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Efficiency Evaluation of Passenger Transport Organizations Using Balanced Scorecards

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ABSTRACT

This study introduces an innovative hybrid approach for the efficiency evaluation of public transport organizations by combining the Data Envelopment Analysis with the Balanced Scorecard's method. Data from various passenger transport organizations was collected, representing metrics relevant to each BSC perspective. DEA was then applied to compute efficiency scores, distinguishing organizations in terms of efficiency in each perspective.

The proposed method considers Learning and Growth, Internal business, Financial and customer perspectives with 20 criteria and provide a comprehensive approach to rank and calculate the outcome pattern of 5 state surface transport companies from the data available from the secondary sources. The hybrid model, by leveraging both DEA and BSC, provides a comprehensive evaluation lens. This approach heralds a paradigm shift in public road transport evaluation.

Keywords: Data Envelopment analysis, Balanced Score card method, Surface transport companies

1. INTRODUCTION

For public road transport organizations there is an impending need for a comprehensive evaluation framework that encapsulates multiple dimensions of organizational performance by incorporating four distinctive perspectives of Balanced Score card method. Each perspective delves into a unique facet of organizational performance, allowing for a comprehensive evaluation.

Applying the BSC to State Surface Road transport organizations invites a more nuanced understanding of performance. It integrates financial outcomes with customer-centric measures, operational processes with continuous learning and innovation. The amalgamation of these perspectives ensures that such organizations are not just efficient in their day-to-day operations but are also poised for sustainable growth and adaptation in an ever-evolving urban landscape.

The four perspectives of BSC and, DEA can evaluate how efficiently a public transport organization utilizes its resources (inputs) to achieve desired outcomes (outputs) in each perspective.

This study aims to synergize these two potent tools, providing an integrated approach for the performance evaluation of public transport organizations. Through this, we aspire to offer transport authorities, policymakers, and stakeholders a deeper, more nuanced understanding of organizational performance, which can inform strategies, resource allocations, and continuous improvement initiatives.

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2. LITERATURE REVIEW

Singh,et al. (2017) attempted to measure the efficiency and effectiveness of fifteen major state transportation units in India for a period of eleven years from 2003 to 2014 using DEA. The work arrived a conclusion that the correction of size can be achieved through the process of merging and demerging or changing the operation scale and it proved to be economically viable and advantageous.

Stevi,et al. (2022) developed a hybrid model to determine the efficacy of companies belonging to surface transport category through integration of DEA, PCA, objective weighing of criteria methods CRITIC, Entropy and MCDM method MARCOS. The study identified the most efficient business performance and less efficient organizations.

Neetu Yadav,et al. (2014) provided a comprehensive review of publications for a period of ten to eleven years from 1991 to 2011 regarding the measurement of workman ship and management activities. The authors arrived at a conclusion that their work is able to uncover the various paths the research is being carried out by different researchers in the fields of management

Bošković and Krstić (2020) in their work on the banking sector in Serbia while evaluating the relative efficiency have applied a hybrid model comprising of BSC and DEA, and found and discovered a synergetic tendency in the evaluation of the performance of the banks.

Tubis and Sylwia (2017) in their work on the companies facilitating passenger traffic in polish market found an abundant opportunities for application of theoretical concepts and the usage of many analytical tools.

Mouhamed Bayane,et al. (2023) developed a hybrid model comprising of IMF SWARA-MARCOS to estimate the weights of criteria and to analyze the strategies for the incorporation of BRT. Authors concluded that the proposed methodology will be instrumental for identifying the best strategy for BRT operation.

Rahman and Chin (2013) evolved in their work on Sustainable urban transport sector that the application of BSC methods using 5 perspectives and 45 criteria has been able to provide an efficient route for the measurement of its performance estimation.

CANITEZ, et al. (2018) in their work on the evaluation of performance of public urban transport companies employed hybrid models by combining AHP technique with BSC method.

Harel,et al. (2008) have applied in their work the BSC along with DEA model for evaluation of a hierarchical structure of constraints in a R&D project and arrived at a conclusion that their work can be applicable to the area of portfolio considerations

Karuna Kumar and Kesava Rao VVS (2020) in their work on Global airlines have applied a hybrid model comprising of BSC and DEA to measure the performance of Airlines.

Olszańska and Prokopiuk (2021) in their work developed a scorecard which is having strategic nature for the application in the transport company to address different parameters like line transport processes, measurement of quality of customer service and the findings in the area of financial sector

Fallah and Najafi (2020) in their work on banking sector have evolved Malmquist index of eleven decision makers, all the criteria belonging to BSC method by applying the DEA method.

Hsu,et al. (2013) in their work in sector of shipping for the evaluation of overall efficiency have developed a hybrid model comprising of both DEA and BSC method and also discovered that their proposed method is having capability to improve the results.

Khalili and Alinezhad (2018) have applied the modification by altering the values of input and output indicators of BSC method for investigation on the calculation of efficiency of a green supply chain utilizing DEA method dependant on based on Malmquist Productivity Index.

Amir,et al. (2020) have applied different MCDM methods along with BSC method in the area of banking sector for evaluation of performance in the state of Columbia.

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Jihong Chen,et al. (2019) adopted hybrid PCA-DEA method in the estimation of the handling of iron ore at the ports of Bohai Bay in the country of China and it is found that the hybrid model adopted worked well with great practicality and along with higher accuracy.

Annapoorni and Prakash (2016) analyzed the performance of District Hospitals in the state of Tamil Nadu using integrated method of PCA-DEA. The findings proved that PCA played a key role in identification of important input and output variables and also selected the DMUs which are efficient and it also helped in the increase of discriminating power of DEA.

Mohammad and Shirouyehzad (2013) have used a hybrid PCA-DEA method to estimate the efficiency of Foolad Technic Company which is utilizing human capital management approach.

Alissar Nasser (2019) have studied the efficiency of health sector units in Lebanon while applying the hybrid PCA-DEA approach and his study resulted in the conclusion that the role of PCA is very high in the reduction of input and output variables and also improves the discriminating power of DEA.

The evaluation of efficiency in passenger transport organizations is a complex endeavor that necessitates a comprehensive framework to capture a broad spectrum of performance indicators. Over the years, multiple tools and techniques have been proposed in the literature to evaluate and enhance the efficiency of these organizations. Among these tools, the Hybrid Balanced Scorecard (BSC) methods have emerged as effective framework.

3. BALANCED SCORECARD PERSPECTIVES FOR DEA

The brief description and significance of each criterion under its respective BSC perspective is presented below.

3.1 Learning and Growth Perspective

The focus here is on enhancing the capabilities of staff and improving institutional knowledge.

