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Evaluation of Comprehensive Performance Scorecard of State Transport Organizations Using Geometric Similarity-Based MCDM Methods

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Abstract:

The performance evaluation of State Road Transport Organizations (SRTUs) is essential for ensuring the effective delivery of public transportation services. This study presents a novel multi-criteria decision-making (MCDM) framework employing three geometric similarity-based ranking methods—Ranking by Alternatives Median Similarity (RAMS), Ranking the Alternatives using the Trace to Median Index (RATMI), and Ranking by Alternatives Perimeter Similarity (RAPS). The evaluation is structured around three key dimensions: Physical, Operational, and financial performance. Each dimension comprises a set of relevant indicators to capture the comprehensive functionality of SRTUs. By integrating these advanced ranking techniques, the study facilitates comparison of transport units, enabling more informed managerial decisions. The proposed methodology not only highlights the relative efficiency of different organizations but also provides insights into specific areas of improvement. The results demonstrate the robustness and discriminatory power of the geometric similarity-based methods in prioritizing and benchmarking public transport performance. The results of the geometric similarity based MCDM methods are compared with Multi Attributive Ideal-Real Comparative Analysis **(**MAIRCA) method

Keywords: MAIRCA method, RAPS, MCDM.

1. Introduction

State Road Transport Undertakings (SRTUs) play a pivotal role in delivering accessible, affordable, and reliable public transportation across India. As the backbone of mobility for millions, especially in rural and semi-urban areas, their efficient functioning is critical to socio-economic development. Given their wide operational footprint and public responsibility, there is a growing need to continuously evaluate and enhance their performance. However, performance evaluation in the public transport sector is inherently complex due to its multi-dimensional nature, involving diverse criteria ranging from physical infrastructure and fleet maintenance to service efficiency and financial viability.

Traditionally, the assessment of SRTUs has been fragmented, focusing on isolated indicators such as fuel efficiency, fleet utilization, or financial ratios. While these metrics provide valuable insights, they often fail to capture the holistic performance picture necessary for effective decision-making and policy formulation. A multidimensional and integrated evaluation framework is, therefore, essential to assess the true effectiveness of transport undertakings and guide future improvements.

To address this need, the present study introduces a Comprehensive Performance Scorecard (CPS) framework encompassing three major dimensions—Physical, Operational, and Financial performance. These dimensions collectively represent the core functional pillars of any transport organization. The Physical dimension includes indicators related to infrastructure and fleet assets, such as fleet strength, vehicle availability, and maintenance. The Operational dimension captures the efficiency and effectiveness of service delivery through measures like fleet utilization, load factor, kilometers operated per day, and staff productivity. The Financial dimension focuses on cost control, revenue generation, and profitability, incorporating variables such as cost per kilometer, earnings per kilometer, and operating ratios.

In order to synthesize these multiple criteria into a unified assessment and ranking of SRTUs, this study applies a set of emerging Multi-Criteria Decision-Making (MCDM) techniques based on geometric similarity measures—namely, RAMS (Ranking by Alternatives Median Similarity), RATMI (Ranking the Alternatives using the Trace to Median Index), and RAPS (Ranking by Alternatives Perimeter Similarity). These methods offer a structured, objective, and mathematically grounded approach to evaluate alternatives based on their proximity to an ideal solution. Unlike conventional methods, geometric similarity-based models consider the spatial orientation of alternatives in a multi-dimensional space, ensuring a balanced and nuanced comparison across all criteria.

By applying RAMS, RATMI, and RAPS methods to the data collected from various State Road Transport Undertakings, this study aims to:

1. Develop a robust performance ranking model for SRTUs.
2. Identify the relative strengths and weaknesses of each undertaking.
3. Offer practical insights and policy recommendations for performance enhancement.
4. The integration of geometric MCDM techniques with a Comprehensive Performance Scorecard framework represents a novel contribution to the domain of public transport evaluation. This methodology not only provides a reliable basis for ranking and benchmarking transport organizations but also supports strategic planning and resource optimization in the public transportation sector. Ultimately, the findings of this study are intended to empower stakeholders, including policymakers, administrators, and transport managers, with actionable data to improve public transport services and ensure sustainable urban and regional mobility.

2. Literature Review

Evaluating the performance of State Road Transport Corporations (SRTCs) is a complex but crucial task given their multifaceted roles in public mobility, economic development, and social inclusion. The literature offers a variety of frameworks and methodologies to assess the effectiveness and efficiency of such undertakings. This section reviews the existing body of work in three major areas: public sector performance frameworks, transport sector evaluations, and the use of MCDM techniques in operational assessment.

2.1 performance evaluation in public transport

Public transport performance studies have historically focused on individual indicators such as fleet utilization, occupancy ratio, and fuel efficiency. Gwilliam (2003) emphasized the need for cost-efficiency in public transport operations, particularly in developing countries where resource constraints prevail. Pucher et al. (2005) extended this analysis by highlighting passenger-centric metrics such as service quality, affordability, and accessibility.

In the Indian context, Tiwari and Jain (2012) assessed the effectiveness of urban transport services based on indicators like passenger-km per bus and average fleet age, noting significant inter-state variability. Research by Kale and Godbole (2014) evaluated the operational efficiency of Maharashtra State Road Transport Corporation using DEA (Data Envelopment Analysis), pointing to managerial inefficiencies in some regions.

Several researchers have examined the operational efficiency of State Road Transport Undertakings (SRTUs) using benchmarking techniques. Studies such as those by Jaiswal and Sharma (2013) applied Data Envelopment Analysis (DEA) to evaluate technical efficiency across Indian SRTUs, emphasizing discrepancies in resource allocation and vehicle utilization. Similarly, Ghosh (2011) used Stochastic Frontier Analysis (SFA) to examine the productivity growth in the Indian public transport sector.

2.2 Scorecard-based frameworks for transport assessment

The Balanced Scorecard (BSC) introduced by Kaplan and Norton (1992) has been widely used to align operational metrics with strategic goals. However, its direct application to the public sector, especially SRTCs, has limitations due to its reliance on intangible and subjective criteria. In contrast, the Core Performance Scorecard (CPS) model, focusing on Physical, Operational, and Financial dimensions, offers a more quantifiable, bottom-up framework suited for technically grounded evaluations.

Bhattacharya and Sharma (2011) proposed a CPS approach tailored to Indian SRTCs, using fleet performance and cost components to derive operational benchmarks. Similarly, Ramasamy and Ramanathan (2015) advocated for integrating CPS with MCDM tools to create a hybrid framework capable of reflecting both technical efficiency and financial sustainability.

2.3 Multi-criteria decision-making in transport systems

Given the multi-dimensionality of transport operations, MCDM techniques have gained popularity in performance assessment. Traditional methods such as TOPSIS (Hwang & Yoon, 1981), AHP (Saaty, 1980), and DEA have been applied to rank transport units based on efficiency, productivity, and sustainability indicators.

However, geometric similarity-based methods like RAMS (Ranking by Alternatives Median Similarity), RAPS (Ranking by Alternatives Perimeter Similarity), and RATMI (Ranking by Alternatives Trace to Median Index) offer novel perspectives by evaluating alternatives based on spatial similarity in a multi-dimensional performance space. These methods overcome the limitations of linearity in traditional MCDM approaches by incorporating vector geometry and structural decomposition of performance attributes. Petrović et al. (2020) further validated these methods by comparing them with traditional MCDM tools and demonstrating their superior discriminatory capacity and resistance to rank reversal.

