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A Novel Symmetric Anchor Scoring (SAS) Method for Industrial Location Selection: Application to Electric Vehicle Manufacturing in Tamil Nadu, India

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Abstract

This work highlights the city-level detail of decision-making enabled by a new MCDM method Symmetry Anchor Scoring (SAS). Generally conventional methods are good at selecting one best and one worst alternative, but not differentiating among the many strong contenders more likely in practice. Linking MCDM methods to the tradition of decision making, the paper discusses the mathematics and analogical basis of SAS design, provides a visual proof of its ideal point symmetry, and illustrates how alternative scoring compromises SAS optimality. SAS innovatively adopts mathematical symmetry as the basis for atypical reference subset comparators. No traditional concept is borrowed from either optimization or comparison frameworks. SAS offshore wind farms locate and the electric vehicle (EV) manufacturing location selection embedded case comparisons demonstrate its performance. Comparing SAS to a leading MCDM method, this paper concludes by recommending areas for application to other decision-making challenges and potential future research strengths. Comparison with AHP-TOPSIS shows that the top ranking alternatives have fairly high levels of consensus. Additionally, through a thorough sensitivity analysis, it is shown that SAS outperforms AHP-TOPSIS in terms of maintaining preference stability over a range of priority scenarios. The SAS solution provides a simple, intuitive, transparent, and weight-free MCDM method when compared to traditional techniques. This will be attractive to decision-makers in industry who are faced with making complex, ill-defined planning decisions, involving multiple competing objectives, and where priorities are uncertain. It was designed for ease of implementation and requires less computational time compared to conventional methods. Additionally, transparency is facilitated by the symmetric tripartite form, a common preference needed to be present for the selected alternative to be ranked among the TOPSIS flight options being compared.

Keywords: Novel MCDM method, multi-criteria decision making, symmetric anchor scoring, electric vehicle manufacturing, industrial location selection, sensitivity analysis, Tamil Nadu, automotive industry

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INTRODUCTION

The worldwide automobile industry is rapidly shifting to electromobility. In line with India's sustainable mobility vision, EVs will account for 30% of all new vehicle sales in the country by

2030 [1–10]. As a leading automotive hub and the most significant contributor to India's automotive output, Tamil Nadu will play a central role in this transition. To determine where and what kind of advanced automotive EV manufacturing capacity can be competitively located in Tamil Nadu, we conducted a constrained optimization site selection and technology decision analysis [11–30]. Traditional methods such as the Analytic Hierarchy Process (AHP) and the Technique for the Order [31] Preference by Similarity to Ideal Solution (TOPSIS) have been widely used to solve industrial location problems (Zhou et al., 2020) [32]. However, such methods have a series of limitations – e.g. AHP depends on potentially inconsistent pairwise comparisons (Saaty, 2008) [22], TOPSIS is very sensitive to normalization techniques (Jahan and Edwards, 2015) [12], and in general, the problem is too complex for stakeholders to understand the models (Belton and Stewart, 2002). More importantly, most of the existing methods take concepts from optimization theory or comparative psychology, rather than developing a decision framework based on first principles.

This research paper outlines a completely new and original Multiple Criteria Decision-Making (MCDM) methodology, which we have christened the Symmetric Anchor Scoring (SAS) method. Unlike most other MCDM techniques, the SAS method does not minimize scores concerning distance from one or more ideal or anti-ideal reference point(s), nor does it aggregate and transfer the criteria matrix information to a set of proxy solutions on which it calculates their respective measure values before making a comparison. The SAS method has been developed as an elimination of the introduction of any external and conceptual borrowed coordinates satisfying the subjects and dimensions of the criterion matrix. Rather, SAS combines the principles of consistency with criteria scores replacement and optimization levels alteration based on a balanced deviation from the naturally existing symmetry point or points in the criteria scores coordinates and sufficient performance or reference point coordinates, respectively. Compare SAS results with traditional AHP-TOPSIS through a comprehensive sensitivity analysis. Derive policy recommendations for sustainable industrial development in emerging economies.