- Staff Productivity (C1): Measures the output per staff member, helping organizations optimize their human resources.
- Staff Strength (C2): Gives insight into the workforce's size, enabling capacity planning.
- Staff Bus ratio (C3): Assesses the number of staff per bus, ensuring optimal staffing for efficient operations.
- Staff Cost/Revenue Earning KMs (C4): Gauges the cost of staffing against the distance covered that earns revenue.
- Staff Cost as % of Total Cost (C5): Provides a snapshot of human resource costs in relation to overall expenses.

3.2 Internal Business Perspective

This perspective examines the operational efficiencies and processes within the organization.

- Fuel efficiency (KM/liter of HSD) (C6): Evaluates the distance covered per liter of fuel, a direct indicator of operational efficiency.
- Vehicle Productivity (KMs/Bus/Day) (C7): Measures the daily productivity of each vehicle in the fleet.
- Occupancy ratio (C8): Assesses the average occupancy of buses, ensuring they are neither underused nor overcrowded.
- Average age of Fleet (C9): Offers insight into the fleet's modernity and potential obsolescence.
- Effective Kms / Revenue earning Kms covered (C10): Gauges the proportion of traveled kilometers that generate revenue.

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3.3 Financial Perspective

Focusing on economic metrics, this perspective provides insight into the financial health and viability of the organization.

- Revenue/KM (C11): Indicates the revenue earned per kilometer, a primary measure of profitability.
- Revenue/Bus/Day (C12): Assesses the daily revenue of each bus, offering insights into its profitability.
- Cost/Km (C13): Measures the cost per kilometer, helping to identify areas of potential savings.
- Cost/Bus/Day (C14): Gauges the daily operational cost of each bus.
- Total Costs per revenue earnings (C15): Indicates the total costs against the revenue generated.

3.4 Customer Perspective

This perspective focuses on the organization's relationship with its users and the quality of service provided.

- Passenger KM Performed (Lakhs) (C16): Evaluates the distance covered with passengers, a measure of service utilization.
- Number of Accidents (C17): A safety metric crucial for assessing the risk to passengers and suggesting areas of improvement.
- Passengers Carried (Lakhs) (C18): Measures the total number of passengers transported, indicating service demand.
- Overaged Vehicles (%) (C19): Provides insights into the percentage of the fleet that is aging or outdated, potentially affecting service quality.
- Fleet Size (C20): Indicates the number of vehicles in the fleet, providing insights into capacity and potential scalability.

These criteria provide a comprehensive framework to assess the performance of public road transport organizations from multiple facets. By analyzing these measures under the BSC's four perspectives, organizations can get a holistic view of their operations, finance, workforce, and customer service. This can inform strategic decisions, improve operational efficiency, and enhance overall service quality.

3.5 Input/Outputs for DEA

DEA can provide quantitative efficiency scores for BSC perspectives, offering a comprehensive view of an organization's performance. Identification of inputs and outputs for BSC perspective to implement DEA is presented below.

3.5.1 Inputs (Resources utilized to produce outputs)

Staff Strength, Staff Bus Ratio, Staff Cost/Revenue Earning KMs, Staff Cost as % of Total Cost, Fuel Efficiency (KM/liter of HSD) Average Age of Fleet, Cost/KM, Cost/Bus/Day, Total Costs per Revenue Earnings, Number of Accidents, Overaged Vehicles (%), Fleet Size are considered as inputs.

3.5.2 Outputs (Results of utilizing inputs)

Staff Productivity, Vehicle Productivity (KMs/Bus/Day) Occupancy Ratio, Effective KMs/Revenue Earning KMs Covered, Revenue/KM Revenue/Bus/Day, Passenger KM Performed (Lakhs), Passengers Carried (Lakhs) are considered as outputs

Inputs generally consist of resources or conditions that the company needs to manage to produce its services. These typically include costs, staffing, and assets like the bus fleet. Outputs, on the other hand, are the results achieved from deploying these inputs effectively. They commonly include measures of revenue, efficiency, and service utilization.

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By evaluating these inputs and outputs, DEA helps in assessing the efficiency of each DMU, identifying benchmarks, and revealing areas for improvement.

4. EFFICIENCY EVALUATION OF PUBLIC PASSENGER ROAD TRANSPORT ORGANIZATIONS

The balanced scorecard criteria are classified into inputs and outputs as discussed in section2. Relevant data on inputs and outputs are collected for 23 public passenger transport organizations from secondary sources. DEA, four phased DEA and DEA-PCA models are implemented, to compute efficiency scores for each public transport organization.

4.1 Super Efficiency Approach

Andersen and Petersen [10] built a new strategy in ranking efficient DMUs. The strategy permits a most efficient DMU (p) to accomplish an efficiency value more than one by eliminating the p^{th} constraint in the actual definition, as given in the model.

$$h_p = \max \sum_{k=1}^{s} v_k * y_{kp}$$

st

$$\sum_{j=1}^{m} u_j * x_{jp} = 1$$

$$\sum_{j=1}^{m} u_j * x_{jp} - \sum_{k=1}^{s} v_k * y_{kp} \geq 0 \quad \forall \quad m = 1, 2 \ldots p, m \neq p$$

$$v_k, u_j \geq 0 \, \forall \, k, j$$

4.2 Four Phased DEA Approach

The hybrid approach of the BSC and DEA has mixed the broad prospective of BSC method along with efficiency focused estimation of DEA. The proposed methodology is explained in the following steps.

Step-1: Identify Key Performance Indicators (KPIs) for BSC.

For all the four BSC perspectives it is required to identify specific KPIs that will be used to gauge performance. In this study, criteria discussed in section 1.1 are considered as KPIs

Step-2: Data collection.

Data on each KPI for every Decision-Making Unit (DMU) is collected from the secondary sources published by Government of India regarding the review of the performance of surface transport companies. In this study, 5 passenger road transportation organizations are considered.

Step-3: Categorize KPIs into inputs/outputs for DEA.

Inputs and outputs developed from the balanced scorecard perspective as discussed in section 2.5 are considered in the study for implementation of 4 phased DEA approach.

Step-4: Apply 4 phased DEA with the proposed inputs and outputs.

In this study, four phased DEA method proposed by Adel Hatami-Marbiniet.et,.al (2010) is used to estimate the efficiency of passenger road transport organizations. The methodology is discussed below.

Phase-1: In this phase, the identification of best relative efficiency of the ideal DMU is achieved. It is done using the relation shown below.