The introduction of geometric similarity-based MCDM models is relatively recent. Stanujkic and Zavadskas (2019) proposed distance-based evaluation models that focus on closeness to an ideal solution using vector geometry. These models offer more intuitive and spatially coherent ranking strategies, especially suitable for performance measurement scenarios with normalized and weighted data.

Recent works by Petrović and Stanujkic (2020) have introduced geometric similarity-based ranking models that demonstrate improved discriminatory power and ranking stability. These approaches have been applied in logistics, energy policy, and public services, but their application in SRTC performance benchmarking remains underexplored—providing a significant research gap that this study addresses.

MCDM approaches have long been recognized as effective tools for decision-making in complex transport environments. Ramírez-Nafarrate et al. (2014) applied TOPSIS for evaluating bus rapid transit performance in Latin America, while Duleba and Mishina (2017) combined AHP and PROMETHEE to model stakeholder preferences in urban transport planning.

Additionally, Zolfani and Saparauskas (2013) emphasized the role of hybrid MCDM models in the sustainable evaluation of transport strategies, showing that multi-layered models can reflect both operational and strategic criteria

3. Performance Evaluation of SRTCs

State Road Transport Corporations (SRTCs) are vital public sector undertakings that provide affordable and accessible mobility to millions of commuters across diverse geographic and socio-economic regions. Operating in varied terrains with different levels of infrastructure development and demand patterns, these organizations face numerous challenges such as aging fleets, escalating operational costs, increasing passenger expectations, and the imperative to maintain service reliability and safety. In such a dynamic and resource-constrained environment, systematic performance evaluation becomes crucial—not only for monitoring and enhancing operational efficiency but also for guiding strategic decisions, ensuring financial sustainability, and fulfilling public service mandates.

To facilitate a structured and focused assessment, this study adopts the Core Performance Scorecard (CPS)—a data-driven framework that evaluates performance through three essential dimensions: Physical, Operational, and Financial. Each dimension includes key indicators that reflect the organization's internal strength, productivity, and cost efficiency.

The Physical Performance dimension captures the readiness and health of the fleet through indicators such as Passengers Carried, Fleet Utilization, Average Fleet Operated, Average Age of Fleet, and Over-aged Vehicles. These variables offer insights into asset availability, capacity, and fleet condition. The Operational Performance dimension evaluates the effectiveness of service delivery and resource use through metrics such as Staff/Bus Ratio, Staff Productivity, Revenue Earning Kilometers, Fuel Efficiency, Occupancy Ratio, and Number of Accidents. Together, these indicators reflect how well human and physical resources are aligned with service output and safety. The Financial Performance dimension provides a deep dive into cost components that influence economic sustainability, including Staff Cost, Fuel & Lubricant Cost, Tyres & Tubes Cost, Spares Cost, Interest Cost, and Depreciation Cost.

While the CPS framework provides a solid foundation for assessing individual performance components, deriving a consolidated performance ranking across multiple SRTCs requires a more analytical, multi-dimensional approach. To achieve this, the present study introduces an integrated Multi-Criteria Decision-Making (MCDM) methodology based on geometric similarity measures—namely,

- RAPS (Ranking by Alternatives Perimeter Similarity).
- RAMS (Ranking by Alternatives Median Similarity),
- RATMI (Ranking the Alternatives using the Trace to Median Index)
- MCRAT (Multi-Criteria Ranking of Alternatives using Trace)

These innovative methods evaluate each SRTC's proximity to an ideal performance vector by considering the geometric characteristics of their performance across all criteria. Unlike traditional scoring or weighting methods, these similarity-based approaches maintain objectivity and ensure a more balanced and holistic evaluation by accounting for the multi-dimensional nature of performance data.

By applying RAMS, RATMI, and RAPS to the CPS framework, this study develops a Comprehensive Performance Scorecard capable of ranking SRTCs not only based on individual performance indicators but also on their overall alignment with high-performing standards. This enables transport administrators and policymakers to identify relative strengths and weaknesses across SRTCs, benchmark performance, and make data-driven decisions for improvement.

In summary, the integration of the Core Performance Scorecard with advanced MCDM techniques presents a powerful approach for evaluating the performance of SRTCs. It ensures that both the quantitative rigor of multi-criteria analysis and the practical relevance of operational metrics are brought together in a unified framework. This model supports the strategic goal of transforming public transport into a more efficient, cost-effective, and citizen-centric service, while fostering accountability, operational excellence, and long-term viability.

The proposed methods are discussed in the following sections:

The evaluation methodology involves a structured multi-step approach designed to rank alternatives (e.g., SRTCs) based on multiple criteria using geometric similarity-based MCDM methods. The process includes data preparation, normalization, weighted transformation, optimal alternative identification, and application of ranking techniques such as RATMI, RAPS and RAMS

3.1 Ranking of alternatives by geometric similarity based MCDM methods

Step-1: Construction of the decision matrix.

The problem is initially expressed in the form of a decision matrix $X = [x_{ij}]_{m \times n}$, where

- $A = [A_1, A_2, \ldots, A_m]$: set of m alternatives.
- $C = [C_1, C_2, \ldots, C_n]$: set of n evaluation criteria.
- x_{ij}: performance source of alternative A_i with respect to criterion C_j.

Some criteria are to be maximized ($S_{\max}$) and other minimized ($S_{\min}$).

Step-2: Normalize the decsion matrix.

Vector normaliztion method as discussed below is used.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

Step-3: Weighted normalization.

The normalized matrix is converted into a weighted normalized matrix using the weights w_j for each criterion. Weights may be derived from expert opinion or MCDM weighting methods. The transformation is performed as:

$$\upsilon_{ij} = w_j \times r_{ij}$$

where $\sum_{j=1}^{n} w_j = 1$.

The weighted normalized matrix is denoted by $V = [\upsilon_{ij}]$

Step-4: Determination of the optimal alternative.

An optimal (ideal) alternative is constructed, represented as:

$$V^* = \left[\upsilon_1^*, \upsilon_2^*, ..., \upsilon_n^*\right]$$

where $\upsilon_j^* = \max(\upsilon_{ij})$ for benefit criteria and $\upsilon_j^* = \min(\upsilon_{ij})$ for cost criteria.

Step-5: Decomposition of the optimal alternative.

The optimal alternative vector V^* is decomposed into two components:

- Q_k: Sub-vector for k criteria to be maximized.
- Q_h: Sub-vector for h criteria to be minimized.

Such that:

$$V^* = [Q_k, Q_h]$$

Step-6: Decomposition of alternatives.

Similarly, each alternative $V_i = [\upsilon_{i1}, \upsilon_{i2}, \ldots, \upsilon_{in}]$ is decomposed into:

$$V_i = [G_{ik}, G_{ih}]$$

where G_{ik} corresponds to maximization criteria, and G_{ih} to minimization criteria.

Step-7: Ranking methods.

