Chapter 54

ARAS: Additive ratio assessment for multi-attribute decision-making

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54.1 Introduction

Multicriteria decision-making (MCDM) methods are widely applied across various domains of human activity to support decision-making processes in complex situations that involve multiple, often conflicting, criteria (Damjanović et al., 2022; Kutut et al., 2013; Pramanik et al., 2021). In an MCDM problem, each alternative is described by a set of criteria, which may be either qualitative or quantitative, and which may differ in terms of measurement scales and directions of optimization (Petrović, Jovanović, Marković, et al., 2025; Zavadskas et al., 2017). Consequently, normalization of criteria values is necessary to ensure mutual comparability (Petrović, Jovanović, Petrović, et al., 2025; Stević et al., 2024).

Unlike the single-criterion approach, which attempts to consolidate all aspects of a problem into a single aggregated measure, the multicriteria approach enables the simultaneous analysis of several conflicting objectives. This makes it particularly suitable for complex real-world scenarios that require the integration of multiple perspectives. Within the MCDM framework, the primary task of the decision-maker is to evaluate the final set of alternatives in order to identify the optimal solution, rank the available options, classify them, or assess the extent to which specific criteria are met (Đalić et al., 2021; Petrović, Marković, et al., 2024).

Among the many MCDM methods developed, the additive ratio assessment (ARAS) method, first introduced in the paper (Zavadskas & Turskis, 2010), offers a systematic approach for evaluating alternatives. This method enables the calculation of the utility of each alternative based on the relative ratios of the criteria values and their associated weights. The core principle of the ARAS method is to assess the composite relative efficiency of each alternative by comparing it to a predefined ideal solution (Zavadskas, Sušinskas, et al., 2012). In doing so, the method integrates all criteria into a single utility function, thus providing clarity and transparency in the decision-making process and facilitating the identification of the most favorable option.

Despite the existence of numerous MCDM techniques, differences in weight application, optimal solution selection, objective scaling, and incorporation of additional parameters often lead to variations in results for the same decision problem, known as the inconsistent ranking problem (Dehshiri & Firoozabadi, 2023). Nevertheless, the ARAS method, as a quantitative approach, provides a structured and transparent decision-making framework, with clearly defined criteria and interrelationships. It enables the ranking of alternatives based on their proximity to the ideal solution, offering a logical basis for decision-making in complex scenarios.

Evaluating the effectiveness of individual MCDM methods in solving complex problems is inherently challenging (Simić et al., 2023). In the ARAS method, the utility value—representing the overall efficiency of a specific alternative—is directly dependent on the relative importance and quantitative values of the analyzed criteria. Based on the derived utility function, a priority list of alternatives can be established, thereby allowing systematic comparison and ranking. The degree of utility is determined through comparison with the optimal (ideal) solution, offering a benchmark to identify potential improvements for specific alternatives (Tupenaite et al., 2010; Zavadskas, Vainiūnas, et al., 2012).

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MCDM combines both deductive and inductive reasoning and is often applied to domains characterized by imprecision or incomplete data (Nedeljković et al., 2021; Zavadskas et al., 2015). In this context, fuzzy multicriteria decision-making (FMCDM) is particularly useful for modeling complex situations with inherent uncertainty (Radović et al., 2018; Shariati et al., 2014; Tadić et al., 2025). Unlike traditional optimization and statistical approaches, which assume a single, well-defined objective, modern engineering and management problems typically involve multiple conflicting goals, diverse stakeholder preferences, and complex evaluation processes. The use of fuzzy data enhances the applicability of the model in real-world contexts, particularly when reliable and accurate data—especially qualitative indicators—are not available (Liao et al., 2019; Sudžum et al., 2024; Zamani et al., 2014).

The main advantages of MCDM methods include their capacity to manage complex decision-making processes, integrate both qualitative and quantitative indicators, increase the transparency of decisions, encourage active stakeholder participation, and support the use of flexible and scientifically grounded procedures. Fuzzy logic further extends this flexibility, especially in analyzing problems involving imprecise or uncertain data.

The ARAS method is particularly appropriate in cases where:

- All criteria are quantitative.
- The aim is to aggregate benefits and compare them to an ideal solution.
- A transparent and straightforward approach is needed.
- There is no requirement for explicit modeling of conflict or uncertainty.

Key advantages of the ARAS method include:

- Simplicity and visual clarity of all steps.
- Logical and easily interpretable decision processes.
- Rapid evaluation of "what-if" scenarios, as changes in weight coefficients lead to immediate changes in ranking outcomes.

However, ARAS may not be suitable in situations where:

- Criteria exhibit significant conflict-methods.
- There is high uncertainty or fuzziness-fuzzy-based methods should be considered.
- No quantitative data is available-in such cases.

To demonstrate the practical application of the ARAS method, two real-world case studies are presented. The first involves the multicriteria ranking of handling equipment in the design of a container terminal, evaluating four alternatives across six criteria. The second case involves a multicriteria analysis of seven logistics companies, assessed against seven criteria by five experts. This analysis aims to identify the most efficient logistics company and provide a comprehensive evaluation of fleet performance.

54.2 Fundamental bibliometric analysis

By using relative utility measures, the ARAS method simplifies complex decision tasks and enables the selection of the most favorable option relative to an ideal reference. Owing to its ease of implementation and interpretability, ARAS has attracted significant scholarly attention. Between 2010 and July 2025, over 450 academic contributions addressed or applied the method. Moreover, it has undergone substantial expansion in both theoretical scope and practical relevance.

Based on the analyzed papers, the ARAS method has been applied across a range of domains, reflecting its flexibility and suitability for various MCDM scenarios (Fig. 54.1) (Web of Science, n.d):

- Period 2010–15: The number of papers was low and variable, ranging from 1 to 5 papers per year, without a clear trend.
- Period 2016–18: There is a slight increase from 9 papers in 2016, a drop to 5 in 2017, and a re-growth to 8 in 2018.
- Period 2019–24: A significant and constant growth is observed, indicating an increase in scientific papers or production activity, with 42 papers in 2024 (the largest number so far).
- Year 2025 (by July): By the middle of the year, 19 papers have already been recorded, indicating that by the end of the year, last year's maximum could be reached or exceeded if the trend continues.

The Fig. 54.1 clearly shows the trend of exponential growth in the number of papers since 2019, which may indicate:

- Increased productivity or investments in the chapter,
- Strengthening of institutions or teams behind the papers,

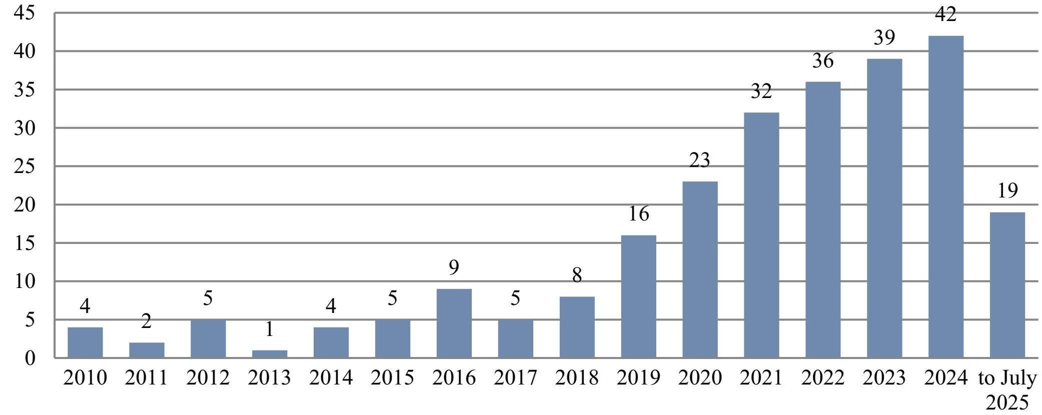

FIGURE 54.1 Number of papers applying the additive ratio assessment method by year.
Authors' calculation.