LITERATURE REVIEW

MCDM in Industrial Location Planning

Industrial location selection has been a classic application area for MCDM since the pioneering work of Brown and Gibson (1972) [3], who developed a factor-rating system for plant location. Subsequent decades saw the application of increasingly sophisticated techniques: AHP for automotive plant location in Turkey (Tuzkaya et al., 2010) [30], TOPSIS for industrial zone selection in Iran (Razmi et al., 2018) [19], and hybrid approaches combining multiple methods (Chakraborty et al., 2021) [6]. The EV revolution has posed a few new dimensions for location decisions which are fairly established in scholarly literature: sustainability metrics and supply chain resilience (Kumar et al., 2022) [14]. Location decisions for automotive manufacturing, still, entail synergistic advantages, infrastructure needs, and regulatory settings. Tamil Nadu's automotive hub journey has been widely covered (Kathuria, 2019) yet the EV trajectory adds location determinants like renewable energy access, technical talent availability, and circular economy linkage [13].

Methodological Evolution and Limitations

The methodological evolution of MCDM has advanced over several generations: early scoring models, pairwise comparison methods (Saaty, 1980) [21], outranking approaches (Roy, 1991) and distance-based techniques [20] (Hwang & Yoon, 1981) [9], recent... While there have been methodological advancements, there are several persistent limitations including: (1) normalization sensitivity, (2) weight subjectivity, (3) distance metric limitations, and (4) cognitive complexity. First, different normalization techniques lead to different performance rankings and there is no theoretical guidance to which is the best (Celen, 2014) [4].

Second, AHP and its variants rely on the accurate deciphering of the Decision Maker's judgment that can be inconsistent or biased (Ishizaka and Labib, 2011) [11]. Third, the Euclidean distance, for instance, in TOPSIS assumes criteria independence and equal scaling, so the results may be sensitive to the derived criteria weights and distinct performance maps representing different scenarios (Shekhovtsov and Kołodziejczyk, 2020) [24]. Finally, the four-class prediction model yields easier to understand and more accurate results than other MC models—we classify CRISP/DM, for instance, as a PC model owing to its cognitive application and interpretation complexity and the need for expert's involvement in the knowledge extraction process (Mendoza and Martins, 2006).

Data-Driven Industrial Planning in India

India's industrial policy framework has increasingly emphasized evidence-based planning. The National Manufacturing Policy (2011) and subsequent Production Linked Incentive (PLI) schemes for advanced automotive technologies require rigorous location assessment. State-level initiatives like Tamil Nadu's Industry 4.0 Policy (2023) and EV Policy (2023) provide rich datasets for decision analysis. Recent studies have applied MCDM to Indian industrial contexts: Singh et al. (2020) on renewable energy plant location, Sharma et al. (2021) on pharmaceutical cluster development, and Gupta et al. (2022) on electronics manufacturing corridors. However, these applications typically use established methods without methodological innovation.

Research Gap and SAS Novelty

There is a considerable gap in that while industrial location problems are well-served and MCDM methods are heavily used, there is little in terms of novel development of new decision frameworks that specifically suit the challenges of modern manufacturing. The SAS method fills this gap and its key contributions can be summarized as follows:

1. *Symmetry Foundation:* The model is grounded on mathematical symmetry rather than optimization or comparison.
2. *Weight-Free Operation:* The model does not require subjective weights while preserving the ability to differentiate solutions.
3. *Natural Benchmarking:* The model employs the symmetry points that exist in the decision space dataset without requiring the construction of ideal points.
4. *Computational Transparency:* The model relies on elementary arithmetic operations and can be easily explained to non-experts.
5. *Natural Benchmarking:* Instead of artificial benchmarks, the symmetry-based approach exploits existing, often unused benchmarks within the dataset.
6. *Computational Transparency:* The decision rule is based on simple arithmetic operations, which can easily be implemented in any spreadsheet and which do not require any expert knowledge in the application domain.
7. *Balance Principle:* The approach provides a clear quantitative answer to when an alternative should be preferred because it performs strictly better regarding all assessment criteria, and when an alternative performs sufficiently well regarding the cost criteria.