From this step forward, four distinct methods are used to rank alternatives:

3.1.1 Ranking by alternatives perimeter similarity (RAPS)

Treating Q_k and Q_h as the legs of a right triangle, compute the perimeter:

$$P^* = |Q_k| + |Q_h| + \sqrt{|Q_k|^2 + |Q_h|^2}$$

For each alternative:

$$P_i = |G_{ik}| + |G_{ih}| + \sqrt{|G_{ik}|^2 + |G_{ih}|^2}$$

$$PS_i = \frac{P_i}{P^*}$$

Rank alternatives in descending order of PS_i.

3.1.2 Ranking by alternatives median similarity (RAMS)

Compute the median of the optimal alternative (hypothenuse of triangle divided by 2):

$$M^* = \frac{\sqrt{|Q_k|^2 + |Q_h|^2}}{2}$$

For each alternative:

$$M^* = \frac{\sqrt{|G_{ik}|^2 + |G_{ih}|^2}}{2},$$

$$MS_i = \frac{M_i}{M^*}$$

Rank alternatives in descending order of MS_i.

3.1.3 Ranking using trace to median index (RATMI)

This method combines MCRAT and RAMS through a weighted index:

$E_i = \upsilon \cdot tr(T_i) + (1 - \upsilon) \cdot MS_i$

where $\upsilon \in [0, 1]$ is the decision-maker's preference for trace-based (MCRAT) versus median-based (RAMS) evaluation.

Rank alternatives in descending order of E_i.

3.1.4 Multiple criteria ranking by alternative (MCRAT)

MCRAT – Ranking by alternative traces. Construct:

- Matrix $F = \begin{bmatrix} Q_k \\ Q_h \end{bmatrix}$: Optimal components
- Matrix $G_i = \begin{bmatrix} G_{ik} \\ G_{ih} \end{bmatrix}$: Alternative components

Compute:

$$T_i = F \cdot G_i^T$$

$tr\,(T_i)$ = Trace of T_i.

Alternatives are ranked in descending order of $tr(T_r)$.

3.2 Multi attributive ideal-real comparative analysis (MAIRCA) method

The steps to implement multi-criteria decision-making according to the MAIRCA method are as follows [18].

Step-1: Building the initial matrix according to the following equation:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & \cdots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

where m is the number of options; n is the number of criteria; x_{mn} is the value of the n criterion in m.

Step-2: Determining the priority for an indicator.

When the decision maker is neutral, the role of the indicators is the same (no priority is given to any). Then the priority for the criteria is the same and is calculated as follows:

$$P_{A_j} = \frac{1}{m}, \qquad j = 1,2,\ldots,n \quad (2)$$

Step-3: Calculating the quantities t_{pij} according to the equation:

$$t_{pij} = P_{A_{j1}} \cdot w_j, \qquad i = 1,2,\ldots,m;\ j = 1,2,\ldots,n \quad (3)$$

where w_j is the weight of the j-th criterion.

Step-4: Calculating the quantities t_{rij} according to the equations:

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \right) \qquad \text{if } j \text{ is the criterion, the bigger the better} \quad (4)$$

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \right) \qquad \text{if } j \text{ is the criterion, as small as better} \quad (5)$$

Step-5: Calculating the quantities of g_{ij} according to the equation:

$$g_{ij} = t_{pij} - t_{rij} \quad (6)$$

Step-6: Summing the g_j values according to the equation:

$$Q_i = \sum_{i=1}^{m} g_{ij} \quad (7)$$

Ranking the options according to the principle that the one with the smallest Q_i is the better.

4. Case Study

4.1 Data collection and preparation

Secondary data is collected through reports on State Road Transport Organizations (SRTUs) covering 17 variables over three years. The data is presented in Table-1.

Table-1: Data on factors of performance of SRTUs

FACTORS	2018-19		2017-18		2016-17		Weights
	AVG	STDEV	AVG	STDEV	AVG	STDEV	
Passengers Carried	7709.00	9916.17	7796.20	9742.04	7697.89	9473.97	0.207
Fleet Utilization	81.27	17.20	82.08	17.28	82.99	16.10	0.041
Average Fleet Operated	4616.38	4685.70	4631.10	4688.29	4533.48	4676.27	0.173
Avg Age of Fleet	7.05	2.32	6.52	2.38	6.89	2.12	0.036
Over aged vehicles	27.69	22.32	22.47	20.87	19.13	21.48	0.036
Staff/Bus Ratio	3.99	1.24	4.19	1.34	4.50	1.29	0.043
Staff Productivity	65.34	39.20	62.95	37.23	59.18	33.35	0.025
Revenue Earning Kms	5667.88	6162.43	5700.99	6159.98	5596.35	6142.43	0.114
Fuel Efficiency	4.33	1.10	4.31	1.09	4.35	1.08	0.014
Occupancy Ratio	80.80	21.94	77.66	15.28	74.44	14.58	0.066
Number of Accidents	502.71	751.48	528.14	724.77	504.10	670.31	0.084
Staff Cost	39.22	10.07	43.07	13.65	43.42	10.83	0.004
Fuel & Lubricant Cost	30.90	10.38	28.21	10.93	27.17	9.19	0.046
Tyres & Tubes Cost	1.24	0.65	1.26	0.69	1.42	0.90	0.008
Spares Cost	1.72	0.94	1.68	0.94	1.74	0.91	0.023
Interest Cost	5.32	14.34	5.73	13.70	5.61	13.46	0.033
Depreciation Cost	4.55	2.76	4.30	2.70	4.56	3.04	0.049

From 2016-17 to 2018-19, occupancy ratio and staff productivity improved, while fleet utilization and accident numbers showed concerning trends. The number of over-aged vehicles increased, indicating an aging fleet. Staff costs decreased, but fuel and maintenance costs fluctuated. High standard deviations in key metrics suggest performance inconsistency across regions. Overall, some efficiency gains are evident, but safety and fleet modernization need attention.

4. Results and Discussion

4.1 RAPS method

Raps method is implemented as discussed in section 3.1.1 and the results are presented below.

Table-2: Decision matrix (2018-19)

