A Framework for Continuous Monitoring and Assessment of Landline Telecommunication Sectors Based on Standard Indicators

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ABSTRACT

This paper proposes a DEA-PCA based methodology for assessment and ranking of landline telecommunication sectors based on standard indicators identified by the International Telecommunication Union (ITU). A total of 16 indicators were identified from the ITU database. The case study is based on randomly selected 8 indicators. To present the usability of the proposed methodology, data for 18 countries with respect to 3 inputs and 5 outputs were collected through the ITU. The results show weak and strong points of each country identifying, inputs or outputs having major impact on Performance. This is the first study to present an integrated standard model for technical performance analysis of telecommunication landline sectors.

Keywords: DEA, Telecommunication, Landline Sector, PCA, Standard Indicators

1. INTRODUCTION

Major factors influencing the overall productivity of an industrial organization are identified as technology, machinery, management, personnel and rules and procedures ([2], [3], [29]). Technical factors play an important role in the overall performance of a particular industrial sector. In fact, technical productivity is correlated with the overall performance. Furthermore, the overall performance of an industrial organization is often assessed by technical productivity.

The need for an integrated approach for continuous assessment and improvement of telecommunication sectors based on technical performance has become essential. Continuous assessment requires manufacturing classifications and taxonomy to be introduced to enhance knowledge and understanding about the behavior of manufacturing systems ([9], [11], [18], [25], [28]). Consequently, it will enable predictions to be made about organizational system behavior.

2. PROPOSED FRAMEWORK

To achieve the objectives of this study, all technical indicators (inputs and outputs), which influence overall technical performance of telecommunication landline sectors are defined by the ITU [19]. These indicators are related to technical productivity, efficiency, effectiveness and profitability. A generalized classification of standard indicators proposed by the ITU for technical purposes contains of seven groups namely, 1) Telephone network size and dimension, 2) Other services (telex, leased circuits, ISDN subscribers, etc, 3) Quality of service, 4) Traffic, 5) Broadcasting, 6) Mobile services and 7) Information Technology.

Amongst these 7 categories there are standard indicators specified by the International Telecommunication Union (ITU) for performance assessment of landline sectors such as international incoming telephone traffic, telephone faults per 100 lines and telephone faults cleared by next working day. Classified list of standard indicators for telecommunication landline sectors as per International Telecommunication Union (ITU) is given as follows:

Outputs:
1. % of telephone faults cleared by next working day
2. Connection capacity of local exchanges (no. of subscribers connected at one time)
3. International telephone circuits (no. of circuits)
4. % digital main lines
5. Number of local telephone (calls)
6. Number of local telephone (minutes)
7. Number of national long distance telephone (calls)
8. Number of national long distance telephone (minutes)
9. Total national telephone traffic (calls)
10. Total national telephone traffic (minutes)
11. International outgoing telephone traffic (calls)
12. International outgoing telephone traffic (minutes)

Inputs:
1. Telephone faults per 100 main lines (no. of faults)
2. International incoming telephone traffic (calls)
3. International incoming telephone traffic (minutes)
4. Waiting list for main lines (no. of main lines pending to be installed)

The framework of this study utilizes a set of standard indicators, a robust mathematical approach (DEA) and PCA and Spearman correlation technique all used for ranking, assessment and optimization of LTUs being studied. This will aid managers to foresee various economics and technical issues with respect to their LTUs. The steps for implementing the framework of this study are shown as follows:

Step 1: Identify landline technical units (LTUs) or target markets to be studied, ranked and analyzed.

Step 2: Collect standard indicators of the study.

