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PERFORMANCE EVALUATION OF AIRLINES BASED ON BALANCED SCORECARD WITH DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Balanced Scorecard (BSC) approach is useful to determine the overall performance of an organization. The approach integrates four perspectives of any business organization. Selection of proper performance measures is the key issue in implementation of BSC to evaluate performance of an organization. In this study, a hybrid approach is proposed to by integrating BSC and Data Envelopment Analysis (DEA)to evaluate the performance of Airlines. In DEA model, virtual ideal and anti-ideal DMUs are defined. The BSC measures are utilized as input and output variables of DEA model. The Proposed methodology improves the discrimination power among the overall performances of alternatives. A case study of 100 world major airlines considered for the study. Data on eight performance enablers under four perspectives for the case study of airlines during 2009 to 2013 is considered. The proposed methodology provides a sense of improvement and dynamics for overall performance evaluation of organizations based on both risk seeker and risk averse decision makers.

1. INTRODUCTION

Performance measurement of business organizations has drawn attention due to the competitiveness among these organizations globally during recent past. Researchers and academicians are focusing on numbers of multi-criteria decision making methods for performance evaluation of business organizations. Top management need to revive the measurement items of performance due to the changes in technological and business process functions faced by the organizations to improve their competitive strategy.

In this context, the measurement items under respective performance dimension are collected and analyzed by the top management so as to integrate these performance dimensions to evaluate performance of the organization. A performance measurement framework helps in system building, by specifying boundaries, dimensions and relationships among the performance measurement dimensions.Performance measurement directly affects the total performance of the organization and the competitive environment. Research, in the field of performance evaluation and ranking of alternatives in disciplines like, Finance, Accounting, Economics, Engineering and Management is helpful to help the organizations to know their strengths and weaknesses with a view to improve further.

Evaluation of relative organizational performance is an advanced decision-making processes provide a ranking list of options (according to the specific priorities that have been made by senior decision makers) to solve problems. Multi Criteria Decision Making (MCDM) methods are useful to prioritize alternatives in organizational performance context. Application of MCDM methods have been considering for selection of alternatives since more than fifty years. Application of MCDM methods includes prioritization, selection and ranking of technology, manufacturing processes, materials, organizations etc.

The ranking of alternatives are determined by various methods like AHP, ANP, PROMETHEE, TOPSIS, DEA, SFA, GRA, GRP etc. Evaluation and ranking of alternatives by these methods sometimes give different ranking patterns. It is very difficult to justify the best method for particular situation or general situation. Hence, selection of suitable MCDM method is again requires decision making. In view of this complexity, combination of MCDMs by properly addressing the merits of the component methods is one of the solutions. Accordingly, academia, industry experts began developed hybrid methods and applied for selection and ranking of alternatives. These hybrid methods, account for the elimination of demerits of component methods and incorporating the meritorious features in the hybrid method.

In this study, hybrid method is proposed by integrating BSC approach with Data Envelopment Analysis method for performance measurement of twenty world airlines. The criteria for Airlines performance measurementis evaluated using criteria derived from Balanced Scorecard.DEA method is implemented to rank the Airlines(DMUs) not only based in their distance from ideal DMU but the distance from anti-ideal (the worst case) to improve the discrimination power of the DMUs during ranking.

2. LITERATURE REVIEW

Mark Velasquez and Patrick (2013) made a critical review on some of the MCDM methods. The authors made a comparison of methods in respect of strengths & weaknesses merits & demerits and applications & limitations.

Iman Ajripour et al., (2019) developed a model for evaluating organization performance using multi-criteria decision-making, i.e. PROMETHEE, ELECTRE, and TOPSIS. The model is implemented in a petrochemical company.

Shradha Gawankar et al., (2015) proposed new approaches to increase performance within the organization by utilizing balanced scorecard concept. Carayannis, Grigoroudis, and Goletsis (2016) developed a framework to measure innovation efficiency by considering multiple objectives in a DEA. The study is extended to both national and regional contexts.

Chen, K. and Guan (2012) developed an efficiency model of national innovation systems for OECD member countries through network data envelopment analysis..

Rouse (2012) described the tools for analyzing the performance andframeworks used to support change management in the aircraft servicing andmaintenance division by BSC-DEA methodology.

Othman et al., (2006) implemented BSC approach for evaluation of Malaysian company. The findings of the study provided some support for the concerns about the problems and limitations of the BSC.

Bohlool Ebrahimi et al., (2014) defined the criteria for IT projects using balanced scorecard and developed a methodology to evaluate these projects. The methodology is illustrated through a numerical example.

JaroslavaKádárová et al., (2015), developed an integrated BSC-DEA framework for efficiency evaluation of processes of the organization. The study is useful for decision making at the various managerial levels to improve the performance of the organization.

Bošković, Aleksandra and Krstić, Ana (2018) developed an integrated BSC-DEA methodology to evaluate relative efficiency of the units of an organization.

M. Shafiee and H. Saleh (2019), proposed integrated BSC with DEMATEL and ANP to evaluate and rank the branches of a bank. Cause and effect relations among the perspectives are made through DEMATEL. ANP is implemented to rank the strategies of the bank. Finally the branches are ranked through Fuzzy DEA.