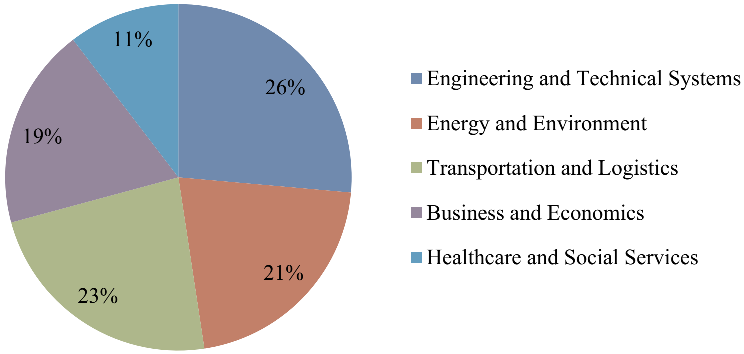

FIGURE 54.2 Percentage of papers by field where the additive ratio assessment method was used.
Authors' calculation.

- Greater visibility and engagement in the scientific community.

The next Fig. 54.2 shows the percentage of academic papers in each field where the ARAS method has been used (Web of Science, n.d).

The data are presented in the form of a pie chart and reveal the following distribution:

- Engineering and technical systems: 26%
  This field demonstrates the highest frequency of ARAS method application, indicating its strong relevance for technical and engineering decision-making processes. The method's ability to handle quantitative data and rank alternatives makes it a natural fit for engineering design and evaluation tasks.
- Transportation and logistics: 23%
  The significant use of the method in this field highlights its suitability for evaluating and optimizing complex logistics systems and transportation processes. ARAS has been used in route selection, supplier evaluation, and transport mode decisions. In these cases, its simplicity and ease of computation provide practical benefits for real-world logistics and supply chain management applications.
- Energy and environment: 21%
  The ARAS method is frequently employed in assessing sustainability, energy efficiency, and environmental impact. A significant number of studies utilize ARAS in energy planning, sustainable energy source selection, and environmental impact assessments.
- Business and economics: 19%
  The ARAS method is employed to facilitate strategic planning, optimize resource allocation, and evaluate investment options. Within this domain, it is particularly useful for financial performance assessment, project prioritization, and

long-term organizational decision-making. Its ability to integrate diverse quantitative and qualitative indicators makes it a valuable tool for comparing alternatives across multiple dimensions in a transparent and systematic manner.

- Healthcare and social services: 11%

Although accounting for the smallest share, this category highlights the emerging potential of the ARAS method in healthcare and social services. There is a growing interest in its application to complex decision-making scenarios in this field—such as selecting hospital locations or prioritizing medical interventions—where both qualitative judgments and quantitative indicators must be considered simultaneously.

The ARAS method is most commonly applied in engineering, transportation and logistics, and energy-related fields, while its use in healthcare and social services remains limited. This distribution demonstrates the method's broad applicability, as well as the potential for further expansion into less-represented sectors.

54.3 Review literature

The ARAS method continues to gain recognition across diverse domains due to its adaptability, simplicity, and capacity to integrate criteria. Its applicability extends well beyond organizational decision-making, as demonstrated by a growing body of literature covering fields such as engineering, environmental management, cultural heritage preservation, sustainable energy planning, transportation infrastructure, healthcare, and human resource selection.

To date, the ARAS method has attracted significant academic interest and has been adapted for various data contexts and practical fields. To better understand its development and support further improvement, this chapter of the paper systematically reviews existing literature on ARAS.

A thorough literature review is therefore essential to gain a deeper understanding of ARAS and support its further advancement.

The method is recognized as an effective tool for solving complex MCDM problems by identifying the most suitable alternative through a relative utility index compared to an ideal solution (Zavadskas & Turskis, 2010). To illustrate the application of this new method, a case study examining microclimatic conditions in office environments is presented. The goal of this study is to evaluate indoor conditions where employees work and to suggest measures for improving the working environment. Evaluation criteria include air exchange rate, relative humidity, temperature, illumination, air velocity, and dew point (Zavadskas & Turskis, 2010).

Initial validation of the ARAS methodology is demonstrated through its application to selecting the best foundation system for a building located on terrain with groundwater presence (Zavadskas et al., 2010). The decision-making framework incorporates a broad set of criteria, including construction cost, installation time, decision complexity, specific advantages and disadvantages of each solution, maintainability and transferability of the foundation type, and prior experience with similar engineering projects. In this context, ARAS demonstrates its utility as a decision-support tool, with potential extensions to other construction-related evaluations, including technology selection and investment planning (Zavadskas et al., 2010).

The method has also shown substantial value in environmental and agricultural applications. Recognizing that greenhouse gases such as nitrous oxide (N_2O), methane (CH_4), and carbon dioxide (CO_2) are major contributors to climate change (Petrović, Bojović, et al., 2023), the paper (Balezentiene & Kusta, 2012) explores sustainable fertilization strategies in Lithuanian grasslands treated with various mineral fertilizers by the ARAS method. By balancing environmental impact and biomass productivity, the study identifies optimal fertilizer treatments, thereby supporting data-driven sustainability practices in agriculture (Balezentiene & Kusta, 2012).

The ARAS method has also been effectively adapted for use in cultural heritage management and urban planning. Governments increasingly seek to develop methodologies that aid in the preservation and prioritization of immovable cultural assets. In this vein, the study (Kutut et al., 2013) employs the ARAS method to prioritize the reconstruction of historically significant buildings in Vilnius. A set of indicators—encompassing historical, archeological, architectural, economic, and social dimensions—is used to formulate a structured algorithm for prioritization. The model offers a transparent and systematic foundation for decision-making, balancing cultural importance with urban development priorities (Kutut et al., 2013).

In the field of sustainable architecture, the method has been used to improve the assessment of green building performance. Paper (Medineckiene et al., 2015) introduces a new MCDM approach for selecting sustainability indicators by combining the Swedish Miljöbyggnad certification system with additional criteria from the LEED framework. Weights are assigned using analytic hierarchy process (AHP) with both the traditional Saaty scale and an alternative scale, while

ARAS is employed for ranking. This hybrid model not only ensures methodological rigor but also aligns with internationally recognized sustainability standards (Medineckiene et al., 2015).

