December 2025

INDUSTRIAL ENGINEERING

International Reviews, Research and Studies in the Field of

EDİTÖR **ASSOC. PROF. DR. HÜSNÜ YEL**

SERÜVEN YAYINEVİ

Genel Yayın Yönetmeni / Editor in Chief • C. Cansın Selin Temana

Kapak & İç Tasarım / Cover & Interior Design • Serüven Yayınevi

Birinci Basım / First Edition • © Aralık 2025

ISBN • 978-625-8682-60-1

Serüven Yayınevi / Serüven Publishing
Türkiye Adres / Turkey Address: Kızılay Mah. Fevzi Çakmak 1. Sokak
Ümit Apt No: 22/A Çankaya/ANKARA
Telefon / Phone: 05437675765
web: www.seruvenyayinevi.com
e-mail: seruvenyayinevi@gmail.com

Baskı & Cilt / Printing & Volume
Sertifika / Certificate No: 47083

INTERNATIONAL REVIEWS, RESEARCH AND STUDIES IN THE FIELD OF INDUSTRIAL ENGINEERING

Editor

Assoc. Prof. Dr. Hüsnü Yel

CONTENTS

CHAPTER

1

NEXT-GENERATION MULTI-CRITERIA DECISION-MAKING METHODS: THEORETICAL FOUNDATIONS, CLASSIFICATION, AND CURRENT APPLICATIONS

Şeyma EMEÇ[1]

1 [0000-0002-4881-7955], Erzurum Technical University, Department of Industrial Engineering, Erzurum, seyma.emec@erzurum.edu.tr

Decision-making is a constantly evolving concept, paralleling the development of human thought processes. Initially made to achieve a single goal, decisions have evolved over time, reflecting evolving understandings and ideas, towards systems designed to achieve multiple goals.

The inherent uncertainty of the future is one of the fundamental factors that complicates decision-making processes. Therefore, decision-makers must evaluate all available options in their entirety and analyze the diverse impacts of each alternative using a holistic approach. Determining the most suitable option requires considering numerous interrelated and often interacting factors. This allows the decision-maker to select the alternative that can most effectively achieve the intended goal, based on scientific and rational principles. This necessity also compels the methods used in decision science to be supported over time by more advanced, flexible, and data-driven models.

The increasing number of complex decision problems, the strengthening of uncertainty conditions, and the diversification of data have led to significant transformations in Multi-Criteria Decision Making (MCDM), a fundamental building block of decision science. The computationally intensive nature of classical methods developed in the 1960s, their reliance on expert judgment, and their incompatibility with modern data structures have increased the need for more flexible, powerful, and adaptable methods. The rise of Industry 4.0, big data analytics, artificial intelligence, and digital transformation has caused MCDM methods to evolve structurally and new categories to emerge in the literature.

In recent years, new methods such as FUCOM, LBWA, BWM, SWARA, CRITIC, MARCOS, EDAS, and MABAC have rapidly become widespread in the literature; modern versions of classical methods have been developed, and hybrid models have been created through the integration of fuzzy theory, grey systems approach, neutrosophic clusters, and machine learning. This development has enabled MCDM to transform from merely a selection and ranking tool into a broad decision support ecosystem based on data science and optimization.

At the same time, areas such as sustainability, energy management, logistics optimization, supply chain, smart manufacturing, textile quality, cybersecurity, route management in public transportation, renewable energy site selection, and autonomous vehicle control have become strong application areas for next-generation MCDM techniques. In particular, AI-powered weighting methods, decision support in big data environments, real-time multi-criteria evaluation, and blockchain-based decision systems stand out as noteworthy trends in the MCDM literature.

The aim of this study is to present the latest trends in multi-criteria decision-making methods within a systematic framework, to explain modern

MCDM approaches, to discuss the rise of hybrid and fuzzy models, to comprehensively examine their application areas, and to reveal the scientific trends that MCDM will follow in the coming years. This chapter will cover a spectrum ranging from classical methods to modern models; new generation weighting techniques, advanced evaluation methods, and MCDM systems integrated with artificial intelligence and digitalization will be examined in detail.

1. The Evolution of Multi-Criteria Decision Making (MCDM) Methods

Multi-Criteria Decision Making (MCDM) methods were developed to provide systematic solutions to decision problems that require the simultaneous evaluation of multiple, and often conflicting, criteria. Approaches developed in the early days of MCDM primarily focused on well-defined and deterministic decision environments, prioritizing mathematical simplicity and ease of computation. However, over time, the structure of decision problems addressed in areas such as sustainability, engineering applications, supply chain management, public policies, and Industry 4.0 has become more complex and multidimensional. This situation has highlighted the limitations of classical methods, such as the need for intensive comparison, high reliance on subjective evaluations, and limited ability to handle uncertainty. In this context, new generation MCDM approaches aimed at making decision processes more flexible and manageable have gained increasing importance in the literature. The new generation weighting and ranking methods discussed in this section are presented holistically in Figure 1, along with their conceptual relationships.