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$$
\begin{aligned}
&\theta_i^* = \max \sum_{r=1}^{s} u_r y_r^{max} \\
&\text{s.t.} \sum_{i=1}^{m} v_i x_i^{max} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad \forall j \\
&u_r, v_i \le \varepsilon_r, \qquad \forall r, i
\end{aligned}
\tag{1}
$$

Everry n DMUs, uses m inputs, denoted by x_{ij} (i = 1..., m, j = 1..., n), to generate outputs denoted by y_{rj} (i = 1...,s, j = 1..., n).

The Equation (1) delivers the highest efficient ideal DMU by using above relation

Similarly, a minimization model may be estimated to evaluate the worst relative efficiency of the ADMU by using the equations below.

$$
\begin{aligned}
&\varphi_{N(\alpha)}^* = \min \sum_{r=1}^{s} y_r^{min} \\
&\text{s.t.} \sum_{i=1}^{m} x_i^{max} = 1, \\
&\sum_{r=1}^{s} y_r^{max} - \sum_{i=1}^{m} \theta_1^* x_i^{min} \ge 0, \\
&\sum_{r=1}^{s} y_{rj} - \sum_{i=1}^{m} x_{ij} \le 0, \qquad \forall j,
\end{aligned}
\tag{2}
$$

The Eq(2) is which addresses the minimization model is used to estimate the worst relative efficiency of the ADMU.

Phase-2: In this phase, the best efficiency score of DMUp is computed.

The best relative efficiency of DMU_p (p = 1,2,...n) are evaluated by the equation (3)

$$
\begin{aligned}
&\theta_p^* = \max \sum_{r=1}^{s} y_{rp} \\
&\text{s.t.} \sum_{i=1}^{m} x_{ip} = 1, \\
&\sum_{r=1}^{s} y_r^{max} - \sum_{i=1}^{m} \theta_1^* x_i^{min} = 0, \\
&\sum_{r=1}^{s} y_{rj} - \sum_{i=1}^{m} x_{ij} \le 0, \qquad \forall j,
\end{aligned}
\tag{3}
$$

The worst relative efficiency of each DMU is estimated by the model shown in **equation (4)**

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$$
\begin{aligned}
&\varphi_p^* = \min \sum_{r=1}^{s} y_{rp} \\
&\text{s.t.} \sum_{i=1}^{m} x_{ip} = 1, \\
&\sum_{r=1}^{s} y_r^{min} - \sum_{i=1}^{m} \varphi_N^* x_i^{max} = 0, \\
&\sum_{r=1}^{s} y_{rj} - \sum_{i=1}^{m} x_{ij} \leq 0, \qquad \forall j,
\end{aligned} \tag{4}
$$

Let $\theta^*_{p(\alpha)}$ is the best possible relative efficiency and $\varphi^*_{p(\alpha)}$ be the worst possible relative efficiency of each DMU for a given α respectively. These two distinctive efficiencies estimations may be leading completely different result. In this situation it is absolutely necessary to take both of them together to provide over all estimation of every DMU

Phase-3: In this phase, estimation of the relative closeness of each DMU is done using the relation shown below.

$$
RC_{p(\alpha)} = \frac{\varphi_p^* - \varphi_N^*}{(\varphi_p^* - \varphi_N^*) + (\theta_i^* - \theta_p^*)}, \qquad \forall j \tag{5}
$$

A big difference between φ_p^* and φ_N^* and a small difference between θ_p^* and θ_1^* mean a good performance for DMU_p.

Phase-4: p = (1, 2,…,n). In this phase, the estimation of ranking order of the DMUs according to their RC as shown in equation (5)

The RC values are arranged in descending order to estimate the alternative passenger road transport organizations

4.3 PCA-DEA Approach

The procedures for the efficiency evaluation using the hybrid PCA-DEA model is presented below.

Step-1: The following formula is used for normalization of the original indicators.

In case of benefit criteria:

$$
n_{ij} = \frac{r_{ij} - r_{min}}{r_{max} - r_{min}}
$$

In case of non-benefit criteria: **(6)**

$$
n_{ij} = \frac{r_{max} - r_{ij}}{r_{max} - r_{min}}
$$

Step-2: Conduction of principal component analysis on the data of the input variables.

Principal Component Analysis is done on input variables using Minitab 16.0. In the principal component analysis, number of principal components are determined based on the eigen values (Eigen value >1.0). The characteristic vectors are derived for every principal component. Principal component scores of each alternative are determined using characteristic vectors and the normalized input data.

Step-3: Conduction of principal component analysis on the data of the output variables.

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Similarly Principal Component Analysis is done on output variables using SPSS 20.0 and Principal component scores of each alternative are determined using characteristic vectors and the normalized output data.

Step-4: Obtain decision matrix for DEA.

The principal component scores of input variables and principal component scores of output variables are used for generation of Decision matrix for DEA.

Step-5: Transformation of Negative principal components of both input and output indicators

Since, it is not possible to have negative input and output values of the DEA model and in order to make them non negative the following procedure is adopted , e=2.7183 is applied as the base and power transformation is done on the decision matrix to obtain the non-negative data of the decision matrix.

Step-6: DEA evaluation.

Super efficiency approach of DEA is implemented on the decision matrix so obtained in the step 5 to determine the efficiency scores of the alternatives.

5. CASE STUDY

In this study a case study of 23public passengerrod transportation organizations in India are considered. Data on 20 criteria for the 23 transportation organizations is obtained from the secondary sources. The case study aims to demonstrate the application MCDM approaches for the efficiency evaluation of public passenger road transport organizations using balanced scorecard indicators. The study focuses on analyzing and ranking the efficiency of the organizations based on four balanced score card perspectives using the afore mentioned MCDM methods. The statistical data on the 20 variables data on the 20 criteria is presented in Table-1.

Table 1: Descriptive Statistics of the PPRTOs

Perspective	Criteria	Description	N	Mean	S.D.	Min	Max
Learning and growth	C1	Staff productivity (B)	23	60.52	32.02	17.16	157.68
	C2	Staff strength (B)	23	22313	25220	525	103043
	C3	Staff bus ratio (B)	23	4.309	1.413	2.18	7.34
	C4	Staff cost/revenue earning KMs (C)	23	25.69	17.91	7.39	76.25
	C5	Staff cost as % of total cost (B)	23	43.37	11.28	24.5	73.31
Internal business perspective	C6	Fuel efficiency (KM/liter of HSD) (B)	23	4.453	0.874	2.04	5.5
	C7	Vehicle productivity (KMs/Bus/Day) (B)	23	245.1	108.1	68.5	376.3
	C8	Occupancy ratio (B)	23	73.11	11.11	58.56	96.96
	C9	Average age of fleet (C)	23	6.517	2.218	2.96	13.85
	C10	Effective Kms/revenue earning Kms covered (B)	23	5208	6003	67	20661
Financial	C11	Revenue/KM (B)	23	4435	2416	2442	12134
	C12	Revenue/Bus/Day (B)	23	9260	3101	3069	16243
	C13	Cost/Km (C)	23	6124	5144	2548	21335
	C14	Cost/Bus/Day (C)	23	12199	7579	4785	41433
	C15	Total costs per revenue earnings (C)	23	2.17	1.644	0	6.47
Customer	C16	Passenger KM performed (Lakhs) (B)	23	170214	195989	67	615727
	C17	Number of accidents (C)	23	467	650	2	2772
	C18	Passengers carried (Lakhs) (B)	23	7495	9767	25	34880