Seyyed Asghar et al., (2009) developed an extended DEA by integrating BSC with DEA. The proposed methodology is illustrated through a numerical example. In the numerical illustration efficiencies of 21 factories are evaluated by considering two inputs and three outputs. The authors concluded that the proposed methodology is applicable to both business and nonprofit organizations.

Jaroslava Kádárová et al., (2013) presented an integration of two the most popular methods (BSC-DEA) for evaluation of vertical transportation company performance. The authors developed each DEA model for each perspective.

Somayyeh Danesh Asgari et al., (2017) introduced a novel approach by integrating BSC and three staged DEA to evaluate the performance of banks under four balanced scorecard perspectives. The approach is implemented through a numerical example of six Iranian banks.

Kaveh Khalili-Damghani and Moslem Fadaei (2018) proposed common weights in the DEA and illustrated through solving five benchmark numerical examples adopted from the literature. The proposed approaches of this study include risk seeking and risk adverse insights of decision makers in order to rank DMUs.

Lotfi et al. (2013) made a review on ranking methods. The review includes: cross efficiency models, DEA with optimal weights, super efficiency methods, benchmarking methods, multivariate statistical analysis and MCDM methods combined with DEA. The review is useful to know importance of these methods.

Amirkhan et al. (2018) developed robust approach in fuzzy environment to overcome the difficulties and limitations associated with the problems having linguistic values for the inputs and outputs of DMUs

3. BALANCED SCORECARD APPROACH

Kaplan and Norton (1992) developed balanced scorecard perspectives for performance evaluation by making an analogy of dials and indicators in an airplane cockpit for successful navigation of aircrafts. In the task of flying, the pilot should know the data on the flying parameters and he should be in position to predict the flying environment from the complex data. Accordingly, the decision makers of an organization needs to analyze the performance of the business organization by considering various perspectives simultaneously. A balanced scorecard indicates the set of measures in a balanced way to supplement the valuable information for performance evaluation. Balanced Scorecard measures the performance of an organization in four perspectives.

Balanced scorecard is a managerial technique to measure and evaluate the performance of the organization and guides towards the successful achievement of organizational goals in methodical way. It is a visual tool that portrays the performance of the organization. It consists of key performance dimensions under four perspectives namely: Financial, customer, learning and Growth and internal business process and these are aligned and the performance of business organizations are evaluated.

3.1 Performance Measurement by Balanced Scorecard

The balanced scorecard approach comprises of three main steps for performance measurement, 1) Identify the criteria for measuring performance of organizations 2) Scorecard development 3) Evaluation and Ranking of alternatives. Balanced Scorecard solution approach is presented below.

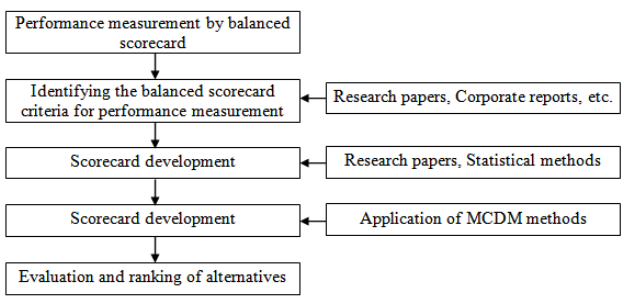

Fig. 1: Performance measurement by balanced scorecard

Identifying criteria for measuring performance

To measure the performance of business organizations, Identification of key performance indicators is the first step to measure the performance of business organizations. In this study, literature on Airline industry (Aidan, et.al., 2009;ABEYI ABEBE BELAY,2017) and from the published annual reports of airlines indicators are identified for measuring performance of the organizations. Wu and Laio (2014) proposed balanced scorecard indicators in respect of airline organizations and are discussed by Karun Kumar and Kesava Rao, 2019.

Development of scorecard

It is necessary to develop scorecard that can be used by the business organizations to measure the performance of organizations.CFA technique is useful to test the hypothesis that a relationship exists between the proposed balanced scorecard and their underlying latent constructs. CFA is made in the study made by Karun Kumar and Kesava Rao (2019) and the study suggested that four factor model with 08 items of balanced score card for evaluation of airlines had a good fit.

Evaluation and ranking of alternatives

Evaluation and ranking of alternatives involves formulation of decision matrix and determination of relative weights of criteria/sub-criteria by considering alternatives and their criteria values. There are subjective and objective methods to determine relative weights of the criteria/sub-criteria. Once the relative weights of the criteria are determined, the alternatives are analyzed based on the specific MCDM method.

In this study, case studies of 20 world airline companies are considered to evaluate the performance of these companies through DEA.

4. DATA ENVELOPMENT ANALYSIS METHOD

Data Envelopment Analysis (DEA) method comes under nonparametric technique, generally used to measure the efficiency of homogenous Decision-Making Units (DMUs). In DEA method, multiple inputs and outputs are considered to evaluate the efficiency of the decision making units. Different models in DEA are available in the literature and are discussed below.

Charnes, Cooper and Rhodes (1978) initially developed a DEA model and named it as CCR model. The model determines the efficiency of DMU by considering the ratio of weighted sum of its outputs to the weighted sum of its inputs. The authors developed a fractional programming problem to determine the weights of inputs/outputs subjected the constraint of relative ratio less than are equal to one. In addition to the determination of efficiency scores, the method also finds inefficiency for each set of the inputs and outputs. The model developed by Banker, Charnes and Cooper (1984) considered additional constant variable (cp). Andersen and Petersen (1993) considered the relative ratio greater than or equal to one as constraint and proposed a new model and named it as Supper Efficiency model. There is a cross efficiency model which determine cross evaluation score for each of those DMUs.