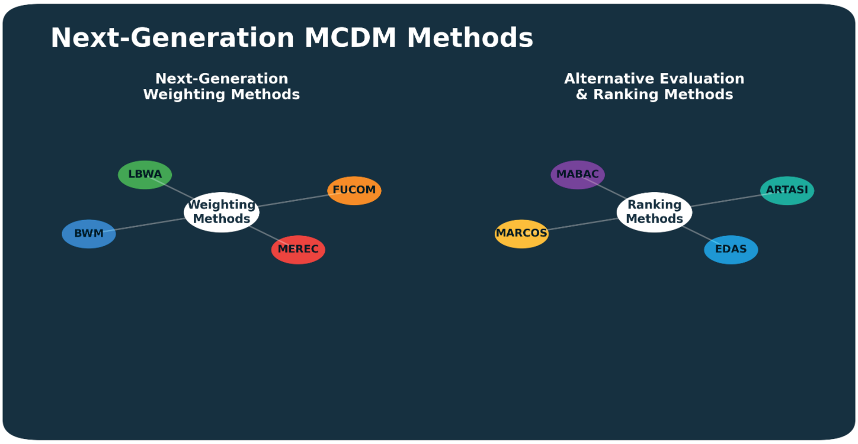


Figure 1. *Classification of Next-Generation Multi-Criteria Decision Making Methods: Weighting and Ranking Methods*

2. Next-Generation Weight Determination Methods

Determining the criterion weights, one of the most critical stages of the Multi-Criteria Decision Making (MCDM) process, directly impacts the evaluation of alternatives and the reliability of the final decision. Traditional weighting methods present various challenges in practice, especially when the number of criteria increases, due to their demand for a high number of comparisons from decision-makers and the increased risk of inconsistencies. New generation weighting methods, developed to overcome these limitations, stand out with their less comparison-based structures, mathematical mechanisms that directly address consistency, and adaptability to different decision-making environments. Thanks to these features, these methods are widely preferred in contemporary MCDM applications, both theoretically and practically.

New generation weighting methods are fundamentally built upon different approaches aimed at determining criterion importance in a more reliable and applicable way. These methods can generally be classified as subjective, objective, and hybrid weighting approaches. Subjective methods focus on the decision-maker's opinions; objective methods focus on the impact of criteria on decision outcomes; and hybrid approaches consider both perspectives together. This classification allows for the selection of the most appropriate method depending on the nature of the decision problem and the availability of data.

This study examines FUCOM, LBWA, BWM, and MEREC methods, which are widely accepted in the literature and represent next-generation weighting approaches. These methods differ from classical approaches in that they reduce the number of comparisons, increase consistency, and are adaptable to different decision-making environments. In the following subsections, the basic logic, application steps, advantages, and limitations of these methods are explained in detail.

2.1. FUCOM (Full Consistency Method)

FUCOM (Full Consistency Method) is a new generation multi-criteria decision-making (MCDM) approach developed by Pamucar et al. [1] for determining weights based on linear programming (LP) and directly centering the principle of consistency. The model requires two fundamental conditions to ensure optimal values of weight coefficients:

(1) the relationships between the weight coefficients of the criteria must be equal to the comparative priorities of the criteria, and

(2) the mathematical transitivity conditions must be met.

In the solution process of the model, the deviation from full consistency value is calculated along with the optimal weight values; this value indicates the degree of deviation from the estimated priorities of the criteria and the reliability of the weights [2].

Strategic Advantages of the FUCOM Method in Decision-Making

• Requires fewer pairwise comparisons (only n-1 for n criteria), thus reducing the mental strain and probability of error for decision-makers.

• Can produce more consistent weighting results in some similar situations, even though it requires much less input than traditional methods.

• Aims to minimize the measure of inconsistency using an optimization-based approach.

• Thanks to its linear programming structure, calculations can be easily performed using Excel solver, LINGO, GAMS, or similar software.

• Can be easily integrated into hybrid MCDM methods. For example, MABAC, MARCOS, EDAS, ARTASI, EDASÇ.

• Can be adapted to different application areas: housing location problem [3], industry 4.0–driven sustainability [4], selecting logistics service providers [5], healthcare quality [6], ergonomic risk assessment [7].

Disadvantages of the FUCOM Method are as follows:

• Initially, placing the criteria in the correct order of importance is critical.

• Since the method is based on subjective evaluations, the decision-maker's experience and knowledge level can be decisive in the results.

• Because it requires a linear programming solution, the implementation process may initially be challenging for users with limited knowledge of mathematical modeling.

• It assumes that the criteria are independent; interactions between criteria are not included in the model.

With these features, FUCOM is a powerful weighting method that provides high consistency while reducing the burden on the decision-maker, but it should be used in conjunction with supporting approaches, especially in uncertain and group decision-making environments.

2.2. LBWA (Level-Based Weight Assessment)

The LBWA method proposed by Zizovic and Pamucar [8] is a new generation and hierarchical weighting method. The basic logic of the method is to divide the criteria into different levels (levels) according to their relative importance and to systematically evaluate the sustainability of the decision processes at each level. In this approach, decision-makers are not expected to make detailed pairwise comparisons between all components; instead, the criteria are evaluated by classifying them according to their importance. The criteria are first positioned around the most important criterion, then the other criteria are assigned to different levels according to their distance from this reference criterion. The weights of the criteria assigned to each level are normalized using a mathematical structure to obtain the final criterion weights. In this respect, LBWA offers a more organized and manageable evaluation process, especially in decision problems with complex and numerous criteria.

Strategic Advantages of the LBWA method in Decision-Making

• Separating criteria into levels makes it easier for decision-makers to understand the evaluation process and proceed systematically.