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Perspective	Criteria	Description	N	Mean	S.D.	Min	Max
	C19	Overaged vehicles (%) (C)	23	21.26	22.6	0	100
	C20	Fleet size N(B)	23	4251	4574	94	16834

Table-2: Classification of balanced scorecard criteria into input/output

Input criteria	Description	Output criteria	Description
C2	Staff strength (IP1)	C1	Staff productivity (OP1)
C3	Staff bus ratio (IP2)	C7	Vehicle productivity (KMs/Bus/Day) (OP2)
C4	Staff cost/Revenue earning KMs (IP3)	C8	Occupancy ratio (OP3)
C5	Staff cost as % of total cost (IP4)	C10	Effective KMs / Revenue earning Kms covered (OP4)
C6	Fuel efficiency (KM/liter of HSD) (IP5)	C11	Revenue/KM (OP5)
C9	Average age of fleet (IP6)	C12	Revenue/Bus/Day (OP6)
C13	Cost/KM (IP7)	C16	Passenger KM performed (Lakhs) (OP7)
C14	Cost/Bus/Day (IP8)	C18	Passengers carried (Lakhs) (OP8)
C15	Total costs per revenue Earnings (IP9)		
C17	Number of accidents(IP10)		
C19	Overaged vehicles (%) (IP11)		
C20	Fleet size (IP12)		

Efficiency evaluation methods are implemented with the above case study.

6. RESULTS AND DISCUSSION

The evaluation of public road transportation organizations using the Super efficiency, four-phased DEA PCA-DEA approaches are implemented to estimate the efficiency values of the public passenger road transport organizations (PPRTOs)elicited in the case study.

6.1 Super Efficiency Approach

A lingo code is developed to the model as discussed in section 3.1. The efficiencies of the alternative state surface passenger transportation organizations (PPRTO) so obtained are presented in Table-3.

Table-3: Efficiency values of PPRTOs (Super efficiency approach)

PPRTOs	Efficiency	Rank	PPRTOs	Efficiency	Rank
PPRTO1	1.3154	19	PPRTO13	0.9890	23
PPRTO2	2.1548	8	PPRTO14	1.0143	22
PPRTO3	1.3674	18	PPRTO15	1.7217	11
PPRTO4	15.0592	1	PPRTO16	1.4886	16
PPRTO5	4.3849	3	PPRTO17	1.5723	14
PPRTO6	2.8440	5	PPRTO18	1.4191	17
PPRTO7	1.7639	10	PPRTO19	2.1696	7
PPRTO8	1.5030	15	PPRTO20	3.1004	4

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PPRTO9	1.2713	20	PPRTO21	1.6330	12
PPRTO10	1.1263	21	PPRTO22	5.9034	2
PPRTO11	2.2419	6	PPRTO23	2.0257	9
PPRTO12	1.6147	13			

From the above results, it is observed that, PPRTO4 With an impressive efficiency score of 15.0592, and ranked 1st. PPRTO22 ranks 2nd with an efficiency score of 5.9034. It's also a high performer but there's a significant gap between it and PPRTO4. PPRTO5 is the third most efficient with an EFF of 4.3849.

PPRTO6, PPRTO20, PPRTO11, and PPRTO19 organizations form the middle tier, with efficiency scores ranging between 2 to 4. They are relatively efficient but not at the top level.

PPRTO2, PPRTO23, PPRTO7, PPRTO15, and PPRTO21 have efficiency scores around 1.5 to 2.5, making them moderately efficient.

PPRTO8 to PPRTO18: These organizations, except for a few outliers, have efficiency scores in the range of 1 to 1.8, making them less efficient than their counterparts.

PPRTO13 and PPRTO14 are at the bottom, with efficiency scores less than 1 indicates the inefficient organizations

6.2 Four Phased DEA Approach

A lingo code is developed to each optimization model of four phased DEA methodology as discussed in section 3.2. The public passenger road transport organizations are ranked based on the relative closeness coefficient. Higher the closeness coefficients better the alternative. Table-4 shows the ranking of the PPRTOs are presented below.

Table-4: Ranking of PPRTOs - Four phased DEA approach

PPRTOs	θp	φp	CC	RANK	PPRTOs	θp	φp	CC	RANK
PPRTO1	1.31536	0.00712	0.99462	13	PPRTO13	0.98904	0.00674	0.99323	22
PPRTO2	2.15475	0.00858	0.99603	9	PPRTO14	1.01425	0.00623	0.99389	17
PPRTO3	1.36742	0.00914	0.99336	20	PPRTO15	1.72169	0.00737	0.99574	11
PPRTO4	15.05924	0.00709	0.99953	1	PPRTO16	1.48860	0.00950	0.99366	18
PPRTO5	4.38486	0.00579	0.99868	2	PPRTO17	1.57231	0.00796	0.99496	12
PPRTO6	2.84400	0.00609	0.99786	4	PPRTO18	1.41906	0.00974	0.99318	23
PPRTO7	1.76391	0.00588	0.99668	7	PPRTO19	2.16964	0.00720	0.99669	6
PPRTO8	1.50286	0.00999	0.99340	19	PPRTO20	3.10041	0.00706	0.99773	5
PPRTO9	1.27130	0.00758	0.99408	15	PPRTO21	1.63300	0.00982	0.99402	16
PPRTO10	1.12634	0.00762	0.99328	21	PPRTO22	5.90337	0.00845	0.99857	3
PPRTO11	2.24193	0.00765	0.99660	8	PPRTO23	2.02573	0.01147	0.99437	14
PPRTO12	1.61472	0.00680	0.99581	10					

PPRTO4 with a coefficient of 0.99953 ranked as 1st followed by PPRTO5 with a coefficient of 0.99868 and PPRTO22 with a coefficient of 0.99857.

PPRTO6 to PPRTO20 have coefficients ranging between 0.996 and 0.998 are above average performers.

