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Financial performance evaluation based on integrated MCDM MEREC–ARAS framework

Evaluacija finansijskih performansi zasnovana na integrisanom VKO MEREC-ARAS okviru

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Abstract

Decision-making based on financial analysis in the modern business environment is a very complex process due to the need to consider often conflicting criteria. By applying multi-criteria decision-making methods to optimize the financial analysis process, a more comprehensive and objective insight into the financial condition and performance of business entities is obtained. By combining traditional financial indicators with modern multi-criteria techniques, such as MEREC and ARAS, we can rank companies based on selected financial criteria, with optimal determination of the weights of the criteria. Empirical analysis confirms that the proposed approach contributes to better and more reliable selection of entities, improves the decision-making process and reduces the subjectivity of analysts. The research results can be of great importance for financial managers, investors and other stakeholders who strive for more efficient and transparent financial decision-making.
Keywords: *financial analysis, multi-criteria decision-making, optimization, MEREC, ARAS*

Sažetak

Donošenje odluka na osnovu finansijske analize u savremenom poslovnom okruženju predstavlja veoma složen proces usled potrebe za razmatranjem često suprotstavljenih kriterijuma. Primenom metoda višekriterijumskog odlučivanja u cilju optimizacije procesa finansijske analize, dobija se sveobuhvatniji i objektivniji uvid u finansijsko stanje i performanse poslovnih subjekata. Kombinovanjem tradicionalnih finansijskih pokazatelja sa savremenim višekriterijumskim tehnikama, kao što su MEREC i ARAS, možemo izvršiti rangiranje preduzeća na osnovu odabranih finansijskih kriterijuma, uz optimalno određivanje težina kriterijuma. Empirijska analiza potvrđuje da predloženi pristup doprinosi boljem i sigurnijem odabiru subjekata, unapređuje proces donošenja odluka i smanjuje subjektivnost analitičara. Rezultati istraživanja mogu biti od velikog značaja za finansijske menadžere, investitore i druge zainteresovane strane koje streme efikasnijem i transparentnijem finansijskom odlučivanju.
Ključne reči: *finansijska analiza, višekriterijumsko odlučivanje, optimizacija, MEREC, ARAS*

1. Introduction

Managing a company in modern business requires constant monitoring of the company's financial strength. With regular financial analysis, we have the opportunity to look at our financial position, as well as to make an adequate decision for the selection of associates. Financial reports represent the basis for making strategies and controlling business, while analysing financial indicators, management sees risks and opportunities for improvement. Financial reporting is a critical aspect of a company's communication with stakeholders, giving them an in-depth summary of its financial performance and position. It involves the preparation and presentation of financial statements and related information, enabling internal and external users to make informed decisions about the financial health of the organization (Mladenović et al., 2023).

Financial analysis is a procedure for examining the relationship between items in financial reports to make a business decision in a timely and reliable manner.

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Through this process, the work will include a detailed assessment of financial statements with the application of indicators such as profitability, liquidity, solvency, and efficiency of capital management. Both external and internal users are interested in information on the financial and overall position of the company contained in the financial statements as a product of the financial reporting process. Accordingly, the information presented must be credible, relevant, comparable, timely, and understandable so that users of financial statements can make quality business decisions based on it. The quality of the content of financial statements largely depends on the chosen accounting policies. They are defined as specific postulates, principles, and methods chosen by the company's management for the preparation and presentation of financial statements (Raičević & Filipov, 2021). Numerous studies have verified the intense need for organizations to improve their qualitative business operations, taking into account the competitors with whom they are compared and compete in the market, while simultaneously striving to achieve business excellence (Miletić & Ćurčić, 2024).

MCDM frameworks, such as MEREC (Method Based on Removal Effects of Criteria)-ARAS (Additive Ratio Assessment), are used for measuring financial performance in numerous industries. The integrated methodology increases decision-making accuracy and addresses multi- criteria evaluation problems. For organizations looking to outperform competitors financially, the MEREC model combines qualitative and quantitative data to provide a comprehensive rating system. Performance evaluation models may determine a company financial situation relative to its competitors, demonstrating the utility of MCDM frameworks in competitive analysis (Lam et al., 2021). Rational rankings from these judgments can greatly influence strategic decision-making.