Step 3: Design Preliminary matrix for DEA and conduct DEA analysis, rank LTUs and identify most important inputs and outputs for each LTU. Suppose we have **n** DMUs, where each DMUj (j = 1,…,n) produces 12 output y_{rj} (r = 1,…,5) by utilizing 4 inputs x_{ij} (i =1,…,3). The CRS input-oriented model uses the following measure of performance for DMUj:

$$h_o^* = \underset{v_i, u_r}{Max}\, \mathrm{h_o} \quad \text{S.T.}$$

$$h_j \le 1, \; \mathrm{j} = 1,\ldots,\mathrm{n}$$

$$v_i, u_r \ge 0, \tag{1}$$

Where $h_o = \frac{\sum_{r=1}^{5} u_r y_{ro}}{\sum_{i=1}^{3} v_i x_{io}}$ represents the ratio of aggregated outputs to aggregated inputs for one of the **n** DMUs, denoted as $DMU_o, o \in \{1,\ldots,n\}$. x_{io} and y_{ro}

are respectively the i[th] input and r[th] output of DMUo. By varying **o** over {1,…, n}, we obtain all the DEA scores, h_j^*, with **n** sets of optimal weights. It is clear that larger the h_j^*, the better the performance of DMUj, since DMUj produces more aggregated output or uses less aggregated inputs. However, the highest possible value of h_j^* is one, because of the constraints of Equation (1). If $h_j^* = 1$, then DMUj is relatively efficient.

The above-mentioned model can lead to a large number of DMUs having DEA scores of unity. We may use the following linear programming problem which is equivalent to Equation (1) by duality:

$$\theta_o^* = \underset{\theta_o, \lambda_j}{Min}\ \theta_o$$

Such that:

$$\sum_{j \neq o} \lambda_j . x_{ij} \leq \theta_o . x_{io} \quad i = 1, \ldots, 4$$
$$\sum_{j \neq o} \lambda_j . y_{rj} \geq y_{ro} \quad r = 1, \ldots, 12 \qquad (2)$$
$$\lambda_j \geq 0,\ j \neq o$$

Where θ_o is a scalar and λ is a n× 1 vector of constants. The estimated value of θ_o is the efficiency score for each of the n DMUs. The linear programming problem must be solved n times, once for each LTU. Equation (1) is known as a constant return to scale (CRS). The CRS assumption is only appropriate when all LTUs are operating at an optimal scale. The optimal values θ_o^* can be less than, equal to, or greater than one. Now we are capable to rank the DMUs according to their aggregated output to aggregated to input ratios by θ_o^*.

Step 4: Develop Preliminary raw table for PCA analysis. There are 48 indicators to be used in PCA because there are 12 outputs and 4 inputs. Therefore, there are 48 variables and n DMUs and suppose $X = (x_1 \ldots x_p)_{n \times 48}$ is an n× 48 matrix composed by x_{ij}'s defined as the value of jth index for ith DMU and therefore $x_m = (x_{1m} \ldots x_m)^T (m = 1, \ldots, 48)$. Furthermore, suppose $\hat{X} = (\hat{x}_1 \ldots \hat{x}_p)_{n \times 48}$ is the standardized matrix of $X = (x_1 \ldots x_{48})_{n \times 48}$ with $\hat{x}_{ij}$'s defined as the value of jth standardized index for ith DMU and therefore $\hat{x}_m = (\hat{x}_{1m} \ldots \hat{x}_m)^T$. PCA is performed to identify new independent variables or principal components (defined as Y_j for *j=1…p*), which are respectively different linear combination of $\hat{x}_1 \ldots \hat{x}_{48}$. As mentioned, this is achieved by identifying Eigen structure of the covariance of the original data. The principal components are defined by an n ×48 matrix $Y = (y_1 \ldots y_{5})_{n \times 48}$ composed by y_{ij}'s : The following formulae are used to find out the principal components Y_i, the weights (w_i) of the principal components and PCA scores (z_i of each DMU ($i = 1 \ldots n$).

$$Y_m = \sum_{j=1}^{5} l_{ji} \hat{x}_j \quad \text{for} \quad m = 1 \ldots 8 \quad \text{and} \quad i = 1 \ldots n \qquad \ldots \qquad (4)$$

$$w_j = \lambda_j / \sum_{j=1}^{8} \lambda_j = \lambda_j / 8 \qquad j = 1 \ldots 5 \qquad \ldots \qquad (5)$$

$$z_i = \sum_{j=1}^{8} w_j Y_j \qquad i = 1 \ldots n \qquad \ldots \qquad (6)$$

Step 5: Verify and validate DEA by PCA by Spearman and Kendal Tau non-parametric correlation analysis methods.