4.1 Comprehensive Common Weights Data Envelopment Analysis Model

In traditional DEA models, each DMU can select the most preferred weights in order to maximize its efficiency score. Therefore, the efficiencies of DMUs are calculated by various weights and, consequently, inefficient DMUs may be evaluated as efficient and discrimination power of DEA may be reduced. As more than one efficient DMU usually exists, ranking will face some difficulties. To overcome these issues, many approaches have been proposed. Kaveh Khalili-Damghani and Moslem Fadaei (2018) proposed comprehensive model by combining the IDMU and ADMU approaches considering a common weight procedure. The proposedRanking method in DEA will resolve the issues likediscrimination power, variable weights of inputs/outputs, inaccurate efficiency estimation for small number of DMUs, incapability in working with zero and negative data, and not having exterior target. The proposed method is presented as shown below.

Suppose n DMUs, each one consumes m different inputs to produce s different outputs which can be shown by xij and yrj, r = 1,2,…,s; j=1,2,…,n; i = 1,2,…,m, respectively.

$$\text{Min } Z = \sum_{j=1}^{n}\delta_j + \sum_{j=1}^{n}\sigma_j$$

S.t. $$\sum_{i=1}^{m}\omega_i x_{ij} - \delta_j = \sum_{r=1}^{s}\mu_r y_{rj}, \qquad j = 1,\ldots,n$$

$$\sum_{i=1}^{m}\omega_i x\min_i = 1$$

$$\sum_{i=1}^{m}\mu_i y\max_r = 1$$

$$\sum_{i=1}^{m}\varphi_i x_{ij} + \sigma_j = \sum_{r=1}^{s}\gamma_r y_{rj}, \qquad j = 1,\ldots,n$$

$$\sum_{i=1}^{m}\varphi_i x\max_i = 1$$

$$\sum_{i=1}^{m}\gamma_r y\min_r = 1$$

$$\omega_i,\ \varphi_i \geq \varepsilon, \qquad \forall i$$

$$\mu_r,\ \gamma_r \geq \varepsilon, \qquad \forall r$$

$$\delta_j,\ \sigma_j \text{ free in sign}, \qquad \forall j$$

The objective function minimizes the summation of distances between DMUs and IDMU and the summation of distances between DMUs and ADMU, concurrently subjected to the constraints as presented in section 4.1.

4.2 Comprehensive Common Weights Data Envelopment Model in Fuzzy Environment

In real-world situations, the representation and manipulationof inexact, incomplete, vague, ambiguous or imprecise informationis a major concern. Prior to Zedeh’s pioneering work in fuzzy sets, probability theory based on

Boolean logic was used to deal withuncertainties (or randomness) of real events and activities. Fuzzy set theory developed by Zadeh (1965) provided a valuable conceptualtool for dealing with imprecise or vague information.In this study, the proposed model is solved in fuzzy environment by considering the variables (Inputs; Outputs; minimum input; maximum output; maximum input; and minimum output) as fuzzy variables and triangular fuzzy number is assumed for these variables. The membership functions of the fuzzy variables are discussed below.

$$(x_{ij})_M + (1-\alpha)*(x_{ij})_L \le \tilde{x}_{ij} \le \alpha*(x_{ij})_M + (1-\alpha)*(x_{ij})_R$$

$$(y_{rj})_M + (1-\alpha)*(y_{rj})_L \le \tilde{y}_{rj} \le \alpha*(y_{rj})_M + (1-\alpha)*(y_{rj})_R$$

$$(x\min_i)_M + (1-\alpha)*(x\min_i)_L \le \tilde{x}\min_i \le \alpha*(x\min_i)_M + (1-\alpha)*(x\min_i)_R$$

$$(x\max_i)_M + (1-\alpha)*(x\max_i)_L \le \tilde{x}\max_i \le \alpha*(x\max_i)_M + (1-\alpha)*(x\max_i)_R$$

$$(y\max_r)_M + (1-\alpha)*(y\max_r)_L \le \tilde{y}\max_r \le \alpha*(y\max_r)_M + (1-\alpha)*(y\max_r)_R$$

$$(y\min_r)_M + (1-\alpha)*(y\min_r)_L \le \tilde{y}\min_r \le \alpha*(y\min_r)_M + (1-\alpha)*(y\min_r)_R$$

Note:

$(x_{ij})_L$ - Minimum value of i^{th} input of j^{th} DMU;

$(x_{ij})_M$ - Average value of i^{th} input of j^{th} DMU;

$(x_{ij})_R$ - Maximum value of i^{th} input of j^{th} DMU;

$(y_{rj})_L$ - Minimum value of r^{th} output of j^{th} DMU;

$(y_{rj})_M$ - Average value of r^{th} output of j^{th} DMU;

$(y_{rj})_R$ - Maximum value of r^{th} input of j^{th} DMU;

$(x\min_i)_L$ - Minimum value of minimum i^{th} input;

$(x\min_i)_M$ - Average value of minimum i^{th} input;

$(x\min_i)_R$ - Maximum value of minimum i^{th} input;

$(x\max_i)_L$ - Minimum value of maximum i^{th} input;

$(x\max_i)_M$ - Average value of maximum i^{th} input;

$(x\max_i)_R$ - Maximum value of maximum i^{th} input;

$(y\min_r)_L$ - Minimum value of minimum r^{th} output;

$(y\min_r)_M$ - Average value of minimum r^{th} output;

$(y\min_r)_R$ - Maximum value of minimum r^th^ output;

$(y\max_r)_L$ - Minimum value of maximum r^th^ output;

$(y\max_r)_M$ - Average value of maximum r^th^ output;

$(y\max_r)_R$ - Maximum value of maximum r^th^ output;

$\alpha \in [0, 1]$ - Possibility value.