When evaluating financial indicators using MCDM methods like MEREC-ARAS, dataset uncertainty and variability must be considered. Baydaş (2022) promotes uncertainty techniques in the financial industry and offers a holistic MCDM-aligned strategy for efficient performance evaluation. Madenoğlu et al. (2022) found that combining multiple MCDM techniques can provide useful insights for analyzing financial performance in energy sectors.

This paradigm's ARAS component is important for its simplicity and decision-making power. Nanda et al. show that the ARAS technique may simplify decision-making and produce optimal solutions based on a relative index in different decision-support scenarios (Nanda et al., 2022). This trait is essential for firms making difficult decisions, especially when sustainability and profitability collide.

The selection of the appropriate strategy is influenced by many criteria, which exacerbate making a final choice. By introducing adequate mathematical models in the selection process, this problem could be overcome. The Multiple-Criteria Decision-Making (MCDM) methods are imposed as a suitable approach because they are convenient for application in conditions when there exist many mutually conflicting criteria (Popović et al., 2022). In financial contexts, MCDM approaches have been widely applied because they allow structuring complex decision-making tasks and, at the same time, combining quantitative and qualitative factors. Profitability is greatly influenced by the amount of costs, since they represent an important item in calculating business results and profits. Namely, high revenues can be annulled if there are high expenses or costs (Mitić & Čolović, 2022).

Of the existing MCDM methods, the focus of this work is MEREC and ARAS. MEREC (Method based on the Removal Effects of Criteria) is an objective method for determining the weights of criteria. The goal of the MEREC method is to recalculate the overall performance of the alternatives by individually removing each criterion; a criterion receives more weight if its removal significantly alters the results. In other words, the MEREC method takes into account the "removal effect," where a criterion is more important if its absence makes large changes in the ratings of the alternatives. This method achieves objective criteria weights without subjective assessments. Keshavarz-Ghorabaee et al. (2021) point out that the basis of MEREC is a causal approach: the weight is higher for a criterion whose absence causes a greater deviation in the rating. ARAS (Additive Ratio Assessment) is an MCDM method for ranking alternatives based on the summation of weighted criteria values. Using the ARAS method, we first create decision matrices including the ideal optimal value for each criterion. After that, the criterion values for each alternative are normalized and weighted by the criterion weights. For each alternative, an aggregate value is calculated, and then the degree of utility is defined as the ratio of this value to the best possible value. The ARAS methodology is simple to apply and does not require iterative procedures, and it allows direct ranking of alternatives according to value.

This paper introduces the combined MEREC–ARAS model as an innovative approach that facilitates objective ranking of companies based on measurable financial indicators, standing in contrast to the dominant practice of relying on subjective evaluation methods. The methodology offers a novel approach to justifying judgments within the domestic business environment.

2. Optimizing decision-making by combining financial and non-financial criteria

Modern business increasingly emphasizes the need for a comprehensive approach to evaluate company performance and decision-making. Traditionally, financial criteria (profit, cash flow, ROI, etc.) were primary but were considered incomplete unless the "softer" aspects of business were taken into account. A classic example of an extended approach is the Balanced Scorecard (Kaplan and Norton, 1992), which introduced a focus on four perspectives: financial, customer, internal processes, and development. This model affirms the need to supplement financial indicators with non-financial performance measures (Waruhiu, 2014). Salehi and Ghorbani (2011) point out that the Balanced Scorecard is an innovative tool that takes into account not only financial indicators but also non-financial indicators equally important for performance evaluation. Optimizing financial analysis through a multi-criteria approach means integrating both types of criteria into one decision-making framework. MCDM methods have so far proven to be extremely successful in solving various problems (Janošik et al., 2024). Černevičienė and Kabašinskas (2022) state that financial decisions often include goals such as risk and cost minimization, but also social profit maximization and environmental damage minimization. The necessity for enhanced decision-making processes is similarly highlighted by Wang et al. (2024) who advocate for the utilization of artificial intelligence and machine learning to improve decision efficiency via predictive analytics. Their research aims to enhance decision-making results by the application of data models and optimization techniques that incorporate both financial and qualitative evaluations, hence expanding the evaluative criteria required for stakeholders. Multi-criteria methods allow managers to see the overall picture and, in this way, can simultaneously maximize profitability and liquidity and minimize risk and harm by giving appropriate weights to each criterion in accordance with the company's strategic priorities. Such an integrated approach optimizes the decision-making process by reducing the possibility of overlooking an important aspect. At the same time, the risk of decisions being made solely on the basis of short-term financial indicators is reduced, but long-term goals such as sustainable growth, care for stakeholders, and investment in innovation are also looked at and taken into account. A study on multi-objective decision-making models demonstrates their practical uses in highway maintenance, showcasing the efficacy of organized decision-making frameworks that simultaneously handle numerous objectives (Bao et al., 2021). The capacity to manage intricate decisions by integrating both operational and strategic factors can improve overall project results and resource distribution. The need of financial literacy in decision-making processes is paramount. Financial literacy enhances individuals' ability to comprehend and maneuver through intricate financial environments, hence impacting investment choices. Research demonstrates that elevated financial literacy is associated with enhanced decision-making abilities, resulting in more favorable financial results (Suresh, 2024; Potrich et al., 2016; Fitriaty, 2023).

