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# A Novel Objective Composite Weighting and Gain-Oriented Ranking Approach (OFGORCUN) for Multi-Criteria Decision Making

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**ABSTRACT**

This study proposes the OFGORCUN (Optimized Factor-based Gain-Oriented Ranking with Composite Utility and Normalization) approach, which is a new method that deals with weighting and ranking processes in multi-criteria decision-making a new method for weighting and ranking in multi-criteria decision-making (MCDM) problems that integrates and makes fully objective the weighting and ranking processes (MCDM) problems in an integrated and completely objective structure. The proposed method offers a more balanced, data-driven weighting mechanism compared to existing approaches in the literature by combining entropy-based information measures, distributional structure as expressed by standard deviation, and dissociation power based on correlations between criteria into a single composite formula to determine criterion weights. In the ranking phase of the method, the final performance scores of the alternatives are obtained using a normalized gain-based benefit function that combines the benefit and cost criteria. To demonstrate the feasibility and performance of the proposed model, the problem of selecting a cargo company was used as a case study, and different logistics service providers were evaluated against multiple operational, cost, and capacity criteria. The findings show that C4 – Total number of distributors is the most decisive and dominant criterion, while the most suitable carrier alternative is A8 DHL. In this context, it shows that the OFGORCUN method has strong decomposition capabilities for high-variance, multidimensional datasets and clearly reveals performance differences between large-scale logistics companies and local companies. In addition, the sequencing results obtained with the method were compared with common MSDV methods such as TOPSIS, MARCOS, and CRADIS, and the method's sensitivity to changes was evaluated using a Monte Carlo simulation. In addition, the effects of changes in criterion weights on the final results were evaluated. Based on the results, the proposed approach produced more consistent and distinctive results. In conclusion, the OFGORCUN method makes a unique contribution to the MCDM literature thanks to its completely objective structure, its lack of parameters, and its integration of multiple information criteria. It is considered a model that can be effectively used as a decision-support tool in logistics, supply chain management, and related fields.

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## 1. Introduction

The disruptive, transformative technological developments that emerged during Industry 4.0 have also made businesses more competitive. In this context, the effectiveness, efficiency, and performance of last-mile distribution within the framework of urban logistics operations have become the most critical and determining factors affecting the success and high customer satisfaction of supply chain operations. The rapid growth and spread of e-commerce due to technological developments and digital transformation, the increase in delivery speeds and accuracy expectations in direct proportion to the customer tolerance level, as well as expectations regarding service quality, the increase in alternatives in international trade and logistics networks incomparably with the past, and the pressures for logistics and delivery companies to develop sustainability and green strategies. Due to such developments, logistics, delivery, and distribution operations are becoming increasingly complex. Especially in rapidly growing cities and metropolitan areas, the significant increase in emissions and external costs, as well as traffic density, negatively affects the operational and sustainability performance of last-mile delivery and distribution practices and causes critical problems. In this context, selecting an appropriate logistics or courier service provider is no longer merely an operational preference but has become a strategic decision-making problem [1]. Recent studies show that in sustainable last-mile delivery processes, criteria such as cost, on-time delivery, environmental impact, brand reliability, and security directly influence the selection of logistics providers [2]. This decision directly affects several performance indicators, including cost efficiency, service quality, on-time delivery, flexibility, and customer satisfaction [3].

Logistics service provider selection is inherently a multi-criteria decision-making (MCDM) problem that requires the simultaneous evaluation of numerous—and often conflicting—criteria. Similarly, studies that apply integrated AHP–TOPSIS frameworks emphasize that selecting a courier company is a typical MCDM problem that should be evaluated under multiple criteria [4]. Decision-makers must consider various dimensions, including cost, delivery time, operational capacity, service network, reliability, and technological infrastructure. This multidimensional structure necessitates supporting the decision-making process with systematic, transparent, and analytical methods [5].

In the literature on last-mile deliveries, several popular decision-making approaches have been used to evaluate and select parcel distribution and last-mile delivery service providers. In this context, while sustainable last-mile parcel delivery solutions and international airline express parcel delivery companies were examined with the Best Worst Method (BWM) [6,7], Boakai and Samanlioglu [8] extended BWM with fuzzy clusters to address the same decision-making problem, and in another study, the decision-making problem regarding the selection of the most suitable courier company was discussed with the AHP & TOPSIS integrated model [4]. In addition, an integrated decision-making model consisting of a combination of the Intuitionistic Fuzzy Set (IFS)-based Full Consistency Method (FUCOM) and the Complex Proportional Assessment (COPRAS) methods was applied in the relevant literature [9], and the fuzzy AHP method was preferred for the selection of Courier Service Providers in the Taiwan context [10]. The graded mean integration representation (GMIR) method, extended with classic fuzzy sets, was used to analyze the customer value of three express shipping providers, UPS, FedEx, and DHL [11]. Similarly, these enterprises were handled using the SERVQUAL–FAHP–TOPSIS integrated decision-making model as logistics service providers [12]. Likewise, Ozcan & Ahiskali [13] examined the selection of these businesses as 3PL service providers using a hybrid AHP, TOPSIS, and Goal Programming (GP) approach. Pardiyono and Indrayani [14] evaluated enterprises providing these services in Indonesia and used the AHP method. Bajec *et al.,* [15] sought a reasonable solution to the decision-making problem by applying the AHP, ANP, TOPSIS, ISM, VIKOR, DEMATEL, and ELECTRE methods separately.

In the context of different definitions, such as logistics service manufacturers, 3PL companies, airline express delivery companies, and courier companies, etc., in the relevant literature, researchers evaluated last-mile parcel delivery companies, and for this, in addition to classical decision-making procedures such as TOPSIS, VIKOR, and ELECTRE, newer methods such as MARCOS and CRADIS were also used [16–20]. While the AHP method [21] is commonly used to determine the weights of the criteria, methods such as entropy, FUCOM, and CRITIC are also used [22,23].

Despite the wide range of decision-making approaches, there remain critical gaps and inadequacies in theoretical evaluation in the relevant literature. First, in most studies, the weights of the criteria were determined using subjective weighting methods such as AHP and BWM, which rely on expert judgments and are therefore biased. These methods are highly dependent on experts' subjective evaluations and judgments and, accordingly, can yield critically inconsistent and biased weights. Objective approaches such as entropy and CRITIC depend on a single objective criterion. They may be insufficient to capture the exact structure of the data and the interactions and relationships among the criteria [23,24]. At the same time, these approaches cannot prevent extreme values from producing artificial weights, and the resulting weights may not be suitable for real-life conditions.

In addition, most decision-making models proposed in the relevant literature are handled and implemented independently of weighting and ranking procedures. It can lead to critical information loss and methodological inconsistencies in evaluation processes. Moreover, most methods in the literature cannot capture or model linear or non-linear relationships and interactions among criteria, nor can they assess their impact on the final results. This situation leads to excessive complexity in evaluation processes and inaccurate measurement of information, resulting in artificial outcomes [23,24].

This study examines the OFGORCUN (Optimized Factor-Based Gain-Oriented Ranking, Composite Utility and Normalization) approach, which was developed as an innovative decision-making approach that has a completely objective evaluation mechanism to fill the research gaps discussed above and eliminate the theoretical evaluation deficiencies, and can also integrate practices such as weighting of criteria and ranking of alternatives under a single roof. introduces and recommends. This innovative decision-making tool combines three key components—(i) entropy-based information content, (ii) data distribution measured by standard deviation, and (iii) discriminating power derived from cross-criteria correlations—under a single weighting framework, simultaneously addressing the information value, variations, and independence of the criteria and producing highly balanced, stable, and reliable weight values.

In the ranking of alternatives, a normalized, gain-oriented benefit function is used to evaluate benefit and cost criteria simultaneously. Accordingly, it becomes possible to evaluate the performance of the alternatives in a clearer, comparable context and to achieve a higher level of discrimination, especially for data sets with high variance. Within this framework, the method enhances the interpretability of results for decision-makers by standardizing final scores.

To demonstrate the practicality and applicability of the OFGORCUN decision-making procedure developed in this study, this study addresses the decision-making problem of selecting last-mile package and parcel delivery companies for banks. It applies to the developed model to solve it. In this context, businesses that provide last-mile delivery services, such as ARAS, YURTİÇİ, MNG, SÜRAT, PTT, TNT, UPS, and DHL, were evaluated against 13 criteria.

The obtained ranking results have been compared to the conclusions acquired using the popular and commonly used decision making procedures, such as A combined compromise solution (CoCoSo) [25], The Multi-Attributive Border Approximation area Comparison (MABAC) [26], The Multi-Attribute Ideal-Real Comparative Analysis (MAIRCA) [27], Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS) [19], The Preference Selection Index (PSI) [28], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [29], The Weighted Aggregates Sum Product Assessment (WASPAS) [30], VIšeKriterijumska Optimizacija I Kompromisno Rešenje (VIKOR) [31], Ranking of Alternatives with Weights of Criterion (RAWEC) [20] An Alternative Ranking Order Method Accounting for Two-Step Normalization (AROMAN) [32], Root Assessment Method (RAM) [33].

This study aims to (i) develop an objective and integrated weighting-ranking method that is completely innovative and provides critical advantages compared to traditional approaches, (ii) combining entropy, variance, and correlation-based measures into a single composite structure, (iii) introducing a novel gain-oriented ranking approach with strong discriminating ability, and (iv) applying the method to a real logistic problem and with other multi-criteria decision making (MCDM) methods. It provides critical advantages and contributions to the literature and decision-makers in the relevant industry.

The rest of this study is organized as follows. Section 2 clearly introduces the basic algorithm and implementation steps of the developed decision-making approach, along with the mathematical operations and concepts. Section 3 summarizes and discusses the results of applying the proposed decision-making model to the problem of selecting a last-mile delivery company. Section 4 presents the results of extensive robustness and validity checks on the proposed model, while Section 5 illustrates the findings, examining the values, insights, and managerial and policy implications. Section 6 concludes the study, describes its limitations, and provides research guidelines for future studies.