Corporate sustainability strategies have also benefited from the ARAS methodology. In the context of corporate social responsibility (CSR), the paper (Karabašević et al., 2016) proposes a model that integrates stepwise weight assessment ratio analysis (SWARA) for weighting stakeholder-relevant criteria with ARAS for ranking company performance. Validated through real-world application, the model demonstrates the effectiveness of MCDM tools in evaluating CSR initiatives and supporting strategic decision-making aligned with stakeholder expectations (Karabašević et al., 2016).

In energy policy and planning, ARAS has proven instrumental in evaluating sustainable energy technologies. Study (Ghenai et al., 2020) offers a comprehensive hybrid model combining SWARA and ARAS to assess renewable energy options—specifically wind power, solar energy, and two types of fuel cells—based on five primary dimensions of sustainability and fourteen subcriteria. Expert evaluations guide the decision process, and results identify onshore wind energy as the most favorable technology, underscoring the model's suitability for long-term energy strategy development (Ghenai et al., 2020).

Similarly, paper (Balki et al., 2020) explores optimizing internal combustion engine parameters under evolving environmental regulations. In response to stricter emission standards and decreasing use of high-emission diesel engines (Nikolić et al., 2025), the study examines spark ignition engines operating on pure ethanol and methanol. Using a SWARA-ARAS approach to analyze 729 experimental configurations, methanol is found to perform best under specific conditions. The findings support the role of FMCDM models in guiding technical decisions for cleaner fuel alternatives (Balki et al., 2020). The method's scalability and robustness are further exemplified in the context of transport infrastructure planning. Selecting high-speed rail (HSR) corridors involves balancing spatial, economic, and social considerations (Nikolić et al., 2025).

Study (Petrović, Jovanović, Marinković, et al., 2025) presents a geographic information system (GIS)-based MCDM framework integrating fuzzy AHP for weighting and ARAS for evaluation, applied to twenty candidate HSR routes across Turkey. The analysis reveals potential travel time reductions of up to 46%, demonstrating the model's utility in guiding strategic transport investments (Eren et al., 2021).

In academic personnel selection, where human capital significantly influences institutional performance, the study (Gottwald & Jovčić, 2022) applies a hybrid entropy-ARAS model to select a PhD candidate at the University of Pardubice. The entropy method is employed for objective criterion weighting, followed by ARAS-based ranking of candidates. Results are presented both graphically and descriptively, illustrating the framework's practical value in structured academic hiring processes (Gottwald & Jovčić, 2022).

Traditional risk assessment methods are frequently limited by subjective bias, data uncertainty, and rigid weighting schemes. To address these shortcomings, the study (Soltani & Aliabadi, 2023) proposes a fuzzy MCDM model that integrates SWARA and ARAS to evaluate occupational hazards in firefighting, based on the Fine–Kinney risk criteria. The approach enhances objectivity and precision in risk prioritization under high-stakes conditions (Soltani & Aliabadi, 2023).

In agriculture, increasing global food demands have heightened interest in sustainable farming methods. Study (Yücenur & Maden, 2024) employs a combined entropy-ARAS approach to determine the optimal locations for geothermal-powered hydroponic greenhouses in Turkey. Considering factors like infrastructure, sustainability potential, and geothermal resource availability, Denizli Province stands out as the top choice. The findings offer strategic insights for eco-friendly agricultural development (Yücenur & Maden, 2024).

The importance of location selection is equally clear in urban logistics, where rapid e-commerce growth and supply chain complexity require optimal warehouse placement. Study (Kozoderović et al., 2025) uses a hybrid SWARA-ARAS model to evaluate five urban locations in Belgrade across eight criteria, identifying Batajnica as the most suitable site because of its operational efficiency, cost benefits, and accessibility (Kozoderović et al., 2025).

Finally, in the increasingly climate-impacted domain of water resource management, a study (Dehkordi et al., 2025) develops an integrated fuzzy Shannon entropy-ARAS framework to evaluate drought scenarios in Iran's Chaharmahal and Bakhtiari provinces. Incorporating expert judgment, the model provides a rigorous and adaptable method for ranking and selecting drought mitigation strategies under uncertainty (Dehkordi et al., 2025).

In today's dynamic economic environment—characterized by rapid technological advancements, shifting market conditions, and evolving societal demands—decision-making processes in economics have become increasingly complex. The selection of the most suitable alternative to maximize profit and resource efficiency often requires the incorporation of both quantitative and qualitative factors, particularly under uncertainty and subjectivity. In this regard, FMCDM methods provide a robust framework, as they can accommodate imprecise and linguistic evaluations commonly found in human judgment (Jovanović et al., 2023).

The enhanced version of the ARAS method, known as additive ratio assessment with fuzzy numbers (ARAS-F), has proven its practical applicability under such uncertain conditions through the use of triangular fuzzy numbers. For example, its application in selecting the optimal location for a logistics center among several alternatives demonstrates its capacity to support complex spatial decisions (Turskis & Zavadskas, 2010a). In this case, four main criteria were considered: investment cost, operational duration, future expansion potential, and market proximity. Within the ARAS-F framework, the overall utility of each alternative is computed based on the weighted contributions of all criteria, while performance is benchmarked against an ideal solution. This comparative structure enables systematic ranking and identifies areas for improvement (Turskis & Zavadskas, 2010a).

Beyond logistical planning, FMCDM models are increasingly applied in human resource decision-making, particularly in the selection of candidates for strategic roles, such as architects or financial executives. These decisions frequently involve subjective factors like creativity, leadership, and personality traits. Fuzzy set theory provides a suitable approach to modeling such ambiguity. In this context, the paper (Keršulienė & Turskis, 2011) introduces an integrated FMCDM model that combines ARAS-F with the SWARA method for determining criterion weights. The model effectively incorporates both linguistic and numerical evaluations from multiple decision-makers via fuzzy linguistic aggregation. A case study on architect selection confirms the method's reliability and practical relevance in real-world decision-making (Keršulienė & Turskis, 2011).

A similar methodology has been applied to the high-stakes selection of a chief accounting officer (CAO)—a role critical for ensuring financial transparency and compliance. Paper (Keršulienė & Turskis, 2014) addresses this issue by presenting a comprehensive fuzzy MCDM framework that integrates fuzzy information fusion, ARAS-F, the fuzzy weighted product model, and the AHP method. It offers a structured approach for handling personnel decisions that involve multiple performance dimensions and high degrees of subjectivity (Keršulienė & Turskis, 2014).

Further reinforcing the applicability of ARAS-F and related methods, the paper (Yapici Pehlivan et al., 2018) investigates strategic distribution channel selection in the context of globalization and technological disruption. Although traditional and fuzzy MCDM approaches have been widely used, integrated frameworks remain underutilized. To address this gap, a hybrid FMCDM model is proposed, incorporating FAHP for criterion weighting and employing WASPAS-F, EDAS-F, and ARAS-F for ranking strategic alternatives. By accommodating uncertainty through linguistic evaluation, the model identifies managerial and financial factors as most influential. Consistent results across all methods confirm the robustness and practical value of this integrated approach in strategic decision-making under dynamic and uncertain conditions (Yapici Pehlivan et al., 2018).