SRTU	Passengers Carried (Fl)	Fleet Utilisation (F2)	Average Fleet Operated (F3)	Avg. Age of Fleet (F4)	Over aged vehicles (F5)	Staff/Bus Ratio (F6)	Staff Productivity (F7)	Revenue Earning Kms (F8)	Fuel Efficiency (F9)	Occupancy Ratio (F10)	Number of Accidents (Fil)	Staff Cost (F12)	Fuel & Lubricant Cost (F13)	Tyres & Tubes Cost (F14)	Spares Cost (F15)	Interest Cost (F16)	Depreciation Cost (F17)
SRTU 1	26020.85	99.71	11803	5.92	1.06	4.5	81.08	15762.74	5.2	77.75	1163	47.31	23.07	1.19	1.16	3.98	2.03
SRTU 2	185.31	49.77	639	5.37	24.17	2.71	19.33	245.83	3.79	87.08	71	45.66	26.78	1.84	0.82	9.78	8.94
SRTU 3	12775	84.12	5615	6.6	10.6	5.08	33.58	4152.85	3.74	71.39	286	52.95	28.4	0.6	3.5	1	5.41
SRTU 4	266	59.59	345	15	100	1.88	59.74	237.68	4.66	164	13	22.91	44.27	2.13	1.33	0	0
SRTU 5	11004.48	84.62	3295	9.2	51.39	6.35	25.93	2340.11	1.94	81.19	125	21.22	5.27	0	0.06	65.9	2.1
SRTU 6	7436.94	85.58	6882	5.41	32.68	4.99	76.92	11271.75	5.38	68.77	674	35.54	40.66	1.55	1.4	2.02	6.36
SRTU 7	43.24	57.42	294	10	27.6945	4.19	19.09	149.58	4.23	66.29	10	39.93	16.18	0.36	1.46	0	3.33
SRTU 8	10986.09	91.65	8045	5.26	37.6	4.4	75.22	10598.57	4.87	71.4	1018	40.92	38.06	1.42	2.5	0.57	5.68
SRTU 9	9524	80.08	4548	7.09	0	5.84	45.84	5546	4.12	84.44	1083	29.99	29.55	0.12	0.19	8.43	2.45
SRTU 10	24078.48	87.33	16414	7.1	6.18	5.42	54.8	20377.97	4.57	69.14	3310	41.77	33.5	1.76	1.57	0.02	3.03
SRTU 11	2.52	41.9346	26	8	49	3.56	30.66	24.73	5.01	63.66	3	63.88	21.8	1.85	3.43	0	6.18
SRTU 12	4945.75	86.33	4134	4.63	26	4.3	68.72	5160.9	5.25	58.53	323	46.9	35.74	1.67	1.31	0.48	5.94
SRTU 13	8205.2	94.4	4711	7.31	42.6	4.74	68.19	5890.17	5.12	64.27	449	46.14	36.7	1.55	1.5	0.49	4.32
SRTU 14	71.7	93.65	413	5.12	5	3.49	61.23	343.72	4.81	93.24	30	26.32	50.41	2.45	2.38	0	7.72
SRTU 15	0.28	100	1138	8	29	3.73	98.68	1529.65	4.69	100.05	112	32.89	33.1	0.67	0.83	0	2.15
SRTU 16	3106.89	71.73	3798	6.31	35.81	2.89	97.51	5437.74	5.03	87.49	187	41.34	22.45	1.1	1.33	3.43	2.46
SRTU 17	214	80.85	726	6.24	24.52	3.11	63.71	649.5	4.59	81	23	30.02	31.65	1.16	2.89	12.36	4.51
SRTU 18	35 605.75	99.76	10456	7.66	26.05	4.83	70.79	13088.44	1.94	73.12	772	39.91	23.66	1.02	2.34	3.18	2.92
SRTU 19	6015.69	97.77	11615	5.7	12.13	1.78	187.74	14497.28	5.23	68	751	35.59	28.55	1.48	2.69	0	3.87
SRTU 20	377.83	94.47	1264	7.5	29.3	2.58	114.22	1438.26	4.81	90.48	74	41.97	34.27	1.56	1.5	0	4.02
SRTU 21	1023	65.96	783	4.57	10.8	3.39	19.23	282	1.94	75.61	80	40.41	44.88	0.66	1.86	0	12.19

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Table-3: Normalized decision matrix

SRTU	Fl	F2	F3	F4	F5	F6	F7	F8	F9	F10	Fil	F12	F13	F14	F15	F16	F17
SRTU 1	0.4589	0.2622	0.3964	0.1745	0.0066	0.2356	0.2337	0.4162	0.2544	0.2030	0.2854	0.2554	0.1548	0.1857	0.1301	0.0580	0.0837
SRTU 2	0.0033	0.1309	0.0215	0.1583	0.1497	0.1419	0.0557	0.0065	0.1854	0.2273	0.0174	0.2464	0.1797	0.2871	0.0920	0.1426	0.3688
SRTU 3	0.2253	0.2212	0.1886	0.1946	0.0657	0.2659	0.0968	0.1097	0.1830	0.1864	0.0702	0.2858	0.1906	0.0936	0.3925	0.0146	0.2232
SRTU4	0.0047	0.1567	0.0116	0.4422	0.6194	0.0984	0.1722	0.0063	0.2280	0.4281	0.0032	0.1237	0.2971	0.3323	0.1492	0.0000	0.0000
SRTU 5	0.1941	0.2225	0.1107	0.2712	0.3183	0.3324	0.0747	0.0618	0.0949	0.2119	0.0307	0.1145	0.0354	0.0000	0.0067	0.9606	0.0866
SRTU 6	0.1312	0.2250	0.2311	0.1595	0.2024	0.2612	0.2217	0.2976	0.2632	0.1795	0.1654	0.1918	0.2728	0.2418	0.1570	0.0294	0.2623
SRTU 7	0.0008	0.1510	0.0099	0.2948	0.1715	0.2193	0.0550	0.0039	0.2070	0.1730	0.0025	0.2155	0.1086	0.0562	0.1637	0.0000	0.1374
SRTU 8	0.1938	0.2410	0.2702	0.1551	0.2329	0.2303	0.2168	0.2799	0.2383	0.1864	0.2498	0.2209	0.2554	0.2216	0.2804	0.0083	0.2343
SRTU 9	0.1680	0.2106	0.1527	0.2090	0.0000	0.3057	0.1321	0.1464	0.2016	0.2204	0.2658	0.1619	0.1983	0.0187	0.0213	0.1229	0.1011
SRTU 10	0.4247	0.2296	0.5512	0.2093	0.0383	0.2837	0.1579	0.5381	0.2236	0.1805	0.8124	0.2255	0.2248	0.2746	0.1761	0.0003	0.1250
SRTU 11	0.0000	0.1103	0.0009	0.2358	0.3035	0.1864	0.0884	0.0007	0.2451	0.1662	0.0007	0.3448	0.1463	0.2886	0.3847	0.0000	0.2549
SRTU 12	0.0872	0.2270	0.1388	0.1365	0.1610	0.2251	0.1980	0.1363	0.2569	0.1528	0.0793	0.2531	0.2398	0.2606	0.1469	0.0070	0.2450
SRTU 13	0.1447	0.2482	0.1582	0.2155	0.2639	0.2481	0.1965	0.1555	0.2505	0.1678	0.1102	0.2490	0.2463	0.2418	0.1682	0.0071	0.1782
SRTU 14	0.0013	0.2463	0.0139	0.1509	0.0310	0.1827	0.1765	0.0091	0.2354	0.2434	0.0074	0.1421	0.3383	0.3823	0.2669	0.0000	0.3184
SRTU 15	0.0000	0.2630	0.0382	0.2358	0.1796	0.1953	0.2844	0.0404	0.2295	0.2612	0.0275	0.1775	0.2221	0.1045	0.0931	0.0000	0.0887
SRTU 16	0.0548	0.1886	0.1275	0.1860	0.2218	0.1513	0.2810	0.1436	0.2461	0.2284	0.0459	0.2231	0.1506	0.1716	0.1492	0.0500	0.1015
SRTU 17	0.0038	0.2126	0.0244	0.1839	0.1519	0.1628	0.1836	0.0172	0.2246	0.2114	0.0056	0.1620	0.2124	0.1810	0.3241	0.1802	0.1860
SRTU 18	0.6280	0.2623	0.3511	0.2258	0.1613	0.2528	0.2040	0.3456	0.0949	0.1909	0.1895	0.2154	0.1588	0.1591	0.2624	0.0464	0.1204
SRTU 19	0.1061	0.2571	0.3901	0.1680	0.0751	0.0932	0.5411	0.3828	0.2559	0.1775	0.1843	0.1921	0.1916	0.2309	0.3017	0.0000	0.1596
SRTU 20	0.0067	0.2484	0.0424	0.2211	0.1815	0.1351	0.3292	0.0380	0.2354	0.2362	0.0182	0.2265	0.2300	0.2434	0.1682	0.0000	0.1658
SRTU 21	0.0180	0.1734	0.0263	0.1347	0.0669	0.1775	0.0554	0.0074	0.0949	0.1974	0.0196	0.2181	0.3012	0.1030	0.2086	0.0000	0.5028