• LBWA reduces the burden of evaluation, especially in problems with a large number of criteria, as it does not require detailed pairwise learning across all criteria.

• Thanks to its level-based structure, excessive weighting differences between criteria are limited, and more balanced results are obtained.

• The calculation process does not require complex optimization techniques and can be easily implemented with simple tools such as Excel.

• LBWA can be effectively used with ranking methods such as MABAC, MARCOS, CODAS, ARTASI, and EDAS.

• It can be adapted to different application areas: cosmetics logistics [9], erp consultant selection [10], sustainable ecotourism [11], monitoring site selection [12], corporate financial performance [13].

The disadvantages of the LBWA method are as follows:

• The level at which criteria are assigned depends entirely on the decision-maker's judgment, and this can affect the results.

• Modeling differences in importance between criteria at the same level can be difficult.

• Incorrect selection of the most important criterion can indirectly affect the entire weighting structure.

• It does not offer an explicit measure of inconsistency as in FUCOM or BWM; this may be considered a disadvantage in some applications.

• The classical LBWA method does not take into account ambiguous or fuzzy evaluations; therefore, fuzzy or interval extensions may be needed.

With these characteristics, LBWA is an effective weighting method, especially in decision problems involving numerous criteria and requiring hierarchical evaluation; however, it requires careful subjective level definitions.

2.3. BMW (Best Worst Method)

BMW (Best Worst Method) was developed by Rezai (2015) [14]. It is a new generation MCDM method used in determining criterion weights. The aim of the method is to reduce the number of matches and increase consistency. In this method, the decision-maker first determines the most important (best) and least important (worst) criteria; then the superiority of the best criterion over other criteria and the superiority of other criteria over the worst criterion are evaluated. The optimization model established in line with these evaluations is solved and criterion weights are obtained.

Strategic Advantages of the BMW method in Decision-Making

• BWM reduces the cognitive load on the decision-maker by requiring significantly less evaluation compared to classical pairwise comparison methods.

• Thanks to its optimization-based structure, it allows for more consistent weights to be obtained among decision-maker judgments.

• The method provides a consistency indicator that measures the inconsistency between comparisons.

• Clearly defining the best and worst criteria increases the comprehensibility of the decision-making process.

• BWM can be easily integrated with ranking methods such as MABAC, MARCOS, EDAS, CODAS, ARTASI, and the like.

• The limited number of comparisons makes the method advantageous for high-dimensional decision problems.

• It can be adapted to different application areas: manufacturing performance evaluation [14], public service performance [15], industry 4.0 barriers [16], transportation optimization [17], green supplier selection [18], ergonomic evaluation [19], unmanned aerial vehicle design [20].

The disadvantages of the BMW method are as follows:

• Incorrectly defining the best and worst criteria can directly affect the weighted results obtained.

• Expert experience is critical, as decision-maker judgments play a decisive role in the results.

• The inclusion of a linear optimization model may make implementation difficult for users with limited mathematical background.

2.4. MEREC (Method Based on the Removal Effect of Criteria)

The MEREC method is a new generation weighting approach developed to determine the criterion weights in multi-criteria decision-making problems. It performs calculations based on the changes in the overall performance values of alternatives when each criterion is removed from the decision problem. This method aimed to reduce the dependence of classical weighting approaches on subjective evaluations and was first introduced to the literature by Keshavarz-Ghorabaee et al. [21].

Strategic Advantages of the the MEREC Method in Decision-Making

• Criterion weights are determined based on the impact of the criteria on performance, independent of the decision-maker's opinions.

• The limited need for expert judgment reduces the impact of subjective errors.

• The actual contribution of each criterion to the decision problem is clearly evaluated through the subtraction effect.

• The "How much does the result change when a criterion is removed?" approach facilitates intuitive understanding of the method.

• It can be effectively used in hybrid structures together with subjective methods such as MEREC, FUCOM, LBWA, and BWM.

• It is successfully applied in many fields such as academic performance assessment [22], carbon emission analysis [23], robot selection [24], renewable energy selection [25], supplier selection [26], wearable health technologies [27], and financial performance evaluation [28].

Disadvantages of the MEREC Method are as follows:

• The reliability of the results is directly dependent on the accuracy and quality of the decision matrix data used.

• In problems with a large number of criteria, performing separate extraction operations for each criterion can prolong the computational process.

• MEREC assumes that the criteria are independent; interactions between criteria are not included in the model.

• The classic MEREC structure does not directly model ambiguous or fuzzy data; this can be overcome with fuzzy or interval expansions.

• In cases where decision-maker priorities are particularly important, it may need to be supported by subjective methods.

With these features, MEREC is a powerful objective weighting method that reveals the true impact of criteria on decision outcomes; however, it should be used in conjunction with supporting approaches in uncertain and interactive decision-making environments.

3. Next-Generation Alternative Evaluation and Ranking Methods

Following the determination of criterion weights, the next and complementary stage of the multi-criteria decision-making process is the evaluation and ranking of alternatives. This stage plays a critical role in revealing the decision-maker's final preference. While classical ranking methods offer effective results for certain problem types, they can exhibit some limitations, especially in complex, uncertain, and multi-dimensional decision environments. Therefore, in recent years, new generation alternative ranking methods have been developed in the literature, offering more flexible, comparative, and outcome-oriented structures, similar to the weighting stage. These methods address the decision-making process more holistically by considering the proximity of alternatives to ideal or reference solutions, their deviations from average solutions, or their goal-based evaluations. Furthermore, thanks to their adaptability to different decision environments and their suitability for integration into hybrid MCDM frameworks, they are widely used in current academic studies and applied problems.