3. Methodology

The original contribution of this research lies in the practical application of a combined MEREC–ARAS model for the financial analysis of domestic companies, aimed at identifying the most reliable business partner based on objectively quantified financial performance. This paper provides an integrated methodological approach that combines the MEREC method, which objectively determines criteria weights, with the ARAS method for ranking alternatives, thereby facilitating a multidimensional, impartial, and transparent evaluation of financial stability.

3.1. MEREC method

The MEREC (Method Based on Removal Effects of Criteria) technique represents a significant advancement in multi-criteria decision-making (MCDM), offering a robust, objective alternative for criterion weighting. Its core principle involves assessing how the omission of each criterion affects the overall evaluation of alternatives, thereby identifying the significance of each criterion based on its impact (Keshavarz-Ghorabaee et al., 2021). If the removal of a criterion substantially alters the ranking outcome, it is assigned a higher weight, ensuring that only empirically influential factors drive the final decision.

What distinguishes MEREC is its independence from subjective bias. Unlike traditional methods relying on expert opinion, MEREC bases weight assignment on statistical outcomes, enhancing the transparency and reliability of the decision-making process (Saidin et al., 2023). This objectivity is particularly relevant in contexts requiring consistency, reproducibility, and fairness in evaluating alternatives.

The MEREC method has been successfully applied across a wide range of fields, including industrial management, sustainable development, innovation performance evaluation, and agriculture (Puška et al., 2022; Ecer & Ayçin, 2023). For instance, Ecer and Ayçin employed MEREC in innovation performance measurement, demonstrating its computational efficiency and superiority over entropy-based approaches.

MEREC's versatility is further enhanced through its integration with other weighting and decision-making approaches. In hybrid frameworks, MEREC has been combined with other objective weighting techniques, including CRITIC, allowing decision problems to be examined from complementary perspectives on criterion importance. While MEREC determines weights according to the effect of removing individual criteria, CRITIC considers both criterion variability and intercriteria correlation. Further extensions of MEREC include fuzzy formulations designed to improve the treatment of uncertainty in objective weighting (Keshavarz-Ghorabaee et al., 2021; Saidin et al., 2023).

The methodology's adaptability has led to innovations such as MEREC-G and MEREC-H, which employ geometric and harmonic means to further refine weight calculation, increasing accuracy in domains with interrelated and conflicting criteria (Keleş, 2023). These evolutions underscore MEREC's capacity to grow alongside the increasing complexity of decision environments.

Since the initial decision matrix contains negative values for some financial indicators, it is necessary to transform these values before applying the MEREC method. For this purpose, the T-score transformation is applied, which enables all values to be converted into positive values while maintaining the relative differences between the alternatives. In this way, the initial data are adjusted to the requirements of the MEREC method and can be used in the further calculation procedure. The computational procedure of the MEREC method could be presented by the following series of steps (Popović et al., 2021).

Step 1. Form a decision matrix. A decision matrix shows the values of each alternative against each criterion. If we have n alternatives and m criteria, the form of the decision matrix will be as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \quad (1)$$

where xij denotes the elements of the decision matrix i.e., performance or rating of alternative i in relation to criterion j (xij > 0).