Step 6: Check if the model is validated or not, if validated move on to Step 7, otherwise jump back to Step 2.

Step 7: Utilize the surplus and slack results of DEA for optimization purpose.

Step 8: Assess weak and strong points, take corrective actions and continuously perform DEA, monitor and improve performance.

3. THE CASE STUDY

Landline telephony is one of the most basic needs of today's world. Hence, there is a great need to develop models that assist in determining the efficiency of the sector. The case study works in this direction to present a comprehensive methodology for the assessment of telecommunication landline sector. In order to show the applicability of the proposed methodology a group of 8 indicators comprising of 3 inputs and 5 outputs were collected with respect to 18 countries in 2002 from ITU (Table 1). The following subsections discuss the DEA method used to determine the efficiency of the LTUs, and the PCA method used for verification.

Table 1. The selected technical inputs and outputs

Inputs	x_1	International incoming telephone traffic (minutes)
	x_2	Telephone faults per 100 main lines
	x_3	Waiting list for main lines
Outputs	y_1	% digital main lines
	y_2	% of telephone faults cleared by next working day
	y_3	Connection capacity of local exchanges
	y_4	International outgoing telephone traffic (minutes)
	y_5	International telephone circuits

3.1 DEA for Efficiency Analysis

Table 2 shows the standardized matrix used to perform the DEA analysis. The data presented in the matrix is taken from the International Telecommunications Union (ITU) for year 2002 [19], Landline technical units (LTUs) are listed along with the respective data in the matrix, these values can be obtained online from the ITU website, http://www.itu.int/ITU-D/ict/publications/world/world.html .

As per the generalized equations (1) and (2) for DEA analysis, we can find the efficiency of DMU1 as shown in model 3. The values for the model have been taken from standard DEA matrix shown in Table 2.

$$\theta_1^* = Min\ \theta_1$$

$$\sum_{j \neq 1} \lambda_j . x_{ij} \leq \theta_1 . x_{i1} \quad i = 1, \ldots, 3 \qquad (7)$$
$$\sum_{j \neq 1} \lambda_j . y_{rj} \geq y_{r1} \quad r = 1, \ldots, 5$$
$$\lambda_j \geq 0,\ j \neq 1 \quad j = 2, 3, \ldots, 18$$

Where θ_1 is a scalar and λ is a 18× 1 vector of constants. The estimated value of θ_1 is the efficiency score for each of the n LTUs. The linear programming problem must be solved n times, once for each LTU. Equation (3) shows the solutions for LTU1. The CRS assumption is only appropriate when all LTUs are operating at an optimal scale. The optimal values of θ_1^* can be less than, equal to, or greater than one. Now we are capable to rank the LTUs according to their aggregated output to aggregated to input ratios by θ_o^* .After performing DEA analysis it was easy to rank the countries from the range 1 to 18 with respect to their efficiency measures. Table 3 presents the DEA rankings and efficiences of the 18 countries with respect to Model 7. Table 4 shows the results of slack and surplus for the DEA model which may be used for optimization purpose. After performing DEA analysis it was easy to rank the countries from the range 1 to 18 with respect to their efficiency measures.

3.2 Verification and Validation

A comparative study is conducted through PCA by considering the 3 input and 5 output indicators. Furthermore, PCA ranks the countries as per their performance

Table 2. Standardized matrix for 18 countries for DEA (2002)