This section discusses the basic characteristics and application logic of new generation ranking methods. Within the scope of this study, ARTASI, MABAC, MARCOS, and EDAS methods, which represent new generation alternative ranking approaches in the literature, are examined. These methods allow for a results-oriented and holistic decision-making process by evaluating alternatives against ideal, average, or target-based reference solutions. The following subsections detail the fundamental evaluation logic, calculation steps, advantages, and limitations of these ranking methods.

3.1. ARTASI (Alternative Ranking by Target-Based Assessment)

ARTASI, developed by Pamucar et al. (2024), is a new generation and goal-oriented evaluation method aimed at ranking alternatives in multi-criteria decision-making problems. The basic approach of the method is based on analyzing the target values determined for each criterion and the distances of the alternatives from these targets. ARTASI offers a more realistic ranking by considering not only the proximity of the alternatives to the ideal solution but also the extent to which they achieve the determined performance targets. Thanks to this structure, the method directly integrates the strategic goals of the decision-makers into the evaluation process and addresses the performance of the alternatives from a holistic perspective.

Strategic Advantages of the ARTASI Method are in Decision-Making

• Alternatives are evaluated according to predefined target values instead of ideal or average solutions.

• The goals and expectations of decision-makers are directly reflected in the ranking process.

• It allows different types of criteria to be evaluated within the same framework.

• It can be easily integrated with weighting methods such as FUCOM, LBWA, BWM, and MEREC.

• Evaluation based on target values facilitates the interpretation of ranking results.

• It can be effectively used in big data platform selection [29], website performance [30], ergonomic risk assessment [31], macroeconomic productivity performance [32], autonomous ship risk assessment [33], modular mega-project supplier selection [34], and engineering problems.

Disadvantages of the ARTASI Method are as follows:

• Choosing inappropriate or unrealistic targets can directly affect ranking results. • Expert opinions are reliant on the process of determining target values.

• ARTASI has a structure that considers criteria independently.

• The classic ARTASI structure does not take into account ambiguous or fuzzy data; this can be remedied with fuzzy or interval extensions. • There are fewer application studies compared to some classic ranking methods.

In these respects, ARTASI offers a strong alternative to classical ranking methods thanks to its decision-maker-centered structure, but it requires careful execution of the goal-setting process.

3.2. MABAC (Multi-Attributive Border Approximation Area Comparison)

The MABAC method is a multi-criteria decision-making approach widely used in the literature, which is based on the concept of the Boundary Approximation Area (BAA) in ranking alternatives. The method was first developed by Pamucar and Ćirović (2015) [35] and aims to evaluate alternatives according to their distances from a defined boundary area. In the traditional MABAC method, the decision matrix is first normalized using Weitendorf's linear normalization approach. Then, a weighted normalized decision matrix is obtained by applying the multiplication principle, which is based on the multiplication of the normalized decision matrix and the criterion weights.

Subsequently, the BAA matrix, which represents the boundary approximation area for each criterion, is determined by taking the geometric mean of the relevant criterion values. The performance of the alternatives is evaluated by calculating the distances of the weighted normalized decision matrix elements from the BAA; alternatives located in the upper approximation area represent better performance, while alternatives in the lower approximation area indicate lower performance. Numerous studies in the literature demonstrate that alternatives can be ranked effectively and consistently based on their positions within the respective fields of approach.

Strategic Advantages of the MABAC Method in Decision-Making

• The performance of alternatives is evaluated based on their distance from the defined boundary approach area, rather than ideal solutions.

• Normalization, weighting, and distance calculation steps are clearly defined.

• It allows different types of criteria to be analyzed within the same evaluation framework.

• Whether alternatives are located in the upper or lower approach area allows for a clear interpretation of performance.

• It can be easily used with weighting methods such as FUCOM, LBWA, BWM, and MEREC.

• It is successfully applied in many areas such as Logistics Center Resource Selection [35], Production Process Parameter Optimization [36], Electric Vehicle Charging Station Selection [37], E-Commerce Platform Selection [38], Sustainable Climate Management [39], and Wearable Health Technologies [40].

Disadvantages of the MABAC Method are as follows:

• The normalization technique used (e.g., Weitendorf linear normalization) can affect the ranking results.

• The way BAA values are calculated can directly affect the relative positions of the alternatives.

• The method is based on the assumption that the criteria are independent of each other.

• The classic MABAC structure does not directly handle ambiguous or fuzzy data; therefore, fuzzy or interval extensions may be needed.

• The number of processing steps may increase when there are many criteria and alternatives.

With these features, MABAC, thanks to its boundary approach domain-based structure, is an effective ranking method that clearly and consistently reveals the relative performance of alternatives, and it is recommended to use it in conjunction with supporting approaches in terms of normalization and uncertainty management.