Since the initial decision matrix in this study contains negative values for some financial indicators, these values were transformed before the normalization procedure. For this purpose, the T-score transformation was applied in order to obtain strictly positive values while preserving the relative position of the alternatives within each criterion. In this way, the initial data were adjusted to the requirements of the MEREC method and could be used in the subsequent calculation procedure:

$$T_{ij} = 50 + 10\frac{x_{ij}-\mu_j}{\sigma_j} \quad (2)$$

where T ij represents the transformed value of alternative i according to criterion j, x ij represents the original value, while μ j and σ j denote the mean and standard deviation of criterion j, respectively.

Step 2. Normalize the decision matrix. Normalized ratings are calculated by scaling to a common scale, using the ratio of the minimum to the observed value for cost criteria and the ratio of the observed to the maximum value for utility criteria:

$$n_{ij}^{x} \square \begin{cases} \frac{\min_k x_{kj}}{x_{ij}} & if \quad j \in B \\ \frac{x_{ij}}{\max_k x_{kj}} & if \quad j \in C \end{cases} \quad (3)$$

where n_ij^x represents the elements of the normalized matrix N, the set of benefit criteria is shown as B, and the set of cost criteria is shown as C.

Step 3. Calculate the overall performance of the alternatives. This is achieved by using an equation in which the sum of the normalized values subtracted for each criterion measures the effect of its removal on the ranking of the alternatives.

$$S_i = ln\left(1 + \left(\frac{1}{m}\sum_j |ln(n_{ik}^{x})|ij\right)\right) \quad (4)$$

where Si represents the overall performance of the alternatives.

Step 4. Calculate the performance of the alternatives by removing each criterion. Using the following equation, the performance of the alternatives is calculated based on the removal of each criterion individually:

$$S_{ij}^{'} = ln\left(1 + \left(\frac{1}{m}\sum_j |ln(n_{ik}^{x})|ij\right)\right) \quad (5)$$

where S_ij^, signifies the overall performance of alternative i regarding the removal of criterion j.

Step 5. Calculate the sum of absolute deviations. The effect of removing criterion j is calculated as the sum of absolute deviations, which measures how much removing that criterion affects the overall performance of each alternative.

$$E_j = \sum_i |S_{ij}^{'} - S_i| \quad (6)$$

where Ej represents the effect of removing criterion j.

Step 6. Define the total weights of the criteria. The final value of the criteria weights is calculated using the following equation:

$$w_j = \frac{E_j}{\sum_k E_k} \quad (7)$$

where wj denotes the weight of the criterion j.

3.2. ARAS method

The Additive Ratio Assessment (ARAS) method has become a significant approach in multi-criteria decision-making (MCDM) owing to its understandable framework, computational ease, and versatility in many choice scenarios. This feature renders ARAS especially appropriate for intricate evaluation contexts where stakeholder agreement and discussion are essential.

The strategy facilitates the creation of significant subgroups of options, offering decision-makers improved insights during discussion stages. ARAS has exhibited significant adaptability in tackling real-world challenges across sectors, including building, technology selection, financial assessment, and waste management.

ARAS's organized framework has demonstrated efficacy in facilitating hybrid decision-making processes. Researchers have effectively combined ARAS with other

MCDM methodologies, like TOPSIS and SWARA, to improve efficacy in group decision-making and ranking consistency (Stanujkić et al., 2017). The hybrid SWARA-ARAS methodology has optimized negotiating outcomes by matching weight evaluations with group dynamics.

The applications of ARAS have expanded to dynamic fields such as technology and entertainment, with research by Meidelfi et al. (2022) demonstrating the method's efficacy in ranking mobile games according to user preferences. Moreover, its practical efficacy has been evidenced in strategic site selection processes for workshops (Krisnawati et al., 2023), illustrating ARAS's ability to assist stakeholders in making optimal decisions by integrating numerous conflicting elements.

In healthcare, ARAS has been utilized to assess general practitioner performance and enhance healthcare delivery, showcasing the method's efficacy in operational decision-making (Putra et al., 2023). Its applicability has been noted in industrial settings such as oil and gas project assessment, confirming its significance for multifactorial analysis in high-stakes sectors (Dahooie et al., 2018).

Subsequent methodological advancements encompass the creation of the Hierarchical Additive Ratio Assessment (ARAS-H), which facilitates the management of hierarchically organized criteria and interdependencies, essential for the analysis of complex systems (Ghram & Moalla Frikha, 2021). These changes signify a significant advancement of the ARAS approach, facilitating enhanced analytical depth and expanded applicability.