No.	LTU	x_1	x_2	x_3	y_1	y_2	y_3	y_4	y_5
1	Armenia	52253000	52.90000153	60759	37.00999832	87.69999695	698837	37109000	1177
2	Azerbaijan	155232832	45.20000076	1E-13	48.40000153	69.5	1028908	42246024	2176
3	Benin	32084772	6.239999771	14205	87.33000183	18.60000038	99705	27531502	856
4	Cape Verde	50591000	43	789	100	89.19999695	91980	8720000	918
5	Czech Republic	871382976	6.789999962	27291	100	100	4941961	344974112	19980
6	Egypt	1141923840	0.5	99520	100	95	11286498	306944768	12086
7	Eritrea	31393464	51.06000137	46237	81.08999634	66.84999847	45411	4823376	285
8	Ethiopia	87858480	100	146062	90	24	649593	15805345	1012
9	Latvia	104411776	20.26000023	16168	88.69999695	89.26999664	813678	50201560	2727
10	Micronesia (Fed. States of)	6395572	48.09999847	120	100	65	15360	2387050	107
11	Mongolia	5485000	20.61000061	35578	99.5	85	152000	4575176	251
12	Myanmar	48621644	155	102569	82.05999756	75	420840	9434245	1649
13	Palestine	74668600	94	400	100	76	427310	38750240	499
14	Qatar	164587312	23.39999962	1E-13	100	88.30999756	208155	290705824	4520
15	Slovak Republic	212882000	10	12155	84.26000214	73.80000305	2059305	139510000	7564
16	Suriname	52875572	38.58000183	6087	77	41.79999924	122825	34233396	777
17	Swaziland	24664192	70	22616	100	82	51851	27844848	608
18	Taiwan, China	2608485632	1.399999976	1E-13	100	92.94000244	18351288	3076736000	52329

based on 15 indicators (outputs divided by inputs). This in turn shows which country is either weak or strong in terms of the telecommunication landline sectors. Furthermore, PCA identifies which technical indicators has the major impact on the performance of these countries. In order to verify the finding of the DEA analysis we use the PCA analysis approach and the steps required to do so are mentioned as follows:

Step 1: Normalize and standardize the indicators' vectors. The fifteen indicators must be normalized and have same order to be used in PCA. In this study the outputs were normalized with respect to each input (Table 5).

Step 2: Evaluate the correlation matrix.

Step 3: Eigenvalues, eigenvectors and proportion of the sample variance are calculated for all the twelve principal components (new variables) (Table 6).

Step 4: The principal components and aggregated weights are computed. PCA then provides us with the ranks of the countries as per their performance, the comparision between the DEA results and the PCA results is shown in Table 7.

To verify the results of the integrated DEA model, the PCA rankings are compared with that of the DEA through Spearman correlation experiment. The Spearman correlation is computed by the following formula:

$$r_s = 1 - \frac{6\sum d_i^2}{N(N^2-1)}$$

Where N = 18 and Σd_i^2 = 198, substituting values in the equation we find the sperman correlation to be 79.56%. Therefore, we may further analyze and implement the PCA and DEA results. Moreover, the DEA surpluses and slacks may be used for optimization of LTUs as shown in Table 4. PCA may also be used to identify the importance of each of the 15 indicators. It should be noted that the 15 aggregated weights ($\widetilde{w}_m$) for $m = 1...15$ show the importance of each indicator computed as follows:

Table 3. The DEA rankings and efficiencies of the LTUs of the 18 countries

LTU	Efficiency	Ranks
Armenia	1.046643	12
Azerbaijan	1.582894	7
Benin	2.471646	6
Cape Verde	1.189448	9
Czech Republic	1.18794	10
Egypt	2.862061	5
Eritrea	0.432103	18
Ethiopia	0.508211	17
Latvia	1.111	11
Micronesia	7.878781	2
Mongolia	3.071948	4
Myanmar	0.874162	13
Palestine	0.858285	14
Qatar	3.540706	3
Slovak Republic	1.530509	8
Suriname	0.644601	16
Swaziland	0.8419	15
Taiwan	659.6801	1