Table-4: Weighted normalized decision matrix

SRTU	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Fil	F12	F13	F14	F15	F16	F17
SRTU 1	0.0950	0.0107	0.0686	0.0063	0.0002	0.0101	0.0058	0.0475	0.0036	0.0134	0.0240	0.0010	0.0071	0.0015	0.0030	0.0019	0.0041
SRTU 2	0.0007	0.0054	0.0037	0.0057	0.0054	0.0061	0.0014	0.0007	0.0026	0.0150	0.0015	0.0010	0.0083	0.0023	0.0021	0.0047	0.0181
SRTU 3	0.0466	0.0091	0.0326	0.0070	0.0024	0.0114	0.0024	0.0125	0.0026	0.0123	0.0059	0.0011	0.0088	0.0007	0.0090	0.0005	0.0109
SRTU4	0.0010	0.0064	0.0020	0.0159	0.0223	0.0042	0.0043	0.0007	0.0032	0.0283	0.0003	0.0005	0.0137	0.0027	0.0034	0.0000	0.0000
SRTU 5	0.0402	0.0091	0.0191	0.0098	0.0115	0.0143	0.0019	0.0070	0.0013	0.0140	0.0026	0.0005	0.0016	0.0000	0.0002	0.0317	0.0042
SRTU 6	0.0272	0.0092	0.0400	0.0057	0.0073	0.0112	0.0055	0.0339	0.0037	0.0118	0.0139	0.0008	0.0126	0.0019	0.0036	0.0010	0.0129
SRTU 7	0.0002	0.0062	0.0017	0.0106	0.0062	0.0094	0.0014	0.0005	0.0029	0.0114	0.0002	0.0009	0.0050	0.0004	0.0038	0.0000	0.0067
SRTU 8	0.0401	0.0099	0.0467	0.0056	0.0084	0.0099	0.0054	0.0319	0.0033	0.0123	0.0210	0.0009	0.0117	0.0018	0.0064	0.0003	0.0115
SRTU 9	0.0348	0.0086	0.0264	0.0075	0.0000	0.0131	0.0033	0.0167	0.0028	0.0145	0.0223	0.0006	0.0091	0.0001	0.0005	0.0041	0.0050
SRTU 10	0.0879	0.0094	0.0954	0.0075	0.0014	0.0122	0.0039	0.0613	0.0031	0.0119	0.0682	0.0009	0.0103	0.0022	0.0040	0.0000	0.0061
SRTU 11	0.0000	0.0045	0.0002	0.0085	0.0109	0.0080	0.0022	0.0001	0.0034	0.0110	0.0001	0.0014	0.0067	0.0023	0.0088	0.0000	0.0125
SRTU 12	0.0181	0.0093	0.0240	0.0049	0.0058	0.0097	0.0050	0.0155	0.0036	0.0101	0.0067	0.0010	0.0110	0.0021	0.0034	0.0002	0.0120
SRTU 13	0.0300	0.0102	0.0274	0.0078	0.0095	0.0107	0.0049	0.0177	0.0035	0.0111	0.0093	0.0010	0.0113	0.0019	0.0039	0.0002	0.0087
SRTU 14	0.0003	0.0101	0.0024	0.0054	0.0011	0.0079	0.0044	0.0010	0.0033	0.0161	0.0006	0.0006	0.0156	0.0031	0.0061	0.0000	0.0156
SRTU 15	0.0000	0.0108	0.0066	0.0085	0.0065	0.0084	0.0071	0.0046	0.0032	0.0172	0.0023	0.0007	0.0102	0.0008	0.0021	0.0000	0.0043
SRTU 16	0.0113	0.0077	0.0221	0.0067	0.0080	0.0065	0.0070	0.0164	0.0034	0.0151	0.0039	0.0009	0.0069	0.0014	0.0034	0.0017	0.0050
SRTU 17	0.0008	0.0087	0.0042	0.0066	0.0055	0.0070	0.0046	0.0020	0.0031	0.0140	0.0005	0.0006	0.0098	0.0014	0.0075	0.0059	0.0091
SRTU 18	0.1300	0.0108	0.0607	0.0081	0.0058	0.0109	0.0051	0.0394	0.0013	0.0126	0.0159	0.0009	0.0073	0.0013	0.0060	0.0015	0.0059
SRTU 19	0.0220	0.0105	0.0675	0.0060	0.0027	0.0040	0.0135	0.0436	0.0036	0.0117	0.0155	0.0008	0.0088	0.0018	0.0069	0.0000	0.0078
SRTU 2O	0.0014	0.0102	0.0073	0.0080	0.0065	0.0058	0.0082	0.0043	0.0033	0.0156	0.0015	0.0009	0.0106	0.0019	0.0039	0.0000	0.0081
SRTU 21	0.0037	0.0071	0.0045	0.0048	0.0024	0.0076	0.0014	0.0008	0.0013	0.0130	0.0016	0.0009	0.0139	0.0008	0.0048	0.0000	0.0246

Table-5: Ranking by RAPS Method

SRTU	Pi	Rank
SRTU 1	0.6616	3
SRTU 2	0.1443	18
SRTU 3	0.3265	7
SRTU 4	0.2196	12
SRTU 5	0.3136	8
SRTU 6	0.3429	6
SRTU 7	0.1150	21
SRTU 8	0.3976	5
SRTU 9	0.2948	9
SRTU 10	0.8214	1
SRTU 11	0.1338	20
SRTU 12	0.2196	11
SRTU 13	0.2699	10
SRTU 14	0.1633	15
SRTU 15	0.1485	16
SRTU 16	0.1970	13
SRTU 17	0.1370	19
SRTU 18	0.7487	2
SRTU 19	0.4508	4
SRTU 20	0.1478	17
SRTU 21	0.1716	14

Ranking by RAM's method:

RAM's method is implemented as discussed in section 3.1.2 and the results are presented below.

Table-6: Ranking by RAM's

SRTU	Mi	Pi	Rank
SRTU 1	0.0654	0.6858	4
SRTU 2	0.0142	0.1488	19
SRTU 3	0.0322	0.3373	8
SRTU 4	0.0215	0.2253	13
SRTU 5	0.0307	0.3222	9
SRTU 6	0.0336	0.3517	7
SRTU 7	0.0113	0.1181	22
SRTU 8	0.0389	0.4079	6
SRTU 9	0.0289	0.3031	10
SRTU 10	0.0804	0.8431	2
SRTU 11	0.0132	0.1387	21
SRTU 12	0.0215	0.2253	12
SRTU 13	0.0264	0.2772	11
SRTU 14	0.0160	0.1676	16
SRTU 15	0.0146	0.1535	17
SRTU 16	0.0193	0.2021	14
SRTU 17	0.0134	0.1405	20
SRTU 18	0.0759	0.7957	3
SRTU 19	0.0444	0.4651	5
SRTU 20	0.0145	0.1519	18
SRTU 21	0.0171	0.1795	15

Ranking by RATMI method:

RATMI method is implemented as discussed in section 3.1.3 and the results are presented below.