Crisp variables in the proposed model in section 4.1 are replaced with fuzzy variables and the optimization model is solved the through Lingo 8.0 solver for different possibility values.

5. INTEGRATED BSC AND DEA

This study, adopted integrated BSC and DEA model for evaluation of twenty world airlines using the data during five financial years. The study adopted balanced scorecard perspectives and their items as evaluation criteria for airlines and proposed comprehensive DEA model to obtain most efficient airlines by considering vague data. Imprecise data is formulated by considering the data based on optimistic, mean and pessimistic perspectives. The flow chart of the methodology is presented below.

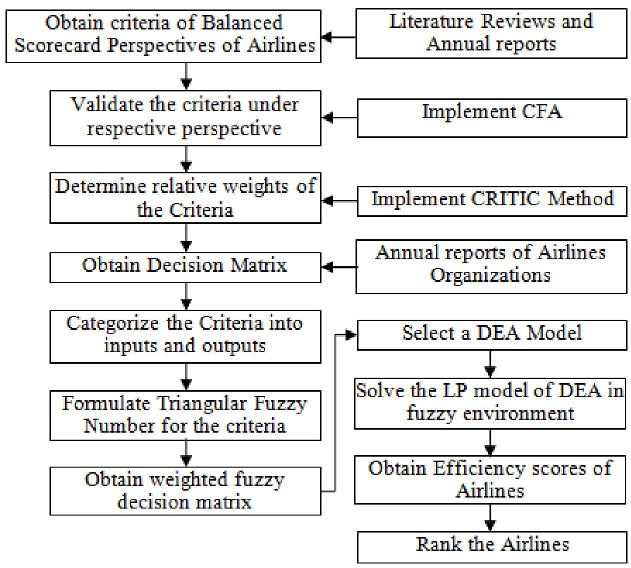

Fig. 2: Flow chart of the proposed methodology

The proposed integrated methodology of BSC and DEA is discussed in the following steps.

5.1 Integrated BSC-DEA Methodology

The proposed integrated methodology of BSC and DEA is discussed as shown below.

Step-1: Obtain criteria of balanced scorecard perspectives of airlines

In this study, balanced scorecard perspectives of Airlines namely: (i) financial perspective -FP (ii) Customer Perspective -CP (iii) Internal

Business perspective-IBP and (iv) Learning and Growth perspective -LGP are considered as discussed in the literature.

Step-2: Validate the criteria under respective perspective

CFA technique is used to test the hypothesis that a relationship exists between the observed variables (Criteria) and their underlying latent constructs (Balanced Scorecard Perspectives). CFA is implemented by considering the secondary data on 11 criteria during 2009-2013 for 20 Airlines companies. The following criteria are identified under respective perspective with good reliability and convergent validity

Table-1: Criteria of balanced scorecard perspectives

Perspectives (Constructs)	Criteria
Financial Perspective (FP)	Operating revenue (OR)
	Net Income (NI)
Customer Perspective (CP)	Revenue Passenger Kilometer (RPK)
	Revenue Ton Kilometer (RTK)
Internal Business Perspective (IBP)	Energy Cost (EC)
	Capital cost (CC)
Learning and Growth Perspective (LG)	Labour Cost (LC)
	Operating Expenses per employee (OE)

Step-3: Determine relative weights of the perspectives

In this study, relative weights of balanced scorecard perspectives are determined through CRITIC method.

Step-4: Obtain decision matrix

Financial and Traffic Data on 8 criteria is collected from financial reports for the Airline companies.

Step-5: Categorize the criteria into inputs and outputs

DEA approach determines performance of organizations in terms of efficiency by considering the criteria as inputs and outputs. In this study, Operation revenue, net income are identified as an output while Revenue Passenger Kilometer, Revenue Ton Kilometer (RTK), energy cost, capital cost,labor and other operating expenses per employee are used as inputs.

Step-6: Formulate triangular fuzzy number for the criteria

The data obtained from various financial years is converted into triangular fuzzy number to know expected possible performance of the alternatives. Let x, y and z be real numbers with $x < y < z$. Then the Triangular Fuzzy Number (TFN) $A = (x, y, z)$. In this study, minimum, average and maximum values of the criteria are considered for formulation of triangular fuzzy numbers.

Step-7: Obtain weighted fuzzy decision matrix

In the proposed method, fuzzy data on the enablers are multiplied with crisp weights of the enablers. The weights obtained in the literature (Karun Kumar and Kesava rao, 2019) are considered to formulate weighted fuzzy decision matrix

Step-8: Select a DEA model

A DEA model which combining the IDMU and ADMU approaches as discussed in section 4.1 is considered to evaluate the performances of Airlines.