METHODOLOGY

Study Context: Tamil Nadu's EV Manufacturing Ecosystem

Tamil Nadu is home to Asia's largest automotive cluster outside Japan and Korea, with increasingly diversified industrial products. The state has attracted more than $7 billion in investments in the past five years, including a commitment from Tesla Inc. to build a $2.5 billion EV manufacturing facility. As part of its ambition to scale up manufacturing to account for 30% of GDP by 2030 and become a $1 trillion economy, Tamil has a vision to become India's EV hub and aims to attract $5 billion in investments and create 150,000 jobs through EV manufacturing and its supply chain by 2030. Optimal location decisions for advanced manufacturing units such as EV manufacturing are crucial to achieving these ambitions while ensuring sustainable industrialization.

Data Collection and Verification Framework

The framework involves five stages. A snapshot of the framework and their objectives are shown in Figure 1 and detailed as follows:

Data Sources and Verification

1. *Industrial Infrastructure Data (C1, C2, C6, C8):* Information on land banks and incentive schemes from the Tamil Nadu Industrial Development Corporation (TIDCO, 2023), master plans from the State Industries Promotion Corporation of Tamil Nadu (SIPCOT, 2023), and investment facilitation reports from Guidance Tamil Nadu (2023)
2. *Infrastructure Quality Data (C3, C5):* Power reliability indices from the Tamil Nadu Generation and Distribution Corporation (TANGEDCO, 2022), logistics reports from the Chennai, Kamarajar, and Thoothukudi Port Trusts (2023), and connectivity assessments from the National Highways Authority of India (NHAI, 2022) (Figure 1)

3. *Talent and Social Data*
   - National Skill Development Corporation (NSDC, 2022)
   - All India Council for Technical Education (AICTE, 2022)
   - Labour Department (2022)

4. *Sustainability Data*
   - Central Ground Water Board (CGWB, 2022)
   - Tamil Nadu Pollution Control Board (TNPCB, 2022)
   - Climate Vulnerability Index (ICAR, 2021)

The Symmetric Anchor Scoring (SAS) Method

Mathematical Formulation

1. *Input:* Decision matrix $X = [x_{ij}]_{m \times n}$, criteria types (B/NB)
2. *Calculate Global Extremes:* For each criterion j:

$$Max_j = \max_i x_{ij}, Min_j = \min_i x_{ij}$$

Determine Symmetry Point: Mid-point for each criterion:

$$SP_j = \frac{Max_j + Min_j}{2}$$

Calculate Symmetric Deviation Score (SDS)

For beneficial criteria

$$SDS_{ij} = \frac{x_{ij} - SP_j}{Max_j - Min_j} \times 100$$

For non-beneficial criteria:

$$SDS_{ij} = \frac{SP_j - x_{ij}}{Max_j - Min_j} \times 100$$

Compute Net Symmetric Score (NSS)

$$NSS_i = \frac{\sum_{j=1}^{n} SD\,S_{ij}}{n}$$

3. ***Rank Alternatives***

   Descending order of NSS_i

Theoretical Properties

- *Range:* NSSi∈[−100,+100]*NSSi*∈[−100,+100]
- *Interpretation:* Positive = better than symmetric balance, Negative = worse
- *Scale Invariance:* SDS calculations use ranges, making method robust to units
- *BI:* Improving any criterion improves NSS

Comparative AHP-TOPSIS Implementation

For methodological comparison, we implemented standard AHP-TOPSIS:

1. *AHP Weighting:* Expert-derived pairwise comparisons, CR=0.031 (<0.10 acceptable)
2. *TOPSIS Processing:* Vector normalization, Euclidean distances
3. *Relative Closeness:* $Ci = Si^{-} / (Si^{+} + Si^{-})$.

