Performance Evaluation of No-frill Airlines

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Abstract

Objective: To establish a resolution on the accomplishment of the economical airways with a view to help the aviation industry in framing strategies about such airlines.
Methodology: Data have been procured from DGCA, India website. Here, the yearly data of each of the airlines have been utilized. The duration of sampling includes six years 2006-07 to 2011-12 taken for the purpose of classification of operating economical airlines in India. The empirical analysis has been performed on the basis of Discriminant Analysis (DA) using SPSS version 16.0.

Findings: The model has classified 22 (87.5%) cases accurately out of 24 cases which is considerably large; hence, the model can be justified as a sound one.

Impact: The work will help one perceive the key areas of strength and accordingly frame feasible strategies in order to improve performance.

Keywords: No-frill Airlines, Performance, Classification, Discriminant Analysis.

1. INTRODUCTION

Performance evaluation is absolutely vital in a service sector like air transport. Improvement of productivity is one of the basic functions of governance. The air transport sector now is in an abnormal state of activity. Resources of this sector are contracting with a rising demands of activities required by the public. Hence, the management of the airline organizations should start earnest strides for the productive and powerful use of accessible assets for ideal yield.. It is definitely a reality that the flight is the indicator of monetary exercises of a country. With the unavoidable trends blowing over the world and globalization turning into an acknowledged wonder, subsequent changes in the social and financial condition will influence, and will be influenced by the aviation. By and by, air transport is one of the principal modes of conveyance. The adaptability of activities, simplicity of openness and all the more, the unwavering quality has earned the trustworthiness on the transport mode to an inexorably higher rate. Owing to denationalization, the dividend of state-owned transporters came to a diminishing state to meet the requirement of progressive airway passengers. It has been discovered that all the Rhadamanthine domiciliary aircrafts in India transported a total of 44.38 million passengers during the year 2007 – 08 resulting into a progress rate of 24% during 2007-08. The matching value was an overwhelming 42% in the preceding year.

In terms of number and nature of independent as well as dependent variables, DA is akin to the analysis of regression For instance, in either method, the predictor variable can be non-metric or metric in nature. Moreover, single or multiple self-reliant variables as well as one dependent variable can be used in the two together. Moreover, through minimization of the sum of squares within group, DA makes use of OLS with a view to estimate the parameters α and

β_i. But when the inherent features of the depending variables are taken into consideration, DA differs noticeably from analysis of regression. In lineal DA, the depending one is of nominal or qualitative and non-metric in inherent qualities; whereas, in the analysis of regression; the depending variable is of metric nature. However, DA, consisting of groups is analogous to logistic regression analysis.

The lineal function of discriminant possesses the structure of a lineal consolidation of the coefficients of the variates and the corresponding variates in the survey. The coefficients of the variables are assessed in a way that the function increases the distance to the greatest possible amount between the two centroids. This can happen if the ratio (λ) of group sums of squares to sum of squares within group is increased to the greatest possible extent. The optimality of the function cannot be achieved for any other combination. It is because of the unjustifiability of the validity of the model in such a case. The coefficients are non-standardized coefficients. However, we can also estimate the standardized coefficients. The mean of a standardized variate being zero, there is no constant term in a standardized function.. The greater the coefficient, the better, is the self-reliant variate for the discrimination between the groups. Another important characteristic of a good independent variable is that of having large weight.

2.Objective of the Research

The primary aim of this survey is to carry out the performance and classification of running economic air carriers in India using DA, which may enable decision makers to take prospective decisions to earn a competitive edge over the other types of airlines.

3.Literature Review

Since the inception year of 2003, no-frills airways (NFA) have been having a sizable influence on the airways industry across India, namely in airdromes and the competing airways. Robust testimony has been observed to establish the fact that the NFAs trigger a higher demand and hence develop new market arenas. Growing number of flights to accommodate higher passenger traffic resulting into a enviable growth of its market shares, generate a priority to assign importance to the domination of NFAs. Emergence of regional airdromes has brought about a phenomenal change in successful competition with the prime airdromes and thus providing new direct flights between Indian city pairs that were not found earlier through traditional airways. As a consequence, it has become obligatory to the traditional airways to adapt to the new market situations with a view to adjust to different business models.