## 2. Methodology

This section introduces the OFGORCUN (Optimized Factor-Based Gain-Oriented Ranking, Compounding Utility and Normalization) framework, an integrated weighting and ranking method developed to address the decision-making problem of evaluating and selecting last-mile parcel delivery service suppliers and producing reasonable solutions. This approach, which is an innovative decision-making mechanism, uses objective information in both weighting and ranking processes and is based on a gain-oriented benefit function. OFGORCUN associates three key objective components, such as (i) entropy-based information content, (ii) dispersion sensitivity through standard deviation, and (iii) correlation-based discrimination power, under an integrated weighting and ranking framework. Moreover, it uses a normalized gain scoring function that simultaneously considers benefit and cost criteria to assess the ranking performance of the alternatives in the evaluation process.

### *2.1 Conceptual Framework*

The innovative weighting and sorting mechanism developed combines two basic stages. In the first stage, the objective weighting process accounts for the current level of knowledge. It produces integrated objective weight values for the criteria within the framework of the distribution and mutual independence of this information, along with the level of dependency. Accordingly, it significantly reduces the risk of distorting the criterion weights when a single subjective or objective method is used, and allows the production of more rational weight values. Second, in the gain-oriented ranking process, the normalized decision matrix is associated with the criterion weights determined in the previous stage, and gain-based performance values are calculated for all alternatives. It is normalized to make the results more interpretable and comparable. The structure of this hybrid decision-making approach enables high discrimination and robust, consistent results, especially in multidimensional data environments.

*Stage 1:* Objective Weighting Procedure: The first six steps of the decision-making tool, developed to determine the criterion weights, are followed, and the criterion weights are calculated based on objective information.

*Step 1:* Generate the Initial Decision Matrix: Given options $A_i(i = 1, \dots, m)$ and measurements $C_j(j = 1, \dots, n)$. The initial decision matrix is constructed as:

$$X = \left[x_{ij}\right]_{mxn} \tag{1}$$

*Step 2:* Normalize the initial decision matrix elements: The cost and benefit criteria are normalized to transform comparable values. For this purpose, Eqs. (2) and (3) are employed for benefit and cost criteria, respectively.

$$r_{ij} = \frac{x_{ij}}{\max\limits_{i} x_{ij}} \tag{2}$$

$$r_{ij} = \frac{\min\limits_{i} x_{ij}}{x_{ij}} \tag{3}$$

This normalization process ensures that all criteria are converted into a unified maximization structure.

*Step 3:* Entropy-Based Information Content (O-Component): First, probability values are computed from the normalized matrix using Eq. (4).

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}} \tag{4}$$

Entropy value for each criterion is acquired with the help of Eq. (5).

$$e_j = -k \sum_{i=1}^{n} p_{ij} \, ln\left(p_{ij}\right), k = \frac{1}{ln(m)} \tag{5}$$

The degree of divergence is then described using Eq. (6).

$$d_j = 1 - e_j \tag{6}$$

This component reflects the information value of each criterion; low-variance or homogeneous criteria receive lower values.

*Step 4:* Standard Deviation (F-Component): Dispersion for each criterion is measured using Eq. (7).

$$\sigma_j = \frac{1}{m} \sum_{i=1}^{m} \left(r_{ij} - \overline{r}_j\right)^2 \tag{7}$$

A greater standard deviation indicates stronger discriminative ability.

*Step 5:* Correlation-Based Discrimination Power (G Component): Using the criterion correlation matrix, the correlation-based discrimination power is computed using Eq. (8).

$$c_j = \sum_{k=1}^{n} \left(1 - p_{jk}\right) \tag{8}$$

Thus, criteria that are less dependent on others exhibit greater discrimination power. This concept extends the CRITIC method's logic.

*Step 6:* Integration of O–F–G Components for Identifying the Final Weights: The three objective components are combined to obtain composite weights using (9).

$$w_j = \frac{d_j . \sigma_j . c_j}{\sum_{j=1}^{n} d_j . \sigma_j . c_j} \tag{9}$$

These weights simultaneously capture information richness, variation, and independence, providing a balanced objective weighting structure.

*Stage 2:* Gain-Oriented Ranking Procedure: In this phase, the ranking performance of each alternative is determined by following the remaining steps of the proposed model.

*Step 7:* Calculation of Gain Scores: The weighted performance score for each alternative is:

$$S_i = \sum_{j=1}^{n} w_j . r_{ij} \tag{10}$$

This score represents the aggregate gain associated with the alternative $A_i$.

*Step 8:* Composite Utility Normalization (CUN): Final scores are normalized into a 0–1 scale:

$$U_i = \frac{S_i - min(S_i)}{max(S_i) - min(S_i)} \tag{11}$$

This transformation provides interpretability and comparability across alternatives.

*Step 9:* Ranking of Alternatives: Alternatives are ranked in descending order of $U_i$. The alternative with the highest composite utility score is determined as the optimal choice.

**3. A Numerical Illustration**

This chapter addresses the selection and evaluation of parcel delivery companies, a real-world decision-making problem faced by banks in their delivery processes when sending documents and financial products such as credit cards, invoices, ledger entries, and other documents to bank customers. The basic research problem addressed in the first stage is defined as follows.

In today's banking and financial ecosystems, banks need to safely deliver a wide range of envelopes and documents to their customers within appropriate delivery times and in a traceable manner. Although digital transformation and the use of advanced technology have contributed to the reduction of physical document and information flows, the obligations determined by legal regulations, the preferences and expectations of customers, the measures and practices regarding fraud prevention, the necessary procedures for verifying customer identities cause the deliveries to be made by banks to customers to continue to be critically important and strategically effective.

Banks and financial institutions face an extremely complex decision-making problem when selecting companies to handle last-mile deliveries, given contradictory and interrelated criteria. The highly sensitive security, legal regulations, and requirements regarding personal information and data of the documents, documents, and financial products subject to deliveries make it necessary to carry out such operations in an extremely strict and uncompromising manner. In addition, the required delivery speed, the need for a wide distribution network due to the spread of customers across a broad geography, the high security requirements inherent to financial products, customer experience and expectations, and strict regulations set by regulatory frameworks make operational processes much more complex. In addition, the legal limitations and regulations that banks and financial institutions are subject to, as well as critical factors such as compliance, auditability, and operational performance for delivery companies, make the selection of last-mile package delivery companies extraordinarily complex.

In addition, it can be seen that the decision-making problem deepens when it is recognized that the delivery companies considered in the decision-making process are relatively superior or perform worse under the evaluation criteria. While some companies have weaknesses in certain criteria due to structural problems and deficiencies, some delivery companies may prefer to remain weak in some areas to benefit from economies of scale, high investment costs, and low profitability amid excessive competition, etc. It makes it even more difficult to evaluate the delivery companies in question. For this reason, banks and financial institutions must evaluate alternatives and develop reasonable solutions to the decision-making problem at hand, taking into account many contradictory and linear or non-linear relationships and interactions in a balanced and reasonable context.

Moreover, because criteria with different dimensions such as economic, social, environmental, operational and technical critically affect the evaluation processes, decision-makers should address this multidimensional decision problem in a balanced manner and address the decision-making problem in question with the help of a systematic, analytical, data-based and reliable decision-making approach that can process both the quantitative and qualitative dimensions of the criteria for these dimensions together and to produce solutions. They need to work.

The intense interactions and relationships between the existing contradictory criteria and the different capabilities and weaknesses of parcel delivery and delivery companies make the evaluation and selection of these companies an extremely complex decision-making problem. In this context, it is a strategic requirement for banks and financial institutions to identify last-mile delivery companies that can manage operational risks, deliver on time and flawlessly, maintain high service quality, fully comply with regulatory standards, and integrate them into their business models as strategic partners. While the failure to model the decision-making process correctly and effectively leads to an uncontrollable increase in the operational costs of the business and a dramatic decrease in customer satisfaction, the failure to make deliveries on time or incorrectly leads to loss of reputation of the business, as well as financial and legal sanctions arising from regulatory requirements, causing additional difficulties and problems.

To address complex decision-making problems in last-mile delivery operations involving shipments from banks to their customers and to produce reasonable, real-life solutions, it is necessary to use a robust, objective, transparent, and analytical decision support system, as well as a data-based approach. This decision-making tool should include variations in business operational performance, as well as the mechanisms and structural capabilities to manage operational risks. Accordingly, banks must choose a last-mile delivery service generator partner that aligns closely with their strategic goals and operational expectations for last-mile package deliveries.

Moreover, last-mile parcel delivery companies are included in the evaluation process as alternatives in this study. The identification and inclusion of these companies in the evaluation process reflect banks' operational requirements for last-mile deliveries. Banks need long-term collaborations with parcel delivery companies that can deliver all kinds of shipments to their customers under strict, critical security measures, on time, reliably, and traceably. In this context, the last-mile parcel delivery companies included in the evaluation process have been determined based on three basic criteria: market suitability, operational capacity, and service availability in the national and international logistics environment.

First, the research identified delivery companies with an established presence in Türkiye's parcel distribution ecosystem. The businesses included in the evaluation process represent a wide range, from large-scale logistics and distribution companies to medium- and small-sized local parcel delivery and courier companies. The positioning of companies for inclusion in the evaluation process within such a broad framework allows banks and financial institutions to present their requirements for delivery processes in a more comprehensive and realistic context. Going beyond short-term operational delivery performance, international express cargo companies operating in the domestic parcel delivery market were included as options in the evaluation process, as they may be needed to ensure compliance with cross-border operational requirements and international delivery operations, alongside traditional local actors.

Secondly, consideration was given to the fact that the operational and sustainability performances of the parcel delivery companies to be included in the evaluation process were measurable and comparable. The data used to compare and rank alternatives include publicly available and institutionally verified operational indicators from real-world operations, such as the scale and number of personnel in the vehicle fleets used by parcel delivery companies, the size of the geographical area they can serve, operational capabilities, and delivery speeds and costs. Depending on the measurable characteristics of parcel delivery companies against the criteria, OFGORCUN can objectively evaluate each alternative while significantly eliminating subjective judgments and decision-makers' biases.

Thirdly, the alternatives discussed in the evaluation process are companies that currently provide distribution and delivery services to the banking and financial industries and have a wide distribution network in this context. These service providers operate trustworthy last-mile delivery operations for their customers, ensuring security, online tracking and tracing, and the timely handling of sensitive and confidential shipments. These enterprises have committed to and guaranteed that these essential services will be included in their offerings, ensuring that the comparative analysis will produce meaningful and critical insights for delivery companies and the banking and financial services industries.