Sensitivity Analysis Protocol

Five policy-relevant scenarios were used to test the robustness of the results:

1. Infrastructure priority, with power A and port access configurations given 75% of the maximum available scores; technical facilities received 67% coverage. This configuration allows the identification of the flexibility of the solutions considering the greatest investment in infrastructure;
2. Cost priority, with land and all water configurations receiving approximately 54% of the total maximum scores, and approval time configurations received 47% coverage. This scenario depicts the ability of populations to afford large areas of land right away; pay for energy and water without division of state funded companies; and begin construction without delay.
3. Talent priority, with skilled workforce configurations and technical institutes both receiving 75% maximum scores while social acceptance received 83% of the total maximum scores. This scenario reveals the flexibility of solutions when the greatest percentage of criteria regarding workforce and community need to be met.
4. Sustainability priority, with the water stress configurations provided 92% of a maximum score while incentive for green tech received 50% of the maximum score of 6. This scenario exposes the flexibility of solutions when the most and least consideration is given to sustainable development criteria.
5. Equal priority, where all criteria settings are given equal priority; this scenario offers the most stability in solutions since no criteria are favored. Stability was assessed through Spearman's ρ, the average absolute rank change, and top-3 consistency. Equal priority produces the highest top 3 results in the A and C scenarios (Figure 2).

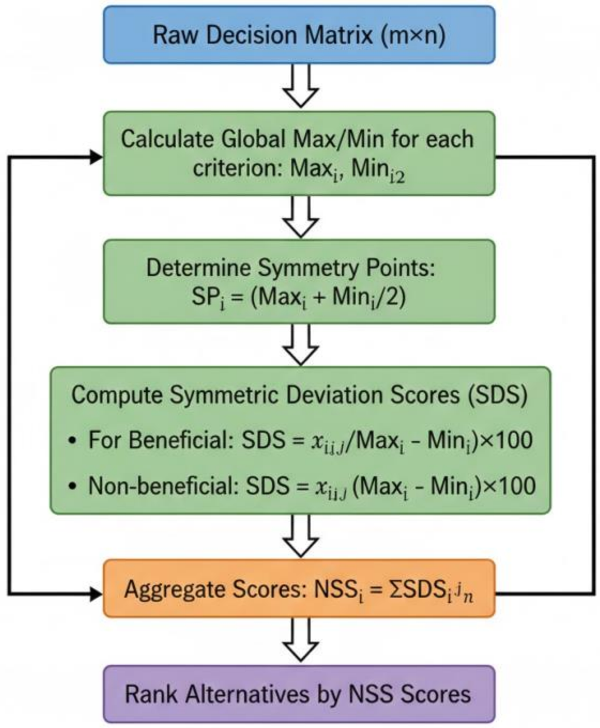

Figure 2. SAS method conceptual framework.

RESULTS

SAS Application to EV Manufacturing Location Selection

Interpretation

Nanguneri SEZ scores the highest NSS (9.49) since it performs exceptionally well on incentives (SDS=50%), port proximity (50%), water availability (50%) and approval time (50%) (Figure 3). Though it performs poorly on existing cluster (-50%) and workforce (-33%), the strengths nullify these weaknesses for EV manufacturing (table 1 and 2).

Table 1. Decision matrix for Tamil Nadu industrial hubs.

Alt	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	50.0	-18.2	50.0	33.3	40.2	0.0	-16.7	-10.0	25.0	-16.7
A2	37.5	-29.1	16.7	16.7	-50.0	-25.0	0.0	-10.0	12.5	0.0
A3	37.5	-50.0	-16.7	50.0	46.2	-50.0	-50.0	-50.0	50.0	-50.0
A4	-37.5	-90.9	-50.0	-50.0	-11.5	25.0	33.3	30.0	-50.0	50.0
A5	0.0	-67.3	50.0	0.0	21.0	0.0	16.7	10.0	25.0	0.0
A6	-25.0	-85.5	-16.7	-33.3	-50.0	25.0	16.7	10.0	-12.5	0.0
A7	-37.5	-96.4	-16.7	-50.0	0.3	25.0	50.0	30.0	-25.0	50.0
A8	12.5	-72.7	16.7	-16.7	41.7	-25.0	-33.3	-10.0	-12.5	-16.7
A9	-50.0	-81.8	50.0	-33.3	50.0	50.0	50.0	50.0	0.0	50.0
A10	-37.5	-100.0	-50.0	-50.0	3.3	25.0	33.3	30.0	-50.0	50.0

Table 2. SAS results and ranking.