According to Goncalves S. (2009), NFAs are pertinent benefactors to the way in which the scenario of travelling for pleasures is in a changeful mode all over the globe. Not only the airways, but also the tour operators have become bound to modify their operating strategies. Different regions are attempting to adapt to this new requirement by taking advantage of all facilities at hand to improve their tourism policies in the growing competitive situation.

A No-frill Airway is one that usually offers low fares in lieu of many traditional facilities to the passengers. The model, that the NFA represents, is not a new concept. A few of the NFAs are connected to major established airways companies, but its evolution has become the reigning model of management very fast. The easy accessibility to the internet secured it a noticeable growth. There is a lot of useful literature describing the growth of NFAs and their improvement to the present state (as shown by Doganis, 2001; Lawton, 2002; and Williams, 2001). Even though a number of airways offer reduced rate of fare on one or more of their routes at particular periods, the simple act of offering low fares does not make them a NFA. NFAs emerged in the 1990s with a particular aim of operating with a lower cost plan than traditional ones with a view to generate lower charges compared with the others(Alamdari and Fagan, 2005; Calder 2002; Lawton 2002; Doganis, 2001) and hence to attract more passengers resulting into a higher growth rate.

Logistic regression has been applied repeatedly in allied financial arenas. Many researchers utilized Multivariate DA as the basic model for prediction. The pioneering work was performed in 1968 by Altman while Ohlson used Logistic regression to develop the default-prediction model in 1980. The primary research on the model focused on categorizing firms as either defaulting or non-defaulting. According to Ohlson, such a replica assumes a state of equal payoff. Clearly, misclassification of a firm which failed to fulfill an obligation as a dependable firm will have a serious impact over a financier. So, we pay our attention on the capability of the replicas to assign a position to the firms as defaulting and non-defaulting ones correctly based on their normal likelihood. Following a similar pattern Zmijewski (1984) settled on a probit Analysis with a view to determine the relationship between the stimulus and the quantal response.

4.Research Methodology

The studies cited above, point out that DA, in context to the operating of no-frill airlines of India, can be a useful tool to the decision makers. The purpose of this survey is to explore a replica for segregating companies into two classes based on their accomplishment: **good** and **poor** performer options, thereby enhancing the various stakeholders' capability to predict the market rate of return. The study examines the efficacy of Revenue Passenger Kilometers Performed (RPKM) as predictors of NFA's performance.

4.1 The Hypotheses of the Research

The present verifiable analysis is intended examining the hypotheses stated below:

H_0 No notable difference will be found between the noticed and the forecast performance in No-frill airlines in a model using Revenue Passenger Kilometers Performed (RPKM).

H_1 There would be a difference between the observed and predicted performance of No-frill airlines in a model using Revenue Passenger Kilometers Performed (RPKM).

4.2 Sample Composition and Period of the Study

In this research, as pointed out earlier, annual data of each of the airlines have been utilized and the data have been procured from the DGCA, India. The sample period includes six years 2006-07 to 2011-12 used for the purpose of classification of running economic airways of India.

Based on the claim of **Burns and Burns (2008**), the size of representative specimen of the dependent variable from the smallest group ought to be at least 5 times more than the count of the self-reliant variables. Similar to the study of regression, DA ought to be performed on the basis of a set of data as big as the bigness of the sample as far as viable; since sample of small size may generate incorrect discriminant function. Here, we have taken 24 as sample size to carry out this research.