In that regard, the alternative parcel delivery companies included in the evaluation process comprise eight, including leading local businesses (ARAS, YURTİÇİ, MNG, SÜRAT, PTT) and major international express operators (TNT, UPS, DHL). Evaluating last-mile parcel delivery companies against banks' delivery requirements offers opportunities for strategic alliances to increase operational efficiency and improve service quality. At the same time, the set of alternatives created in the context of these companies provides a comprehensive evaluation environment and decision-making area for bank decision-makers within the developed decision-making procedure. In addition, the evaluation criteria established in this study are aligned with the operational, financial, and security requirements of the banking sector. They can serve as a roadmap to guide practitioners and decision-makers in their decision-making processes. Since banks handle highly sensitive consignments—such as credit cards, PIN envelopes, customer documentation, and regulatory correspondence- the criteria should reflect both the risk dimensions and the logistical performance indicators that influence secure, reliable delivery. In that regard, the criteria have been determined within the framework of three complementary and basic components: the banking industry's requirements for last-mile parcel deliveries, the operational and sustainability performances and capacities of delivery companies, and the accessibility and availability of numerical data.

First, a comprehensive review was conducted to identify banks' expectations of businesses that deliver last-mile parcels and the requirements in the banking industry context. In this context, the researchers concluded that banking transactions are critical and require strict confidentiality, traceability, fast, timely delivery, and compliance with legal regulations. As a result, within the framework of these requirements, basic criteria such as service speed, number of branches, fleet size, personnel capacity, and geographical coverage have been determined as the criteria to be included in the evaluation process, as they directly affect the ability of last-mile parcel delivery companies to perform time-critical and safety-sensitive deliveries.

Second, the operational capabilities of courier companies were analyzed to ensure that the selected criteria reflect real performance differentiators among alternatives. Indicators such as total distribution personnel, total number of vehicles, main route carrying capacity, and international service capability are included in the evaluation process, as they are the main criteria banks often consider when requesting delivery services from external sources for their shipments to customers. Cost-related criteria such as unit shipment price, number of transfer points, and international delivery fees also reflect operational costs in the decision-making process. They are included in the analysis to create an evaluation environment that encompasses the financial and economic dimensions of this process. These economic and financial criteria are critical for effective decision-making, as they directly and frequently affect budget management and customer experiences in the operational context.

Moreover, the determination of criteria and their inclusion in the evaluation process is limited to the availability and accessibility of accurate, objective, measurable, interpretable, and comparable data for the comparison of alternatives; criteria for which numerical data are not obtainable are not included in the evaluation process. Therefore, the data used is derived from real operational data published or provided by businesses that produce last-mile delivery services, which have precise numerical values. It enables the multi-criteria decision-making tool to be free of subjective and biased attitudes and reproducible. In addition, using only precise, numerical data in the evaluation process enables the OFGORCUN approach, a completely objective decision-making procedure, to be smoothly applied.

This systematic, analytical, and structured evaluation process determined a comprehensive set of criteria consisting of thirteen criteria, including the organizational capacities of last-mile parcel delivery companies, the scope and scale of the distribution network, performance levels regarding delivery operations, cost optimization and effectiveness, and the ability to produce delivery services on an international level. Pre-assessment and negotiations enable last-mile delivery companies to act as strategic partners, analysing their suitability for banks and identifying and modelling requirements in the context of operational excellence and risk management for the banking industry. After the alternatives and criteria were identified, objective, crisp data and information were collected. Afterward, the computational processes of the proposed model have been implemented as follows:

*Stage 1:* Objective Weighting Procedure: In this stage, the objective weights for each criterion were determined by following the six implementation steps outlined in the suggested procedure.

*Step 1:* The initial decision matrix was constructed as shown in Table 1.

**Table 1**
The initial decision matrix

| A | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 41 | 3320 | 8800 | 1300 | 790 | 6 | 0.87 | 28 | 56 | 300 | 255 | 17189 | 40.2 |
| A2 | 38 | 5000 | 16000 | 2700 | 900 | 6 | 1.16 | 33 | 74 | 550 | 230 | 17184 | 39.84 |
| A3 | 17 | 3000 | 8000 | 1100 | 871 | 6 | 1.22 | 26 | 62 | 270 | 250 | 17189 | 49.5 |
| A4 | 17 | 1278 | 4000 | 450 | 556 | 6 | 0.81 | 24 | 44 | 200 | 220 | 10800 | 40.47 |
| A5 | 180 | 3860 | 40000 | 2830 | 4250 | 4 | 0.81 | 36 | 91 | 2830 | 256 | 17189 | 13.45 |
| A6 | 74 | 7000 | 58000 | 5000 | 45 | 4 | 1.8 | 7 | 21 | 1220 | 265 | 17189 | 24.68 |
| A7 | 113 | 10300 | 495000 | 125000 | 5100 | 4 | 1.93 | 45 | 82 | 5900 | 265 | 17189 | 130.6 |
| A8 | 51 | 31000 | 510000 | 140000 | 40 | 4 | 11.39 | 58 | 96 | 7000 | 265 | 17189 | 48.33 |

*Step 2:* Depending on the fact that the values in the first decision matrix are determined according to different criteria, such as fleet size, cost, and distance, in the context of different criteria, the raw data obtained in the first stage should be converted into a comparable common scale. In this context, normalization enables criteria with different values to contribute proportionally to the evaluation process. The normalized values of the matrix elements were computed using Eqs. (2) and (3). Afterward, the normalized decision matrix is generated as illustrated in Table 2.

For example, the normalized value of the A1-C1 element (benefit criterion) has been computed as follows:

$$r_{A1-C1} = \frac{x_{A1-C1}}{\max_{i} x_{A1-C1}} = \frac{41}{180} = 0.228$$

for the A1-C8 element of the matrix (cost criterion) is calculated as follows:

$$r_{A1-C8} = \frac{\min_i x_{A1-C8}}{x_{A1-C8}} = \frac{7}{28} = 0.250$$

**Table 2**
The normalized decision matrix

| A | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 0.228 | 0.107 | 0.017 | 0.009 | 0.155 | 1.000 | 0.931 | 0.250 | 0.583 | 0.043 | 0.962 | 1.000 | 0.335 |
| A2 | 0.211 | 0.161 | 0.031 | 0.019 | 0.176 | 1.000 | 0.698 | 0.212 | 0.771 | 0.079 | 0.868 | 1.000 | 0.338 |
| A3 | 0.094 | 0.097 | 0.016 | 0.008 | 0.171 | 1.000 | 0.664 | 0.269 | 0.646 | 0.039 | 0.943 | 1.000 | 0.272 |
| A4 | 0.094 | 0.041 | 0.008 | 0.003 | 0.109 | 1.000 | 1.000 | 0.292 | 0.458 | 0.029 | 0.830 | 0.628 | 0.332 |
| A5 | 1.000 | 0.125 | 0.078 | 0.020 | 0.833 | 0.667 | 1.000 | 0.194 | 0.948 | 0.404 | 0.966 | 1.000 | 1.000 |
| A6 | 0.411 | 0.226 | 0.114 | 0.036 | 0.009 | 0.667 | 0.450 | 1.000 | 0.219 | 0.174 | 1.000 | 1.000 | 0.545 |
| A7 | 0.628 | 0.332 | 0.971 | 0.893 | 1.000 | 0.667 | 0.420 | 0.156 | 0.854 | 0.843 | 1.000 | 1.000 | 0.103 |
| A8 | 0.283 | 1.000 | 1.000 | 1.000 | 0.008 | 0.667 | 0.071 | 0.121 | 1.000 | 1.000 | 1.000 | 1.000 | 0.278 |

*Step 3:* Entropy measures how much useful information a criterion provides. If the values under a criterion are similar across alternatives, that criterion carries less informative value. For this purpose, Eqs. (4), (5), and (6) were employed. The entropy-based information matrix has been formed as shown in Table 3.

**Table 3**
The entropy-based information matrix

| A | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 0.077 | 0.051 | 0.008 | 0.005 | 0.063 | 0.150 | 0.178 | 0.100 | 0.106 | 0.016 | 0.127 | 0.131 | 0.104 |
| A2 | 0.072 | 0.077 | 0.014 | 0.010 | 0.072 | 0.150 | 0.133 | 0.085 | 0.141 | 0.030 | 0.115 | 0.131 | 0.105 |
| A3 | 0.032 | 0.046 | 0.007 | 0.004 | 0.069 | 0.150 | 0.127 | 0.108 | 0.118 | 0.015 | 0.125 | 0.131 | 0.085 |
| A4 | 0.032 | 0.020 | 0.004 | 0.002 | 0.044 | 0.150 | 0.191 | 0.117 | 0.084 | 0.011 | 0.110 | 0.082 | 0.104 |
| A5 | 0.339 | 0.060 | 0.035 | 0.010 | 0.339 | 0.100 | 0.191 | 0.078 | 0.173 | 0.155 | 0.128 | 0.131 | 0.312 |
| A6 | 0.139 | 0.108 | 0.051 | 0.018 | 0.004 | 0.100 | 0.086 | 0.401 | 0.040 | 0.067 | 0.132 | 0.131 | 0.170 |
| A7 | 0.213 | 0.159 | 0.434 | 0.449 | 0.406 | 0.100 | 0.080 | 0.062 | 0.156 | 0.323 | 0.132 | 0.131 | 0.032 |
| A8 | 0.096 | 0.479 | 0.447 | 0.503 | 0.003 | 0.100 | 0.014 | 0.048 | 0.183 | 0.383 | 0.132 | 0.131 | 0.087 |
| $e_j$ | 0.867 | 0.781 | 0.550 | 0.445 | 0.701 | 0.990 | 0.934 | 0.874 | 0.965 | 0.715 | 0.999 | 0.996 | 0.916 |
| $d_j$ | 0.133 | 0.219 | 0.450 | 0.555 | 0.299 | 0.010 | 0.066 | 0.126 | 0.035 | 0.285 | 0.001 | 0.004 | 0.084 |

For example, the entropy-based information value of the A1-C1 element (benefit criterion) has been computed as follows:

$$p_{A1-C1} = \frac{r_{A1-C1}}{\sum_{i=1}^{n} r_{A1-C1}} = \frac{0.228}{2.950} = 0.077,$$

for the A1-C8 element of the matrix (cost criterion) is calculated as follows:

$$p_{A1-C8} = \frac{r_{A1-C8}}{\sum_{i=1}^{n} r_{A1-C8}} = \frac{0.250}{2.494} = 0.100$$

Then, the entropy value for each criterion was determined using Eq. (5), and the divergence value of the criterion was determined by employing Eq. (6).