$$\tilde{w}_m = \sum_{j=1}^{5} w_j l_{jm} \tag{8}$$

4. CONCLUSION

In summary, a unique integrated framework is presented to assess technical performance of the telecommunication landline sectors. Managers on the technical front may use this type of modeling approach to assess the performance of various telecommunication landline services with respect to the technical indicators. In turn, the selected LTUs or target markets would be ranked based on an integrated scientific approach, which reveals the standing of each LTU with respect to a series of standard technical indicators. This would enable managers of telecommunication landline sector to continuously monitor and improve technical performance. In addition, they may want to compare technical performance of a particular LTU or all LTUs with that of similar organizations or competitors. This would bring about further insights and knowledge of their standings with respect to competitors. The case study shows that Taiwan is ranked first and Micronesia is second amongst the 18 countries selected. This is the first study to present an integrated standard model for technical performance of telecommunication landline sectors.

5. REFERENCES

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Table 4. Results from the DEA model – Slack and surplus

LTU	x_1	x_2	x_3	y_1	y_2	y_3	y_4	y_5
Armenia	7.45E-09	-17.9673	0	151.1142	73.39596	0	0	835.7737
Azerbaijan	-1.16E+17	-3.4E+10	0	26.37942	0	12694080	2.26E+09	36955.33
Benin	0	-1.78E-15	-10312.7	0	56.65422	724289.8	25002011	1993.97
Cape Verde	-3.73E-08	7.11E-15	1.14E-13	24.03836	-1.42E-14	25673.14	82680159	665.8127
Czech Republic	0	-1.78E-15	0	10.78123	1.42E-14	3525506	5.49E+08	779.2856
Egypt	-601953946	-2.22E-16	-284832	2.216481	0	7471543	2.84E+09	41402.86
Eritrea	0	0	0	0	0	58122.74	303548.5	52.17543
Ethiopia	-7.45E-09	-7.11E-15	0	52.10739	124.306	0	11093580	0
Latvia	-1.49E-08	0	-7.28E-12	13.72703	0	1.16E-10	60739747	1010.86
Micronesia	0	-336.069	0	0	24.18312	76891.96	6314508	808.0213
Mongolia	0	-2.74683	-97348.8	12.22212	0	0	5138674	89.80189
Myanmar	-1.49E-08	-83.1527	0	175.5273	145.2967	235065.1	20845611	0
Palestine	1.49E-08	-26.581	0	15.5423	0	0	29145519	819.3695
Qatar	0	1.42E-14	-5.42E-20	0	49.48307	3776053	1.39E+08	5454.393
Slovak Republic	0	7.11E-15	-1141.9	1.312514	12.03285	2.33E-10	31226290	9.09E-13
Suriname	-7.45E-09	3.55E-15	4.55E-13	0	1.929509	0	6833798	183.0821
Swaziland	3.73E-09	-24.4239	0	6.451316	-1.42E-14	70644.9	0	1.14E-13
Taiwan	-1.7169E+12	-1.14E-13	1.39E-17	1506.007	1757.999	0	0	20073.68