3.3. MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution)

The MARCOS method was developed by Stević, Pamučar, Puška, and Chatterjee in 2020 [41]. The method is a new generation multi-criteria decision-making approach that aims to compare different alternatives or sets using a large number of criteria. The main purpose of the method is to measure the performance of alternatives through their relationships with ideal and anti-ideal reference solutions and to obtain a ranking based on these relationships. The MARCOS method is based on calculating a utility degree for each alternative by considering the relative positions of the alternatives and the reference values. Thanks to this structure, a more holistic and compromise-based ranking process is offered by evaluating the positions of the alternatives not only relative to each other but also relative to the best and worst cases.

Strategic Advantages of the MARCOS Method in Decision-Making

• More meaningful results are obtained by evaluating alternatives together with ideal and anti-ideal solutions.

• The extent to which alternatives deviate from the best and worst cases is clearly revealed.

• The normalization, weighting, and utility degree calculation steps have a clear structure.

• It is less affected by changes in the number of alternatives or criteria (rank reversal) compared to other methods. • It maintains its mathematical consistency in complex decision problems involving a large number of alternatives. • It allows the analysis of different types of criteria within the same evaluation framework.

• It can be easily integrated with weighting methods such as FUCOM, LBWA, BWM, and MEREC.

• Utility degree values clearly reflect the relative performance of alternatives.

• It has been successfully used in many different application areas such as third-party logistics selection [41], aviation fuel supplier evaluation [42], insurance sector financial performance [43], countries' tourism performance [44], and Hazardous Waste Disposal Technologies [45].

Disadvantages of the Marcos Method are as follows:

• The way ideal and anti-ideal solutions are defined can affect the ranking results.

• The normalization technique used can lead to changes in the relative positions of the alternatives.

• The method is based on the assumption that the criteria are independent of each other.

• The classical MARCOS structure does not accommodate ambiguous or fuzzy data; this can be remedied with fuzzy or interval extensions.

• The number of calculation steps may increase when there are many alternatives and criteria.

In these respects, the MARCOS method, thanks to its comparison-based structure with reference solutions, is a powerful ranking method that comprehensively evaluates the performance of alternatives; however, it requires careful execution of the normalization and reference determination stages.

3.4. EDAS (Evaluation Based on Distance from Average Solution)

The EDAS method is an approach developed for ranking alternatives in multi-criteria decision-making problems, and it evaluates them based on their distances from the average solution. The method was first introduced to the literature by Ghorabaee, Zavadskas, Amiri, and Turskis (2015). The basic logic of the EDAS method is based on evaluating each alternative by considering its positive deviations (PDA) and negative deviations (NDA) relative to the average solution on a criterion basis. In this way, alternatives are positioned not only according to ideal or worst-case solutions, but also according to the average solution, which represents the overall performance level in the decision problem. With this structure, EDAS offers a more balanced and comparative ranking and contributes to a holistic approach to the decision-making process.

Strategic Advantages of the EDAS Method in Decision-Making

• Evaluating alternatives based on the average solution helps prevent overly optimistic or pessimistic results.

• The concepts of positive and negative distances make it easier for decision-makers to understand the results obtained.

• Criteria with different structures can be analyzed within the same evaluation framework.

• It can be used effectively with weighting methods such as FUCOM, LBWA, BWM, and MEREC.

• It is successfully applied in many fields such as Automotive Industry Decision Analysis [46], Biomedical Waste Disposal [47], Supply Chain Sustainability [48], Athlete Smart Bracelet Selection [49], Smart Sustainable Manufacturing [50], and engineering.

Disadvantages of the EDAS Method are as follows:

• Alternatives with outlier values can affect the average solution, leading to changes in ranking results.

• The EDAS method operates on the assumption that the criteria are independent of each other.

• The classic EDAS structure does not include ambiguous or fuzzy data; therefore, fuzzy or interval extensions may be needed.

• The normalization method used can affect the relative performance of the alternatives.

With these features, the EDAS method, thanks to its average-based structure, is an effective ranking method that evaluates the performance of alternatives in a balanced way; however, it should be applied carefully, especially in decision problems involving outliers.

This chapter comprehensively examines the historical evolution of multi-criteria decision-making (MCDM) methods, along with the new generation weighting and ranking approaches that have gained prominence in recent years. Problems such as the high comparison burden, risk of inconsistency, and limited compatibility with modern data structures of classical methods can be overcome in a more manageable, consistent, and application-oriented way using methods like FUCOM, LBWA, BWM, and MEREC. Similarly, new generation ranking methods such as ARTASI, MABAC, MARCOS, and EDAS enhance the interpretability and robustness of the decision-making process by evaluating alternatives not only based on proximity to the ideal solution but also using different reference logics such as goal-based, boundary approach space, compromise solution, or deviation from the mean solution. In this respect, the chapter provides decision-makers with both a theoretical understanding and a practical roadmap for method selection.

The key lines that will determine the direction of the MCDM literature in the coming period are: The increasing prevalence of fuzzy/grey/neutrosophic extensions that enhance uncertainty management, the rise of hybrid models compatible with big data and real-time decision support requirements, and the growing visibility of AI-based learning weighting/ranking approaches are expected. Furthermore, as the multidimensionality of decision problems increases in high-impact areas such as sustainability, energy, logistics, smart manufacturing, and security, frameworks that utilize a combination of methods appropriate to the problem structure (e.g., objective-subjective weighting hybrids and goal/consensus-based rankings) will become more valuable than relying on a single approach. Therefore, future studies should evaluate methods not only based on computational success but also on criteria such as data quality, application scalability, explainability, and alignment with decision-maker objectives, further strengthening the role of Multi-Criteria Decision Making (MCDM) in the interdisciplinary decision ecosystem.