*Step 4:* Standard deviation measures the dispersion (variability) of normalized values under each criterion. In this step, the criteria with greater variability are recognized as more discriminative, and consistent (low-variation) criteria contribute less to decision differentiation. It forms the F component, representing a criterion's discriminatory strength. Eq. (7) is used to compute the standard deviation values.

*Step 5-6:* To compute the correlation-based Discrimination Power (G Component) for each criterion, Eq. (8) was employed. The divergence, standard deviation, and correlation-based discrimination power values for the criteria were identified in Table 4. Then, three objective components of the model were integrated, and the final weight coefficients of the criteria were calculated.

**Table 4**
The $d_j, \sigma_j, and\ c_j$values

| A | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $d_j$ | 0.133 | 0.219 | 0.450 | 0.555 | 0.299 | 0.010 | 0.066 | 0.126 | 0.035 | 0.285 | 0.001 | 0.004 | 0.084 |
| $\sigma_j$ | 0.309 | 0.312 | 0.437 | 0.432 | 0.384 | 0.178 | 0.328 | 0.284 | 0.263 | 0.390 | 0.064 | 0.131 | 0.271 |
| $c_j$ | 7.612 | 6.183 | 5.146 | 5.246 | 7.923 | 5.796 | 6.265 | 8.771 | 6.844 | 4.850 | 6.495 | 8.346 | 8.635 |
| $w_j$ | 0.061 | 0.082 | 0.196 | 0.242 | 0.176 | 0.002 | 0.026 | 0.061 | 0.012 | 0.104 | 0.000 | 0.001 | 0.038 |
| rank | 7 | 5 | 2 | 1 | 3 | 11 | 9 | 6 | 10 | 4 | 13 | 12 | 8 |

*Stage 2:* Gain-Oriented Ranking Procedure: In this stage, the ranking performance of each alternative is determined by following the remaining steps of the proposed model.

*Step 7:* Each alternative's performance score was computed using weighted sums given in Eq. (10).

This score represents the aggregate gain associated with the alternative $A_i$. For example, the $S_i$value of A1 is computed as follows:

$$S_{A1} = \sum_{j=1}^{n} (0.061x.0.228)+\ldots+(0.0038x0.335) = 0.1222$$

*Step 8:* Composite Utility Normalization (CUN): Final scores were normalized into a 0–1 scale using Eq. (11).

For example, the $U_i$value of A1 is computed as follows:

$$U_i = \frac{S_i - min(S_i)}{max(S_i) - min(S_i)} = \frac{0.1222 - 0.0983}{0.7720 - 0.0983} = 0.0355$$

Computations were repeated for the remaining alternatives, and the acquired results are presented in Table 5.

**Table 5**
The $S_i$and $U_i$values of the alternatives

| Code | Alternatives | $S_i$ | $U_i$ | RANK |
|---|---|---|---|---|
| A1 | ARAS | 0.1222 | 0.0355 | 6 |
| A2 | YURTİÇİ | 0.1323 | 0.0505 | 5 |
| A3 | MNG | 0.1075 | 0.0138 | 7 |
| A4 | SÜRAT | 0.0983 | 0.0000 | 8 |
| A5 | PTT | 0.3693 | 0.4022 | 3 |
| A6 | TNT | 0.1921 | 0.1392 | 4 |
| A7 | UPS | 0.7720 | 1.0000 | 1 |
| A8 | DHL | 0.6764 | 0.8581 | 2 |

When the results were examined, the C4 Total number of distributors (0.2425) was determined to be the most dominant and decisive criterion. It is followed by C3 Total number of personnel (0.1956) and C5 Number of branches (0.1758) criteria, respectively. In the middle ranks, the criteria, such as C10 Number of delivery vehicles (0.1040) > C2 Total number of vehicles (0.0816) > C8 Number of transfers (0.0608) > C1 Company experience (0.0605) > C13 International service fee (0.0378) > C7 Cargo unit cost (0.0263) > C9 Number of main line vehicles (0.0122) were ranked. In the last three ranks, C6 Delivery speed (0.0019), C12 Maximum service distance (0.0009), and C11 Number of countries served (0.0001) were sorted. Secondly, A7 UPS is identified as the most appropriate strategic partner for the banks as a last-mile delivery company, and others are ranked as follows: A8 DHL > A5 PTT > A6 TNT > A2 YURTİÇİ > A1 ARAS > A3 MNG > A4 SÜRAT.

**3. Robustness and Validity Check**

In this section, the criterion weights were first changed, and the effects of these changes on the ranking performance of the Alternatives were examined. Then, a comparison was made between the results obtained with different ranking methods and those from this study. Thirdly, the model's resistance to changes was measured using a Monte Carlo simulation, and in the last stage, the accuracy of the proposed model in addressing the rank reversal problem was assessed.

*3.1 Examination of the changing criteria weights on the ranking results.*

A structured and systematic analysis process has been developed to assess the robustness and validity of the OFGORCUN procedure. This evaluation and analysis process starts from the most effective and dominant criterion. The criterion's weight is gradually reduced from 10% in each scenario to zero. The difference resulting from the reduction is added to the weights of the other criteria to ensure that the sum of the criterion weights equals 1. This application, which is carried out for the first criterion discussed, is repeated for the other criteria. In this context [34], 130 scenarios are created, and the recommended decision-making model with different criterion weights is applied across all of them. The following shows the mathematical operations and calculations performed to examine the effects of changes in criterion weights on the final ranking results.

*a. Identifying the weight vector's baseline*

Let the initial OFGORCUN weights be represented as:

$$\mathrm{w}^{(0)} = (w_1, w_2, \dots, w_n)$$

where:

- $w_j$ depicts the baseline weight of the criterion $C_j$
- $n = 13$ in this current investigation
- $\sum_j w_j = 1$

The criteria are ranked from most to least influential:

$$w_{(1)} \geq w_{(2)} \geq \cdots \geq w_{(n)}$$

This ranking identifies the sequence of reduction.

*b. Progressive reduction of the most influential and decisive criterion*

For each scenario, the most influential criterion's weight is reduced by 10% of its baseline value:

$$w_{(1)}^{(k)} = w_{(1)}^{(0)} \cdot (1 - 0.1k)$$

where:

- $k = 1,2,3, \dots, K_1$
- $K_1$is the number of reductions until

$$w_{(1)}^{(k)} \leq 0$$

The weight decrement at step $k$is:

$$\Delta w_{(1)}^{(k)} = w_{(1)}^{(0)} - w_{(1)}^{(k)}$$

*c. Redistribution of the lost weight to remaining criteria*

The lost weight $\Delta w_{(1)}^{(k)}$is not discarded; instead, it is redistributed proportionally across all remaining criteria:

$$w_j^{(k)} = w_j^{(0)} + \Delta w_{(1)}^{(k)} \cdot \frac{w_j^{(0)}}{\sum_{m\neq(1)} w_m^{(0)}} \forall j \neq (1)$$

It ensures:

- Total weight remains equal to 1
- Weight structure changes in a controlled, mathematically consistent manner

After redistribution:

$$\sum_{j=1}^{n} w_j^{(k)} = 1$$

*d. Transition to the next criterion*

Once the weight of the most influential criterion reaches zero:

$$w_{(1)}^{(K_1)} = 0$$

The procedure restarts with the second most influential criterion:

$$w_{(2)}^{(k)} = w_{(2)}^{(0)}(1 - 0.1k)$$

Furthermore, the reduction and redistribution procedures repeat.

Similarly, for the criterion $C_{(p)}$:

$$w_{(p)}^{(k)} = w_{(p)}^{(0)}(1 - 0.1k)$$

Redistribution formula generalizes to:

$$w_j^{(k)} = w_j^{(0)} + \Delta w_{(p)}^{(k)} \cdot \frac{w_j^{(0)}}{\sum_{m\neq(p)} w_m^{(0)}} \forall j \neq (p)$$

The process for the criterion $C_{(p)}$continues until:

$$w_{(p)}^{(k)} \leq 0$$

and then moves to $C_{(p+1)}$.

*e. Total Number of Scenarios*

Each criterion typically undergoes approximately 10 steps of 10% reduction:

$$K_p \approx 10$$

Thus:

$$\text{Total Scenarios} = \sum_{p=1}^{n} K_p = 13 \times 10 = 130$$

This produces 130 distinct weighting structures:

$$\mathrm{w}^{(1)}, \mathrm{w}^{(2)}, \dots, \mathrm{w}^{(130)}$$

Each scenario captures a different decision environment and enables a robust sensitivity analysis. Figure 1 presents the results of the sensitivity analysis.