Step-9: Solve the LP model of DEA in fuzzy environment

Linear programming model of proposed DEA approach is formulated in fuzzy environment by considering the inputs and outputs as fuzzy triangular numbers.

Step-10: Obtain efficiency scores of airlines

Linear programming model of proposed DEA approach is coded in Lingo 8.0 and solved to obtain the efficiency scores of airlines. In the proposed method two types of efficiencies are calculated by considering two sets of weights (□i, □r) and (□i,□r).

Step-11: Performance ranking of airlines

By combine the efficiency scores obtained from two sets of common weights, the linear combination of corresponding efficiency scores by adopting the normalization scheme proposed by Zhou et al.(2007).

$$\Delta_k(\beta)=\beta\frac{\Gamma_k-\Gamma_{min}}{\Gamma_{max}-\Gamma_{min}}+(1-\beta)\frac{\Gamma'_k-\Gamma'_{min}}{\Gamma'_{max}-\Gamma'_{min}}$$

where □max= max{□k, k = 1,2,....,n}, □min = min {□k, k = 1,2,....,n}, □□max = max {□□k, k = 1,2,...,m}, □□min = min {□□k, k = 1,2,…,m}, =efficiency of DMU obtained by considering weights(□□k= efficiency of DMU obtained by considering weights and 0 □□□ 1 is an adjusting parameter, which may reflect the preference of a decision-maker on the best and worst sets of weights. □k(□) is a normalized compromise grade in the range [0,1].

The proposed methodology as illustrated in the above steps is implemented with a case study of twenty world airlines

6. CASE STUDY

The study is developed based on an empirical study of selected 20 Airlines. The secondary data during 2009-2013 on shortlisted 08 criteria in the study is obtained from annual reports of respective Airline companies. An integrated BSC-DEA methodology developed in section 5.1 is implemented. The financial and traffic data of 20 Airlines on 08 criteria during five financial years (FY 2008-09 to 2012-13) is considered from the literature.

7. RESULTS AND DISCUSSION

In this study, Operating revenue (OR, Net Income (NI) are considered as output criteria. Revenue Passenger Kilometer (RPK), Revenue Ton Kilometer (RTK), Energy Cost (EC), Capital Cost (CC), Labour Cost (LC), and Operating expenses per Employee (OE)are considered as input criteria. The proposed integrated balanced scorecard and DEA method is implemented to a case study of twenty world Airlines. The results are presented and discussed in the following sections.

7.1 Decision Matrix

Financial and Traffic Data on 8 criteria is collected from financial reports for the Airline companies during financial years FY2008-09 to 2012-13 is considered.

7.2 Inputs and Outputs

In this study, Operation revenue, net income are identified as an output while Revenue Passenger Kilometer, Revenue Ton Kilometer (RTK), energy cost, capital cost,labor and other operating expenses per employee are used as inputs.

7.3 Triangular Fuzzy Number for the Criteria

The data obtained from various financial years is converted into triangular fuzzy number to know expected possible performance of the alternatives. In this study, minimum, average and maximum values of the criteria are considered for formulation of triangular fuzzy numbers. The triangular fuzzy data is presented Table-2.

7.4 Weighted Fuzzy Decision Matrix

In the proposed method, fuzzy data on the enablers are multiplied with crisp weights of the enablers. The weights obtained in by CRITIC method are considered to formulate weighted fuzzy decision matrix.
Relative weights of criteria:
Relative weights of criteria are obtained by CRITIC method and are show in Table-3.
Weighted fuzzy decision matrix is shown in Table-4.

7.5 DEA Model in Fuzzy Environment

DEA model which combining the IDMU and ADMU approaches as discussed in section 4.1 is extended in fuzzy environment to evaluate the performances of Airlines.
Linear programming model of proposed DEA approach is formulated in fuzzy environment by considering the inputs and outputs as fuzzy triangular numbers. Lingo code is developed for the DEA model in fuzzy environment.

7.6 Ranking of Airlines

Linear programming model of proposed DEA approach is coded in Lingo 8.0 and solved to obtain the efficiency scores of airlines. In the proposed method two types of efficiencies are calculated by considering two sets of weights (□i, □r) and (□i, □r). The Lingo code is run for different possibility values (α = 0.0,0.25,0.5,0.75 and 1.0) as discussed in step 10 of section 5.1. Further, performance ranking of airlines is arrived by combining the efficiency scores obtained from two sets of common weights as discussed in step 11 of section 5.1 for the specified possibility levels. Ranking of air lines at different possibility levels are presented in table 5.