The ARAS approach is a dependable and versatile instrument in the MCDM toolkit. Its congruence with decision-makers' tastes, user-friendliness, and capacity to interact with hybrid models render it very appropriate for both strategic and operational decision-making processes. Continuous methodological enhancements and practical applications will likely solidify ARAS's status as a premier framework for addressing complex selection and ranking issues.

The process of solving decision making problems using ARAS method, similarly to the MEREC method, starts with forming the decision matrix and determining weights of criteria. After these initial steps, the remaining part of solving MCDM problem using ARAS method can be precisely expressed using the following steps: (Karabašević et al., 2016).

Step 1. Determine the optimal performance rating for each criterion. In this step, the optimal performance score for each criterion is set. If the decision maker does not have predetermined preferences, the optimal performance scores are calculated as:

$$x_{0j} = \begin{cases} \max\limits_{i} x_{ij}; & j \in \Omega_{\max} \\ \min\limits_{i} x_{ij}; & j \in \Omega_{\min} \end{cases} \tag{8}$$

where represents the optimal performance rating of j-th criterion, denotes the benefit criteria, i.e. the higher the values are, the better it is; and denotes the set of cost criteria, i.e. the lower the values are, the better it is.

Step 2. Calculate the normalized decision matrix. The normalized performance ratings are calculated using the following Eq.:

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \;; & j \in \Omega_{\max} \\ \dfrac{1/x_{ij}}{\sum_{i=0}^{m} 1/x_{ij}}; & j \in \Omega_{\min} \end{cases} \tag{9}$$

where signifies the normalized performance rating of i-th alternative in relation to the j-th criterion, i = 0, 1, ..., m.

Step 3. Calculate the weighted normalized decision matrix. The weighted normalized performance scores are calculated by multiplying each normalized value by the corresponding criterion weight. In this way, we take into account the relative importance of each criterion in the evaluation of each alternative using the following formula:

$$v_{ij} = w_j \; r_{ij} \tag{10}$$

where represents the weighted normalized performance rating of i-th alternative in relation to the j-th criterion, i = 0, 1, ..., m.

Step 4. Calculate the overall performance rating, for each alternative. The overall performance scores are calculated using the following formula:

$$S_i = \sum_{j=1}^{n} v_{ij} \tag{11}$$

where indicates the overall performance rating of i-th alternative, i = 0, 1, ..., m.

Step 5. Calculate the degree of utility for each alternative. In this step, the utility level of each alternative is calculated to determine how good each alternative is in relation to the optimal one. The result is obtained using the following formula:

$$Q_i = \frac{S_i}{S_0} \tag{12}$$

where represents the degree of utility of i-th alternative, and is the overall performance index of optimal alternative, i = 1, 2, ..., m.

Step 6. Rank alternatives and/or select the most efficient one. The considered alternatives are ranked in descending order, i.e., the alternative with the highest value of the utility degree is the best ranked.

4. Results

The empirical analysis included eight (n = 8) domestic limited liability company, similar size, assuring uniformity and consistency within the sample. The names of the companies featured in this research are omitted to prevent any form of promotion or disparagement of the entities involved. The selection criterion relied on the availability of comprehensive and verifiable financial records for the fiscal year 2023, obtained from the official database of the Agency for Business Registers (APR) of the Republic of Serbia, thereby confirming the dataset's reliability and legitimacy.

The investigation utilized Microsoft Excel and applied standard financial analysis techniques covering profitability, liquidity, asset management efficiency, and capital structure. The key indicators calculated were net profit margin, return on assets (ROA), and return on equity (ROE) as measures of profitability; the quick ratio and current ratio as measures of liquidity; receivables turnover and inventory turnover as measures of asset management efficiency; and the debt-to-equity ratio (D/E ratio) as a measure of capital structure.