4.3 Variables Specification

we have considered an analogous set of airways for the specimen data in order to analyze the performance and classification pattern of running economic airways in India through DA, Here, we have concentrated on four such airways ,namely, Spice jet, Jetlite, Indigo as well as Go air which operated during 2006-07 to 2011-12 years for this detailed study. Here, size of the group of airplanes abbreviated as FS, Total number of staff members abbreviated as TE and Total expenditures for operation abbreviated as TOE, have been selected as the predictor variable and Revenue Passenger Kilometers Performed (RPKM) has been chosen for the response variable.

As already discussed, we have considered dependent variable as **good** or **poor** and six independent variables. Test for Normality was performed with these interpretative variates. The outcome of the test of normality has been summed up in the table- 1 below and the results show that three of the variates are normally distributed.

Table-1: Kolmogorov-Smirnov Test for one-Sample

One-Sample Kolmogorov-Smirnov Test

		TOE	TE	FS
N		24	24	24
Normal Parameters[a]	Mean	1.9420E4	2151.67	20.21
	Std. Deviation	1.2208E4	1.062E3	12.004
Most Extreme Differences	Absolute	.220	.150	.161
	Positive	.220	.150	.161
	Negative	-.102	-.125	-.103
Kolmogorov-Smirnov Z		1.079	.733	.788
Asymp. Sig. (2-tailed)		.195	.656	.564

a. Test distribution is Normal.

From table-1 above, we observe that value for P for all the six variates exceed 0.05 implying that these variates are normally distributed. The variates were also subjected to a test using a Q-Q plot and P-P plot as shown in the annexure I. Three variables were found to pass the test of normality; this is anticipated from the pecuniary data. The three independent variables that were considered for final analysis are described below:

Predictor Variables: Three are the ones which have been contemplated as the most significant predictors of dependent variable. These three predictor variables are given below:

Size of the air-fleet (FS)
It consists of the total quantity of aircrafts used by the airway. It is representative of the capital investment. It can also refer to the fleet as the total quantity of aircrafts in inventory.

Total count of Employees (TE)
The term **Total employee** has been used here to mean the total count of staff members engaged in an airway including the pilots, cabin crews, ground staff, reservation executives etc. which represents the labour input.

Total Expenses for operation(TOE)
Running an airline is exorbitantly expensive. Major cost incurred as fuel costs, salary of pilots and other staff. Innumerable other expenses do also exist including costs for maintenance, charges paid to airports, charges paid to the government, the expenses for running the computer systems to track the bookings, commissions paid to travel agents and charges paid for the Web sites, expenditure for training the pilots, and other allied incidental expenses. All these expenditures form the total expenses for operation that implies the working capital.

Response Variable: One dependant variable has been considered as the most important one in classifying the performance of an airline. The dependent variable has been described under:

Revenued Passenger Kilometers Performed (RPKM)

An RPKM means an estimate of the count of commuters transported through an airway. An RPKM is counted when a passenger is transported one kilometer in exchange of some paid fare. In other words, a passenger is called a **revenue passenger** for whom an aircraft receives some revenue,. This excludes the privileged passengers travelling each without fares or with a discounted fare. The product of the count of revenue commuters for flight stage of an airway and the covered distance of the stage is defined as RPK. It is, therefore, an estimate of the size of sales of the commuter traffic.

Table 2: Dependent variable

Category of Airline based on RPKM	Criteria
GOOD	Sales above Mean value of RPKM
POOR	Sales below Mean value of RPKM

Table -3: Encoding of the Dependent Variable

Value in original	Intrinsic value
poor	**0**
Good	**1**

As the outcome or the dependent variable is a diploid one, we have taken GOOD = 1 and POOR = 0 to indicate the performance of airlines. Out of to 24 samples 17 were found as poor and 7 as good.

4.4 Statistical Method and Software Used

With a view to obtain replies to the queries of the research under consideration, the straight forward technique of DA has been applied as the methodology of analysis of this survey. Here, all the self-reliant variates constitute the variables in the replica simultaneously. This empirical investigation has been done using multivariate analysis such as discriminant analysis as per the respective objective of the research using SPSS version 16.0.