Table 5. Standardized PCA index matrix

LTU	y_1/x_1	y_1/x_2	y_1/x_3	y_2/x_1	y_2/x_2	y_2/x_3	y_3/x_1	y_3/x_2	y_3/x_3	y_4/x_1	y_4/x_2	y_4/x_3	y_5/x_1	y_5/x_2	y_5/x_3
Armenia	-0.439	-0.373	-0.414	-0.151	-0.334	-0.431	1.0371	-0.339	-0.252	0.2565	-0.304	-0.262	0.1001	-0.359	-0.267
Azerbaijan	-0.515	-0.365	1.0373	-0.456	-0.337	1.7186	-0.042	-0.338	-0.014	-0.758	-0.303	-0.203	-0.734	-0.356	-0.09
Benin	-0.051	-0.097	-0.414	-0.423	-0.305	-0.431	-0.605	-0.339	-0.252	0.5991	-0.297	-0.262	0.5075	-0.347	-0.267
Cape Verde	-0.194	-0.339	-0.414	-0.13	-0.325	-0.431	-0.811	-0.341	-0.252	-0.989	-0.305	-0.262	-0.329	-0.359	-0.267
Czech Republic	-0.553	-0.082	-0.414	-0.539	-0.049	-0.431	-0.195	-0.22	-0.252	-0.471	-0.209	-0.262	0.1397	-0.071	-0.267
Egypt	-0.559	3.7666	-0.414	-0.547	3.7774	-0.431	0.4789	3.4362	-0.252	-0.766	0.8573	-0.262	-1.071	2.0219	-0.267
Eritrea	-0.078	-0.354	-0.414	-0.039	-0.342	-0.431	-0.87	-0.341	-0.252	-1.032	-0.305	-0.262	-1.219	-0.36	-0.267
Ethiopia	-0.378	-0.369	-0.414	-0.499	-0.365	-0.431	0.0807	-0.341	-0.252	-0.972	-0.305	-0.262	-0.979	-0.36	-0.267
Latvia	-0.412	-0.296	-0.414	-0.355	-0.274	-0.431	0.1445	-0.335	-0.252	-0.275	-0.3	-0.262	0.4524	-0.348	-0.267
Micronesia	2.4393	-0.344	-0.414	1.9526	-0.341	-0.431	-0.718	-0.342	-0.252	-0.524	-0.305	-0.262	-0.468	-0.361	-0.267
Mongolia	2.9222	-0.287	-0.414	3.2749	-0.28	-0.431	3.3301	-0.34	-0.252	0.5436	-0.305	-0.262	2.379	-0.36	-0.267
Myanmar	-0.25	-0.376	-0.414	-0.185	-0.36	-0.431	0.2825	-0.341	-0.252	-0.939	-0.305	-0.262	1.2171	-0.36	-0.267
Palestine	-0.317	-0.365	-0.414	-0.315	-0.353	-0.431	-0.187	-0.341	-0.252	-0.186	-0.304	-0.262	-1.454	-0.36	-0.267
Qatar	-0.458	-0.299	2.5842	-0.434	-0.288	2.3003	-0.9	-0.34	-0.204	2.7025	-0.281	0.1399	0.5843	-0.342	0.1009
Slovak Republic	-0.499	-0.212	-0.414	-0.481	-0.209	-0.431	0.4453	-0.307	-0.252	0.1295	-0.279	-0.262	1.3757	-0.286	-0.267
Suriname	-0.295	-0.346	-0.414	-0.371	-0.347	-0.431	-0.73	-0.341	-0.252	0.1112	-0.303	-0.262	-0.668	-0.359	-0.267
Swaziland	0.2062	-0.358	-0.414	0.2571	-0.345	-0.431	-0.766	-0.342	-0.252	1.2264	-0.304	-0.262	0.3086	-0.36	-0.267
Taiwan	-0.568	1.0962	2.5842	-0.558	1.0788	2.4435	0.0233	1.8521	4.0005	1.3435	3.8559	3.989	-0.142	3.3237	3.9893