Table 1. Decision Matrix

No.	Net profit margin	ROA	ROE	Current ratio	Quick ratio	D/E ratio	Inventory turnover	Receivables turnover
1	-0.01268	-0.01537	-0.11227	1.46513	0.34160	0.77347	3.62004	8.47161
2	0.00831	0.00692	0.26885	3.27997	2.10206	0.79572	3.11123	8.10435
3	0.03847	0.02594	0.96982	0.70821	-0.14025	0.97635	2.72031	3.45936
4	0.17091	0.14955	2.96741	7.12371	5.79588	0.25779	10.10147	4.89456
5	0.00567	0.00838	0.17619	2.39595	-5.58306	0.08566	3.61799	4.17186
6	0.04186	0.08948	0.90350	3.17467	0.43252	0.34407	6.76229	7.15840
7	0.04511	0.06692	5.23500	13.61625	1.75743	0.40989	3.99297	17.79970
8	0.01853	0.04914	7.70101	13.35973	-11.80040	0.03157	17.16834	110.38926

Source: Authors

Table 2. T-score transformed decision matrix

No.	Net profit margin	ROA	ROE	Current ratio	Quick ratio	D/E ratio	Inventory turnover	Receivables turnover
1	40.17546	37.44923	41.05121	41.41749	52.42335	59.59220	44.09120	46.46785
2	44.12579	41.89052	42.48666	45.14795	55.89640	60.27157	43.00457	46.36050
3	49.80192	45.68026	45.12678	39.86162	51.47275	65.78680	42.16972	45.00283
4	74.72720	70.30957	52.65049	53.04888	63.18358	43.84677	57.93305	45.42232
5	43.62894	42.18142	42.13766	43.33082	40.73515	38.59107	44.08682	45.21109
6	50.43992	58.34061	44.87700	44.93151	52.60272	46.48119	50.80184	46.08401
7	51.05157	53.84553	61.19112	66.39450	55.21651	48.49089	44.88763	49.19433
8	46.04920	50.30286	70.47908	65.86722	28.46955	36.93952	73.02517	76.25706

Source: Authors

Table 3. Calculating the overall performance rating

No.	Net profit margin	ROA	ROE	Current ratio	Quick ratio	D/E ratio	Inventory turnover	Receivables turnover	*Si'*
1	1.00000	1.00000	1.00000	0.96243	0.54307	0.90584	0.95642	0.96847	0.09807
2	0.91048	0.89398	0.96621	0.88291	0.50933	0.91617	0.98059	0.97071	0.13718
3	0.80671	0.81981	0.90969	1.00000	0.55310	1.00000	1.00000	1.00000	0.12887
4	0.53763	0.53263	0.77969	0.75141	0.45058	0.66650	0.72790	0.99076	0.34668
5	0.92084	0.88781	0.97422	0.91994	0.69889	0.58661	0.95652	0.99539	0.14537
6	0.79650	0.64191	0.91475	0.88716	0.54122	0.70654	0.83008	0.97654	0.22823
7	0.78696	0.69549	0.67087	0.60038	0.51560	0.73709	0.93945	0.91480	0.28434
8	0.87245	0.74448	0.58246	0.60518	1.00000	0.56150	0.57747	0.59015	0.33001

Source: Authors

Table 4. Sum of absolute deviations

No.	Net profit margin	ROA	ROE	Current ratio	Quick ratio	D/E ratio	Inventory turnover	Receivables turnover
1	0.00000	0.00000	0.00000	0.00435	0.07170	0.01127	0.00506	0.00364
2	0.01027	0.01229	0.00375	0.01366	0.07636	0.00959	0.00214	0.00324
3	0.02389	0.02207	0.01046	0.00000	0.06729	0.00000	0.00000	0.00000
4	0.05641	0.05728	0.02224	0.02558	0.07306	0.03652	0.02847	0.00082
5	0.00895	0.01295	0.00283	0.00906	0.03949	0.05938	0.00482	0.00050
6	0.02290	0.04511	0.00890	0.01198	0.06303	0.03517	0.01870	0.00236
7	0.02279	0.03476	0.03827	0.04918	0.06434	0.02911	0.00589	0.00841
8	0.01234	0.02687	0.04979	0.04618	0.00000	0.05326	0.05060	0.04855
Ei	0.15755	0.21133	0.13624	0.16000	0.45527	0.23430	0.11569	0.06753

Source: Authors

The table above shows the sum of absolute deviations for each alternative obtained as a result of introducing individual criteria.