4.5 The statistical Technique – DA

The method of DA aims to find out the lineal consolidation of those variates that segregate the collections of instances in the best possible way based on a set of independent variates. Such consolidations are known as functions of discriminant and they possess the structure shown as under:

$$d_{ij}=b_{0j}+b_{1j}x_{i1}+...+b_{pj}x_{ip} ,$$

where, d_{ij} denotes the magnitude of the j^{th} function of discriminant for the i^{th} instance; the count of predictors is denoted by p, b_{ij} denotes the magnitude of the i^{th} coefficient of the j^{th} function and x_{ij} denotes the magnitude of the i^{th} instance of the j^{th} predictor.

MIN (#Collections-1, #predictors) denotes the count of functions.

The methodology selects an initial function automatically to segregate the groups as far as possible. It then selects another function which is not correlated with the first function and performs as much further segregation as possible. The procedure is continued finding out functions in this process until it reaches the highest number of such functions as determined by the count of predictors and classes in the dependent variable.

The following are the presumptions of our model:

- Correlations among the predictors are not high;
- There is no correlation between the central tendency (mean) and the dispersion (variance) of a predictor under study;
- The association between two forecasters remains the same among all groups.
- Each forecaster is normally distributed.

Classification of a multivariate data vector into one of two populations requires a tool. For example, categorization of students of an institution is as likely to succeed or fail or classification of an organ transplant patient as likely to survive or not requires such a tool. Discriminant analysis is meant for classification of observations from a multivariate data set into two or more populations. In the case of two populations defined by $\prod_1 \equiv Np\,(\mu_1, \Sigma_1)$ and $\prod_2 \equiv Np\,(\mu_2, \Sigma_2)$, we can obtain a rule for the classification so that it can be used to categorize an element, say $\underline{x}$, belonging to one of the two populations. We assume that each $\underline{x}$ is a p-variate normal. Training samples are required to be obtained for the estimation of the mean and covariance of each population, and to deduce the classification rule, when the population parameters are unknown, as is often the case,

Let us assume that the measures of $\underline{\mu_1}$, $\underline{\mu_2}$, Σ_1 and Σ_2 as $\underline{\bar{x}_1}$, $\underline{\bar{x}_2}$, s_1 and s_2, respectively. If the covariance matrices for the populations, Σ_1 and Σ_2 are equal, then the common covariance matrices for the populations, Σ_1 and Σ_2 will be equal. So, the common covariance matrix, Σ, is replaced by the pooled measure, $s_p = \frac{(n_1-1)s_1+(n_2-1)s_2}{n_1+n_2-2}$

The measures $\underline{\bar{x}_1}$, $\underline{\bar{x}_2}$, s_1, s_2 and s_p are called unbiased estimators with n1 and n2 as the sizes of the two populations. We next consider the classification of $\underline{x}$ into $\prod_1$ or $\prod_2$. For this purpose, the optimal linear discriminant functions, $\underline{a}\ \underline{x}$, are used; where $\underline{\hat{a}} = S_p^{-1} (\underline{\bar{x}_1} - \underline{\bar{x}_2})$ This is done with a purpose to assign $\underline{x}$ into a population based on the decision rule.

We next classify $\underline{x}$ into $\prod_1$, if $\underline{\hat{a}}\ \underline{x}$, > ½ $(\underline{\bar{x}_1} - \underline{\bar{x}_2})' S_p^{-1} (\underline{\bar{x}_1} - \underline{\bar{x}_2})$

Alternatively, we classify $\underline{x}$ into $\prod_2$ if $\underline{\hat{a}}\ \underline{x}$, > ½ $(\underline{\bar{x}_1} - \underline{\bar{x}_2})' S_p^{-1} (\underline{\bar{x}_1} - \underline{\bar{x}_2})$

Classification functions. The classification functions are utilized to find out to which assemblage (group) each instance belongs with maximum probability. The number of groups is equal to the number of classification functions.