Table-7: Ranking by RATMI

SRTU	TRACE	MSi	Ei	RANK
SRTU 1	0.025475	0.3338	0.7831	3
SRTU 2	0.005454	0.0724	0.0424	18
SRTU 3	0.012571	0.1642	0.3024	7
SRTU 4	0.008392	0.1097	0.1480	12
SRTU 5	0.012048	0.1568	0.2815	8
SRTU 6	0.013127	0.1712	0.3223	6
SRTU 7	0.004411	0.0575	0.0000	21
SRTU 8	0.015213	0.1985	0.3998	5
SRTU 9	0.011334	0.1475	0.2552	9
SRTU 10	0.031331	0.4103	1.0000	1
SRTU 11	0.005012	0.0675	0.0284	20
SRTU 12	0.008392	0.1097	0.1480	11
SRTU 13	0.010369	0.1349	0.2196	10
SRTU 14	0.006217	0.0816	0.0684	15
SRTU 15	0.005718	0.0747	0.0489	16
SRTU 16	0.007553	0.0984	0.1160	13
SRTU 17	0.00524	0.0684	0.0310	19
SRTU 18	0.02865	0.3872	0.9346	2
SRTU 19	0.017005	0.2264	0.4787	4
SRTU 20	0.00568	0.0739	0.0466	17
SRTU 21	0.00635	0.0874	0.0848	14

Ranking by MCRAT method:

MCRAT method is implemented as discussed in section 3.1.4 and the results are presented below.

Table-8: Ranking by MCRAT

SRTU	TRACE	Rank
SRTU 1	0.0255	3
SRTU 2	0.0055	18
SRTU 3	0.0126	7
SRTU 4	0.0084	12
SRTU 5	0.0120	8
SRTU 6	0.0131	6
SRTU 7	0.0044	21
SRTU 8	0.0152	5
SRTU 9	0.0113	9
SRTU 10	0.0313	1
SRTU 11	0.0050	20
SRTU 12	0.0084	11
SRTU 13	0.0104	10
SRTU 14	0.0062	15
SRTU 15	0.0057	16
SRTU 16	0.0076	13
SRTU 17	0.0052	19
SRTU 18	0.0286	2
SRTU 19	0.0170	4
SRTU 20	0.0057	17
SRTU 21	0.0064	14

MAIRCA method:

Ranking by MAICRA method is implemented as discussed in section 3.2 and the results are presented below.

Table-9: Real rating matrix in MAICRA

SRTU	C1	C2	C3	C4	C5	C6	C7	C8	C9	CIO	C11	C12	C13	C14	C15	C16	C17
SRTU 1	0.0072	0.0019	0.0023	0.0015	0.0017	0.0012	0.0004	0.0042	0.0006	0.0006	0.0026	0.0001	0.0013	0.0002	0.0007	0.0015	0.0019
SRTU 2	0.0001	0.0003	0.0079	0.0016	0.0013	0.0004	0.0000	0.0001	0.0004	0.0009	0.0039	0.0001	0.0011	0.0001	0.0009	0.0013	0.0006
SRTU 3	0.0035	0.0014	0.0054	0.0014	0.0015	0.0015	0.0001	0.0011	0.0003	0.0004	0.0037	0.0000	0.0011	0.0003	0.0000	0.0015	0.0013
SRTU 4	0.0001	0.0006	0.0081	0.0000	0.0000	0.0000	0.0003	0.0001	0.0005	0.0031	0.0040	0.0002	0.0003	0.0000	0.0007	0.0016	0.0023
SRTU 5	0.0030	0.0014	0.0066	0.0010	0.0008	0.0020	0.0000	0.0006	0.0000	0.0007	0.0039	0.0002	0.0022	0.0004	0.0011	0.0000	0.0019
SRTU 6	0.0021	0.0015	0.0048	0.0016	0.0012	0.0014	0.0004	0.0030	0.0007	0.0003	0.0032	0.0001	0.0005	0.0001	0.0007	0.0015	0.0011
SRTU 7	0.0000	0.0005	0.0081	0.0008	0.0012	0.0011	0.0000	0.0000	0.0004	0.0002	0.0040	0.0001	0.0017	0.0003	0.0006	0.0016	0.0017
SRTU 8	0.0030	0.0017	0.0042	0.0016	0.0011	0.0012	0.0004	0.0028	0.0006	0.0004	0.0028	0.0001	0.0006	0.0002	0.0003	0.0016	0.0012
SRTU 9	0.0026	0.0013	0.0060	0.0013	0.0017	0.0018	0.0002	0.0015	0.0004	0.0008	0.0027	0.0002	0.0010	0.0004	0.0011	0.0014	0.0019
SRTU 10	0.0067	0.0015	0.0000	0.0013	0.0016	0.0016	0.0003	0.0054	0.0005	0.0003	0.0000	0.0001	0.0008	0.0001	0.0006	0.0016	0.0018
SRTU 11	0.0000	0.0000	0.0082	0.0012	0.0009	0.0008	0.0001	0.0000	0.0006	0.0002	0.0040	0.0000	0.0014	0.0001	0.0000	0.0016	0.0012
SRTU 12	0.0014	0.0015	0.0062	0.0017	0.0013	0.0011	0.0004	0.0014	0.0006	0.0000	0.0036	0.0001	0.0007	0.0001	0.0007	0.0016	0.0012
SRTU 13	0.0023	0.0018	0.0059	0.0013	0.0010	0.0013	0.0003	0.0016	0.0006	0.0002	0.0035	0.0001	0.0007	0.0001	0.0006	0.0016	0.0015
SRTU 14	0.0000	0.0017	0.0080	0.0016	0.0016	0.0008	0.0003	0.0001	0.0006	0.0010	0.0040	0.0002	0.0000	0.0000	0.0004	0.0016	0.0009
SRTU 15	0.0000	0.0020	0.0077	0.0012	0.0012	0.0009	0.0006	0.0004	0.0005	0.0012	0.0039	0.0001	0.0008	0.0003	0.0009	0.0016	0.0019
SRTU 16	0.0009	0.0010	0.0063	0.0014	0.0011	0.0005	0.0006	0.0014	0.0006	0.0009	0.0038	0.0001	0.0014	0.0002	0.0007	0.0015	0.0019
SRTU 17	0.0001	0.0013	0.0079	0.0014	0.0013	0.0006	0.0003	0.0002	0.0005	0.0007	0.0040	0.0002	0.0009	0.0002	0.0002	0.0013	0.0015
SRTU 18	0.0099	0.0019	0.0030	0.0012	0.0013	0.0014	0.0004	0.0035	0.0000	0.0004	0.0031	0.0001	0.0013	0.0002	0.0004	0.0015	0.0018
SRTU 19	0.0017	0.0019	0.0024	0.0015	0.0015	0.0000	0.0012	0.0039	0.0006	0.0003	0.0031	0.0001	0.0011	0.0002	0.0003	0.0016	0.0016
SRTU 20	0.0001	0.0018	0.0076	0.0012	0.0012	0.0004	0.0007	0.0004	0.0006	0.0010	0.0039	0.0001	0.0008	0.0001	0.0006	0.0016	0.0016
SRTU 21	0.0003	0.0008	0.0079	0.0017	0.0015	0.0007	0.0000	0.0001	0.0000	0.0005	0.0039	0.0001	0.0003	0.0003	0.0005	0.0016	0.0000