Table-2: Triangular fuzzy data

Airlines	OR			NI			RPK			RTK			EC			CC			LC			OE		
Aer Lingus	866.035	1562.845	1892.45	9.148	39.0916	65.174	5400	12535.2	14807	132.098	217.634	259.498	148.942	361.544	474.474	126.692	184.081	205.277	125.113	302.791	368.371	136.704	170.597	297.013
Aeroflot	3345.9	6062.991	9133.754	85.8	245.372	491.3	29900	55018.92	85300	1118.5	1956.22	2959.72	725.4	1582.42	2484.003	53.1	180.038	276.691	538.9	952.181	1423.61	233.5	722.887	2018.237
Air Asia	892.194	1362.524	1622.94	114.97	260.32	380.247	16890	21152.8	26607	28.346	79.1758	254.892	264.211	509.722	702.346	186.277	369.408	517.405	87.141	147.875	193.955	111.837	144.003	169.007
Air China	7523.592	13373.28	15979.43	587.58	997.228	1822.15	75473.77	115279.82	141967.95	629.895	988.772	1165.75	2117.73	4434.64	5647.52	1543.87	2156.24	2833.98	970.205	1753.08	2279.42	1962.54	3184.44	3836.409
Air Newzealand	2797.809	3300.638	3602.184	13.65	66.9952	141.966	25829	26936.6	27733	614.052	698.925	771.451	109.655	710.262	959.963	1144.43	1398.36	1641.19	662.35	770	852.016	341.601	390.596	433.697
Allegiant Air	557.94	781.1134	996.15	49.398	72.3248	91.779	4762.41	5902.5392	7129.416	52.938	68.292	81.228	165	300.616	385.558	77.486	120.038	141.449	90.006	121.957	158.627	96.179	120.906	145.919
Cathay Pacific	8587	11660.6	12882	145	738.4	1825	89440	99194.4	104571	3834	4398	4871	2224	4182	5188	1309	1480.8	1687	1618	1906.4	2183	1791	2181.2	2375
Cebu Pacific Air	489.885	756.6674	966.117	12.062	80.4876	153.538	7056	10181.4	12927	68.651	90.9944	114.46	154.677	319.994	459.984	68.139	109.611	190.554	27.096	52.7686	72.084	132.561	172.711	209.639
China Eastern Airlines	5707.805	11441.54	14343.44	28.789	460.456	780.554	60942.09	96912.744	120461.13	1359.7	2079.63	2447.81	1794.04	3845.35	4986.922	1574.05	2104.52	2499.7	753.758	1439.09	2186.83	1131.34	1972.75	2996.282
Copa Holdings	1256.076	1871.905	2608.332	241.057	310.903	427.471	4597.265	6593.2876	9032.318	180.87	252.282	343.597	300.816	542.264	783.092	168.703	280.594	413.983	157.879	214.676	276.156	199.555	259.013	338.385
EasyJet PLC	4159.278	5410.172	6657.806	111.047	337.108	622.313	50566	60168.2	67573	252.04	293.053	331.483	1258.95	3544.99	11326.8	110.735	343.865	489.407	547.438	692.16	841.216	2053.44	2365.28	2656.555
Emirates Group	11779.86	15288.67	21109.65	267.277	773.795	1481.9	101762	144646.6	188618	6036.41	7658.74	9869.28	3242.09	5190.22	7583.694	2551.68	3214.18	4108.89	245.82	1560.59	2160.62	2142.73	2666.99	3475.077
Ethiopian	1107.521	1567.918	2098.64	40.666	94.2908	122.498	9389	14155.6	21358	164.469	289.384	361.273	512.475	758.111	1056.087	182.006	239.872	332.298	65.765	105.942	228.463	126.092	240.498	298.353
Garuda Indonesia	1714.944	2838.623	3759.45	13.583	68.6394	110.843	18000	24038.52	31950	264.091	478.16	617.876	478.526	997.539	1420.139	413.353	595.812	843.818	144.598	286.945	699.821	314.397	509.507	706.183
JetBlue Airways	3292	4399.6	5441	61	108	168	16131.137	19183.468	22272.219	149	263.6	432	945	1485.8	1899	578	615.6	678	776	958.6	1135	783	968	1129
Norwegian	1161.242	1864.305	2649.832	21.786	43.6626	78.455	10602	17806.2	26881	219.642	297.373	385.61	226.136	513.491	800.597	307.513	511.865	797.935	209.219	315.267	424.002	75.433	114.568	158.024
Singapore Airlines	7441.988	9493.863	12067.68	205.031	515.529	913.899	16604.88	73175.656	93765.6	915.815	1066.64	1255.35	3076.93	4095.45	4715.269	1904.66	2056.77	2518.63	106.362	115.378	127.009	1607.11	1972	2213.444
Southwest Airlines Co	10350	14579.8	17699	99	382.2	754	46275.146	56843.928	64852.838	719	927.4	1132	3044	4838.2	6120	965	1480.8	1838	3468	4265.4	5035	2055	2685.8	3229
Turkish Airlines	4557.787	7046.397	9855.085	11.022	312.689	641.865	40130	62684	91997	2215.19	2866.56	4075	987.259	2224.38	3451.314	865.272	1111.76	1605.45	913.47	1280.41	1614.9	691.376	4580.23	17467.91
WestJet	1998.47	2923.554	3555.241	86.013	165.422	260.874	22260.131	27093.163	31522.197	182.513	267.227	335.996	499.871	816.427	1009.091	313.321	425.091	492.459	409.918	574.199	700.278	1474.32	1949.89	2250.874

Table-3: Relative weights of criteria

Criteria	OR	NI	RPK	RTK	EC	CC	LC	OE
Relative Weight	0.1034	0.1555	0.1051	0.1383	0.1070	0.1222	0.1651	0.1035