Each function can be used to calculate *scores of classification* for each instance of each group by using the following formula:

$s_k = c_k + w_{k1} * x_1 + w_{k2} * x_2 + \ldots + w_{kn} * x_n$

Here, groups are represented by different values of subscript *k*; the subscripts *1, 2, ..., n* represent the *n* variates; c_k is a fixed value for the k^{th} group, w_{kj} is the weight for the *j*th variate in the calculation of the score of classification for the k^{th} group; x_j is the studied value for the respective instance for the *j*'th variable.S_k is the final score of classification.

The classification functions are used to calculate the scores of classification readily for some newly obtained values(observations).

Mahalanobis distances (MD): If two or more correlated variates exist in the space then the distance between any two values of such variables is called MD. When the values of such variates are plotted to form a 3-D scatter diagram, their axes will not be orthogonal and hence simple Euclidean distance cannot be used as a measure of the distance between such variates. In such situations MD is the only way to get the correct measure.

Mahalanobis distances and classifications: For each of the groups in our sample we can find out the mean position for all variates in the multivariate space of our model. The points are known as group *centroids*. For each of the cases, the Mahalanobis distance may be computed from each such centroid. The instance may be categorized as pertaining to the group to which it is the nearest, i.e., where the MD is the minimum.

Classification of probabilities (Posterior): Based on the Mahalanobis distances to perform the categorization, the probability may now be computed to ascertain whether an instance of a particular situation belonging to a given collection is actually proportionate to the MD from the centroids of that collection or not. (Actually, the proportionality is not true, the reason being our assumption of a MVND around each of the centroids). As we calculate the position of each instance based on our existing concept of the values for the instance on the variates in the replica, the probability value thus obtained are known as ***posterior*** probabilities. In brief, it is the probability, computed on the basis of our concept of the values of other variates that the respective instance pertains to a particular collection. A few packages can be used to calculate those probabilities for all instances (or for selected instances only for conducting the cross-validation).

In reality, It is the researcher to justify whether the uneven number of instances in different collections in the specimen is a representation of the actual distribution of the population, or whether it is only the outcome of the sampling procedure performed randomly. In case first case, we would set the ***apriori*** probabilities to be proportionate to the sizes of the collections in our specimen while in the other instance, we shall mention that the ***apriori*** probabilities are same in each group. The mentioning of various ***apriori*** probabilities can largely make a difference to the correctness of the prediction.

4.6 Empirical Result and Analysis

Table 4: Group Statistics

Group Statistics

RPKM		Mean	Std. Deviation	Valid N (listwise) Unweighted	Valid N (listwise) Weighted
Poor	TOE	1.4243E4	6435.23207	17	17.000
	TE	1.6419E3	518.02593	17	17.000
	FS	15.2941	7.40578	17	17.000
Good	TOE	3.1992E4	14163.97853	7	7.000
	TE	3.3897E3	1041.16165	7	7.000
	FS	32.1429	13.09489	7	7.000
Total	TOE	1.9420E4	12208.79967	24	24.000
	TE	2.1517E3	1062.09419	24	24.000
	FS	20.2083	12.00355	24	24.000

Table 4 demonstrates the nonparametric statistics comprising the central tendency (mean) and dispersion (standard deviation) for all the variates of two collections taken together, i.e., poor and good group. The standard deviations of the predictor variables (of both the groups) are far apart from each other; it indicates better distinguishing power of the dataset.

Table 5: Equality Test of Group Means

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
TOE	.544	18.412	1	22	.000
TE	.416	30.862	1	22	.000
FS	.575	16.244	1	22	.001

Table 5:presents means of two collections taken for study for all predictor variables with high value F's showing strong statistical evidence of significant differences.