References

1. Pamučar, D., Stević, Ž., & Sremac, S.: A new model for determining weight coefficients of criteria in mcdm models: Full consistency method (fucom). symmetry, 10(9), 393. (2018).
2. Ecer, F. : FUCOM sübjektif ağırlıklandırma yöntemi ile rüzgâr çiftliği yer seçimini etkileyen faktörlerin analizi. Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi, 27(1), 24-34. (2021).
3. Kılıç, R., Emeç, Ş., & Erkayman, B. (2022). Integrated fuzzy FUCOM and fuzzy MARCOS approaches for housing location problem. Journal of Brilliant Engineering, 3(4).
4. Ali, S. S., Torğul, B., Paksoy, T., Luthra, S., & Kayikci, Y. (2024). A novel hybrid decision-making framework for measuring Industry 4.0-driven circular economy performance for textile industry. Business Strategy and the Environment, 33(8), 7825-7854.
5. Blagojevic, M., Blagojevic, D., Danilevicius, A., Krmac, E., & Biancardo, S. A. (2025). Application of the FUCOM and MARCOS methods for selecting logistics service providers. J. Intell Manag. Decis, 4(4), 288-297.
6. Bolayır, B. (2026). Assessment of Türkiye's Healthcare Quality Standards Using the FUCOM Method: FUCOM Method. In Multi-Criteria Decision Making Methods and Sustainable Applications in the Digital Age (pp. 241-272). IGI Global Scientific Publishing.
7. Tatar, V., Ayvaz, B., & Pamucar, D. (2025). A quantitative ergonomic risk assessment model of maritime port operations: An integrated spherical fuzzy-FUCOM-ARTASI approach. Ocean & Coastal Management, 267, 107710.
8. Zizovic, M., Pamucar, D.: New model for determining criteria weights: level based weight assessment (LBWA) model. Decis. Mak. Appl. Manag. Eng. 2, 126–137 (2019).
9. Dündar, S., & Karadağ, İ. (2025). Selection of a Facility Location for a Cosmetics Company by Integrated F-LBWA and I-RAWEC Methods. International Journal of Fuzzy Systems, 1-20.
10. Asan, H. (2025). Evaluation of Consultant Selection Criteria with Level Based Weight Assessment (LBWA) Method in Intelligent ERP (Enterprise Resource Planning) Perspective. Celal Bayar Üniversitesi Sosyal Bilimler Dergisi, 23(01), 29-52.
11. Yalçın, G. C., Kara, K., Simic, V., Yıldırım, A. T., & Pamucar, D. (2026). A neutrosophic level-based weight assessment and root assessment method for holistic ecotourism area selections. Operational Research, 26(1), 13.
12. Das, A. (2025). Fundamental Distinction of Surface Water Potential Zones and Identification of Suitable Monitoring Locations in the Mahanadi Watershed, Odisha, Using Level Based Weight Assessment (LBWA), Geographical Infor-

mation System (GIS), and Decision Tree (DT) Techniques. In Biotechnological Removal of Emerging Pollutants from Wastewater Systems (pp. 59-87). Singapore: Springer Nature Singapore.

13. Özekenci, S. Y. (2024). Financial performance measurement of companies in the BIST sustainability 25 index with LBWA and MEREC-based CRADIS methods. Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty, 11(3), 1184-1211.

14. Bagherian, A., Chauhan, G., & Srivastav, A. L. (2024). Data-driven prioritization of performance variables for flexible manufacturing systems: revealing key metrics with the best–worst method. The International Journal of Advanced Manufacturing Technology, 130(5), 3081-3102.

15. Jovanović, B., Šarac, D., & Čačić, N. (2024). Performance benchmarking of European postal incumbents with TOPSIS and BMW-TOPSIS. Utilities Policy, 91, 101845.

16. Kumar, R., Kumar, P., Singh, R. K., Vaish, A., & Sharma, G. (2024). A framework for evaluating the barriers to adopting Industry 4.0 in Indian SMEs: an approach of best-worst method. Journal of Management Analytics, 11(4), 705-737.

17. Bouraima, M., Badi, I., Stević, Ž., Kiptum, C. K., Pamucar, D., & Marinkovic, D. (2024). A novel vehicle routing algorithm for route optimization using best-worst method and ranking alternatives for similarity to ideal solution. Engineering Review: Međunarodni časopis namijenjen publiciranju originalnih istraživanja s aspekta analize konstrukcija, materijala i novih tehnologija u području strojarstva, brodogradnje, temeljnih tehničkih znanosti, elektrotehnike, računarstva i građevinarstva, 44(4-SI 2024), 57-76.

18. Öztürk, M., Torğul, B., & Paksoy, T. (2022). Interval Type-2 Fuzzy Rule-Based Bwm Approach for Sustainable Supplier Selection. Konya Journal of Engineering Sciences, 10(2), 312-336.

19. Delice, E. K., & Can, G. F. (2020). A new approach for ergonomic risk assessment integrating KEMIRA, best–worst and MCDM methods. Soft Computing, 24(19), 15093-15110.