PPRTO2, PPRTO7, PPRTO11, PPRTO12, PPRTO15, and PPRTO17 are Mid-range Performers have coefficients in the range of 0.995 to 0.996

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PPRTO1, PPRTO9, PPRTO13 to PPRTO16, PPRTO21, and PPRTO23 are Lower Performers having coefficients range from 0.993 to 0.995.

PPRTO18 with the lowest coefficient of 0.99318 and is ranked as 23rd

6.3 PCA-DEA Approach

In this approach, initially the original data is normalized and PCA is implemented using Minitab 16. PCA transform several mutually independent indicators that safe guard the most of the information in the original data into reduced components. The PCA results so obtained are discussed below.

6.3.1 Normalized data

The data is normalized as discussed in step 1 of section 4.3 and the normalized data of the alternatives is presented in Table-5.

Table-5: Normalized data

PPRTOs	INPUTS												OUTPUTS							
	IP1	IP2	IP3	IP4	IP5	IP6	IP7	IP8	IP9	IP10	IP11	IP12	OP1	OP2	OP3	OP4	OP5	OP6	OP7	OP8
PPRTO1	0.5469	0.4864	0.8838	0.4460	0.9133	0.7704	0.9711	0.8239	0.6498	0.5653	0.8848	0.7131	0.4491	1.0000	0.2471	0.8018	0.0748	0.6716	0.8746	0.6886
PPRTO2	0.0298	0.2267	0.6201	0.5177	0.4827	0.7805	0.7145	1.0000	1.0000	0.9733	0.6490	0.0311	0.0233	0.0000	0.4159	0.0097	0.2101	0.0000	0.0106	0.0050
PPRTO3	0.3295	0.6376	0.6776	0.4249	0.4913	0.5702	0.8744	0.8483	0.6743	0.8928	0.7888	0.3277	0.1169	0.3744	0.2682	0.2009	0.2648	0.4656	0.2840	0.5049
PPRTO4	0.0000	0.0329	0.3173	0.0000	0.6156	0.0000	0.3326	0.9511	0.8216	1.0000	0.0000	0.0000	0.1457	0.0653	0.7927	0.0002	0.6253	0.3389	0.0049	0.0007
PPRTOS	0.0402	0.7422	0.0000	0.8470	0.0000	1.0000	0.2172	0.4594	0.8069	0.9130	0.9549	0.0233	0.0000	0.1125	0.0000	0.0109	1.0000	0.7170	0.0133	0.0282
PPRTO6	0.2668	0.8740	0.2377	1.0000	1.0000	0.5831	0.0000	0.0000	0.9378	0.9545	0.9584	0.2063	0.0582	0.3281	0.0799	0.1220	0.7368	1.0000	0.1522	0.3302
PPRTO7	0.3625	0.5058	0.9463	0.6968	0.9769	0.8365	0.9952	0.8423	0.7447	0.7986	0.9843	0.3912	0.4335	0.9933	0.1995	0.5183	0.0000	0.4607	0.5688	0.2261
PPRTO8	0.0850	0.1531	0.7906	0.5880	0.4798	0.4454	0.8740	0.8800	0.5630	0.9791	0.8397	0.1562	0.3274	0.3878	0.2458	0.1001	0.2063	0.4003	0.0839	0.0000
PPRTO9	0.0136	0.2810	0.4755	0.1410	0.6618	0.3535	0.8514	0.9853	0.2226	0.9949	0.4694	0.0102	0.0371	0.0414	0.4044	0.0044	0.2457	0.0645	0.0065	0.0012
PPRTO10	0.3624	0.4671	0.8940	0.6175	0.8092	0.7916	0.9637	0.8256	0.8052	0.6217	0.7633	0.4387	0.3876	0.8450	0.2406	0.4750	0.0805	0.5707	0.5498	0.2855
PPRTO11	0.4152	1.0000	0.6807	0.5454	0.6098	0.7025	0.8413	0.6680	0.7741	0.4791	1.0000	0.2730	0.1391	0.6527	0.6609	0.2770	0.0808	0.4265	0.3202	0.2985
PPRTO12	1.0000	0.6453	0.8854	0.6493	0.7890	0.7741	0.9464	0.8275	0.2750	0.0000	0.9349	1.0000	0.2688	0.7604	0.2654	1.0000	0.1015	0.5538	1.0000	0.7006
PPRTO13	0.1956	0.4864	0.9001	0.6091	0.9046	0.6970	0.9647	0.8597	0.8249	0.8534	0.8327	0.2315	0.3377	0.7626	0.1432	0.2324	0.0711	0.4877	0.2574	0.1412
PPRTO14	0.2321	0.5581	0.8979	0.5718	0.9075	0.6575	0.9740	0.8410	0.8543	0.8386	0.5173	0.2674	0.3472	0.8626	0.0208	0.2810	0.0548	0.5208	0.2878	0.2365
PPRTO15	0.0110	0.2810	1.0000	0.9619	0.7746	0.7851	1.0000	0.9741	0.7791	0.9906	0.9592	0.0170	0.2790	0.4419	0.1414	0.0132	0.0427	0.2105	0.0199	0.0020
PPRTO16	0.0306	0.2422	0.8615	0.6749	0.7543	0.5372	0.9222	0.7603	0.0000	0.9852	0.7653	0.0581	0.5494	0.8284	1.0000	0.0579	0.1616	0.7513	0.0019	0.0010
PPRTO17	0.1689	0.3236	0.8163	0.4839	0.8728	0.7888	0.9349	0.7526	0.4304	0.9018	0.8201	0.2364	0.5127	0.8933	0.9018	0.2789	0.0669	0.5727	0.4623	0.0913
PPRTO18	0.0158	0.1550	0.8118	0.6800	0.6590	0.7732	0.8841	0.8827	0.7692	0.9773	0.9638	0.0225	0.3058	0.3594	0.4896	0.0196	0.1589	0.3086	0.0295	0.0052
PPRTO19	0.5228	0.5853	0.8593	0.6189	0.8931	0.5886	0.9137	0.7685	0.7103	0.7134	0.9314	0.6156	0.3364	0.8652	0.2427	0.6147	0.0963	0.6248	0.7025	1.0000
PPRTO20	0.2240	0.0000	0.9583	0.7677	0.9249	0.8558	0.9842	0.8622	0.5188	0.7668	0.9361	0.6232	1.0000	0.8936	0.2458	0.6531	0.0509	0.5324	0.7239	0.1618
PPRTO21	0.0330	0.1880	0.8777	0.6138	0.7572	0.7208	0.9548	0.8240	0.7349	0.9794	0.9184	0.0643	0.5745	0.7784	0.7177	0.0646	0.1100	0.5875	0.0022	0.0105
PPRTO22	0.0023	0.6066	0.9524	0.7169	0.6127	0.7208	0.9799	0.8591	0.9771	0.9798	1.0000	0.0017	0.3569	0.9382	0.2198	0.0058	0.0262	0.4983	0.0002	0.0068
PPRTO23	0.0004	0.0097	0.5449	0.9353	0.1503	0.7557	0.5279	0.8515	0.8134	0.9765	0.7837	0.0033	0.1114	0.0147	0.7727	0.0000	0.2639	0.0443	0.0000	0.0008

6.3.2 PCA on input variables

Eigenvalues:

In this study 12 input variables are used. The results are presented in Table-6. There are 12 components. Eigenvalues are the variances of these principal components. Three components were extracted (these three components that had an eigenvalue greater than 1). The first three components together account for 76.176% of the total variance.