Finally, study (Mistarihi et al., 2025) contributes to the discourse on sustainable energy planning, focusing on the United Arab Emirates' efforts to advance green energy solutions. Also, the same study proposes a robust evaluation model that integrates multiple methods—the complex proportional assessment (COPRAS), Fuzzy COPRAS, ARAS, and Fuzzy ARAS—to assess renewable energy alternatives. Solar and wind energy emerged as top priorities, with the hybrid FCOPRAS—ARAS-F approach delivering the most consistent rankings (Mistarihi et al., 2025).

Additionally, the improved ARAS method has been applied to the supplier selection process, aiming to identify the vendor that best meets stakeholder requirements (Turskis & Zavadskas, 2010b). The selection and weighting of criteria were aligned with stakeholder goals and priorities. To address this problem, an advanced version of the ARAS method, incorporating gray values—ARAS-G—was utilized. The proposed model provides a robust analytical foundation for decision-making in areas such as sustainable development, environmental impact assessment, and the selection of technologies, structural systems, and investment alternatives (Turskis & Zavadskas, 2010b).

The energy sector—particularly within the European Union (EU)—represents a critical arena where the complexity of policy objectives, ranging from greenhouse gas emissions reduction (Petrović et al., 2020) to the promotion of renewable energy, necessitates the application of advanced decision-support methodologies. In response to this challenge, the paper (Baležentis & Streimikiene, 2017) investigates the use of MCDM techniques to evaluate and rank energy development scenarios. By employing a combination of weighted aggregated sum product assessment (WASPAS), ARAS, and technique for order preference by similarity to ideal solution (TOPSIS) methods, along with sensitivity analysis to examine the influence of criterion weight variation, the study demonstrates the significant impact of model architecture on scenario outcomes (Baležentis & Streimikiene, 2017).

In parallel with the global emphasis on decarbonization and energy security, hydrogen production from renewable sources is gaining momentum as a cornerstone of sustainable energy strategies. Addressing this imperative, the study (Almutairi et al., 2021) conducts a detailed assessment of 15 cities in Iran's Fars province to identify the most suitable locations for renewable hydrogen production. The study employs a comprehensive suite of MCDM methods—ARAS, simple additive weighting (SAW), combinative distance-based assessment (CODAS), and TOPSIS—to evaluate cities based on criteria such as solar and wind energy potential, topographical suitability, infrastructure readiness, disaster risk, and labor availability. The analysis concludes with the identification of Izadkhast as the most favorable location, offering a replicable and transparent framework for strategic planning in emerging hydrogen economies (Almutairi et al., 2021).

Extending the discourse on sustainable infrastructure planning, the paper (Rekik et al., 2025) introduces an integrated framework for wind farm site selection in Tunisia, combining GIS-based spatial analysis with FAHP and six distinct MCDM methods, among which ARAS and COPRAS feature prominently. The proposed approach highlights the critical role of integrated, multimethod evaluation frameworks in advancing renewable energy deployment while balancing ecological sensitivity and socio-economic equity (Rekik et al., 2025).

Financial performance is a key indicator of an organization's fiscal stability and its ability to meet debt obligations, making it essential in credit evaluation processes. To support objective and accurate assessment, the paper (Heidary Dahooie et al., 2019) proposes a model that integrates the correlation coefficient and standard deviation (CCSD) weighting method with a hybrid fuzzy C-means and additive ratio assessment (FCM-ARAS) approach. The model is applied to 58 Iranian manufacturing firms seeking bank loans, using eight financial criteria such as the debt ratio, equity-to-assets ratio, and return on assets (ROA). While CCSD guarantees objectivity in weighting, the FCM-ARAS method allows for clustering and ranking of firms, providing valuable insights for financial decision-making (Heidary Dahooie et al., 2019).

The management of end-of-life vehicles (ELVs) has become a pressing environmental issue, with recycling processes playing a central role in achieving environmental and economic sustainability. In this context, study (Karagöz et al., 2021) applied an extended version of the ARAS method within an interval type-2 fuzzy environment to determine the optimal location for an ELV recycling center in Istanbul—the Turkish city with the highest number of registered vehicles. The results confirmed the reliability and practical value of the proposed approach over traditional MCDM techniques (Karagöz et al., 2021).

The ARAS method, known for its efficiency in handling complex decision-making problems by evaluating alternatives relative to an ideal solution, has faced challenges related to attribute interdependence and sensitivity to scaling. To enhance its robustness, scientific paper (Wang et al., 2024) introduces a novel T-spherical fuzzy environment, incorporating new cross-entropy and aggregation operators to improve adaptability and accuracy. A group decision-making model was developed and validated through a case study on sustainable supplier selection for power battery echelon utilization in 5 G base stations, confirming its effectiveness (Wang et al., 2024).

In the domain of transport safety, the study (Xie & Chen, 2024) presents a hybrid model (meethod based on the removal effects of criteria [MEREC]–ARAS–quantile-based k-means clustering [QBKM]) combining removal effects of criteria MEREC, ARAS, and QBKM to assess road safety performance. By enhancing clustering stability and integrating multicriteria evaluation, the model identifies regional disparities and supports evidence-based policymaking for improved safety outcomes (Xie & Chen, 2024).

Similarly, addressing environmental challenges in freight transport, the study (Görçün et al., 2024) proposes a multilayered framework integrating neutrosophic Delphi, MGqNS-based SWARA, and ARAS methods to evaluate the sustainability of transportation modes. Results highlight "cargo security" and "accident rates" as key decision criteria, with maritime transport emerging as the most sustainable mode. These findings offer strategic insights for developing eco-efficient logistics networks (Görçün et al., 2024).

Further advancing methodological understanding, the paper (Aleksic et al., 2019) offers a comprehensive review of the ARAS framework, analyzing at least 95 academic contributions between 2010 and 2020. The review encompasses bibliometric trends, theoretical enhancements—including the integration of uncertainty and hybrid data—and practical applications. It also identifies current limitations and future directions for improving the robustness and applicability of the ARAS method (Liu & Xu, 2021).

In recent years, the increasing complexity of decision-making environments—driven by technological progress, globalization, regulatory requirements, and sustainability goals—has required the development and use of robust MCDM frameworks. In various fields like human resource management, sustainable construction, corporate responsibility, energy policy, and distribution strategies, the ARAS method, especially its fuzzy and hybrid versions, has been key in supporting rational, transparent, and flexible decision-making under uncertainty. Overall, these studies highlight the flexibility and effectiveness of ARAS and fuzzy ARAS methods in solving complex, multidimensional decision problems across many sectors. By combining qualitative and quantitative data, including expert judgment and hybrid modeling techniques, these approaches offer valuable decision-support tools that can improve strategic planning, operational efficiency, and sustainable development.

54.4 Conceptual framework of the additive ratio assessment method

The classic ARAS method is relatively simple and intuitive, and is often used in engineering management, logistics, economics, and other fields where a choice between multiple options is required based on multiple criteria.