Table-4: Weighted fuzzy decision matrix

Airlines	OR			NI			RPK			RTK		
Aer Lingus	89.54802	161.5981	195.6793	1.42251	6.07874	10.1346	567.54	1317.4495	1556.2157	18.2692	30.0988	35.8886
Aeroflot	345.9661	626.9132	944.4302	13.3419	38.1554	76.3972	3142.49	5782.4885	8965.03	154.689	270.546	409.329
Air Asia	92.25286	140.885	167.812	17.8778	40.4797	59.1284	1775.139	2223.1593	2796.3957	3.92025	10.95	35.2516
Air China	777.9394	1382.797	1652.273	91.3687	155.069	283.344	7932.2932	12115.909	14920.832	87.1145	136.747	161.224
Air Newzealand	289.2935	341.286	372.4658	2.12258	10.4178	22.0757	2714.6279	2831.0367	2914.7383	84.9234	96.6613	106.692
Allegiant Air	57.691	80.76713	103.0019	7.68139	11.2465	14.2716	500.52929	620.35687	749.30162	7.32133	9.44478	11.2338
Cathay Pacific	887.8958	1205.706	1331.999	22.5475	114.821	283.788	9400.144	10425.331	10990.412	530.242	608.243	673.659
Cebu Pacific Air	50.65411	78.23941	99.8965	1.87564	12.5158	23.8752	741.5856	1070.0651	1358.6277	9.49443	12.5845	15.8298
China Eastern Airlines	590.187	1183.055	1483.111	4.47669	71.6009	121.376	6405.0137	10185.529	12660.465	188.047	287.613	338.531
Copa Holdings	129.8783	193.5549	269.7015	37.4844	48.3454	66.4717	483.17255	692.95453	949.29662	25.0143	34.8906	47.5195
EasyJet PLC	430.0693	559.4118	688.4171	17.2678	52.4203	96.7697	5314.4866	6323.6778	7101.9223	34.8571	40.5292	45.8441
Emirates Group	1218.038	1580.849	2182.738	41.5616	120.325	230.435	10695.186	15202.358	19823.752	834.836	1059.2	1364.92
Ethiopian	114.5177	162.1227	216.9994	6.32356	14.6622	19.0484	986.7839	1487.7536	2244.7258	22.7461	40.0218	49.9641
Garuda Indonesia	177.3252	293.5136	388.7271	2.11216	10.6734	17.2361	1891.8	2526.4485	3357.945	36.5238	66.1296	85.4523
JetBlue Airways	340.3928	454.9186	562.5994	9.4855	16.794	26.124	1695.3825	2016.1825	2340.8102	20.6067	36.4559	59.7456
Norwegian	120.0724	192.7691	273.9926	3.38772	6.78953	12.1998	1114.2702	1871.4316	2825.1931	30.3765	41.1267	53.3299
Singapore Airlines	769.5016	981.6654	1247.798	31.8823	80.1648	142.111	1745.1729	7690.7614	9854.7646	126.657	147.516	173.615
Southwest Airlines Co	1070.19	1507.551	1830.077	15.3945	59.4321	117.247	4863.5178	5974.2969	6816.0333	99.4377	128.259	156.556
Turkish Airlines	471.2752	728.5974	1019.016	1.71392	48.6232	99.81	4217.663	6588.0884	9668.8847	306.361	396.445	563.572
WestJet	206.6418	302.2955	367.6119	13.375	25.7232	40.5659	2339.5398	2847.4915	3312.9829	25.2415	36.9575	46.4682

Airlines	EC			CC			LC			OE		
Aer Lingus	15.9368	38.6853	50.76872	15.4818	22.4947	25.0848	20.6562	49.9907	60.8181	14.1489	17.6568	30.74085
Aeroflot	77.6178	169.319	265.7883	6.48882	22.0007	33.8116	88.9724	157.205	235.037	24.1673	74.8188	208.8875
Air Asia	28.2706	54.5403	75.15102	22.763	45.1416	63.2269	14.387	24.4142	32.022	11.5751	14.9044	17.49222
Air China	226.597	474.507	604.2846	188.661	263.493	346.312	160.181	289.434	376.332	203.123	329.59	397.0683
Air Newzealand	11.7331	75.9981	102.716	139.85	170.879	200.553	109.354	127.127	140.668	35.3557	40.4266	44.88764
Allegiant Air	17.655	32.1659	41.25471	9.46879	14.6686	17.2851	14.86	20.1351	26.1893	9.95453	12.5137	15.10262
Cathay Pacific	237.968	447.474	555.116	159.96	180.954	206.151	267.132	314.747	360.413	185.369	225.754	245.8125
Cebu Pacific Air	16.5504	34.2393	49.21829	8.32659	13.3944	23.2857	4.47355	8.7121	11.9011	13.7201	17.8755	21.69764
China Eastern Airlines	191.962	411.452	533.6007	192.349	257.172	305.463	124.445	237.593	361.045	117.094	204.18	310.1152
Copa Holdings	32.1873	58.0222	83.79084	20.6155	34.2886	50.5887	26.0658	35.443	45.5934	20.6539	26.8079	35.02285
EasyJet PLC	134.708	379.314	1211.967	13.5318	42.0204	59.8055	90.382	114.276	138.885	212.531	244.807	274.9534
Emirates Group	346.903	555.354	811.4553	311.815	392.772	502.106	40.5849	257.653	356.718	221.773	276.034	359.6705
Ethiopian	54.8348	81.1178	113.0013	22.2411	29.3123	40.6068	10.8578	17.491	37.7192	13.0505	24.8915	30.87954
Garuda Indonesia	51.2023	106.737	151.9549	50.5117	72.8083	103.115	23.8731	47.3746	115.54	32.5401	52.7339	73.08994
JetBlue Airways	101.115	158.981	203.193	70.6316	75.2263	82.8516	128.118	158.265	187.389	81.0405	100.188	116.8515
Norwegian	24.1966	54.9436	85.66388	37.5781	62.5499	97.5077	34.5421	52.0505	70.0027	7.80732	11.8578	16.35548
Singapore Airlines	329.231	438.213	504.5338	232.749	251.337	307.777	17.5604	19.0489	20.9692	166.336	204.102	229.0915
Southwest Airlines Co	325.708	517.687	654.84	117.923	180.954	224.604	572.567	704.218	831.279	212.693	277.98	334.2015
Turkish Airlines	105.637	238.009	369.2906	105.736	135.857	196.186	150.814	211.396	266.619	71.5574	474.054	1807.929
WestJet	53.4862	87.3577	107.9727	38.2878	51.9461	60.1785	67.6775	94.8003	115.616	152.592	201.813	232.9655