Table-6: Eigenvalues

Component	Initial Eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	4.069	33.909	33.909	4.069	33.909	33.909	3.509	29.238	29.238
2	3.001	25.005	58.914	3.001	25.005	58.914	2.855	23.793	53.031
3	2.072	17.263	76.176	2.072	17.263	76.176	2.777	23.145	76.176
4	0.959	7.989	84.165						
5	0.859	7.155	91.320						
6	0.525	4.377	95.698						
7	0.233	1.938	97.636						

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8	0.144	1.200	98.836							
9	0.075	0.628	99.464							
10	0.041	0.339	99.802							
11	0.018	0.147	99.949							
12	0.006	0.051	100.000							

Principal components:

Component Matrixof the input indicators are presented below.

Table-7: Principal component matrix

Input variables	Component		
	1	2	3
IP1	0.858	0.033	-0.467
IP2	0.432	0.594	-0.355
IP3	0.612	-0.546	0.493
IP4	0.262	0.668	0.560
IP5	0.538	-0.295	-0.083
IP6	0.512	0.449	0.571
IP7	0.547	-0.661	0.431
IP8	-0.049	-0.846	0.290
IP9	-0.216	0.443	0.186
IP10	-0.824	0.002	0.404
IP11	0.603	0.504	0.506
IP12	0.871	-0.095	-0.340

Out of 12 input components only three components which are having eigen values 4.0691, 3.006, 2.0715 have been accounted for 33.9% , 25% and 17.3% of the total variance and their cumulative variance is found to be 76.176%. Thus, most of the data structure can be captured in two or three underlying dimensions. The significant principal components are presented below.

Principal component scores:

The coefficients listed under PCs are used to calculate the principal component scores and are presented below.

Table-8: Principal component scores of input variables

PPRTOs	IP1	IP2	IP3
PPRTO1	1.3901	0.3934	-0.1127
PPRTO2	-1.0203	0.0556	-0.1031
PPRTO3	0.2647	-0.2131	-0.4722
PPRTO4	-0.7245	-0.8853	-3.3966
PPRTO5	-0.7797	-2.4869	1.0584
PPRTO6	0.3970	-3.0491	0.7596
PPRTO7	0.4671	0.5947	0.7104
PPRTO8	-0.6326	0.4061	-0.3733
PPRTO9	-0.4147	0.1896	-2.0386
PPRTO10	0.6340	0.3386	0.1820
PPRTO11	1.0524	-0.7909	0.3055
PPRTO12	2.9797	0.1355	-0.1348
PPRTO13	0.0199	0.4655	0.2178

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PPRTO14	0.1915	0.3064	-0.3352
PPRTO15	-0.9635	1.0022	1.1233
PPRTO16	-0.3856	0.6377	-0.3923
PPRTO17	0.0338	0.4791	-0.0532
PPRTO18	-0.9329	0.5759	0.6011
PPRTO19	1.1097	0.0766	0.0152
PPRTO20	0.2543	1.1035	0.5609
PPRTO21	-0.7233	0.6589	0.3883
PPRTO22	-0.7731	0.3755	0.9184
PPRTO23	-1.4439	-0.3696	0.5710

6.3.3 PCA on output variables

Eigenvalues of output variables

In this study 8 output variables are used. The results are presented in Table-10. There are 8 components. Three components were extracted and these three components that have an eigenvalue greater than 1. The first three components together account for 84.514% of the total variance.

Table-10: Eigenvalues

Component	Initial Eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	3.990	49.873	49.873	3.990	49.873	49.873	2.815	35.191	35.191
2	1.696	21.206	71.079	1.696	21.206	71.079	2.643	33.038	68.230
3	1.075	13.435	84.514	1.075	13.435	84.514	1.303	16.284	84.514
4	.735	9.182	93.696						
5	.350	4.379	98.074						
6	.116	1.452	99.526						
7	.027	.342	99.868						
8	.011	.132	100.000						

Principal components:

Principal component matrix of the Output indicators is presented below.

Table-11: Principal components of output variables

Output variables	Component		
	1	2	3
OP1	0.626	-0.596	0.328
OP2	0.861	-0.311	0.251
OP3	-0.258	-0.611	0.127
OP4	0.923	0.168	-0.212
OP5	-0.533	0.678	0.392
OP6	0.508	0.354	0.766
OP7	0.922	0.169	-0.214
OP8	0.740	0.478	-0.238

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Out of 8 output components only three components which are having eigen values 3.990, 1.696, 1.075 have been accounted for 49.873% , 21.206% and 13.435% of the total variance and their cumulative variance is found to be 84.514%.. Thus, most of the data structure can be captured in two or three underlying dimensions. The significant principal components are presented below.

Principal component scores of output variables:

The principal component scores and are presented in Table-12.

Table-12: Principal component scores of input variables

PPRTOs	OP1	OP2	OP3
PPRTO1	1.7150	0.6776	0.3293
PPRTO2	-0.3396	-1.0441	-1.8396
PPRTO3	0.6678	-0.8340	-0.1992
PPRTO4	-1.0158	-0.9559	0.0679
PPRTO5	-0.1954	-2.3063	1.9522
PPRTO6	0.2398	-1.6522	2.3985
PPRTO7	0.6358	0.7919	-0.2174
PPRTO8	-0.4590	-0.2138	-0.1454
PPRTO9	-0.3849	-1.0311	-1.5320
PPRTO10	0.6238	0.4842	0.1612
PPRTO11	0.0812	0.1341	-0.5326
PPRTO12	2.2630	0.1502	-0.3733
PPRTO13	0.0758	0.2242	-0.0024
PPRTO14	0.3814	0.2219	0.1100
PPRTO15	-0.3837	-0.1723	-0.9918
PPRTO16	-1.7064	1.3009	1.2374
PPRTO17	-0.7174	1.3730	0.3004
PPRTO18	-0.7768	-0.0430	-0.5492
PPRTO19	1.9166	0.1242	0.1028
PPRTO20	0.2658	1.7745	0.4168
PPRTO21	-1.3555	1.1066	0.6522
PPRTO22	-0.7031	0.5271	0.2218
PPRTO23	-0.8282	-0.6375	-1.5675

Decision matrix for DEA:

Decision matrix is formed by considering the principal component scores of input and output variables and is presented below.

