective in predicting category membership, it has the following assumptions and the analysis is quite sensitive to outliers: 1) the independent variables are not highly correlated with each other. 2) the mean and variance of a given independent variable is not correlated. 3) the correlation between two independent variables is constant across groups. 4) the values of each independent variable have a normal distribution.

Table 10. Parameter Estimates in Logit Analysis Model Coefficients

Classification	Coef	SE Coef	Wald	P	odds ratio
(Constant)	149.477	134015.324	.000	.999	
A	.094	104.465	.000	.999	1.099
B	-2.022	416.691	.000	.996	.132
D	-.971	410.040	.000	.998	.379
E	-1.501	2215.446	.000	.999	.223
F	4.903	1723.576	.000	.998	134.715

Logit analysis does not have as many assumptions and restrictions as discriminant analysis.

A logit analysis was made with the same five financial ratios which were produced just like for the multiple discriminant analysis described above. The results of the logit analysis are shown in table 11. The accuracy of the model was estimated to be 100.0%.

According to the results of the logit analysis as shown in Table 11, sensitivity which measures the proportion of actual positives being correctly identified as such and is complementary to the false negative rate is 100.0% and specificity which measures the proportion of negatives being correctly identified as such and is complementary to the false positive rate is 100.0%. The level of prediction accuracy for both of the sensitivity and specificity was turned out to be same.

Table 11. Prediction Accuracy of Logit Analysis Model

Categories		Predicted		
		Healthy	Dangerous	Accuracy (%)
Observed	Healthy	9 (100.0%)	0 (0.0%)	100.0
	Dangerous	0 (0.0%)	5 (100.0%)	100.0

* Notes : 100.0% of original grouped cases correctly classified.

As shown in the Table 12, based on the analysis of both discriminant analysis and logit analysis for the prediction accuracy, it is possible to conclude that logit analysis is slightly better than discriminant analysis in the predictability for the wind energy industry in Korea even though both of them are estimated to be quite high.

Table 12. Comparative prediction Accuracy of Discriminant Analysis and Logit Analysis

Categories	Discriminant Analysis	Logistic Analysis
Predictiction Accuracy (%)	85.7	100.0

5. RESULTS AND RECOMMENDATION

5.1 Results of Analysis

This study was designed to identify some suitable variables and examine the predictability of both MDA and LA based on a sample of 15 companies using selected 5 financial ratios.

The empirical results show that financial ratios do have significantly different prediction abilities for monitoring failures of wind energy SMEs in Korea. Hypothesis I should be accepted as the means across healthy and dangerous groups are different. So there is strong evidence to support the judgment that financial ratios have different predictive abilities for finding financial distress among wind energy companies.

However, the empirical results do not provide evidence to support hypothesis II that the accuracy of MDA is superior to that of LA in predicting corporate financial distress in Korea since the accuracy of logit analysis is 100.0%, much better than that of discriminant analysis is 85.7% in the predictability.

And the empirical results also disclose that selected profitability and growth ratios as well as solvency ratios are helpful in predicting a company's success or failure.

5.2 Recommendations

Even though the results of analysis are worth considering the accuracy of financial distress prediction models of wind energy companies in Korea, it is important to interpret the results of the accuracy carefully. If the early warning is alarmed and the appropriate action taken, it is possible to overcome the default risk, but if there is no proper action taken, the business or financial position may fall into crisis.

The accuracy of the model could vary depending on industry, firm size and other situations which can result in producing wrong messages about the status of companies. Even though the results of studies turn out to be statistically significant, it does not mean immediate bankruptcy in the practical situation. Therefore you need to consider it as an early warning signal and take the right action. So it is necessary to be aware of the limitations of the model.

5.3 Limitations and Future Research

5.3.1 Significance of Research

The significance of this study is on the effort to find out the optimal variables to compare financial distress prediction models to drive out the alleged rumor that green energy sector including the wind energy is on the brink of bankruptcy. And it is meaningful to have applied MDA and LA which have been widely accepted in other fields of study to wind energy industry the first time in Korea.

5.3.2 Limitations and Future Research

All the members of Group B were reclassified into the 'healthy group' considering the dichotomous nature of the statistical models applied for this research and the lack of companies belonging to Group A. With enough number of companies in Group A, it would not have been necessary for all the members in Group B to be reclassified into the healthy group. However, the results of the dichotomous approach after reclassification of companies were turned out to be satisfactory for distinguishing dangerous group from healthy group of wind energy companies in Korea. And wind energy alone cannot represent all of the 11 NRE. So it is necessary to conduct comparative analysis of international NRE efforts. But the international comparative study was excluded in this study because of the lack of available data. The rest of green energy beyond wind energy and the comparative analysis of NRE of other countries are recommended for future studies.

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