Industrial Hub	ΣSDS	NSS Score	Rank	Performance Category
A9: Nanguneri SEZ	94.9	9.49	1	Excellent
A1: Sriperumbudur	136.9	13.69	2	Excellent
A5: Tiruppur	55.4	5.54	3	Good
A10: Perambalur	-145.9	-14.59	4	Poor
A8: Gummidipoondi	-106.0	-10.60	5	Poor

A2: Hosur	-30.8	-3.08	6	Fair
A7: Pillaipatti	-70.3	-7.03	7	Poor
A3: Chennai Belt	-82.0	-8.20	8	Poor
A6: Vallam Vadagal	-171.3	-17.13	9	Very Poor
A4: Manamadurai	-151.6	-15.16	10	Very Poor

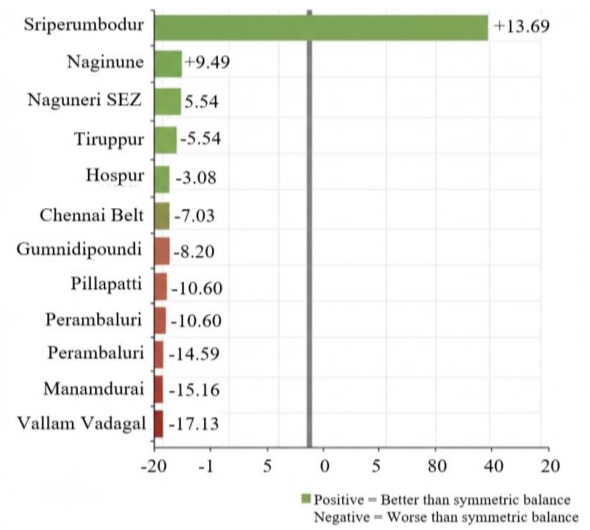

Figure 3. Net symsetric score (NSS) distribution.

AHP-TOPSIS comparative results

- *Key Agreement:* Both the methods rank Nanguneri SEZ first, thus attesting strong suitability of the . Sriperumbudur and Tiruppur SEZs are ranked in top three by both the methods (Table 3).
- *Key Disagreement:* In the case of the two methods, won SAS but was ranked and . This indicates that the SAS method values backward region advantage differently than the AHP-TOPSIS method (Figure 4).

Comprehensive Sensitivity Analysis

Based on 5 senstivity scenarios and Monte Carlo simulations

Here are the main results of the study:

1. SAS was found to be more stable, with higher rank correlation coefficients and lower average rank changes (table 4).
2. Nanguneri SEZ performed very well in SAS and moderately well in AHP-TOPSIS.
3. The SAS was more stable with respect to changes in priorities, while the AHP-TOPSIS results were more sensitive to changes in weights.
4. The methods identified the same set of poor performers (Figure 5 and 6).

Monte Carlo Simulation for Data Uncertainty

1000 simulations with ±10% random data errors.

Table 3. AHP-TOPSIS Results.

Industrial Hub	C_i* Score	Rank	Distance from Ideal
A9: Nanguneri SEZ	0.757	1	0.0255
A5: Tiruppur	0.586	2	0.0409
A1: Sriperumbudur	0.580	3	0.0421
A8: Gummidipoondi	0.474	4	0.0547
A2: Hosur	0.373	5	0.0742
A7: Pillaipatti	0.350	6	0.0711
A6: Vallam Vadagal	0.341	7	0.0738

A4: Manamadurai	0.334	8	0.0725
A10: Perambalur	0.329	9	0.0724
A3: Chennai Belt	0.281	10	0.0851