Table-13: Decision matrix

PPRTOs	Inputs			Outputs		
	IP1	IP2	IP3	OP1	OP2	OP3
PPRTO1	1.3901	0.3934	-0.1127	1.7150	0.6776	0.3293
PPRTO2	-1.0203	0.0556	-0.1031	-0.3396	-1.0441	-1.8396
PPRTO3	0.2647	-0.2131	-0.4722	0.6678	-0.8340	-0.1992
PPRTO4	-0.7245	-0.8853	-3.3966	-1.0158	-0.9559	0.0679
PPRTO5	-0.7797	-2.4869	1.0584	-0.1954	-2.3063	1.9522
PPRTO6	0.3970	-3.0491	0.7596	0.2398	-1.6522	2.3985
PPRTO7	0.4671	0.5947	0.7104	0.6358	0.7919	-0.2174
PPRTO8	-0.6326	0.4061	-0.3733	-0.4590	-0.2138	-0.1454

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PPRTOs	Inputs			Outputs		
	IP1	IP2	IP3	OP1	OP2	OP3
PPRTO9	-0.4147	0.1896	-2.0386	-0.3849	-1.0311	-1.5320
PPRTO10	0.6340	0.3386	0.1820	0.6238	0.4842	0.1612
PPRTO11	1.0524	-0.7909	0.3055	0.0812	0.1341	-0.5326
PPRTO12	2.9797	0.1355	-0.1348	2.2630	0.1502	-0.3733
PPRTO13	0.0199	0.4655	0.2178	0.0758	0.2242	-0.0024
PPRTO14	0.1915	0.3064	-0.3352	0.3814	0.2219	0.1100
PPRTO15	-0.9635	1.0022	1.1233	-0.3837	-0.1723	-0.9918
PPRTO16	-0.3856	0.6377	-0.3923	-1.7064	1.3009	1.2374
PPRTO17	0.0338	0.4791	-0.0532	-0.7174	1.3730	0.3004
PPRTO18	-0.9329	0.5759	0.6011	-0.7768	-0.0430	-0.5492
PPRTO19	1.1097	0.0766	0.0152	1.9166	0.1242	0.1028
PPRTO20	0.2543	1.1035	0.5609	0.2658	1.7745	0.4168
PPRTO21	-0.7233	0.6589	0.3883	-1.3555	1.1066	0.6522
PPRTO22	-0.7731	0.3755	0.9184	-0.7031	0.5271	0.2218
PPRTO23	-1.4439	-0.3696	0.5710	-0.8282	-0.6375	-1.5675

Negative to positive transformation of decision matrix:

The process for conversion of non-negative data has been has been discussed earlier

Table-14: Non negative data for PCA-DEA

PPRTOs	Inputs			Outputs		
	IP1	IP2	IP3	OP1	OP2	OP3
PPRTO1	3.8340	4.4425	4.2839	4.4214	3.9839	3.1689
PPRTO2	1.4237	4.1047	4.2935	2.3668	2.2622	1.0000
PPRTO3	2.7086	3.8360	3.9244	3.3743	2.4723	2.6405
PPRTO4	1.7195	3.1639	1.0000	1.6907	2.3504	2.9075
PPRTO5	1.6642	1.5622	5.4551	2.5110	1.0000	4.7918
PPRTO6	2.8409	1.0000	5.1562	2.9463	1.6541	5.2381
PPRTO7	2.9111	4.6438	5.1071	3.3422	4.0982	2.6223
PPRTO8	1.8113	4.4553	4.0233	2.2474	3.0925	2.6942
PPRTO9	2.0292	4.2387	2.3580	2.3215	2.2752	1.3076
PPRTO10	3.0780	4.3877	4.5786	3.3303	3.7905	3.0008
PPRTO11	3.4964	3.2583	4.7021	2.7876	3.4404	2.3071
PPRTO12	5.4237	4.1846	4.2619	4.9694	3.4565	2.4664
PPRTO13	2.4638	4.5146	4.6144	2.7822	3.5306	2.8372
PPRTO14	2.6354	4.3556	4.0614	3.0878	3.5282	2.9496
PPRTO15	1.4804	5.0513	5.5199	2.3227	3.1340	1.8479
PPRTO16	2.0583	4.6869	4.0044	1.0000	4.6072	4.0771
PPRTO17	2.4777	4.5282	4.3435	1.9891	4.6793	3.1400
PPRTO18	1.5111	4.6250	4.9977	1.9297	3.2633	2.2904
PPRTO19	3.5537	4.1257	4.4118	4.6231	3.4306	2.9424
PPRTO20	2.6983	5.1526	4.9575	2.9722	5.0808	3.2565
PPRTO21	1.7206	4.7081	4.7849	1.3510	4.4129	3.4918
PPRTO22	1.6709	4.4246	5.3150	2.0033	3.8334	3.0614
PPRTO23	1.0000	3.6795	4.9676	1.8782	2.6688	1.2721

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PCA-DEA Evaluation:

Super efficiency approach of DEA is implemented on the above decision matrix to determine the efficiency scores of the alternatives.

Table-15: Efficiency values of PPRTOs (PCA-DEA approach)

PPRTOs	Efficiency	Rank	PPRTOs	Efficiency	Rank
PPRTO1	1.0430	11	PPRTO13	0.9117	23
PPRTO2	1.0550	10	PPRTO14	0.9587	15
PPRTO3	0.9446	18	PPRTO15	0.9522	16
PPRTO4	3.0474	1	PPRTO16	1.0891	8
PPRTO5	1.5285	3	PPRTO17	1.0409	12
PPRTO6	2.1828	2	PPRTO18	0.9391	21
PPRTO7	0.9515	17	PPRTO19	1.1066	5
PPRTO8	0.9441	19	PPRTO20	1.0795	9
PPRTO9	0.9437	20	PPRTO21	1.1034	6
PPRTO10	0.9228	22	PPRTO22	1.0151	13
PPRTO11	0.9864	14	PPRTO23	1.2417	4
PPRTO12	1.0986	7			

The Table-15 provided illustrates the efficiency values of 23 different Alternative Public Passenger Road Transport Organizations (PPRTOs). Their efficiencies are further ranked from the most efficient (Rank 1) to the least efficient (Rank 23).