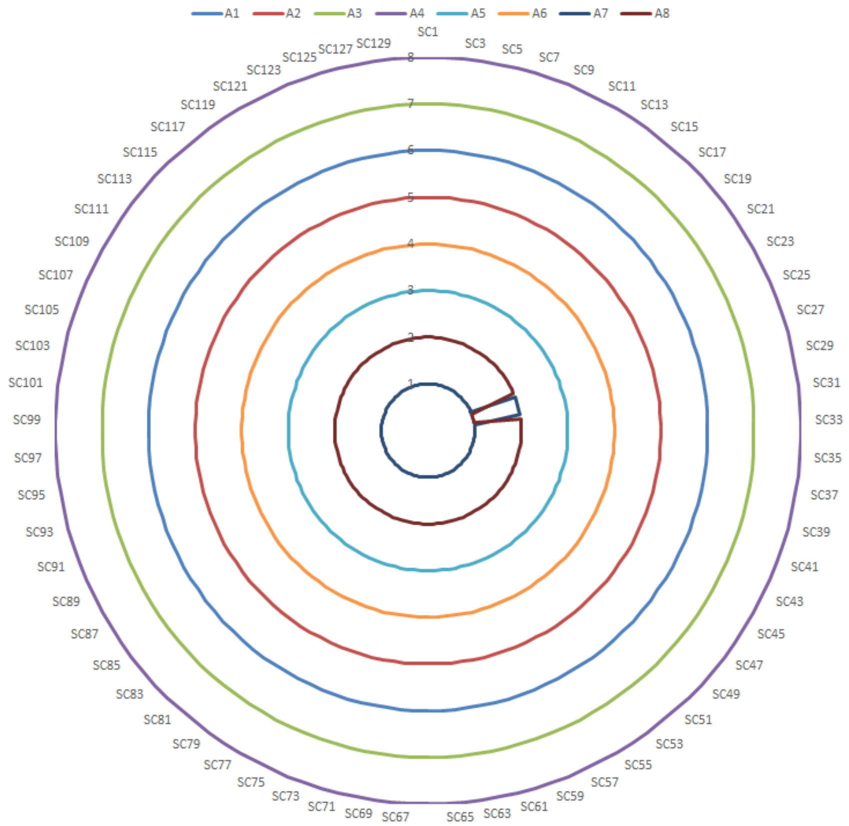


**Fig. 1.** Re-ranking the alternatives for 130 scenarios

The results show that when the weight of the C3 criterion decreases by 60% or more, the A8 and A7 alternatives are mutually replaced, and the other Criteria maintain their ranking positions across all scenarios. However, the average similarity rate was calculated as 0.990. The literature on decision-making methods generally agrees that a similarity value above 0.700 is acceptable [35–37]. The obtained value is even higher than the 0.850 suggested by Belton *et al.,* [38] and Saaty [39]. It shows that the proposed decision-making approach is maximally robust to changes in the weights of the criteria.

### *3.2 Comparative Analysis*

To compare the proposed decision-making procedure with the decision-making methods in the relevant literature, the ranking results obtained with the help of the suggested decision-making model are compared to the solution produced by using methods, i.e., A combined compromise solution (CoCoSo) [25], The Multi-Attributive Border Approximation area Comparison (MABAC) [26], The Multi-Attribute Ideal-Real Comparative Analysis (MAIRCA) [27], Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS) [19], The Preference Selection Index (PSI) [28], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [29], The Weighted Aggregates Sum Product Assessment (WASPAS) [30], VIšeKriterijumska Optimizacija I Kompromisno Rešenje (VIKOR) [31], Ranking of Alternatives with Weights of Criterion (RAWEC) [20] An Alternative Ranking Order Method Accounting for Two-Step Normalization (AROMAN) [32], Root Assessment Method (RAM) [33], that have been proven many times to produce popular and rational solutions. Figure 2 illustrates the results obtained.

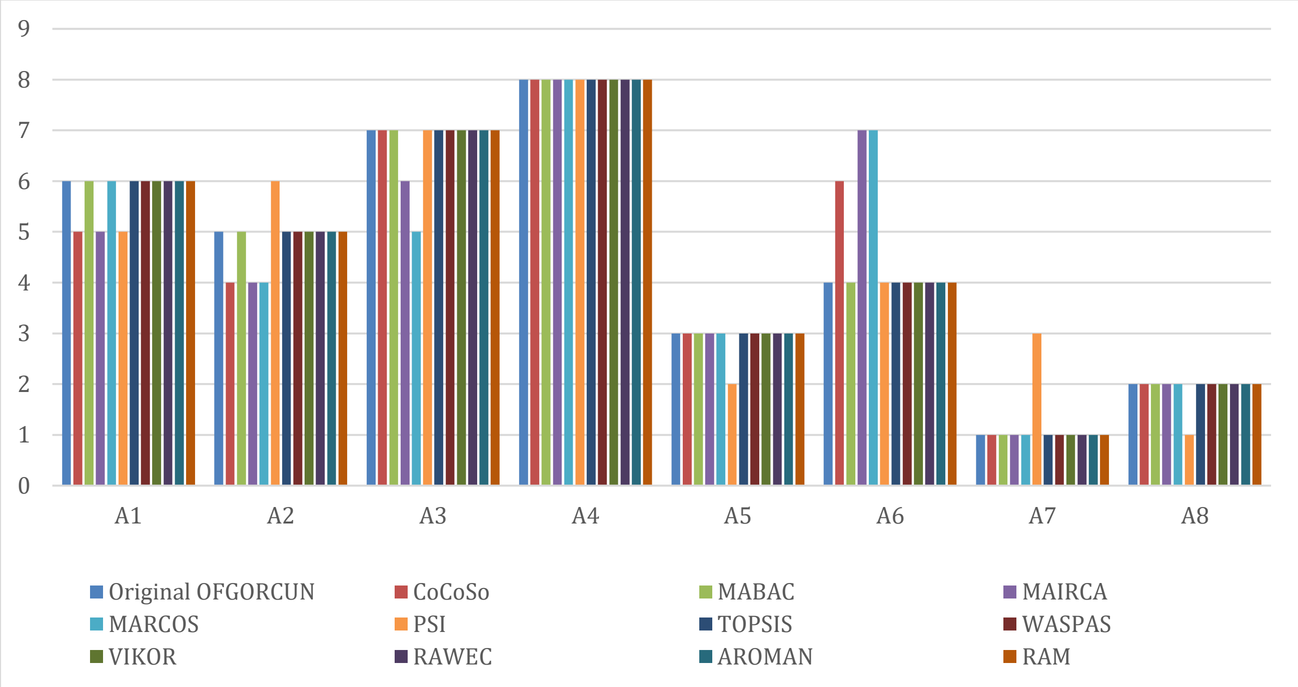


**Fig. 2.** The results of the comparative analysis

The analysis results show that it produces the same rankings as decision-making procedures developed as innovative mechanisms, such as OFGORCUN MABAC, TOPSIS, WASPAS, VIKOR, RAWEC, AROMAN, and RAM, which have been shown to yield reasonable results many times in the popular and relevant literature. The correlation between the results of the proposed decision-making method and those obtained using the CoCoSo method was 0.929, and it was determined that the positions of A1, A2, and A6 in the ranking varied. In addition, another finding of the analysis is a close correlation between PSI (0.905), MAIRCA (0.857), and MARCOS (0.833) and the results of the OFGORCUN method. Finally, the mean correlation between all methods and the proposed decision-making tool's results was 0.957, a value considered extremely high.

These results clearly and strongly demonstrate the stability, reliability, and soundness of the proposed decision-making procedure. The fact that methods with different normalization and calculation methods produce similar rankings shows that the OFGORCUN method yields optimal or near-optimal results for the decision-making problem at hand, and that the decision-making mechanism is not overly sensitive to criterion weights. In addition, the extremely high mean correlation value indicates that although the proposed decision-making tool is partially sensitive to variations in data structure, it does not change the results and produces significantly stable results.

Ultimately, the results of the sensitivity and comparative analyses show that the proposed decision-making tool is highly compatible with classical and new decision-making techniques and has methodological consistency robust enough to produce the same ranking results as most of them, while small differences in the decision-making procedures used are within acceptable analytical limits. The findings largely support the coherent, robust, and valid position of the OFGORCUN method and clearly confirm that this decision-making tool is a highly reliable, objective, robust, and highly distinctive decision-making procedure.

*3.1 The results of the Monte Carlo Simulation*

A multi-stage Monte Carlo simulation was conducted to test the OFGORCUN decision-making approach's ability to produce stable results under conditions of uncertainty and ambiguity. The main purpose of the simulation is to observe how random changes and fluctuations in the criterion weights in the initial decision matrix affect the ranking performance of the alternatives. This analysis process is critical, especially for robustness, stability, sensitivity, and ranking consistency, which are important in the multi-criteria decision-making literature. In this context, the simulation carried out has four basic components. In the context of the first basic component, random uncertainties and ambiguities were added to the specific weight values of all criteria in the decision matrix. The method used in this context:

$$x'_{ij} = x_{ij} \cdot (1 + N(0, \sigma))$$

Here: $x_{ij}$: the original decision matrix element value, $x'_{ij}$: new value with added uncertainty, $N(0, \sigma)$: the normal distribution, its mean is 0, and standard deviation is σ, and in this study, σ is taken as 0.05 (±%5 variability).

This procedure simulates the changes that may occur by incorporating real-world scenarios such as measurement errors related to criteria, operational fluctuations, sudden performance changes, and reporting uncertainties into the model. Since uncertainty is added in the form of a multiplier, large criterion values are affected by larger fluctuations, and small values are affected by narrower variations. It aligns perfectly with the nature of logistics data sets. The criterion weights were randomly generated but reproduced consistently across iterations. For this:

$$w' \sim \text{Dirichlet}(\alpha)$$
$$\alpha_j = w_j^{(0)} \cdot 100 + 0.01$$

is used. In this design, it is aimed that the sum of the weight vector is 1 in each iteration (Dirichlet property), that the weight distribution is concentrated around the original weights instead of randomly, that the variance of the weights is proportionally related to the original weights, and that mild and moderate uncertainties are applied to the weight values. This method is considered one of the most accurate approaches in modeling decision-maker uncertainty in the literature. In each iteration, both the data set and the weight vector were simultaneously distorted. In each iteration, the proposed model was applied repeatedly, and the results obtained were evaluated.

The order of the alternatives was determined according to the U scores obtained. This approach represents the most "challenging" variation scenario due to changes in data, weight differentiation, normalized values, and criterion dependency structures, and each iteration becomes a new decision problem. The ranking obtained in each iteration was determined using the equation below, and three basic statistical values were calculated.

$$\text{Order}_k = \arg\ \max\ (U_i^{(k)})$$

For each alternative:

$$P(\text{Rank } 1)_i = \frac{\text{Rank1 Frekansı}}{10\ 000}$$

This metric measures how dominant the alternative is under uncertainty. The rankings of each alternative over 10,000 iterations were calculated with a weighted average using the following equation:

$$\bar{R}_i = \sum_{r=1}^{8} r \cdot P(\text{Rank } r)_i$$

This metric indicates the overall performance level of the alternative. It shows how many times each alternative is ranked. Thus, not only the "mean" but the complete distribution is observed. In addition, in each iteration $\rho_k = \text{Spearman}(R_0, R_k)$ is computed.

This metric measures how faithful the method is to its original order, how much the ranking is distorted under uncertainty, and the model's noise immunity.