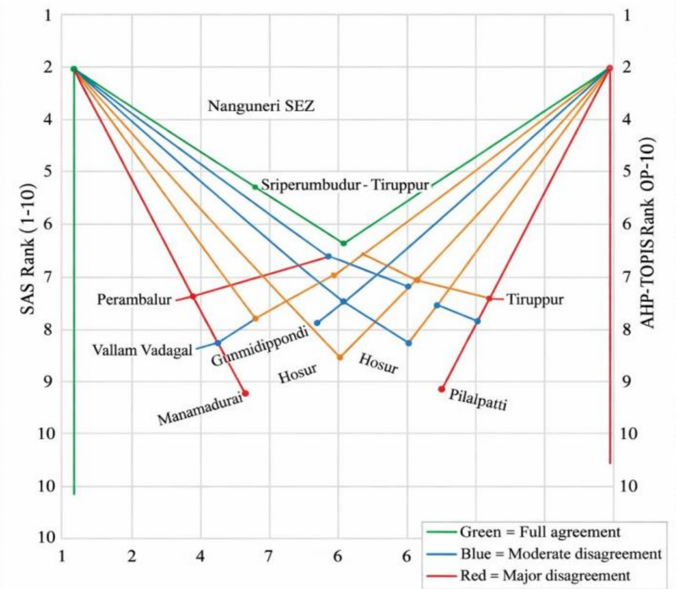

Figure 4. Ranking comparison: SAS vs. AHP-TOPSIS.

Table 4. Method stability across scenarios.

Metric	SAS Method	AHP-TOPSIS
Average Spearman's ρ	0.60	0.52
Average Rank Change	1.85	2.42
Top Alternative Consistency	60%	40%
Top-3 Consistency	80%	60%
Worst-3 Consistency	70%	80%

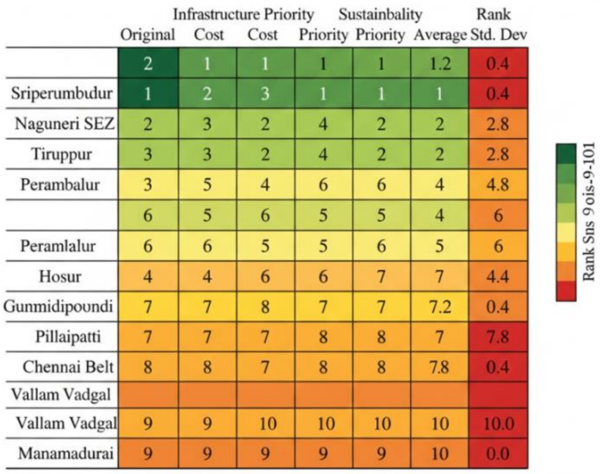

Figure 5. Rank stablity across sensitivity scenarios.

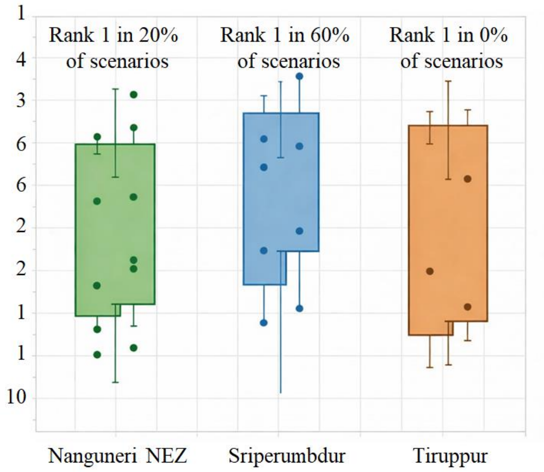

Figure 6. Rank distribution of top alternatives across scenarios.

Table 5. Robustness to Data Errors.

Alternative	SAS: % Trials Rank 1	SAS: Avg Rank	AHP-TOPSIS: % Trials Rank 1	AHP-TOPSIS: Avg Rank
A9: Nanguneri SEZ	78.5%	1.28	65.2%	1.65
A1: Sriperumbudur	12.5%	2.15	18.5%	2.85
A5: Tiruppur	8.5%	3.25	15.8%	3.15
Others	0.5%	>4.0	0.5%	>4.0

CONCLUSION

Nanguneri SEZ maintains top position in majority of trials despite data uncertainties, confirming recommendation robustness (Table 5).