The advantages of the ARAS method are its simplicity to implement and understand. It shows a clear relative relationship between the alternatives and the ideal solution and is easily combined with other MCDM methods.

The ARAS method is based on the idea of additive optimality: the best alternative is the one that has the highest overall utility when all criteria values are added together, taking into account their weights. The essence of the method can be represented through the following characteristics:

1. Additive nature of decision-making. The basis of the method is an additive approach to decision-making: the total utility of the alternative is obtained collectively, by adding the values of all criteria, taking into account the relative importance (weight) of each criterion. This is analogous to economic rationality—the more benefits (or the fewer costs), the better the solution. This is in contrast to methods that use ratios or distances (e.g., TOPSIS (Aleksic et al., 2019)), because ARAS uses absolute utility values, which allows direct comparison between alternatives.
2. Introduction of an ideal (optimal) alternative. One of the key philosophical bases of the method is defining the ideal solution. The ideal alternative does not necessarily appear in reality—it is hypothetical and represents a "perfect" combination of values of all criteria. This serves as a fixed point of comparison—each realistic alternative is measured against the ideal.
3. Normalization as an expression of relative value. Normalization of criterion values has a double role:
   - Eliminates differences in measurement units, which allows, for example, liters, kilometers, and euros to add up.
   - Converts values into relative shares, which reflect the contribution of an individual criterion to the total value through a proportion.
4. This highlights the relative effectiveness of each alternative in the context of the total available value for that criterion.
5. Inclusion of criteria weights—the role of preferences. The method uses the weight coefficients of the criteria to reflect the decision maker's preferences. This introduces a subjective component: the importance of each criterion determines how much it contributes to the final score. This is important because different situations may have different priorities: cost may be more important in one decision, while reliability is key in another.
6. The utility coefficient is a measure of relative dominance. The utility coefficient $Q_i = S_i/S_0$ shows how close each alternative is to the ideal. If $Q_i = 1$, the alternative is identical to the ideal. If it is close to zero, then the alternative is bad. This is essentially a relative ranking, but derived from absolute aggregate values, which are conceptually clearer to many decision makers.
7. Compromising character. The method allows for a compromise solution: no single alternative has to dominate in all criteria, but it can have the best overall performance. This means that the alternative is not required to be the best in every criterion, but to create a balanced result that leads to high utility overall.

Compared to other methods, ARAS is similar to the SAW method (Tupenaite et al., 2010), but differs in that it introduces normalization and an ideal solution, thus adding a layer of interpretation (Table 54.1). ARAS is an upgrade of the SAW method and is more suitable when comparison with the "best possible solution" is important. ARAS is more suitable when it is necessary to quantify the closeness to the ideal in absolute values, while TOPSIS is better for scenarios with clearly defined boundaries (ideal and antiideal) (Petrović, Mihajlović, et al., 2023). VlseKriterijumska Optimizacija I Kompromisno Resenje is more suitable for conflict situations where you have to balance between criteria, while ARAS is better for evaluating the overall performance compared to the ideal (Opricovic, 2009). AHP is better in situations where there is no numerical data, while ARAS is better for pure quantitative decisions with clearly defined criteria (Komatina et al., 2022; Petrović, Jovanović, et al., 2023).

TABLE 54.1 Comparison of additive ratio assessment (ARAS) with popular methods.

Method	Basis	Utility type	The essence of the comparison
ARAS	Additive sum	Absolute	Relationship to the ideal aggregate value
TOPSIS	Geometric distance	Relative	Distance from ideal and antiideal solutions
SAW	Additive sum	Absolute	Direct addition without normalization
VIKOR	Compromise and balance	Relative	Proximity to ideal + regret measure
AHP	Hierarchy and comparison	Relative	Matrix comparison of criteria and decisions

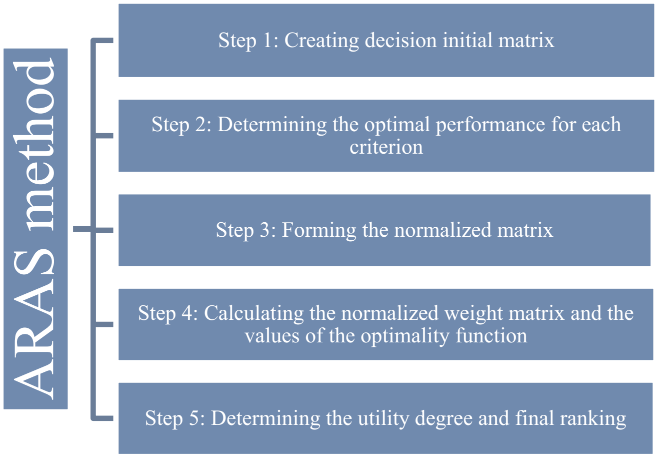

FIGURE 54.3 Basic steps of the additive ratio assessment (ARAS) method.

The procedure for solving a multicriteria decision-making problem (Fig. 54.3) using the classical ARAS method can be systematically defined through the following steps (Zavadskas & Turskis, 2010):

Step 1. Construction of the decision matrix based on the complete set of considered alternatives and the defined or adopted criteria.

Step 2. Determination of the optimal performance for each criterion. In this step, the decision-maker defines the optimal value for each criterion. If the decision-maker does not express specific preferences, the optimal performance can be determined according to predefined rules or standard procedures:

$$x_{0j} = \begin{cases} \max\limits_{i} x_{ij}; & j \in \Omega_{\max} \\ \min\limits_{i} x_{ij}; & j \in \Omega_{\min} \end{cases} \tag{54.1}$$

In this context, x_{0j} denotes the optimal performance of the j-th criterion, where $\Omega_{\max}$ represents the set of benefit criteria, and $\Omega_{\min}$ represents the set of cost criteria.

Step 3. Calculation of the normalized decision matrix. The normalized matrix is obtained by transforming the initial decision matrix in accordance with the type of each criterion and can be calculated as follows:

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}; & j \in \Omega_{\max} \\ \frac{1/x_{ij}}{\sum_{i=0}^{m} 1/x_{ij}}; & j \in \Omega_{\min} \end{cases} \tag{54.2}$$

criteria, $i = 0, 1, \ldots, m$.

Step 4. Determination of the overall performance for each alternative. The overall performance of a given alternative is calculated by aggregating the weighted normalized values of all criteria, as defined by the following expression:

$$S_i = \sum_{j=1}^{n} w_j r_{ij} \tag{54.3}$$

In this expression, S_i denotes the total (aggregated) performance of the i-th alternative, where $i = 0, 1, \ldots, m$.

Step 5. Calculation of the degree of utility for each alternative. The degree of utility is determined by comparing the total performance of each alternative to that of the optimal alternative, as expressed by the following formula:

$$Q_i = \frac{S_i}{S_0} \tag{54.4}$$

In this formula, Q_i represents the degree of utility of the i-th alternative, S_0 is the overall performance index of the optimal alternative, and $i = 1,2,\ldots, m$.

The relative efficiency of the alternatives is determined based on the degree of utility values, expressed through the Q_i ratios, which range between 0 and 1. After calculating the degree of utility, the alternative with the highest Q_i value is considered the most preferred option.