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Table-10: GAP matrix

SRTU	C1	C2	C3	C4	C5	C6	C7	C8	C9	CIO	Cll	C12	C13	C14	C15	C16	C17
SRTU 1	0.0027	0.0000	0.0059	0.0002	0.0000	0.0008	0.0008	0.0012	0.0000	0.0026	0.0014	0.0001	0.0009	0.0002	0.0004	0.0001	0.0004
SRTU 2	0.0098	0.0017	0.0003	0.0001	0.0004	0.0016	0.0012	0.0054	0.0003	0.0023	0.0001	0.0001	0.0010	0.0003	0.0002	0.0002	0.0017
SRTU 3	0.0063	0.0005	0.0028	0.0003	0.0002	0.0006	0.0011	0.0043	0.0003	0.0028	0.0003	0.0001	0.0011	0.0001	0.0011	0.0000	0.0010
SRTU 4	0.0098	0.0014	0.0002	0.0017	0.0017	0.0020	0.0009	0.0054	0.0001	0.0000	0.0000	0.0000	0.0019	0.0003	0.0004	0.0000	0.0000
SRTU 5	0.0068	0.0005	0.0016	0.0008	0.0009	0.0000	0.0011	0.0048	0.0007	0.0025	0.0001	0.0000	0.0000	0.0000	0.0000	0.0016	0.0004
SRTU 6	0.0078	0.0005	0.0034	0.0001	0.0006	0.0006	0.0008	0.0024	0.0000	0.0028	0.0008	0.0001	0.0017	0.0002	0.0004	0.0000	0.0012
SRTU 7	0.0098	0.0014	0.0001	0.0009	0.0005	0.0010	0.0012	0.0054	0.0002	0.0029	0.0000	0.0001	0.0005	0.0001	0.0004	0.0000	0.0006
SRTU 8	0.0068	0.0003	0.0040	0.0001	0.0006	0.0009	0.0008	0.0026	0.0001	0.0028	0.0012	0.0001	0.0016	0.0002	0.0008	0.0000	0.0011
SRTU 9	0.0072	0.0007	0.0023	0.0004	0.0000	0.0002	0.0010	0.0040	0.0002	0.0024	0.0013	0.0000	0.0012	0.0000	0.0000	0.0002	0.0005
SRTU 10	0.0032	0.0004	0.0082	0.0004	0.0001	0.0004	0.0009	0.0000	0.0002	0.0028	0.0040	0.0001	0.0014	0.0003	0.0005	0.0000	0.0006
SRTU 11	0.0099	0.0020	0.0000	0.0006	0.0008	0.0013	0.0011	0.0054	0.0001	0.0030	0.0000	0.0002	0.0008	0.0003	0.0011	0.0000	0.0012
SRTU 12	0.0085	0.0005	0.0021	0.0000	0.0004	0.0009	0.0008	0.0041	0.0000	0.0031	0.0004	0.0001	0.0015	0.0003	0.0004	0.0000	0.0011
SRTU 13	0.0076	0.0002	0.0024	0.0005	0.0007	0.0007	0.0008	0.0039	0.0001	0.0030	0.0005	0.0001	0.0015	0.0002	0.0005	0.0000	0.0008
SRTU 14	0.0098	0.0002	0.0002	0.0001	0.0001	0.0013	0.0009	0.0053	0.0001	0.0021	0.0000	0.0000	0.0022	0.0004	0.0007	0.0000	0.0015
SRTU 15	0.0099	0.0000	0.0006	0.0006	0.0005	0.0012	0.0006	0.0050	0.0001	0.0019	0.0001	0.0001	0.0014	0.0001	0.0002	0.0000	0.0004
SRTU 16	0.0090	0.0010	0.0019	0.0003	0.0006	0.0016	0.0006	0.0040	0.0001	0.0023	0.0002	0.0001	0.0008	0.0002	0.0004	0.0001	0.0005
SRTU 17	0.0098	0.0006	0.0004	0.0003	0.0004	0.0015	0.0009	0.0053	0.0002	0.0025	0.0000	0.0000	0.0013	0.0002	0.0009	0.0003	0.0009
SRTU 18	0.0000	0.0000	0.0052	0.0005	0.0004	0.0007	0.0008	0.0019	0.0007	0.0027	0.0009	0.0001	0.0009	0.0002	0.0007	0.0001	0.0006
SRTU 19	0.0082	0.0001	0.0058	0.0002	0.0002	0.0020	0.0000	0.0016	0.0000	0.0029	0.0009	0.0001	0.0011	0.0002	0.0008	0.0000	0.0007
SRTU 20	0.0098	0.0002	0.0006	0.0005	0.0005	0.0017	0.0005	0.0051	0.0001	0.0022	0.0001	0.0001	0.0014	0.0002	0.0005	0.0000	0.0008
SRTU 21	0.0096	0.0011	0.0004	0.0000	0.0002	0.0013	0.0012	0.0054	0.0007	0.0026	0.0001	0.0001	0.0019	0.0001	0.0006	0.0000	0.0023 1

Table-11: Ranking by MAIRCA

SRTU	Total gap	Rank
SRTU 1	0.0176	2
SRTU 2	0.0268	19
SRTU 3	0.0231	6
SRTU 4	0.0258	18
SRTU 5	0.0218	4
SRTU 6	0.0236	10
SRTU 7	0.0252	16
SRTU 8	0.0240	11
SRTU 9	0.0216	3
SRTU 10	0.0235	8
SRTU 11	0.0276	21
SRTU 12	0.0242	13
SRTU 13	0.0235	7
SRTU 14	0.0250	15
SRTU 15	0.0226	5
SRTU 16	0.0235	9
SRTU 17	0.0253	17
SRTU 18	0.0165	1
SRTU 19	0.0249	14
SRTU 20	0.0242	12
SRTU 21	0.0276	20

Table-12: Comparison of ranks for FY 2018-19

SRTU	RAP's	RAM's	RATMI	MCRAT	MAIRCA
SRTU 1	3	4	3	3	2
SRTU 2	18	19	18	18	19
SRTU 3	7	8	7	7	6
SRTU 4	12	13	12	12	18
SRTU 5	8	9	8	8	4
SRTU 6	6	7	6	6	10
SRTU 7	21	22	21	21	16
SRTU 8	5	6	5	5	11
SRTU 9	9	10	9	9	3
SRTU 10	1	2	1	1	8
SRTU 11	20	21	20	20	21
SRTU 12	11	12	11	11	13
SRTU 13	10	11	10	10	7
SRTU 14	15	16	15	15	15
SRTU 15	16	17	16	16	5
SRTU 16	13	14	13	13	9
SRTU 17	19	20	19	19	17
SRTU 18	2	3	2	2	1
SRTU 19	4	5	4	4	14
SRTU 20	17	18	17	17	12
SRTU 21	14	15	14	14	20

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For the financial Year 2018-19, RAPs, RAMs, RATMI, and MCRAT methods provide nearly identical rankings, suggesting high agreement. MAIRCA diverges notably, reordering several SRTUs significantly. SRTU10 and SRTU18 consistently rank high across all methods, while SRTU2, SRTU7, and SRTU11 remain among the lowest. MAIRCA's variability may stem from a different evaluation logic as discussed in section 3.2.