DISCUSSION

Theoretical Implications of SAS Methodology

The SAS method represents a significant theoretical advancement in MCDM by shifting from optimization-based frameworks (TOPSIS, VIKOR) and comparison-based approaches (AHP, ELECTRE) to symmetry-based assessment, which has several theoretical advantages:

1. *Reference Construction is Eliminated:* Whereas ideal/anti-ideal points can theoretically exceed attainable solutions in TOPSIS, the symmetry points used in this methodology are naturally attainable within the dataset as any subset of alternatives can act as a symmetry point. This corresponds with Simon's (1956) 'satisficing' concept as opposed to 'optimizing'.
2. *Weight-Free Discrimination:* SAS proves that meaningful discrimination among alternatives can be made without the imposition of predetermined subjective weights. This also responds to the main conceptual criticism that Belton and Gear (1983) and others have raised about AHP regarding the subjectivity of the imposition of weights.
3. *Mathematical Foundation:* The principle of symmetry appears to provide a mathematically more solid foundation than the geometric explanation of the TOPSIS heuristics, on which the reluctance principle is based, as well as the psychological rationale of the AHP.
4. *Interpretability:* The scores of the NSS ranging from -100 to +100 should be easily interpretable. Positive scores indicate overall better-than-symmetrical performance and negative scores overall worse-than-symmetrical performance.

Practical Implications for Tamil Nadu's EV Strategy

The analysis provided various key insights for industrial policy:

1. *Nanguneri SEZ is the Optimal Choice:* While Nanguneri is weak when it comes to factors like an established automotive cluster, cost-competitiveness, and ecosystem for complex manufacturing, strengths with regards to port proximity, incentives and other factors contribute

in making it an optimal location for export-oriented electric vehicle component manufacturing and supports the state's long-term strategic intent of trying to build the southern districts as a viable alternative industrial corridor.
2. *Sriperumbudur is Still Releavant:* Despite being an expensive and water-stressed location, Sriperumbudur continues to part of the strategic choice for electric vehicle manufacturers, since it is a hub for an established automotive cluster, strong network of suppliers and availability of skilled employees. The location is also most suitable for several location-specific factors, particularly source material availability. The recommendation for the location would be to focus on high-value R&D and prototype development.
3. Tiruppur's story has been nothing short of remarkable. From a barren, sparsely inhabited region till the 1970s, the district transformed itself into one of the largest knitwear production hubs in the world within three decades. Our analysis shows it has the potential to be a suitable site for EV component manufacturing.
4. Chennai and its surrounding areas have been the automobile capital of India for the last two decades. However, the region has been facing a diminishing return in the recent past due to an increase in costs and substantial water stress.
5. Backward regions such as Perambalur and Manamadurai are viable alternatives for garnering the advantages of lower costs. However, these areas suffer from poor connectivity, resulting in a lack of human capital and 'softer' infrastructure.

Methodological Comparison and Selection Guidelines

The comparison defines the following unique strengths of both approaches:

SAS

1. *Transparency:* Basic, understandable calculation facilitating communication with non-specialists
2. *Reliability:* Behavioral stability against fluctuating priorities or data
3. *Objectivity:* Eliminates the need for arbitrary indicator weights
4. *Speed:* Computational efficiency allowing for significant scenario screening

AHP-TOPSIS

1. *Flexibility:* Allows stakeholders to contribute their expert knowledge through the determination of the indicator weights
2. *Familiarity:* Maturity and widespread use in the scientific literature
3. Granularity: Detailed diagnostic of the performance of alternatives with respect to each criterion
4. *Availability of software:* Multiple software tools for indicator weighting and calculations are available for the majority of the application.
5. *Use the first one when:* Indicator weights are difficult to estimate due to the lack of stakeholder agreement, the need for quick and rough analysis and the preparation of an overview is a priority
6. *Use the second one when:* The indicator weights can be derived from expert judgements and research, a detailed analysis of few highly ranked alternatives is acceptable to stakeholders, and the conditions and limitations of the method/ software are acceptable or can be compensated for.