54.5 Numerical example 1

During the design phase of the container terminal, it is necessary to perform a multicriteria ranking of the alternatives (manipulators) using the ARAS method, based on the selected criteria. The objective is to identify the most suitable alternative that aligns with the adopted criteria (Table 54.2), given the weighting coefficients [0.153, 0.083, 0.100, 0.230, 0.213, 0.220], which were determined using the Entropy method (Petrović, Mihajlović, et al., 2023).

The alternative solutions considered in the analysis include: $A_{1:}$ front forklift, A_2: side forklift truck, A_3: front forklift equipped with a telescopic arm, and A_4: side portal manipulator.

The alternative solutions considered in the analysis include:

A_1: front forklift,
A_2: side forklift,
A_3: front forklift equipped with a telescopic arm, and
A_4: side portal manipulator.
The criteria considered in the evaluation of the alternative solutions are as follows:
f_1: cost of handling equipment [$],
f_2: performance [t/h],
f_3: travel distance [m],
f_4: storage area [m^2],
f_5: degree of warehouse area utilization, and
f_6: degree of warehouse volume utilization.

Since the decision-maker does not have his preferences, in the first step, the determination of the extreme performances (Table 54.3), that is, the minimum and maximum values of the criterion A_0, is carried out according to Eq. (54.1):

In Step 3, the normalized decision matrix (Table 54.4) is constructed in accordance with Eq. (54.2). For example, the normalized value r_{11} of a cost-oriented (minimization) criterion is calculated as follows:

$$r_{11} = \frac{1/x_{11}}{\sum_{i=0}^{4} 1/x_{i1}} = \frac{\frac{1}{310000}}{\frac{1}{310000} + \frac{1}{310000} + \frac{1}{380000} + \frac{1}{420000} + \frac{1}{580000}} = 0.2446$$

Meanwhile, the normalized value r_{21} of a benefit-oriented (maximization) criterion is calculated as follows:

$$r_{21} = \frac{x_{21}}{\sum_{i=0}^{4} x_{i1}} = \frac{10}{16 + 10 + 15 + 16 + 14} = 0.1408$$

In the fourth step, the overall performance of each alternative is determined. For example, the value of S_1, calculated according to Eq. (54.3), is shown in Table 54.5:

$$S_1 = \sum_{j=1}^{6} w_1 r_{1j} = 0.153 \cdot 0.2446 + 0.083 \cdot 0.1408 + 0.100 \cdot 0.1414 + 0.230 \cdot 0.1216 + 0.213 \cdot 0.1129 + 0.220 \cdot 0.1119$$

$$S_1 = 0.0374 + 0.0117 + 0.0142 + 0.0280 + 0.0241 + 0.0246$$

TABLE 54.2 Initial decision matrix.

Optimization direction	f_1	f_2	f_3	f_4	f_5	f_6
	min	max	min	min	max	max
A_1	310000	10	444	23300	0.72	0.239
A_2	380000	15	322	10300	1.38	0.457
A_3	420000	16	316	15800	1.14	0.379
A_4	580000	14	270	19000	1.57	0.530

TABLE 54.3 Decision matrix with weight coefficients and optimal performance.

Optimization direction	f_1	f_2	f_3	f_4	f_5	f_6
	min	**max**	**min**	**min**	**max**	**max**
Weight coefficients	0.153	0.083	0.100	0.230	0.213	0.220
A_0	310000	16	270	10300	1.57	0.530
A_1	310000	10	444	23300	0.72	0.239
A_2	380000	15	322	10300	1.38	0.457
A_3	420000	16	316	15800	1.14	0.379
A_4	580000	14	270	19000	1.57	0.530

TABLE 54.4 Normalized decision matrix.

Optimization direction	f_1	f_2	f_3	f_4	f_5	f_6
	min	**max**	**min**	**min**	**max**	**max**
Weight coefficients	0.153	0.083	0.100	0.230	0.213	0.220
A_0	0.2446	0.2909	0.2325	0.2750	0.2461	0.2482
A_1	0.2446	0.1408	0.1414	0.1216	0.1129	0.1119
A_2	0.1995	0.2113	0.1950	0.2750	0.2163	0.2141
A_3	0.1805	0.2254	0.1987	0.1793	0.1787	0.1775
A_4	0.1307	0.1972	0.2325	0.1491	0.2461	0.2482

TABLE 54.5 Weighted-normalized decision-making matrix and solution results.

	f_1	f_2	f_3	f_4	f_5	f_6	S_i	Q_i	Rank
A_0	0.0374	0.0242	0.0233	0.0633	0.0525	0.0546	0.2554	1.0000	
A_1	0.0374	0.0117	0.0142	0.0280	0.0241	0.0246	0.1400	0.5483	4
A_2	0.0305	0.0176	0.0195	0.0633	0.0461	0.0471	0.2242	0.8779	1
A_3	0.0276	0.0188	0.0199	0.0413	0.0381	0.0391	0.1847	0.7234	3
A_4	0.0200	0.0164	0.0233	0.0343	0.0525	0.0546	0.2012	0.7877	2

$$S_1 = 0.1400$$

In the final step, the utility degree Q_i for each alternative can be calculated. For instance, the utility degree Q_1 for alternative A_1, determined according to Eq. (54.4), can be calculated as follows:

$$Q_1 = \frac{S_1}{S_0} = \frac{0.1400}{0.2554} = 0.5483$$

The value of Q_i in this context represents the overall evaluation of each alternative with respect to the defined criteria, taking into account both the positive and negative aspects of each option. A higher Q_i value indicates that the alternative is more aligned with the decision-making objectives, that is, it demonstrates better overall performance across all considered criteria. Based on the obtained Q_i values, all alternatives are then ranked in descending order: $A_2 > A_4 > A_3 > A_1$ (Table 54.5), where the alternative with the highest Q_i is evaluated as the most optimal choice—A_2 ($Q_2 = 0.8779$) representing the side forklift. This approach enables more objective and rational decision-making, particularly in complex situations involving multiple conflicting criteria.

54.6 Numerical example 2

In order to identify the most efficient logistics company and conduct a comprehensive evaluation of fleet performance, a multicriteria decision analysis using the ARAS method is required. The analysis includes seven logistics companies, denoted as $A_i = (A_1, A_2, ..., A_7)$, which are evaluated according to seven relevant criteria $C_j = (C_1, C_2, ..., C_7)$. These criteria, presented in Table 54.6, encompass key operational aspects that enable a comprehensive and balanced assessment of the economic, operational, and environmental performance of the vehicle fleet.

The criteria have been carefully selected to ensure representativeness and objectivity in the evaluation. Each criterion in Table 54.6 includes a detailed explanation of its significance and role in the logistics context, as well as the corresponding unit of measurement and type (maximization or minimization criterion), in accordance with the nature of the assessed characteristics. Economic criteria focus on cost efficiency and profitability; operational criteria emphasize reliability, availability, and resource utilization, while environmental criteria reflect alignment with modern sustainability requirements and environmental protection standards.