Table 6: Covariance Matrices showing Box's Test of Equality

Log Determinants

RPKM	Rank	Log Determinant
Poor	3	32.155
Good	3	31.938
Pooled within-groups	3	32.806

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

The independent variables considered here would not possess any multicollinearity. The multicollinearity of the variables can be checked by using the correlation matrix. Moreover, with a view to check the relationship among the independent variates, we can determine the regression of one independent variate upon the remaining ones. Stepwise discriminant analysis is an alternative way to solve the problem of multicollinearity. If there exists any multicollinearity in the data, it may be rectified. From Log Determinant table. Now, it is seen that the data are adequate for discriminant analysis as rank values are 3 in both the cases, where the predictor variables are three.

Table 7: Result of Box's M Test

Test Results

Box's M		15.615
F	Approx.	2.066
	df1	6
	df2	820.206
	Sig.	.055

Tests null hypothesis of equal population covariance matrices.

The transformed value of Box's M is used to test the basic presumption in DA that the covariance -variance matrices are equivalent. The method examines in contrast the equality of log determinants of different classes, called F ratio, in the dependent variate. Theoretically, the F is equivalent to the F of ANOVA analysis. In the test, The null hypotheses (H_0) in the covariance- variance matrices of the collections are identical in the population of the test. If the value of p (Sig.) of the test is less than 0.05, the null hypothesis is dismissed at 5 per cent level of significance. So, the presumption of equality of covariance- variance matrices is justified. The homogeneity of the variance/covariance matrices of variables in both the groups is assumed. This Testing has been performed in both the groups by using .the Box's M test. Hence,, the Box's M test is significant (p value is 0.055) indicating that the assumptions necessary for DA hold good.

Table 8: Summary of Discriminant Function

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.410[a]	100.0	100.0	.765

a. First 1 canonical discriminant functions were used in the analysis.

Now, to consider the fitness of the overall model, we would like to focus on the eigen value. It gives information on each of the generated functions of discriminant. In DA, the largest number of functions of discriminant generated equals the count of collections minus 1. In our instance, the dependent variate has two classes; so only one function of discriminant has been produced. The ratio of between collections' sum of squares to the sum of squares within collections is defined as Eigen value. The larger the Eigen value, (Eigen value should be greater than 1); the better is the replica possessing the capability of discrimination between the collections. Here, the Eigen value is 1.410 showing the goodness of the model for discriminating between the groups.

Again, the square of the canonical correlation is pointed out by the percentage of variability interpreted by a replica in the grouping variable. The multivariate analysis of correlation called canonical correlation is calculated on Z by using the formula shown below:

Canonical correlation = $\sqrt{\frac{SS_{Between\_groups}}{SS_{Total}}}$

Here, the value of canonical correlation is 0.765 and it implies 58.5 percentages of variation explained by the model.

Table 9: Wilks' Lambda and Significance

Wilks' Lambda

Test of...	Wilks' Lambda	Chi-square	df	Sig.
1	.415	18.032	3	.000

Our next focus will be on the lambda of Wilks. It is utilized to point out the implication of discriminant function evaluated in DA. The value of the lambda of Wilks represents the percentage of total variation not explained by the discriminant replica under study. Here, the lambda value of Wilks has been found to be 0.415. This value implies that 41.5 percent of variability is not explained by the model.

Table-10: Coefficients of Standardized Canonical Discriminant Function

Standardized Canonical Discriminant Function Coefficients

	Function
	1
TOE	-.055
TE	1.093
FS	-.066

Table-10 represents an indicator of significance of each forecaster as the regression coefficients (beta's) according to established standard do in multiple regression. The sign implies the course of the relationship. Total employee (TE) has been found to be the most powerful forecaster; whereas, total operating expenses (TOE)and fleet size(FS) (negative sign) are found to be less important as predictors.