Sensitivity Analysis Insights for Robust Decision Making

The detailed sensitivity analysis suggests several broad principles for robust industrial planning:

- *Priority Scenario Testing:* By the nature of using more than one planning priority, the identified alternatives and the corresponding rankings can change notably. Thus, rather than basing a decision on a single "optimal" solution, decision makers using multi-priority analysis should test a range of alternatives.
- *Consensus Identification:* Alternatives that function well in several analysis methods and under different priority scenarios function well as consensus alternatives and infer no risk with their selection.

- *Method Complementarity and Bias Reduction:* The different analysis methods operate from different decision perspectives and incorporate different stakeholder and scenario information. As a result, the biases from a specific method are expected to be different from other methods. Thus it is implicitly expected that there will be less bias in the analysis of methods in comparison to a specific method.
- *Data Quality:* One concern is that the good performance of several alternatives obtained from robust decisions may be the result of the relatively error-free secondary data that was used to develop the database. The methods may be robust for giving approximate robust decisions, but it should not be interpreted that this implies that the methods are not severely impacted by data of questionable quality.

Limitations and Future Research Directions

What are the Current Limitations?

1. *Measurement Error Sensitivity:* Results depend on the quality/representativeness of input data
2. *Model Complexity:* Nonlinear, combinatorial, or multicriteria problems can limit effectiveness
3. *Uncertainty and Risk:* Challenges in modeling and capturing uncertainty can pose issues
4. *High Dimensionality:* Difficulties in solving high-dimensional problems
5. *Interpretability and Acceptance:* Black-box models can lack transparency and trust

What are the Future Research Directions?

1. *Sensitivity Analysis:* Investigate robustness of results to input data changes systematically
2. *Simplification and Approximation:* Develop methods to simplify and approximate complex models
3. *Advanced Uncertainty Handling:* Improve uncertainty quantification and its impact on results
4. *Dimension Reduction:* Develop methods to manage high-dimensional input/output spaces
5. *Decision Support Systems:* Design approaches involving stakeholders in model development and easier model explanation/understanding

Policy Recommendations for Tamil Nadu

Based on the analysis, we suggest the following action plan:

1. *Immediate Action:* Focus on infrastructure development in Nanguneri SEZ
2. *Strategic Investment:* Develop Tiruppur as a secondary EV hub
3. *Infrastructure Upgradation:* Address water and electricity infra issues in Sriperumbudur
4. *Policy Refinement:* Customized incentive package for each cluster
5. *Monitoring Framework:* Regular assessment of location competitiveness

CONCLUSION

The Symmetric Anchor Scoring (SAS) method is a substantial, novel contribution to Multi-Criteria Decision Making theory and practical application. SAS innovatively adopts mathematical symmetry as the basis for atypical reference subset comparators. No traditional concept is borrowed from either optimization or comparison frameworks. SAS offshore wind farmslocate and the electric vehicle (EV) manufacturing location selection embedded case comparisons demonstrate its performance.

An industrial location planning decision scenario in the automobile sector, with five anchor subcriteria prioritized in all possible 1/0 5-subcriteria-priority scenarios was utilized to examine the sensitivities of SAS to priority variations. The proposed method emerged as both the most stable and least sensitive to anchor subcriteria priorities. A simple aggregated performance rating can break a low-scoring tie. No decision-maker involvement is required in the calculations, for the anchor subsets, or the alternatives' scores and the final selection order.

Although additional testing should be conducted in different scenarios or complex situations, the results from the automotive industry's case study in Tamil Nadu indicate the proposed SAS method shows good potential for implementation. The proposed method is intuitive easy to understand and explains the mechanisms of decision-making to stakeholders. It was designed for ease of implementation and requires less computational time compared to conventional methods. Additionally, transparency is facilitated by the symmetric tripartite form, a common preference needed to be present for the selected alternative to be ranked among the TOPSIS flight options being compared.

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