The data utilized for determining the weighting coefficients and ranking the alternatives of the criteria were obtained via online questionnaires. The study involved five experts—decision makers (DM1-DM5), whose individual responses are detailed in Table 54.7.

To establish the relative importance of the criteria, expert judgments were collected using a structured nine-point linguistic scale:

1. Extremely low (AL),
2. Very low (VL),
3. Low (L),
4. Medium-low (ML),
5. Medium (M),
6. Medium-high (MH),
7. High (H),
8. Very high (VH), and
9. Absolutely high (AH).

TABLE 54.6 The selected and used criteria.

	Criteria	Explanation of criteria	Unit	Type
C_1	Fleet size	Number of company-operated vehicles	Number	Min
C_2	Cost of fuel consumption	Annual fuel expenses for transportation	EUR/year	Min
C_3	Vehicle operating hours	The time a fleet vehicle was in use	h/year	Min
C_4	Total mileage	Total annual mileage of all vehicles	km/year	Max
C_5	Volume of cargo transported	Annual volume of cargo carried by vehicles	t/year	Max
C_6	Vehicle utilization rate	Efficiency of load capacity usage during transportation	%	Max
C_7	CO_2 emissions per ton-km	Carbon dioxide emitted per transported ton per km	kg CO_2/tkm	Min

TABLE 54.7 Expert evaluation of criteria importance.

		C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	DM1	H	VH	ML	M	MH	M	MH
	DM2	MH	M	M	MH	VH	MH	ML
	DM3	VH	MH	MH	ML	M	M	M
	DM4	EH	H	VH	M	MH	VH	MH
	DM5	H	MH	M	MH	VH	MH	ML
A_2	DM1	VH	MH	M	MH	VH	MH	M
	DM2	M	ML	L	ML	M	MH	L
	DM3	MH	M	M	MH	H	VH	ML
	DM4	H	M	ML	MH	MH	VH	L
	DM5	VH	MH	MH	VH	VH	H	M
A_3	DM1	MH	ML	MH	VH	MH	VH	L
	DM2	ML	L	M	MH	M	MH	M
	DM3	M	L	ML	ML	M	VH	ML
	DM4	VH	MH	MH	M	VH	H	MH
	DM5	MH	M	ML	M	MH	VH	MH
A_4	DM1	M	L	M	MH	MH	VH	ML
	DM2	L	VL	MH	VH	VH	MH	L
	DM3	ML	L	MH	VH	MH	M	MH
	DM4	H	MH	M	MH	M	ML	VH
	DM5	VH	M	MH	MH	H	VH	MH
A_5	DM1	ML	L	M	MH	M	ML	M
	DM2	VL	L	ML	M	L	ML	ML
	DM3	L	VL	ML	ML	VL	L	M
	DM4	MH	ML	M	VH	M	ML	VH
	DM5	VH	MH	H	H	MH	M	H
A_6	DM1	L	L	MH	VH	MH	M	M
	DM2	MH	ML	M	MH	ML	L	ML
	DM3	M	L	MH	MH	M	ML	M
	DM4	ML	VL	VH	H	VH	MH	ML
	DM5	L	VL	H	VH	M	ML	M
A_7	DM1	L	L	VH	H	MH	ML	L
	DM2	ML	L	MH	VH	M	L	ML
	DM3	VL	EL	H	H	MH	L	L
	DM4	ML	ML	MH	VH	ML	VL	M
	DM5	VL	VL	VH	H	VH	M	MH

A survey was conducted to gather expert opinions regarding the significance of each criterion. The experts provided linguistic evaluations for all criteria and alternatives, based on the linguistic descriptors.

These qualitative assessments were subsequently transformed into precise numerical values. The resulting crisp scores were then aggregated to form consolidated judgments. Tables 54.8 and 54.9 present the linguistic assessments and the corresponding crisp values.

The decision matrix is obtained by calculating the arithmetic mean of the evaluations provided by the experts (decision-makers) for each alternative A_i and each criterion C_j. For instance, for alternative A_1 and criterion C_1 (highlighted in Bold in Table 54.8), the element x_{11} would be as shown in Table 54.9:

$$x_{11} = \frac{\sum C_{1n}}{n} = \frac{8+6+7+9+8}{5} = 7.60$$

The weight coefficients were derived from the decision matrix (Table 54.9) using the FANMA method (Petrović, Jovanović, et al., 2024), resulting in the following values: [0.1571, 0.1172, 0.1336, 0.2090, 0.1098, 0.1358, and 0.1374].

In the first step, the decision matrix is constructed, followed by determining the extreme performances—that is, the maximum and minimum values of the criteria for the reference alternative A0 —calculated according to Eq. (54.1).

In the following step, the normalized decision matrix is constructed (Table 54.10) according to Eq. (54.2). For example, the normalized value r_{11} of the criterion with a minimization orientation is:

$$r_{11} = \frac{1/x_{11}}{\sum_{i=1}^{7} 1/x_{i1}} = \frac{\frac{1}{7.60}}{\frac{1}{3.00}+\frac{1}{7.60}+\frac{1}{6.60}+\frac{1}{5.60}+\frac{1}{5.40}+\frac{1}{4.40}+\frac{1}{4.20}+\frac{1}{3.00}} = 0.0740$$

while the normalized value r_{41} of the criterion with a maximization orientation is:

$$r_{41} = \frac{x_{41}}{\sum_{i=1}^{7} x_{i1}} = \frac{5.20}{7.60+5.20+5.80+5.40+6.40+6.00+6.80+7.60} = 0.1024$$

In the fourth step, the overall performance for each alternative is determined. For example, the overall performance value S_1, calculated according to Eq. (54.3), is shown in Table 54.11:

$$S_1 = \sum_{j=1}^{7} w_1 r_{1j} = 0.1571 \cdot 0.0740 + 0.1172 \cdot 0.0693 + 0.1336 \cdot 0.1239 + 0.2090 \cdot 0.1024 + 0.1098 \cdot 0.1325 + 0.1358 \cdot 0.1312 + 0.1374 \cdot 0.1157$$

$$S_1 = 0.0116 + 0.0081 + 0.0166 + 0.0214 + 0.0145 + 0.0178 + 0.0159$$

$$S_1 = 0.1060$$

At the final stage of the procedure, the utility degree Q_i is calculated for each alternative. For alternative A_1, the utility degree Q_1, determined according to Eq. (54.4), can be calculated as follows:

$$Q_1 = \frac{S_1}{S_0} = \frac{0.1060}{0.1570} = 0.6749$$

The ranking of alternatives indicates the relative efficiency of each in comparison to the ideal solution (A_0), which has the highest overall evaluation value $S_i = 0.1570$ and serves as the reference point with a utility degree $Q_i = 1.0000$. The best-ranked alternative, A_7, with value $Q_7 = 0.8685$, occupies the first position as it shows the greatest similarity to the ideal solution. Following it are alternatives A_6 with $Q_6 = 0.7962$, and A_2 with $Q_2 = 0.7830$, which take second and third places respectively due to their high and balanced criterion values. Alternatives A_4 with $Q_4 = 0.7672$, and A_3 with $Q_3 = 0.7638$, are positioned fourth and fifth because of slightly lower scores. Although competitive, alternative A_5 ranks sixth with $Q_5 = 0.7149$, while A_1 is ranked lowest with $Q_1 = 0.6749$, indicating its greatest deviation from the ideal value. This distribution demonstrates how even small differences in values can impact the final ranking, and the method enables precise identification of the best alternatives according to the specified criteria.