The obtained weights rank the criteria according to their importance within the analyzed sample. The Quick ratio has the highest weight (0.29603), followed by the D/E ratio (0.15235), ROA (0.13741), and Current ratio (0.10404). Net profit margin has a similar weight (0.10244), while ROE, Inventory turnover, and Receivables turnover have lower weights. These results indicate that liquidity and capital structure have the greatest discriminatory importance in the evaluation of the analyzed companies.

In conclusion, MEREC is a cornerstone methodology in the MCDM landscape. It ensures the objectivity of weight allocation, mitigates bias, and adapts well to integration with both classical and contemporary techniques. Its applications across diverse domains and continuous methodological refinements position it as a critical tool for decision-makers striving for clarity, efficiency, and empirical rigor in complex evaluative scenarios. It is definitely possible to reveal the effects of certain accounting policies with the help of subject, financial accounting report and consequently to reveal the quality of accounting profit from the income statement (Parnicki et al., 2021).

Table 5. Final weight of the MEREC method criteria

Criterion	Ej	wj
Net profit margin	0.15755	0.10244
ROA	0.21133	0.13741
ROE	0.13624	0.08859
Current ratio	0.16000	0.10404
Quick ratio	0.45527	0.29603
D/E ratio	0.23430	0.15235
Inventory turnover	0.11569	0.07522
Receivables turnover	0.06753	0.04391
Total		1.00000

Source: Authors

Table 6. Determining the optimal performance score for each criterion

	Net profit margin	ROA	ROE	Current ratio	Quick ratio	D/E ratio	Inventory turnover	Receivables turnover
Direction	max	max	max	max	max	min	max	max
OV	74.72720	70.30957	70.47908	66.39450	63.18358	36.93952	73.02517	76.25706

Source: Authors

For the benefit criteria, the maximum value was taken as the optimal value, while for the cost criterion, D/E ratio, the minimum value was taken into account.

Table 7. Total value of the utility function (OV)

No.	Net profit margin	ROA	ROE	Current ratio	Quick ratio	D/E ratio	Inventory turnover	Receivables turnover
OV	0.15741	0.14950	0.14980	0.14236	0.13641	0.13985	0.15438	0.16012
1	0.08463	0.07963	0.08725	0.08880	0.11318	0.08669	0.09321	0.09757
2	0.09295	0.08907	0.09031	0.09680	0.12068	0.08571	0.09091	0.09734
3	0.10491	0.09713	0.09592	0.08547	0.11113	0.07853	0.08915	0.09449
4	0.15741	0.14950	0.11191	0.11374	0.13641	0.11782	0.12247	0.09537
5	0.09190	0.08969	0.08956	0.09291	0.08795	0.13387	0.09320	0.09493
6	0.10625	0.12405	0.09539	0.09634	0.11357	0.11114	0.10740	0.09676
7	0.10754	0.11449	0.13006	0.14236	0.11921	0.10654	0.09489	0.10329
8	0.09700	0.10696	0.14980	0.14123	0.06146	0.13985	0.15438	0.16012

Source: Authors

The normalized values presented in Table 7 were calculated on the basis of the transformed decision matrix, taking into account the direction of optimization for each criterion.

Table 8. The weighted normalized decision matrix

No.	Net profit margin	ROA	ROE	Current ratio	Quick ratio	D/E ratio	Inventory turnover	Receivables turnover
OV	0.01613	0.02054	0.01327	0.01481	0.04038	0.02131	0.01161	0.00703
1	0.00867	0.01094	0.00773	0.00924	0.03351	0.01321	0.00701	0.00428
2	0.00952	0.01224	0.00800	0.01007	0.03572	0.01306	0.00684	0.00427
3	0.01075	0.01335	0.00850	0.00889	0.03290	0.01196	0.00671	0.00415
4	0.01613	0.02054	0.00991	0.01183	0.04038	0.01795	0.00921	0.00419
5	0.00941	0.01232	0.00793	0.00967	0.02603	0.02039	0.00701	0.00417
6	0.01088	0.01705	0.00845	0.01002	0.03362	0.01693	0.00808	0.00425
7	0.01102	0.01573	0.01152	0.01481	0.03529	0.01623	0.00714	0.00454
8	0.00994	0.01470	0.01327	0.01469	0.01820	0.02131	0.01161	0.00703

Source: Authors

The weighted normalized values were obtained by multiplying the normalized values by the corresponding criterion weights determined using the MEREC method.