20. Turanoğlu Şirin, B. (2023). A hybrid approach based on fuzzy BWM and MAIRCA for selection of engine in rotary wing unmanned aerial vehicle design. Journal of Intelligent & Fuzzy Systems, 45(3), 3767-3778.

21. Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2021). Determination of objective weights using a new method based on the removal effects of criteria (MEREC).Symmetry,13(4), 525. https://doi.org/10.3390/sym13040525.

22. Kara, K., Yalçın, G. C., Kaygısız, E. G., & Edinsel, S. (2024). Assessing the academic performance of Turkish Universities in 2023: a MEREC-WEDBA hybrid methodology approach. Journal of Operations Intelligence, 2(1), 252-272.

23. Turkiye's Carbon Emission Profile: A Global Analysis with the MEREC-PROMETHEE Hybrid Method.

24. Bui, H. A., & Nguyen, X. T. (2024). A novel multicriteria decision-making process for selecting spot welding robot with removal effects of criteria techniques. International Journal on Interactive Design and Manufacturing (IJIDeM), 18(2), 1033-1052.

25. Wang, C. N., Nguyen, H. K., & Nhieu, N. L. (2025). Optimizing Energy Choices: MEREC-TOPSIS Analysis of Renewable Technologies. Computational Economics, 1-21.

26. Ristono, A. (2024). Additive Ratio Assessment for Supplier Selection Using Compromise Weighting of Step Weight Assessment Ratio Analysis and The Method Based on Removal Effects of a Criteria: A Case Study in the Indonesian Leather Industry. International Journal of Industrial Engineering, 35(4), 1-18.

27. Fan, J., Lei, T., & Wu, M. (2024). MEREC-MABAC method based on cumulative prospect theory for picture fuzzy sets: Applications to wearable health technology devices. Expert Systems with Applications, 255, 124749.

28. Kara, K., Özyürek, H., Yalçın, G. C., & Burgaz, N. (2024). Enhancing financial performance evaluation: The MEREC-RBNAR hybrid method for sustainability-indexed companies. Journal of Soft Computing and Decision Analytics, 2(1), 236-257.

29. Pamucar, D., Simic, V., Görçün, Ö. F., & Küçükönder, H. (2024). Selection of the best Big Data platform using COBRAC-ARTASI methodology with adaptive standardized intervals. Expert Systems with Applications, 239, 122312.

30. Kara, K., Yalçın, G. C., Kaygısız, E. G., Simic, V., Örnek, A. Ş., & Pamucar, D. (2024). A picture fuzzy CIMAS-ARTASI model for website performance analysis in human resource management. Applied Soft Computing, 162, 111826.

31. Tatar, V. (2025). Assessment of Ergonomic Risk Factors for Sustainable Agricultural Practices Based on Picture Fuzzy Lodeci-Artasi Approach. Bitlis Eren Üniversitesi Fen Bilimleri Dergisi, 14(3), 1891-1920.

32. Kahreman, Y. (2025). Investıgatıng the Productıve Capacıty Performance of E7 Countrıes Using the WENSLO-ARTASI Model. EKOIST Journal of Econometrics and Statistics, (42), 154-174.

33. Tatar, V. (2026). Optimization-based decision support model for risk assessment of autonomous ships: Spherical fuzzy FUCOM-ARTASI approach. Ocean Engineering, 345, 123486.

34. Memarpour, A., & Abbasi, M. (2025). Evaluation of Suppliers in Modular Megaprojects Using LOPCOW-ARTASI in an Uncertain Environment. jims, 23(77), 85-132.

35. Pamučar, D., & Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). Expert systems with applications, 42(6), 3016-3028.

36. Raj, D., Maity, S. R., & Das, B. (2024). Optimization of process parameters of laser cladding on AISI 410 using MEREC integrated MABAC method. Arabian

Journal for Science and Engineering, 49(8), 10725-10739.

37. Bi, H., Gu, Y., Lu, F., & Mahreen, S. (2025). Site selection of electric vehicle charging station expansion based on GIS-FAHP-MABAC. Journal of Cleaner Production, 145557.

38. Wang, J., Darwis, D., Setiawansyah, S., & Rahmanto, Y. (2024). Implementation of MABAC Method and Entropy Weighting in Determining the Best E-Commerce Platform for Online Business. J. Ilm. Teknol. Harapan-JiTEKH, 12, 58-68.

39. Puška, A., Hodžić, I., Štilić, A., & Murtič, S. (2024). Evaluating European Union countries on climate change management: A fuzzy MABAC approach to the climate change performance index. Journal of Green Economy and Low-Carbon Development, 3(1), 15-25.

40. Fan, J., Lei, T., & Wu, M. (2024). MEREC-MABAC method based on cumulative prospect theory for picture fuzzy sets: Applications to wearable health technology devices. Expert Systems with Applications, 255, 124749.

41. Wang, C. N., & Dang, T. T. (2024). Third-party logistics provider selection in the Industry 4.0 era by using a fuzzy AHP and fuzzy MARCOS methodology. IEEE Access, 12, 67291-67313.

42. Ecer, F., Tanrıverdi, G., Yaşar, M., & Görçün, Ö. F. (2025). Sustainable aviation fuel supplier evaluation for airlines through LOPCOW and MARCOS approaches with interval-valued fuzzy neutrosophic information. Journal of Air Transport Management, 123, 102705.