The efficiency scores vary widely across the alternatives, indicating a significant disparity in their performance. The efficiency scores range from as low as 0.9117 (PPRTO13) to as high as 3.0474 (PPRTO4). This suggests that there are substantial differences in how well these alternatives are utilizing their inputs to generate outputs.

Top performers:

PPRTO4 is the best efficient with the highest efficiency value of 3.0474, followed by PPRTO6 and PPRTO5 with values of 2.1828 and 1.5285 respectively. These top 3 organizations are notably more efficient than the rest.

Middle tier performers:

Alternatives with efficiency scores around 1 (e.g., PPRTO1, PPRTO2, PPRTO11) might be considered as moderately efficient. While they are not at the top of the rankings, they are still performing reasonably well. Further analysis could reveal opportunities for improvement in their processes to enhance efficiency.

Inefficient Alternatives: Alternatives with low efficiency scores (e.g., PPRTO13, PPRTO18, PPRTO9) are ranked lower, suggesting that they are using inputs less effectively to generate outputs. Exploring these alternatives could uncover inefficiencies in their operations or resource allocation that need attention.

PCA-DEA methodology used to calculate these efficiency scores is crucial. PCA (Principal Component Analysis) might have been used to reduce dimensionality and emphasize the most important variables. DEA (Data Envelopment Analysis) compares alternatives' relative efficiency in a multi-dimensional context.

Comparison of Rankings:

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Comparison of efficiency of 23 PPRTOs are presented in Table-16.

Table-16: Comparison of rankings

PPRTOs	DEA-super		4 phased DEA		PCA-DEA	
	Efficiency	Rank	Closeness coefficient	Rank	Efficiency	Rank
PPRTO1	1.3154	19	6.55474E-06	13	1.0430	11
PPRTO2	2.1548	8	1.3865E-05	9	1.0550	10
PPRTO3	1.3674	18	1.65425E-05	20	0.9446	18
PPRTO4	15.0592	1	6.91782E-06	1	3.0474	1
PPRTO5	4.3849	3	-3.06217E-09	2	1.5285	3
PPRTO6	2.8440	5	1.50902E-06	4	2.1828	2
PPRTO7	1.7639	10	4.20416E-07	7	0.9515	17
PPRTO8	1.5030	15	2.07689E-05	19	0.9441	19
PPRTO9	1.2713	20	8.82746E-06	15	0.9437	20
PPRTO10	1.1263	21	9.02426E-06	21	0.9228	22
PPRTO11	2.2419	6	9.21723E-06	8	0.9864	14
PPRTO12	1.6147	13	5.00436E-06	10	1.0986	7
PPRTO13	0.9890	23	4.67654E-06	22	0.9117	23
PPRTO14	1.0143	22	2.17725E-06	17	0.9587	15
PPRTO15	1.7217	11	7.83581E-06	11	0.9522	16
PPRTO16	1.4886	16	1.83686E-05	18	1.0891	8
PPRTO17	1.5723	14	1.07558E-05	12	1.0409	12
PPRTO18	1.4191	17	1.9525E-05	23	0.9391	21
PPRTO19	2.1696	7	6.97517E-06	6	1.1066	5
PPRTO20	3.1004	4	6.31626E-06	5	1.0795	9
PPRTO21	1.6330	12	1.99354E-05	16	1.1034	6
PPRTO22	5.9034	2	1.34588E-05	3	1.0151	13
PPRTO23	2.0257	9	2.81987E-05	14	1.2417	4

6.4 Ranking Consistency Analysis

Ranking consistency methods are crucial tools in multiple Criteria decision-making (MCDM) and other fields where the reliability of ranking outcomes is of paramount importance. In this study, notable method to measure ranking consistency is the Correlation Coefficient is considered.

6.4.1 Correlation analysis

Correlation coefficients of the proposed methods are presented in the following table

Table-17: Correlation coefficients

Method	Super efficiency	Four phased	PCA-DEA
Super efficiency	1.000	0.663	0.891
Four phased	0.663	1.000	0.686
PCA-DEA	0.891	0.686	1.000

From the table it is observed that, there is a high positive and significant correlation (0.891) at p=0.05 between super efficiency and PCA-DEA methods. There is also high correlation (0.686)of PCA-DEA with and Four Phased DEA method and also high correlation (0.663)of super efficiency approach of DEA and Four Phased DEA method

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6.4.2 Aggregate ranking

The algorithm proposed by Mohammadi and Jafar Rezaei (2020), is adopted to obtain aggregate ranking. The ranking algorithm is presented below. The algorithm is implemented through Matlab14 to arrive final ranking. Aggregate ranks of the alternatives are presented in Table-18

Table-18: Aggregate rank

PPRTOs	Aggregate rank	PPRTOs	Aggregate rank
PPRTO1	16	PPRTO13	23
PPRTO2	7	PPRTO14	18
PPRTO3	20	PPRTO15	13
PPRTO4	1	PPRTO16	15
PPRTO5	2	PPRTO17	14
PPRTO6	3	PPRTO18	21
PPRTO7	11	PPRTO19	6
PPRTO8	17	PPRTO20	5
PPRTO9	19	PPRTO21	12
PPRTO10	22	PPRTO22	4
PPRTO11	8	PPRTO23	9
PPRTO12	10		

Different methods, including PCA-DEA, Super Efficiency DEA (SE-DEA), and Four-Phased DEA, offer varying approaches to this evaluation, each with its own strengths and considerations. Hence, in this study, ensemble ranking is important because it enhances the reliability, accuracy, and robustness of ranking outcomes. It addresses the limitations of individual ranking methods and provides a more comprehensive and stable assessment in complex and diverse scenarios

7. CONLUDING REMARKS

Converting Balanced Scorecard (BSC) criteria into inputs and outputs for efficiency evaluation using Data Envelopment Analysis (DEA) methods involves translating the organization's strategic objectives and performance metrics into measurable variables that can be analyzed within the DEA framework. The efficiency evaluation of a Public Passenger Road Transport organization is a complex endeavor that requires a thorough and robust approach. The application of Super Efficiency DEA, Four-Phased DEA, and the Hybrid PCA-DEA method offers valuable insights into the organization's performance and efficiency. Each method contributes unique perspectives and advantages, enhancing the understanding of efficiency in this context. This multifaceted method offers a nuanced understanding of efficiency levels, enabling organizations and policymakers to make informed decisions and strategic investments to optimize resource utilization, enhance operational efficiency, and ultimately improve the overall performance of the public transportation sector.

DEA can be integrated with advanced analytics techniques, such as machine learning and predictive modeling, to enhance its predictive capabilities. This integration can help organizations forecast future efficiency trends and identify potential inefficiencies before they occur.

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