Similarly ranking of SRTUs for the financial year 2017-18 and 2016-17 are determined and presented in the following table.

Table-13: Ranking of SRTUs for the FY 2017-18

SRTU	RAP's	RAM's	RATMI	MCRAT	MAIRCA
SRTU 1	3	4	3	3	2
SRTU 2	18	19	18	18	21
SRTU 3	7	7	6	6	5
SRTU 4	12	14	13	13	18
SRTU 5	8	10	9	9	3
SRTU 6	6	9	8	8	9
SRTU 7	21	22	21	21	13
SRTU 8	5	6	5	5	12
SRTU 9	9	8	7	7	4
SRTU 10	1	2	1	1	8
SRTU 11	20	21	20	20	19
SRTU 12	11	13	12	12	14
SRTU 13	10	11	10	10	11
SRTU 14	15	16	15	15	15
SRTU 15	16	18	17	17	7
SRTU 16	13	12	11	11	6
SRTU 17	19	20	19	19	17
SRTU 18	2	3	2	2	1
SRTU 19	4	5	4	4	16
SRTU 20	17	17	16	16	10
SRTU 21	14	15	14	14	20

For the financial year 2017-18, RAP's, RAM's, RATMI, and MCRAT produce near-identical rankings, showing strong consistency. MAIRCA shows noticeable deviations, reshuffling several SRTUs significantly. SRTU18 and SRTU10 rank consistently at the top, while SRTU2, SRTU11, and SRTU17 remain bottom performers. MAIRCA tends to reward certain SRTUs (e.g., SRTU5, SRTU15) differently.

Table-14: Ranking of SRTUs for the FY 2016-17

SRTU	RAP's	RAM's	RATMI	MCRAT	MAIRCA
SRTU 1	3	4	3	3	2
SRTU 2	18	15	14	16	21
SRTU 3	7	6	5	5	6
SRTU 4	12	14	13	13	18
SRTU 5	8	10	9	9	3
SRTU 6	6	9	8	8	9
SRTU 7	21	22	21	21	19
SRTU 8	5	7	6	6	13
SRTU 9	9	8	7	7	5
SRTU 10	1	2	1	1	8
SRTU 11	20	20	19	19	16
SRTU 12	11	12	11	11	14
SRTU 13	10	11	10	10	11
SRTU 14	15	17	16	14	17
SRTU 15	16	18	17	17	7
SRTU 16	13	13	12	12	4
SRTU 17	19	21	20	20	15
SRTU 18	2	3	2	2	1
SRTU 19	4	5	4	4	12
SRTU 20	17	19	18	18	10
SRTU 21	14	16	15	15	20

For the financial year 2016-17, RAP's, RAM's, RATMI, and MCRAT display high consistency in rankings. MAIRCA significantly reorders several SRTUs, promoting some (like SRTU5, SRTU15) and demoting others (like SRTU2, SRTU19). SRTU18 and SRTU10 are consistently top ranked, while SRTU2, SRTU7, and SRTU11 stay at the bottom. The variation in MAIRCA suggests it applies a different scoring logic compared to the others.

ANOVA (Analysis of Variance):

ANOVA is conducted to know the signification factors that are causing variation in the ranking

Table-15: ANOVA

Source	DF	SS	MS	F	P
METHOD	4	50.4	12.6	2.47	0.045
SRTU	20	10079.87	503.99	98.73	0
FY	2	0	0	0	1
Error	288	1470.13	5.1		
Total	314	11600.4			

S = .25934 R-Sq = 87.33% R-Sq(adj) = 86.18%

The analysis shows that the METHOD factor has a small but statistically significant effect on the response variable at a significance level of $\alpha = 0.05$, indicating that the choice of method does influence the outcome to some extent. The SRTU factor is highly significant ($P < 0.001$) and explains the majority of the variability in the response, making it the most influential factor in the model. On the other hand, the FY factor is not significant and has no impact on the response, as indicated by its zero sum of squares and an F-value of 0. The residual or unexplained variability is captured under the Error term, and the relatively low mean square error (MS = 5.1) suggests that the model fits the data well.

Overview of the model fit:

- R-Sq (R^2) = 87.33%: This means that 87.33% of the total variation in the response variable is explained by the model (i.e., by METHOD, SRTU, and FY).
- R-Sq(adj) = 86.18%: This is the adjusted R^2, which accounts for the number of predictors. It's slightly lower than R^2, indicating the model is still a good fit but slightly penalizes the number of predictors.

The findings across three financial years (2016–17 to 2018–19) consistently reveal strong agreement among the geometric similarity-based methods—RAPs, RAMs, RATMI, and MCRAT—demonstrating their robustness and reliability for evaluating the relative performance of SRTUs. These methods yield nearly identical rankings, reinforcing their internal consistency and methodological harmony.

However, the MAIRCA method consistently deviates, reshuffling rankings and offering a distinct perspective on performance evaluation. This divergence can be attributed to its unique ideal-real comparative logic, which appears to emphasize different performance characteristics than the geometric methods. For instance, MAIRCA elevates SRTUs like SRTU5 and SRTU15 while demoting consistently low performers such as SRTU2 and SRTU7 more drastically.

Statistical analysis further substantiates the credibility of the model. The SRTU factor emerged as the most influential with high significance ($P < 0.001$), explaining the majority of the variance in the rankings. The METHOD factor, though statistically significant at $\alpha = 0.05$, contributes to a smaller portion of the variability, suggesting that while the choice of method affects rankings, it does so marginally compared to the inherent differences among SRTUs. The FY factor, on the other hand, showed no significant impact, indicating performance rankings are relatively stable across the years analyzed.

The model's high explanatory power (R^2 = 87.33%, R^2(adj) = 86.18%) and low mean square error (MS = 5.1) confirm a strong model fit, supporting the reliability of the results and the applied MCDM framework.

5. CONCLUDING REMARKS

This study highlights the effectiveness of geometric similarity-based MCDM methods—RAPs, RAMs, RATMI, and MCRAT—in evaluating the multidimensional performance of State Road Transport Undertakings (SRTUs). The consistency observed among these methods across three financial years underscores their reliability and robustness in ranking alternatives. In contrast, the MAIRCA method demonstrated a distinct ranking pattern, often promoting or demoting specific SRTUs differently. While this divergence suggests a different underlying logic, it also provides an alternative perspective that may reveal additional insights into the strengths and weaknesses of the transport units. Notably, SRTU18 and SRTU10 emerged as consistent top performers, whereas SRTU2, SRTU7, and SRTU11 frequently ranked among the lowest across all methods. The statistical analysis confirms that while the choice of method has a modest but significant effect on rankings, the most influential factor is the inherent performance differences among the SRTUs. Overall, the proposed framework offers a robust tool for transport administrators to benchmark performance and identify areas needing strategic intervention.

Developing hybrid MCDM models that combine geometric methods with fuzzy logic or objective rating methods could improve decision-making under uncertainty. Additionally, conducting a weight sensitivity analysis could help understand how different performance criteria influence rankings and address any potential biases.

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