Table-5: Ranking of airlines at different α values

Airlines	**α = 0.00**	**α = 0.25**	**α = 0.50**	**α = 0.75**	**α = 1.00**
Aer Lingus	1	1	2	6	7
Aeroflot	8	13	12	12	12
Air Asia	10	15	18	20	20
Air China	13	14	13	10	6
Air New Zealand	14	19	17	17	14
Allegiant Air	4	4	4	5	5
Cathay Pacific	17	18	16	16	11
Cebu Pacific Air	19	20	20	19	19
China Eastern Airlines	15	17	14	11	10
Copa Holdings	2	3	3	1	1
Easy Jet PLC	6	8	8	15	18
Emirates Group	18	9	19	18	16
Ethiopian	12	12	11	9	9
Garuda Indonesia	7	11	9	7	8
JetBlue Airways	3	2	1	2	3
Norwegian	11	6	7	8	17
Singapore Airlines	16	5	6	4	4
Southwest Airlines Co	5	7	5	3	2
Turkish Airlines	20	16	15	14	15

Airlines	**α = 0.00**	**α = 0.25**	**α = 0.50**	**α = 0.75**	**α = 1.00**
WestJet	9	10	10	13	13

From the above Table 5 it is observed that ranking is sensitive to the possibility value. The possibility value indicates the decision maker's attitude on uncertainty. Ranking of Airlines at α=1.00 indicates the ranking at mean perspective. Ranking of Airlines at α=0.00 indicates the ranking obtained by considering complete certainty in the data. Hence the decision maker can consider ranking of Airlines based on attitude on uncertainty in the data. However, Final crisp ranking is obtained by Copeland method (Moghimi and Yazdi, 2013)

7.7 Final Ranking by Copeland Method

This method starts with the end of the Borda's method. This method calculates not only the number of Borda, but also the number of losses for each alternative. Difference between the preference value for each row and column for each alternative is calculated. Alternatives are ranked based on the descending order of the difference value. The Table 6 shows the difference values of the alternatives.

Table-6: Final ranking of airlines

Airlines	Superiority	Inferiority	Difference	Rank
Aer Lingus	17	2	15	3
Aeroflot	7	12	-5	13
Air Asia	1	18	-17	19
Air China	8	11	-3	12
Air New Zealand	2	17	-15	18
Allegiant Air	16	3	13	4
Cathay Pacific	5	14	-9	15
Cebu Pacific Air	0	19	-19	20
China Eastern Airlines	6	13	-7	14
Copa Holdings	19	0	19	1
EasyJetPLC	9	10	-1	11
Emirates Group	3	16	-13	17
Ethiopian	11	8	3	9
Garuda Indonesia	13	6	7	7
JetBlue Airways	18	1	17	2
Norwegian	12	7	5	8
Singapore	14	5	9	6

Airlines				
Southwest Airlines Co	15	4	11	5
Turkish Airlines	4	15	-11	16
WestJet	10	9	1	10

From the final ranking of Airlines obtained through Copeland method shown in table.From the results it is observed that Copa Holdings is ranked as first with difference value of 19 followed by JetBlue Airways with difference value of 17. Cebu Pacific Air is ranked least efficient with difference value of 19.

8. CONCLUDING REMARKS

Integrated BSC-DEA model is considered as one of the most important hybrid MCDM methods in performance measurement in the present competitive business environment. The proposed methodology is suitable to evaluate the performance of business organization of manufacturing/service, small/large and public/private. Using the proposed approach, the performance of Airline organizations are from an academic perspective and useful for reforms in Airline organizations. The integrated model is useful to align the goals of the organization towards scorecard perspectives and identify the roles and responsibilities of stake holders to improve the performance of the organization as whole.

There is limited study in the literature in assessing the efficiency of major airline using integrated BSC-DEA model. Furthermore, the relative performance of airlines on their operational efficiency is assessed based on time-series data (2009-2013) on eight criteria. The present study is limited to the factors considered in the study is not sufficient to all categories of airlines. Further studies, might reconsider the variables as input and output based on their effect on the objectives of the airlines. The Study can be extended to analyze the potential presence of unobserved bias in the proposed methodology by considering stochastic frontier analysis.

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