The application of the ARAS method not only allows for determining the relative efficiency of each logistics company under consideration but also facilitates their ranking based on the achieved overall utility values: $A_7 > A_6 > A_2 > A_4 > A_3 > A_5 > A_1$. This method is characterized by transparency, simplicity, and the ability to incorporate criteria of varying types and importance. The result of this analysis is a ranking list of logistics companies that can serve as

TABLE 54.8 Expert evaluation of the relative importance of decision-making criteria.

		C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	DM1	**8**	7	4	5	6	5	6
	DM2	**6**	5	5	6	7	6	4
	DM3	**7**	6	6	4	5	5	5
	DM4	**9**	8	7	5	6	7	6
	DM5	**8**	6	5	6	7	6	4
A_2	DM1	7	6	5	6	7	6	5
	DM2	5	4	3	4	5	6	3
	DM3	6	5	5	6	8	7	4
	DM4	8	5	4	6	6	7	3
	DM5	7	6	6	7	7	8	5
A_3	DM1	6	4	6	7	6	7	3
	DM2	4	3	5	6	5	6	5
	DM3	5	3	4	4	5	7	4
	DM4	7	6	6	5	7	8	6
	DM5	6	5	4	5	6	7	6
A_4	DM1	5	3	5	6	6	7	4
	DM2	3	2	6	7	7	6	3
	DM3	4	3	6	7	6	5	6
	DM4	8	6	5	6	5	4	7
	DM5	7	5	6	6	8	7	6
A_5	DM1	4	3	5	6	5	4	5
	DM2	2	3	4	5	3	4	4
	DM3	3	2	4	4	2	3	5
	DM4	6	4	5	7	5	4	7
	DM5	7	6	8	8	6	5	8
A_6	DM1	3	3	6	7	6	5	5
	DM2	6	4	5	6	4	3	4
	DM3	5	3	6	6	5	4	5
	DM4	4	2	7	8	7	6	4
	DM5	3	2	8	7	5	4	5
A_7	DM1	3	3	7	8	6	4	3
	DM2	4	3	6	7	5	3	4
	DM3	2	1	8	8	6	3	3
	DM4	4	4	6	7	4	2	5
	DM5	2	2	7	8	7	5	6

TABLE 54.9 Decision matrix and maximum and minimum values of the criteria.

Logistics company	Criteria						
	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Optimization direction	min	min	min	max	max	max	min
Weight of criteria—w	0.1571	0.1172	0.1336	0.2090	0.1098	0.1358	0.1374
Optimal value—A_0	3	2.6	4.6	7.6	6.6	7	4
A_1	7.60	6.40	5.40	5.20	6.20	5.80	5.00
A_2	6.60	5.20	4.60	5.80	6.60	6.80	4.00
A_3	5.60	4.20	5.00	5.40	5.80	7.00	4.80
A_4	5.40	3.80	5.60	6.40	6.40	5.80	5.20
A_5	4.40	3.60	5.20	6.00	4.20	4.00	5.80
A_6	4.20	2.80	6.40	6.80	5.40	4.40	4.60
A_7	3.00	2.60	6.80	7.60	5.60	3.40	4.20

TABLE 54.10 Normalized decision matrix.

Optimization direction	x_1	x_2	x_3	x_4	x_5	x_6	x_7
	min	**min**	**min**	**max**	**max**	**max**	**min**
Weight of criteria—w	0.1571	0.1172	0.1336	0.2090	0.1098	0.1358	0.1374
A_0	0.1874	0.1706	0.1455	0.1496	0.1410	0.1584	0.1446
A_1	0.0740	0.0693	0.1239	0.1024	0.1325	0.1312	0.1157
A_2	0.0852	0.0853	0.1455	0.1142	0.1410	0.1538	0.1446
A_3	0.1004	0.1056	0.1339	0.1063	0.1239	0.1584	0.1205
A_4	0.1041	0.1168	0.1195	0.1260	0.1368	0.1312	0.1113
A_5	0.1278	0.1232	0.1287	0.1181	0.0897	0.0905	0.0997
A_6	0.1338	0.1585	0.1046	0.1339	0.1154	0.0995	0.1258
A_7	0.1874	0.1706	0.0984	0.1496	0.1197	0.0769	0.1377

TABLE 54.11 Weighted-normalized decision-making matrix and solution results.

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	S_i	Q_i	Rank
A_0	0.0294	0.0200	0.0194	0.0313	0.0155	0.0215	0.0199	0.1570	1.0000	
A_1	0.0116	0.0081	0.0166	0.0214	0.0145	0.0178	0.0159	0.1060	0.6749	7
A_2	0.0134	0.0100	0.0194	0.0239	0.0155	0.0209	0.0199	0.1229	0.7830	3
A_3	0.0158	0.0124	0.0179	0.0222	0.0136	0.0215	0.0166	0.1199	0.7638	5
A_4	0.0164	0.0137	0.0160	0.0263	0.0150	0.0178	0.0153	0.1205	0.7672	4
A_5	0.0201	0.0144	0.0172	0.0247	0.0099	0.0123	0.0137	0.1123	0.7149	6
A_6	0.0210	0.0186	0.0140	0.0280	0.0127	0.0135	0.0173	0.1250	0.7962	2
A_7	0.0294	0.0200	0.0131	0.0313	0.0131	0.0104	0.0189	0.1364	0.8685	1

a basis for strategic decision-making, improvement of internal processes, or the selection of an optimal logistics partner within the supply chain.

54.7 Conclusions

This chapter provides a thorough overview of the ARAS method application conducted from 2010 to July 2025. It focuses on its theoretical development, expanding application areas, and future research directions. According to key findings from bibliometric analysis, scholarly interest in the ARAS method has shown a steady increase, especially after 2019.

In practice, ARAS has been applied in five main areas: Engineering and Technical Systems, Transportation and Logistics, Energy and Environment, Business and Economics, and Healthcare and Social Services. The chapter outputs are thematically diverse, covering many journals and subject areas; however, there is a noticeable concentration in journals related to engineering and technical systems. This demonstrates the method's broad utility and operational flexibility.

After reviewing the method's fundamental principles, theoretical progress, and practical applications, several challenges are identified. These primarily relate to group decision-making processes, data organization, and decision timing. Theoretically, the ARAS method has significantly improved through integration with alternative ranking techniques, interdisciplinary tools, and adaptation to various data environments. These advancements have enhanced its robustness, versatility, and practical usability.

Future research should address key gaps such as building consensus, understanding decision-makers' risk preferences, improving data processing, managing multiperiod decision scenarios, and developing quick-response strategies. These issues are expected to guide future studies and further advance the ARAS methodology.

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