According to the outcomes, A7 UPS, which sorted first in the rankings generated by the proposed decision-making model, maintained its position in 9723 (0.9723) of 10,000 iterations. Besides, DHL, which was second in the original ranking, had a probability of 0.0277 of ranking second in these iterations. While the probability of any alternative to these two package delivery companies being the first choice is zero, this shows that neither UPS nor DHL is the most suitable option. The fact that UPS (A7) dominates the first place with a value of 0.9723 in ten thousand iterations proves that the results obtained using the OFGORCUN technique are not random but rather reveal an extremely strong and stable structural stability. Despite the addition of data noise and weight variation, UPS maintained a strong lead in the ranking. These results make UPS's operational structure, wide distribution network, and ability to compete in the international environment, and to manage costs flexibly depending on its transportation capacity, stand out from its competitors. One of the most striking results from the Monte Carlo simulation is the Rank Distribution Heat Map, generated from changes in conditions across 10,000 iterations and showing the ranking distributions of the alternatives.

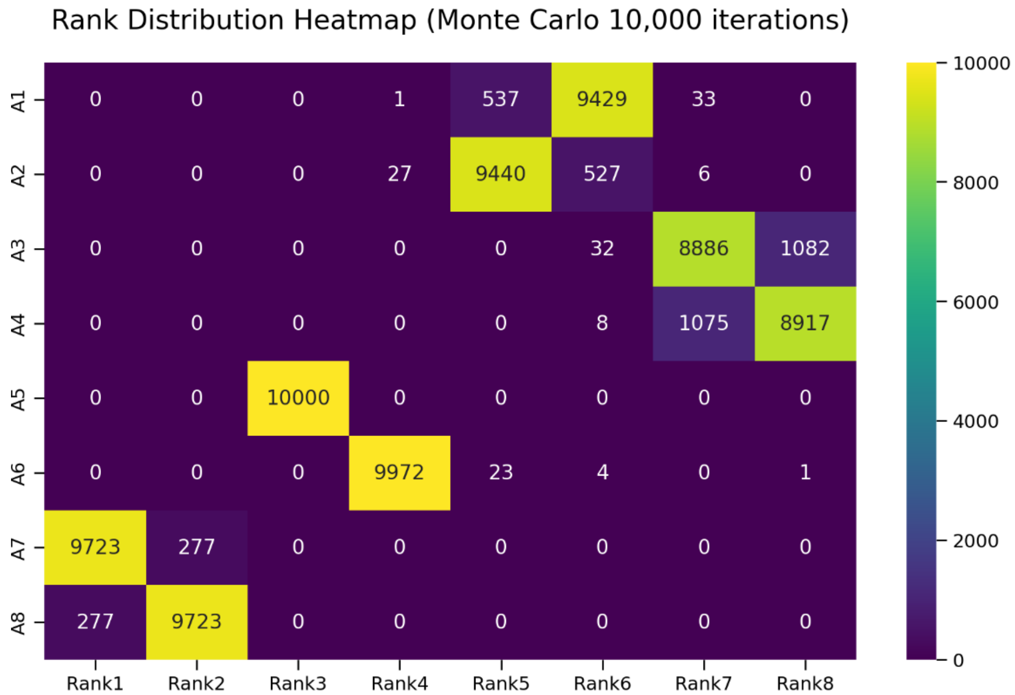


**Fig. 3.** The rank distribution heatmap

Figure 3 shows that alternative A1 retained its original order obtained using the proposed decision-making tool in 9429 of 11 iterations, ranking fifth in 537 of 11 iterations, seventh in 33 of 11 iterations, and fourth in 1 of 11 iterations. While alternative A5 maintained its current ranking performance in all iterations, the ranking positions of alternatives A7 and A8 varied mutually in 277 iterations. These simulation results show that the proposed decision-making model's ability to produce rankings is improved, and the resulting rankings are extremely stable. The A7 (UPS) and A8 (DHL) alternatives have largely maintained their ranking positions. Similarly, A5 (PTT) has shown outstanding ranking stability, maintaining third place despite all changes.

In addition, the fact that there is no change in the last positions of the A3 (MNG) and A4 (SÜRAT) alternatives despite all the changes made in the iterations causes the weaknesses and disadvantages of these two companies in terms of operational capacity, number of branches, experience and international reach to produce a stable and stable ranking result that does not allow the ranking results to change even under uncertain conditions. These results show that the distinction between high- and low-performing alternatives is unambiguous. The potential of all alternative companies to rank first is illustrated in the chart below (Figure 4).

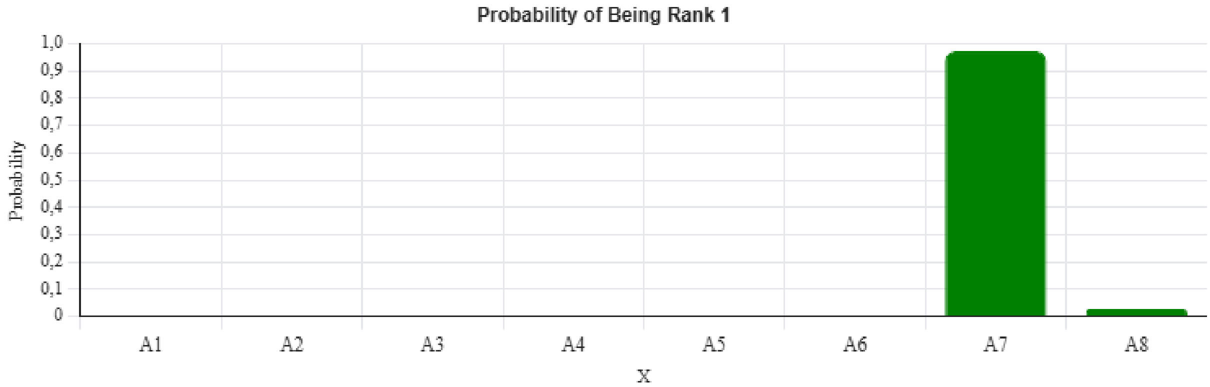


**Fig. 4.** Probability of Being Rank 1

According to the simulation results, A7 (UPS) ranked first in almost all 10,000 iterations. The fact that UPS did not lose its lead despite the application of data and weight noise shows that the model's lead identification mechanism works completely independently of random effects. A8 (DHL), on the other hand, rarely came close to first place, but this probability is very low. There is a 0% chance of ranking first among all other alternatives. This result strongly demonstrates that UPS has a structural advantage throughout the data. The average ranks calculated for each alternative in the Monte Carlo simulation are shown in the graph below (Figure 5).

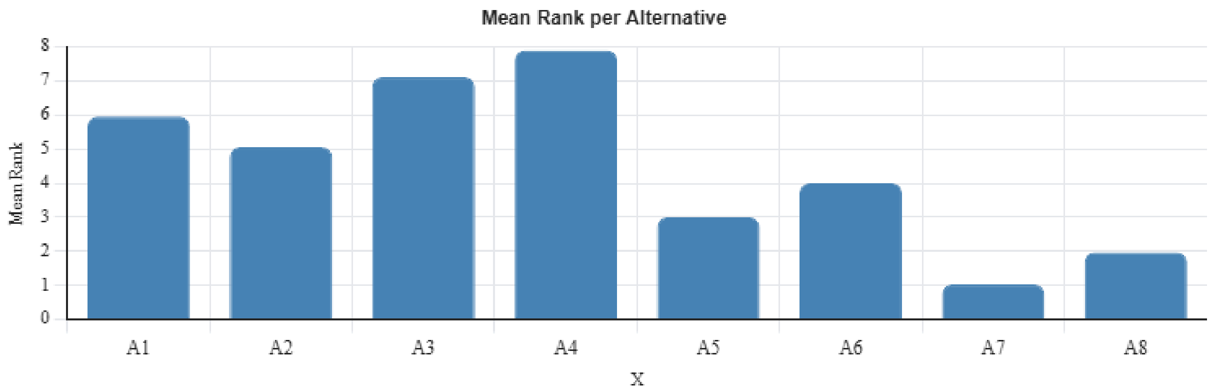


**Fig. 5.** Mean rank per alternative

This graph shows that the ranking structure is maintained intact even under uncertainty.

UPS (A7) → Average rank ≈ 1.02

DHL (A8) → Average rank ≈ 1.97

PTT (A5) → Average rank = 3.00

These three alternatives continue their tendency to rank 1st, 2nd, and 3rd, respectively, with very high determination. On the other hand, MNG (A3) and SPEED (A4) form the last two positions in the average ranks, confirming that their performance structure is systematically weak. This finding suggests that OFGORCUN's disaggregation power is evident, as it consistently ranks low-capacity companies. The probability of alternatives ranking in the top three places is given in the chart below, Figure 6.

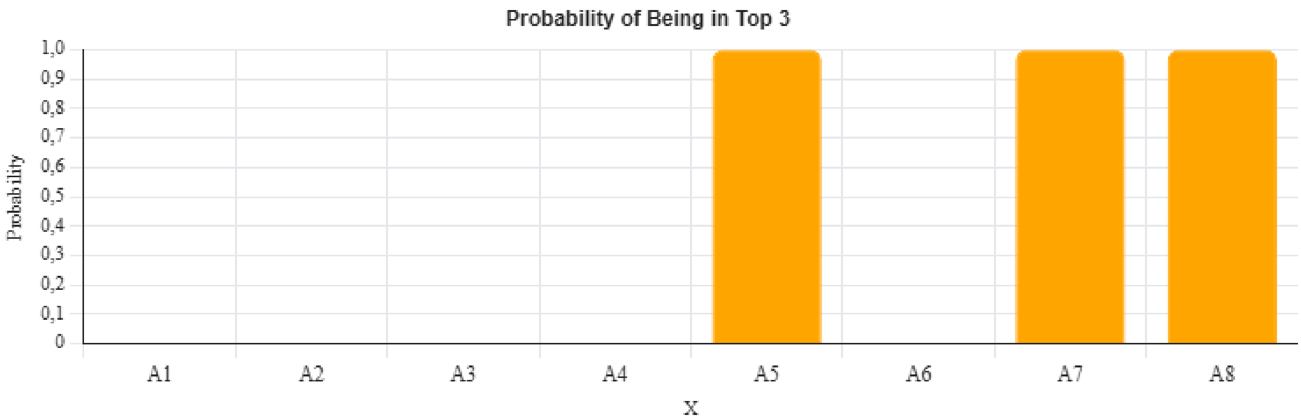


**Fig. 6.** Probability of Being in Top 3

According to these findings, UPS (A7), DHL (A8), and PTT (A5) are among the top three, each with 100%. All other alternatives have zero chance of making it into the top 3. This result shows that there are structurally three strong players in the decision problem and that even under uncertainty, the model decisively detects the performance superiority of these three alternatives. When the findings of the Monte Carlo simulation are evaluated as a whole, it is seen that the OFGORCUN method is extremely robust, Steadfast under uncertainty, noise-tolerant, with high decomposition power, statistically reliable, and does not disrupt the ranking structure. It becomes clear that it is an MCDM approach.