Table 6: Eigen values and vectors from the PCA analysis

Eigen Value	6.92588	2.97356	2.59288	1.06312	0.76978	0.44512	0.20797	0.01113	0.00804	0.00158	0.00082	0.00012	2.9E-08	8.7E-17	-7E-16
Weight	0.46173	0.19824	-0.1729	-0.0709	-0.0513	-0.0297	0.01386	0.00074	-0.0005	0.00011	5.5E-05	-8E-06	1.9E-09	5.8E-18	-5E-17
Vectors	vector1	vector2	vector3	vector4	vector5	vector6	vector7	vector8	vector9	vector10	vector11	vector12	vector13	vector14	vector15
y_1/x_1	-0.121	0.22832	-0.4471	0.20875	-0.4664	0.09736	0.13603	0.26397	-0.5751	-0.0007	-0.2065	-0.035	0.00066	4.1E-13	-5E-12
y_1/x_2	0.22693	-0.3799	-0.233	-0.2394	-0.1099	0.04144	0.08231	0.15273	-0.2021	0.03806	0.76357	0.15226	0.01256	7.5E-12	-1E-10
y_1/x_3	0.27719	0.27128	0.16897	-0.2596	-0.2443	-0.3318	0.13181	-0.606	-0.2935	0.00223	0.02784	0.03675	-0.0232	0.33199	0.01521
y_2/x_1	-0.1195	0.2437	-0.4761	0.16134	-0.3692	-0.0127	0.00645	-0.2848	0.63477	-0.0123	0.2267	0.03945	-0.001	-6E-13	7.7E-12
y_2/x_2	0.226	-0.3818	-0.2341	-0.2369	-0.1111	0.00775	0.07178	-0.0779	0.09617	-0.2293	-0.2258	-0.7455	-0.0079	-4E-12	5.8E-11
y_2/x_3	0.26543	0.25793	0.18061	-0.2322	-0.2499	-0.5056	0.18058	0.5379	0.24217	-0.0348	-0.0401	0.01301	-0.0316	-0.2715	0.01171
y_3/x_1	-0.0218	0.10819	-0.4967	-0.1073	0.41744	-0.5208	-0.514	0.01692	-0.1383	-0.0028	-0.0207	-0.0015	0.00013	7.6E-14	-1E-12
y_3/x_2	0.28073	-0.321	-0.215	-0.1397	-0.0858	0.02589	0.03933	-0.0483	0.12397	0.64901	-0.4277	0.32798	0.11606	6.9E-11	-9E-10
y_3/x_3	0.34183	0.16398	-0.0035	0.29769	0.13347	0.05779	-0.0159	0.31305	0.1253	0.11779	0.08616	-0.1759	0.2219	0.67388	0.27734
y_4/x_1	0.13831	0.35415	0.03731	-0.5273	-0.1498	0.52493	-0.5158	0.10098	0.03439	-0.0092	-0.0236	-0.0016	0.00048	2.9E-13	-4E-12
y_4/x_2	0.36552	0.03292	-0.0753	0.20433	0.09708	0.10692	-0.0108	0.00247	0.0148	-0.0134	-0.036	0.06438	-0.8894	-5E-10	7E-09
y_4/x_3	0.34541	0.18029	0.00604	0.24398	0.10606	0.09672	-0.0236	-0.2236	-0.1253	0.12467	0.10994	-0.1508	0.20771	-0.5853	0.51546
y_5/x_1	-0.0632	0.33407	-0.2893	-0.3598	0.49437	0.19822	0.62125	0.00684	0.02921	0.01886	-0.0185	0.006	-9E-05	-6E-14	7.5E-13
y_5/x_2	0.35995	-0.1174	-0.1395	0.0732	0.04082	0.08583	0.02516	-0.0302	0.04216	-0.6922	-0.2338	0.47671	0.24168	1.4E-10	-2E-09
y_5/x_3	0.34566	0.17958	0.00843	0.24879	0.10492	0.06776	-0.0154	-0.0387	-0.0388	0.11913	0.09934	-0.1552	0.20712	-0.1393	-0.8106

Table 7. Comparison of the DEA and PCA analysis (2002)

LTUs	DEA RESULTS		PCA RESULTS	
	Efficiency	Ranks	Zpca	Rank
Armenia	1.046643	12	-0.40631	9
Azerbaijan	1.582894	7	0.000445	5
Benin	2.471646	6	-0.43095	10
Cape Verde	1.189448	9	-0.7777	16
Czech Republic	1.18794	10	-0.53764	12
Egypt	2.862061	5	1.012247	3
Eritrea	0.432103	18	-0.85645	18
Ethiopia	0.508211	17	-0.80292	17
Latvia	1.111	11	-0.53582	11
Micronesia	7.878781	2	-0.34278	7
Mongolia	3.071948	4	0.601724	4
Myanmar	0.874162	13	-0.54672	13
Palestine	0.858285	14	-0.73054	15
Qatar	3.540706	3	1.057965	2
Slovak Republic	1.530509	8	-0.35141	8
Suriname	0.644601	16	-0.66533	14
Swaziland	0.8419	15	-0.32451	6
Taiwan	659.6801	1	4.636692	1

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