Table 11: Structure Matrix

Structure Matrix

	Function
	1
TE	.997
TOE	.770
FS	.724

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

The correlations between each forecaster variate with each discriminant function are displayed in the table above and such a table is called a structure matrix. These are also known as Pearson coefficients. They are structure coefficients or discriminant loadings. They serve purpose of factor loadings in factor analysis. Here, three predictor variates demonstrate a level of confidence and efficacy like the function that distinguishes between **poor** and **good.**

Table -12: Coefficients of Discriminant Functions in Canonical form

Canonical Discriminant Function Coefficients

	Function
	1
TOE	.000
TE	.002
FS	-.007
(Constant)	-3.097

Unstandardized coefficients

The coefficients presented in table-12 above are the coefficients of the canonical variate. Scores of canonical variates are computed by using these coefficients for each instance.

Table 13: Functions at Group Centroids

Functions at Group Centroids

RPKM	Function
	1
Poor	-.730
Good	1.772

Unstandardized canonical discriminant functions evaluated at group means

Another significant way of interpreting the results of discriminant analysis is by describing each collection in terms of its profile, using the means of each collection of values of the forecaster variate.. These means of each of the collections are termed as centroids. These are shown in the table of Group Centroids. In our instance, **poor** categories generate a mean of -.730 while the **good** categories generate a mean of 1.772. Instances with scores around the centroids are forecast as belonging to that collection.

Table-14: Discriminant Classification Result

Classification Results[b,c]

		RPKM	Predicted Group Membership: Poor	Predicted Group Membership: Good	Total
Original	Count	Poor	16	1	17
		Good	1	6	7
	%	Poor	94.1	5.9	100.0
		Good	14.3	85.7	100.0
Cross-validated[a]	Count	Poor	16	1	17
		Good	2	5	7
	%	Poor	94.1	5.9	100.0
		Good	28.6	71.4	100.0

a. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b. 91.7% of original grouped cases correctly classified.

c. 87.5% of cross-validated grouped cases correctly classified.

The classification matrix serves as the correctness of a replica in categorizing an instance into one of two presumed groups. The matrix of classification depicts the gist of accurate and inaccurate classification of instances in both the collections based on the discriminant replica developed. The table-14 above demonstrates the comparative study of the noticed and the forecast performance of the airlines to the range that the forecast can be done accurately. This table presents the level of success of the classification for the specimen studied. The count and percentage of instances accurately classified and misclassified have been shown. It is obvious that 16 out of 17 RPKM i.e. 94.1% of the POOR group is classified correctly group is and on the other hand, 6 RPKM out of 7 are good, i.e. 85.7% of the GOOD group is classified correctly. After cross validation 94.1% of the POOR correctly classified and 71.4% of the GOOD group is classified correctly. As a whole 91.7% of original grouped instances are accurately categorized and 87.5% of cross-validated grouped instances are accurately categorized by the model which is significantly good.

5. Conclusion

No-frill Airways (NFAs) have made an extremely large impact on the airways industry all over India. There is strong evidence that NFAs trigger appeal and promote markets. Performance evaluation is necessary in an industry providing aviation services. Efficiency expansion is the core function of management. This study attempts to study performance and classification pattern of operating LCAs in India. The main purpose of this study is to analyze the performance and classification of operating NFAs in India using Discriminant Analysis (DA), which will help to plan some the future course of action to take advantage of any future competition.. Out of 24 cases, 22 (87.5%) instances were accurately categorized by the model which is significant enough; hence, the replica can be justified as valid. The research effort will facilitate the airline managers to understand their key areas of strength and accordingly frame their strategies and policies for decision making in order to improve performance and gain feasible benefit.