Companies with strong operational capacity, such as UPS, DHL, and PTT, have held the top positions in the ranking under both normal and uncertain conditions. Companies with limited operational capacity, such as MNG and SÜRAT, are concentrated at the bottom of all iterations. It suggests that the OFGORCUN method accurately reflects real operational differences, exhibiting high stability in decision analysis rather than high sensitivity to random changes.

In addition, the fact that most correlation results (range 0.95–1.00 on the Spearman correlation histogram) are clustered at high values indicates that the agreement between the original and simulated sequencing is almost complete. It is a strong testament to the method's soundness.

The Monte Carlo analysis strongly confirms that the OFGORCUN method performs well under both data and weight uncertainty, maintains the decision structure without distorting the order, and is a highly reliable method in the multi-criteria decision-making literature. The findings show that the method can be effectively applied to complex, multidimensional, and uncertain real-world problems such as logistics service provider selection.

### *3.2 Rank Reversal Test*

Rank reversal is one of the most widely recognized structural weaknesses in the field of multi-criteria decision-making, as even minor changes in the composition of the alternative set can lead certain methods to produce substantial distortions in the resulting ranking order. Such distortions weaken the internal coherence of the decision model, introduce instability into the evaluative structure, and diminish the level of trust decision makers can place in the method's outcomes. Because of these concerns, resistance to rank reversal has become a fundamental expectation for any newly proposed methodological framework seeking acceptance in the academic MCDM literature. To assess the performance of the OFGORCUN method in this context, an extensive two-stage robustness analysis was conducted using score structures from 10,000 Monte Carlo iterations, ensuring the model was evaluated not only under deterministic conditions but also under conditions characterized by significant data and weight uncertainty.

The first stage of the analysis focused on removing the worst-performing alternative in each Monte Carlo iteration and then re-evaluating the decision model using the remaining seven alternatives. This procedure is traditionally interpreted as a test of local rank reversal resistance, since it examines whether excluding an inherently weak alternative induces structural changes in the ranking of the superior alternatives. The results, visualized as a rank reversal heatmap, showed that the Spearman correlation coefficient between the original and updated rankings remained 1.000 across all experimental repetitions. This finding confirms that, across all 2,000 iterations, removing the lowest-performing option did not change the relative ordering of the remaining alternatives. The dominant alternatives, represented by UPS (A7), DHL (A8), and PTT (A5), preserved their positions without exception, while the mid-tier and lower-tier alternatives also maintained their internal order. Such an outcome provides compelling evidence that the OFGORCUN method exhibits complete ranking stability even under targeted perturbations of the decision set.

The second stage of the robustness assessment introduced a more demanding scenario in which alternatives were removed sequentially, starting with the lowest-ranked at each step and continuing until only two remained. After each removal, the model was recalculated, and the resulting ranking structure was compared with the original ordering using the Spearman correlation coefficient. This procedure is regarded as a test of global rank reversal resistance, since it evaluates the method's capacity to remain stable under dramatic reductions in the cardinality of the alternative set. Many traditional MCDM methods, including TOPSIS, WASPAS, MAIRCA, and PSI, display marked instability under this form of analysis because their decisional geometry becomes distorted as alternatives are progressively eliminated. In contrast to these commonly used techniques, the OFGORCUN method demonstrated flawless performance: the Spearman correlation coefficient remained 1.000 at every elimination stage, resulting in fourteen thousand distinct elimination scenarios in which no changes were observed in the ordering of the surviving alternatives. UPS (A7) consistently retained the first position, DHL (A8) remained in second place across all iterations and stages, and PTT (A5) maintained its third position without deviation. This exceptional consistency indicates that the internal ranking core generated by the OFGORCUN method is not only stable but structurally resilient to both data perturbation and decision set contraction.

The aggregate evaluation of the two robustness analyses confirms that the OFGORCUN method is fully resistant to both local and global rank reversal phenomena. The fact that Spearman correlation values remained at the theoretical maximum in all tests, and that no ranking changes were observed in any iteration or stage, underscores the exceptional methodological coherence of the weighting structure generated by the O–F–G components of the method, which combine entropy-based dispersion, variance-based separation, and correlation-driven discriminative capacity. Such a degree of stability is rarely encountered in the MCDM literature, where most classical methods tend to suffer from ranking distortions as alternatives are added or removed. The robustness of the OFGORCUN method demonstrates its suitability for both academic inquiry and practical decision-making contexts, particularly in fields such as finance, logistics, and risk management, where even minor deviations in ranking outcomes can have substantial operational implications. The results of this comprehensive analysis, therefore, establish OFGORCUN as a highly reliable, consistent, and structurally superior decision-making framework capable of maintaining ranking integrity across a wide range of uncertainty conditions. Figure 7 illustrates the results of the rank reversal test.

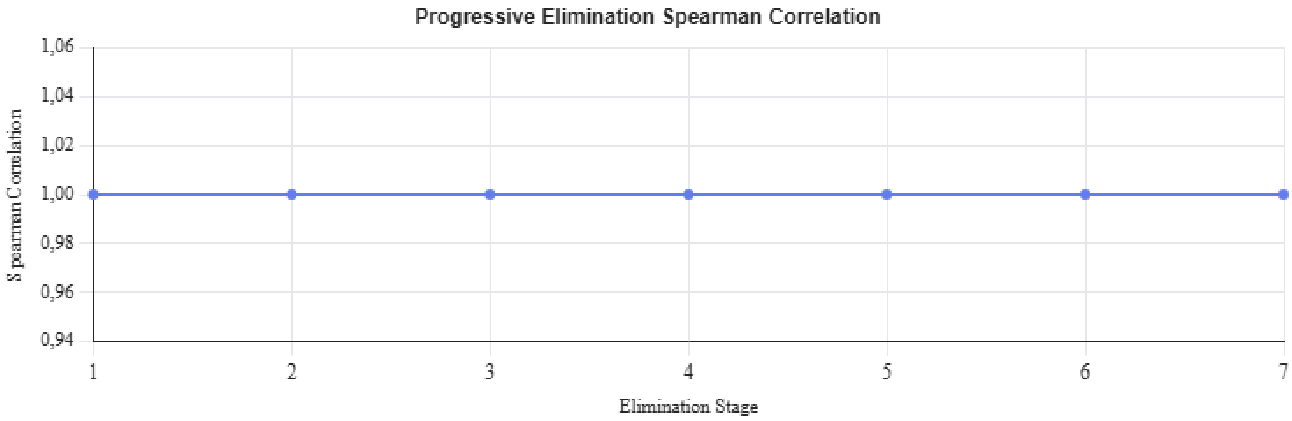


**Fig. 7.** The results of the rank reversal test

### 3. Results

This chapter discusses and interprets the results and empirical findings from applying the OFGORCUN method, an innovative weighting and ranking mechanism, to the decision-making problem of evaluating and selecting last-mile parcel delivery companies that provide solutions for banks' delivery operations. The evaluation process is based on banks' multidimensional requirements for the delivery of their shipments to their customers on time, in a secure, traceable, and compliant manner. The results of the analysis were examined in the context of the criteria's relative weights and the ranking performance of the alternatives. In this context, the managerial and policy implications of the findings, along with the valuable insights they provided, were evaluated. At the same time, the theoretical and methodological contributions of the proposed innovative decision-making mechanism, along with its advantages, were discussed in detail. In this direction, the main objective goes beyond demonstrating the theoretical contributions and algorithmic performance of the developed decision-making procedure and to provide valuable insights in addition to applicable, reliable, and practical managerial and policy implications for the banking and financial services industries, as well as for other industries, when faced with similar decision-making problems.

The OFGORCUN procedure developed and proposed in this study produces objective weight values of the criteria by combining entropy-based information content, statistical distribution, and correlation-derived discrimination power. The relative weights obtained perfectly reflect the level of knowledge of each criterion attribute and the dynamic environment in the operational context, and help decision-makers understand which dimensions of the criteria are clearer, more powerful, and dominant in the operational and sustainability performance of last-mile parcel delivery companies.

The results obtained by applying the OFGORCUN method reveal that the most effective and dominant criteria are, by far, C4 (Number of distributors), C3 (Total personnel), and C5 (Number of branches) factors. These criteria represent the operational capabilities and capacities of last-mile parcel delivery companies, as well as their geographical limitations in terms of access and distribution, in a holistic context. The dominance and determination of these criteria confirm that banks prioritize strong, scalable package delivery companies capable of delivering across a wider geographical area in their strategic partner selection for last-mile deliveries. Since banks provide financial services to individuals residing in even the most remote settlements, especially during the technological transformation process, making strategic alliances with delivery companies that can reach almost every point increases the resilience of banks in the strategic context, contributes critically to their ability to meet customer satisfaction and expectations at a higher level and to reduce possible bottlenecks in delivery and distribution processes.

When the managerial implications of the findings are considered, it is clear that the organizational size and scale of delivery companies are the most decisive and driving forces of operational performance in last-mile deliveries for banks. In delivery and distribution operations, the possibility of encountering critical problems such as insufficient field personnel in terms of number and experience, or disruption of delivery operations for various reasons, delays or losses in deliveries, and deliveries to the wrong recipients increases significantly. Depending on this result, banks may draw several policy inferences when preparing service-level agreements or conducting supplier due diligence, such as setting strict, sanctioned criteria for minimum staff capacity, mandatory branch scope, and distribution density.