Table 9. Ranking of alternatives

Rank	Company	Si	Ki
1	4	0.13015	0.89707
2	7	0.11628	0.80145
3	8	0.11074	0.76332
4	6	0.10928	0.75325
5	2	0.09973	0.68740
6	3	0.09720	0.66996
7	5	0.09695	0.66823
8	1	0.09459	0.65196

Source: Authors

The alternatives were ranked in descending order according to the utility degree K i . Company 4 achieved the highest utility degree and was therefore ranked as the best alternative, followed by Companies 7 and 8.

By ranking and research conclusion, we can conclude that the company marked as number 4 has the highest Ki value (0.89707), which indicates that this company has the most favorable overall balance of the analyzed financial and operational indicators. Its position is the result of the combined effect of profitability, liquidity, capital structure, and asset management efficiency, evaluated using the objective criteria weights obtained by the MEREC method.

The assessment criteria should be continuously reviewed and adjusted in accordance with changes in the business environment and the needs of decision-makers. In this way, the proposed evaluation framework can remain relevant and support more reliable and transparent managerial decision-making (Đukić et al., 2024).

The MEREC approach was employed to determine the objective weights of the selected criteria based on the effects of their removal from the decision matrix. These weights were then incorporated into the ARAS method, which enabled the overall ranking of the analyzed companies according to their utility values. As a result of this integrated analytical procedure, Company 4 was identified as the most favorable alternative, followed by

Companies 7 and 8. The proposed hybrid approach contributes to greater transparency and consistency in financial performance evaluation and provides a useful basis for partner selection and strategic financial decision-making.

5. Conclusion

The research indicated that the integrated MEREC–ARAS model offers a reliable and methodologically sound framework for improving financial analysis in contexts characterized by competing criteria and considerable complexity. The study has enabled a clear evaluation of financial performance by objectively determining the significance of criteria using the MEREC approach and evaluating alternatives with the ARAS technique. The results demonstrated that Company 4 holds the highest position among the evaluated companies, followed by Companies 7 and 8, based on the overall utility values obtained through the integrated MEREC–ARAS procedure.

This framework significantly enhances the quality of managerial and investment decision-making by reducing subjectivity and integrating systematic, data-driven approaches into the assessment of business organizations. The integration of these two approaches ensures analytical precision and enables the creation of objective, criteria-based financial assessments that are reproducible, adaptable, and pertinent across many economic sectors. The proposed framework serves as a crucial decision-support instrument for financial managers, investors, and strategic planners, relevant in partner selection, supplier evaluation, or investment analysis, particularly in scenarios necessitating decisions based on multidimensional and often incomplete data.

Nonetheless, particular limitations of this study must be acknowledged. The analysis used data from a single fiscal year, which limited the model's ability to depict temporal dynamics or fluctuations in financial performance over time. Moreover, the model focused exclusively on quantitative financial measures, disregarding qualitative, non-financial, or industry-specific factors that could substantially influence decision-making. The study utilized data from a limited number of firms, perhaps constraining the generalizability of the results to broader or more diversified corporate environments.

Because of these limitations, future research should focus on testing the model in changing situations by using financial data from multiple years, which would allow for the study of trends, fluctuations, and the long-term reliability of financial indicators. Furthermore, incorporating qualitative dimensions such as the quality of corporate governance, stakeholder trust, innovation orientation, and market competitiveness would facilitate a more comprehensive evaluation of organizations. The incorporation of fuzzy logic systems may augment the model's ability to manage ambiguity and subjectivity, especially when decision criteria are vaguely described or assessed by expert judgment. Artificial intelligence elements, like machine learning algorithms, have the potential to improve prediction accuracy and decision-making resilience under unpredictable conditions.

Furthermore, the incorporation of participatory methods like the Delphi methodology can yield organized expert consensus in weighting and validating chosen indicators, hence enhancing methodological rigor and stakeholder alignment. The deployment of the model across several sectors, such as information technology, manufacturing, and logistics, would evaluate its scalability and flexibility in diverse operational and financial environments.

The article presents a practical and theoretically sound methodology for financial decision-making, delivering a systematic and replicable framework that facilitates coherent, transparent, and strategically informed assessments. Its implementation offers significant potential for both private-sector professionals and public-sector policymakers seeking to enhance the accuracy and effectiveness of their financial evaluations.

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