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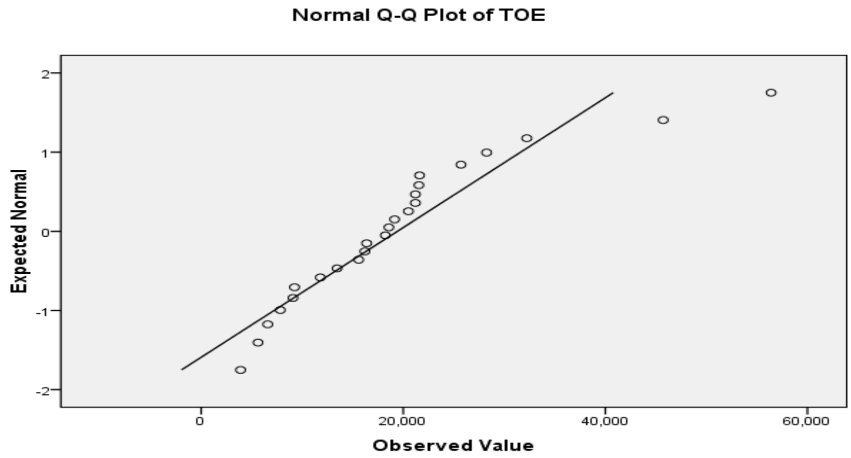
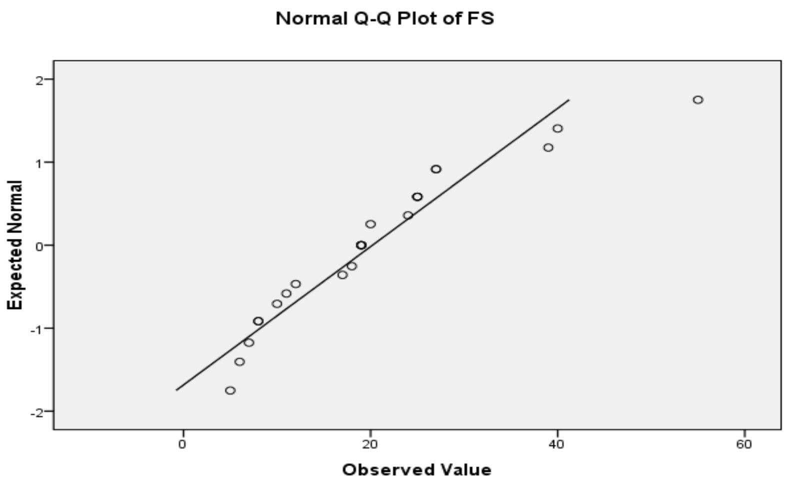
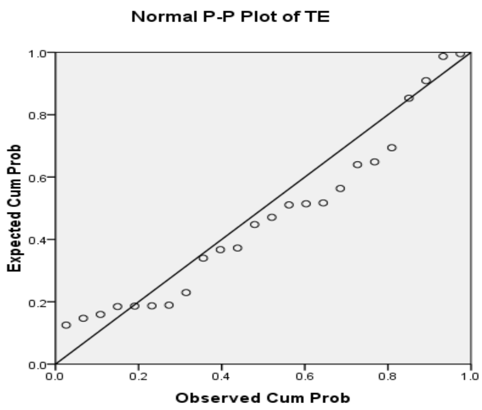
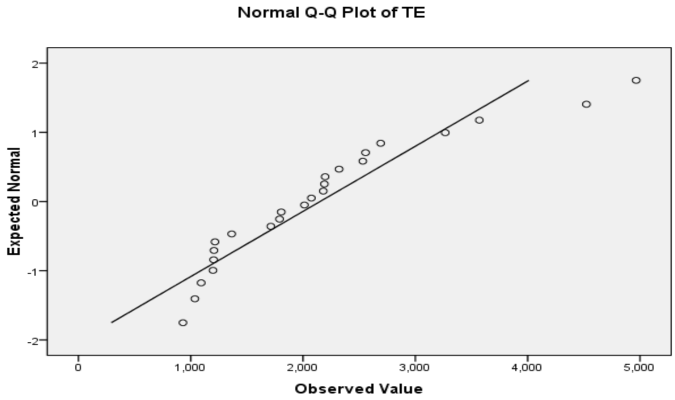
Annexure I








Normal Q-Q Plot of TE
Expected Normal
Observed Value
2
1
0
-1
-2
0
1,000
2,000
3,000
4,000
5,000