In contrast, criteria such as C6 (Delivery speed), C12 (Maximum service distance), and C11 (Number of countries served) received insignificant weights. It reflects two structural facts: (i) International coverage is not a critical feature, as most of the banks' deliveries related to their shipments to their customers occur within national borders; and (ii) the speed of delivery, while intuitively important, shows a low distribution among companies; This means that almost all companies claim similar speed standards, reducing its distinctive power.

These conclusions highlight that rapid deliveries are a priority for practitioners when selecting last-mile parcel delivery firms, especially for regulatory authorities and strategists who plan and organize operations. Instead, the operational capacity, capabilities, and reliability of businesses can guide long-term strategic partnerships, paving the way for more rational and reasonable solutions. In this context, banks aiming to carry out delivery operations more effectively and efficiently can develop measures to improve their distribution infrastructure rather than increasing nominal delivery speeds, which can provide marginal benefits, and instead achieve critical advantages in overcoming capacity-related bottlenecks.

The ranking results obtained using the OFGORCUN decision-making framework developed in this study reveal a meaningful, distinct, and consistent performance hierarchy among the last-mile parcel delivery companies evaluated. The ranking results show that the UPS (A7) alternative is the last-mile package delivery company with the best ranking performance, followed by DHL (A8) and PTT (A5). In this context, it is evident that the operational scales of all three companies are strong and wide; they have a very high workforce resource and a very wide distribution network, supported by large distribution and delivery fleets. It proves that their place in the ranking is empirically and theoretically consistent and correct.

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The fact that PTT (A5) ranks third reveals an extremely critical strategic insight in terms of showing that they can remain competitive in the production of a highly sophisticated logistics service thanks to the reliability of being a public enterprise, as well as having a large number of branches and a wide geographical network spread over a wide geographical area that facilitates access to every point, the execution of last-mile parcel delivery services by the public authority. PTT's ranking performance remained unchanged, maintaining third place across 10,000 iterations of the Monte Carlo simulation, despite the changed conditions and artificial ambiguities. This finding highlights the importance of banks and financial institutions forming strategic partnerships with national parcel delivery companies that can reach every point across a wide geographical area, including the most remote locations.

At the lower end of the ranking, MNG (A3) and SÜRAT (A4) occupy the last two positions. The ranking results obtained using the OFGORCUN method show that MNG (A3) and SÜRAT (A4) are the last two companies with the lowest performance. Evaluations of these companies reflect weaknesses in both, such as limited distribution networks and branches across the country, and fewer delivery personnel. At the same time, they operate with lower operational efficiency and performance than their competitors. The weaknesses and limitations of these two delivery firms make it difficult for banks to meet the requirements for last-mile delivery of their shipments to customers. It also provides insights that collaborating with businesses that provide low-scale last-mile parcel delivery services can lead to reductions in service quality, more incorrect deliveries, and increased compliance risks.

The OFGORCUN decision-making framework developed in this study makes critical contributions to the multi-criteria decision-making literature by offering a systematic, analytical, and data-based approach that provides an objective, robust, reliable, flexible, and reproducible evaluation tool for addressing multi-criteria decision-making issues. The main innovation of this method is based on integrating three different objective information dimensions, such as entropy (variability), standard deviation (dispersion), and correlation-based discrimination (independence), under an integrated decision-making procedure. This method's structure enables the alternatives to be evaluated based on their variable characteristics and differences, beyond the information they provide in the context of the criteria. It produces more reliable and rational weight values than traditional decision-making tools that work with a single metric.

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The results obtained using the OFGORCUN technique demonstrate that it is an extremely powerful and reliable mathematical tool for selecting and evaluating last-mile parcel delivery companies in decision-making environments where improving the proposed decision-making approach and ensuring the appropriate infrastructure and scale are critical. Integrating the method's unique ability to incorporate information structures into the weighting mechanism and its capacity to rank gain-oriented results yields much better, more realistic performance than many traditional decision-making approaches, with greater stability and distinctiveness in the results.

As a critical indicator, the results of all robustness and validity checks confirm that, although uncertainties and ambiguities are introduced into the evaluation processes, the results are highly consistent and stable, and they are significantly resistant to change. The model's ability to produce stable, consistent, and reliable results makes it extremely important, especially for sensitive, regulatory-pressured industries such as banking. The findings not only make critical contributions to the decision-making literature but also provide extremely valuable insights for practitioners and decision-makers in the relevant industry, as well as managerial and policy implications.

Overall, OFGORCUN emerges as a superior alternative among existing MCDM methods, offering unparalleled robustness, methodological integrity, computational efficiency, and practical strategic value.

## 4. Conclusions

The OFGORCUN (Optimized Factor-Based Gain-Oriented Ranking, Compounding, and Normalization) technique is introduced in this investigation. It is an innovative framework that integrates entropy-based information content, statistical distributions, and correlation-driven discrimination power into a single decision-making framework. This decision-making approach has been applied to the evaluation and selection of last-mile parcel delivery companies in the banking industry. The empirical results reveal that the proposed decision-making approach produces extraordinarily stable rankings beyond balanced, data-based weighting of the criteria. In this respect, it stands out compared to traditional decision-making techniques.

The results of the analysis obtained in the context of the impact level and dominance of the criteria reveal that the size and scale of the organization measured in the context of the number of distributors and personnel and the number of branches of the last mile delivery companies and the capacity to produce delivery services are the most dominant and decisive criteria in the selection of the enterprises that will carry out the last mile delivery operations of the banks. These findings highlight the importance of companies' scale and their distribution and delivery infrastructures in reducing and managing errors, mistakes, and risks that may arise in last-mile deliveries. In light of this finding, it may be a strategic decision for bank managers involved in the decision-making process to prioritize companies with wide distribution networks, strong human resources, and high operational scalability in choosing a last-mile delivery company. However, while capabilities such as the ability to deliver quickly and internationally are decisive in other industries, they are seen as less decisive in operations, especially in domestic operations related to banks' shipments to customers.

When the ranking results for the alternatives discussed in the study are examined, UPS, DHL, and PTT are the most suitable last-mile package delivery companies in a stable, consistent context for the proposed decision-making procedure. UPS and DHL are standout delivery firms depending on their operational capacity, technological maturity, and solid distribution networks. PTT ranks among the top three, thanks to its wide national logistics network and strong corporate reliability.

These results were tested through a comprehensive robustness and validity check, and the results obtained confirmed the methodological consistency, stability, and reliability of the decision-making model. In addition to the top-ranked alternatives, the bottom-ranked alternatives also showed solid ranking stability. However, the weaknesses and disadvantages of the last two ranked enterprises, such as MNG and SÜRAT, in terms of scale and capacity caused these two alternatives to rank last in all scenarios.

The theoretical and methodological contributions and advantages of the OFGORCUN technique far exceed the results of the empirical analysis in this study. When the unique structural advantages of the proposed decision-making tool are compared with those of traditional decision-making tools, it becomes clear that it has the potential to accelerate and advance the literature on decision-making methods. In addition, the normalized gain-based ranking mechanism, which underpins this method, provides strong discrimination power in high-variance datasets and produces rankings that are more reliable and better suited to real-world scenarios than distance- or reference-based techniques such as TOPSIS, VIKOR, MARCOS, and MAIRCA. In addition, the results of the comprehensive Monte Carlo simulation showed that the proposed decision-making method produced reliable and stable results for criterion weights and alternative ranking performance. The decision-making model exhibited complete resilience against the rank reversal problem, one of the most fundamental limitations of decision-making methods, and the Spearman correlation coefficient was 1 in each scenario ($\rho$ = 1,000). These results show that the ranking does not change whether an alternative is included or excluded from the evaluation. While this degree of robustness confirms the reliability of the proposed decision-making model in a practical context, it represents a level of superiority rarely seen in the literature on decision-making methods.

On the other hand, despite the methodological and theoretical contributions and advantages, as well as the strong managerial and policy implications and valuable insights, this study also has some limitations that need to be taken into account. The initial decision matrix is derived from objective, crisp data, and subjective criteria, such as customer satisfaction, service culture, incident management capability, or corporate sustainability, are not included in the evaluation process. Incorporating such subjective criteria into the analysis can yield a more holistic, multidimensional evaluation framework. Secondly, the analyses conducted focused on banks and last-mile parcel delivery companies operating in Turkey. Although the proposed decision-making model is methodologically extensible, some adjustments are needed to generalize the findings and inferences to last-mile delivery companies operating in different geographies. Thus, it illustrates that the conclusions and insights obtained are not directly generalizable. The model assumes that linear relationships hold among the normalized gains. This assumption may make it difficult to capture the interactions and trade-offs among the criteria. Finally, in this study, disruptions in supply chains, seasonal fluctuations, and changes and dynamic conditions arising from regulatory mechanisms are also missing from the evaluation process.

In light of the identified gaps, promising directions for future research on the OFGORCUN method may emerge. Firstly, integrating subjective expert opinions into the OFGORCUN framework via the proposed hybrid approach could facilitate the integration of objective statistical data and managerial expertise, thereby improving the method's suitability for qualitative environments. Secondly, future studies may extend the proposed model to incorporate fuzzy sets, interval data, and probabilistic environments to address issues of vagueness, incomplete data, and ambiguity inherent in actual logistics environments. Thirdly, the extension and validation of the proposed method across different domains, such as healthcare logistics, emergency response, e-commerce, and public transportation, could be conducted to test its versatility. Fourthly, a comparative computational study could be conducted to assess the execution efficiency and performance of the proposed method for ultra-high-dimensional data, thereby mapping the efficiency profile across different domains. Lastly, integrating machine learning approaches, such as sensitivity-based feature selection and criteria reduction via clustering, could further enhance the model's suitability for complex, ultra-high-dimensional environments.

In conclusion, the proposed OFGORCUN method is a compelling and innovative approach to the MCDM paradigm by combining methodological and empirical robustness. The proposed method's superior stability, immunity to rank reversal, and consistency with actual operational structures make it an effective approach to strategic supplier evaluation. The proposed method has tremendous potential for future research and applications in decision sciences and operations management.

## AI use

The authors used Microsoft Copilot and Grammarly to polish the language and tone of the manuscript and to correct typos and grammatical mistakes. Authors carefully read the content after language improvement and confirm, to the best of their knowledge, that the content is accurate.

## Conflicts of Interest

The authors declare no conflicts of interest.

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