43. AKBULUT, O. Y. (2025). Analysis of the corporate financial performance based on grey PSI and grey MARCOS model in Turkish insurance sector. Knowledge and Decision Systems with Applications, 1, 57-69.

44. Štilić, A., Puška, A., Božanić, D., & Đurić, A. (2024). Ranking European Countries Using Hybrid MEREC-MARCOS MCDA Based on Travel and Tourism Development Index. Tourism: An International Interdisciplinary Journal, 72(4), 592-608.

45. Yazar, E. A., Adar, T., & Kilic-Delice, E. (2024). Comprehensive evaluation of hazardous solid waste treatment and disposal technologies by a new integrated AHP&MARCOS approach. International Journal of Information Technology & Decision Making, 23(03), 1229-1259.

46. Imran, R., & Ullah, K. (2025). Circular intuitionistic Fuzzy EDAS approach: a new paradigm for decision-making in the automotive industry sector. Spectrum of Engineering and Management Sciences, 3(1), 76-92.

47. Zulqarnain, R. M., Naveed, H., Askar, S., Deveci, M., Siddique, I., & Castillo, O. (2024). Assessment of bio-medical waste disposal techniques using interval-valued q-rung orthopair fuzzy soft set based EDAS method. Artificial intelligence review, 57(8), 210.

48. Alioğulları, E., Türkan, Y. S., Çakmak, E., & Tirkolaee, E. B. (2024). Evaluation

of risk strategies for supply chain sustainability with interval-valued neutrosophic fuzzy EDAS. Heliyon, 10(19).

49. Albayrak, Ö., & Erkayman, B. (2018). Bulanik Dematel ve EDAS yöntemleri kullanilarak sporcular için akilli bileklik seçimi. Ergonomi, 1(2), 92-102.

50. Batwara, A., Sharma, V., & Makkar, M. (2025). Prioritization of the approaches for overcoming smart sustainable manufacturing barriers using stochastic fuzzy EDAS method. International Journal on Interactive Design and Manufacturing (IJIDeM), 19(3), 1927-1949.

Chapter

2

AN APPLICATION OF MONTHLY PRODUCTION PLANNING WITH STOCHASTIC PROGRAMMING IN A COMPOSITE PIPE FACTORY

***Esra CİN*[1]**

***Sibel ATAN*[2]**

1 Esra Cin, Ankara Hacı Bayram Veli Üniversitesi, Uygulamalı Yöneylem Araştırması Doktora Programı
ORCID: 0000-0003-4762-6839
2 Prof. Dr. Sibel Atan, Ankara Hacı Bayram Veli Üniversitesi, İktisadi ve İdari Bilimler Fakültesi
ORCID: 0000-0002-4868-753X

INTRODUCTION

Production constitutes the basis of economic activities and business administration. In order to survive in the global competitive environment, businesses must be able to utilize their resources at minimum cost and deliver the product to the buyer at the promised time and quality. An effective and efficient production planning helps an enterprise to determine its human, material and equipment requirements, to organize production programs according to the needs of marketing demand, to arrange various inputs at the right time and in the right quantity, and to make the most economical use of various inputs.

In this study, the production planning of a composite pipe factory will be carried out with chance constrained stochastic programming technique under various conditions for pipe production. Numerical data on the constrained resources of this composite pipe factory, which operates on order and produces different qualities of products, are determined and a stochastic production planning model with chance constraints is established.

Various studies in this field have reviewed in the literature. Among these studies, Basar and Eyupoglu (2023) calculated the optimum production quantities and maximum profit for a large-scale automotive sub-industry enterprise by using linear programming on a mathematical model. Meydan B. (2023) conducted a review study on the use of quantitative methods in production planning under uncertainty. The research is based on studies published in leading journals scanned in the Web of Science database. Moret et al. (2017) aimed to make long-term planning by taking into account the uncertainty related to strategic energy plans, based on the concerns of countries regarding climate change and energy supply security. Demand, cost, prices, resource availability and transportation parameters are considered uncertain and MILP method is used for the solution. Chatterjee et al. (2016) tried to find the optimal production level for mine production planning under commodity price or market uncertainty. In this study, Gaussian simulation and smoothing spline algorithm were used as methods. Chen and Sarker (2015) examine the impact of learning effect and demand uncertainty and provide some important managerial insights for practitioners in production planning and performance management. In the study, fuzzy optimization method is used and demand is assumed to be uncertain. Aksaraylı and Pala (2015) stated that in production planning, the coefficients of variables and constraints such as product selling price, amount of demand for goods, labor capacity may not be deterministic. In this case, they mentioned that the linear programming model would give insufficient results in solving the problem and modeled the office products production system with a chance-constrained stochastic programming approach that can give more accurate results under uncertainty. Silva and Marins (2014) addressed a real production problem in the Brazilian Sugar and Ethanol Milling Company. The researchers presented results by solving the problem with fuzzy goal programming method under harvest-related uncertainties in order to plan production, storage and logistics. In his study, H. Lee (2014) addressed the problem of optimizing vehicle performance with a stochastic and dynamic programming approach. Under the uncertainty of raw material supply, demand, resource, market, policy and technology, the power demand of the driver is represented by a Markov process and the optimization problem is formulated. W. White (2013) used a stochastic programming model for resource and production planning and considered production function uncertainties as stochastic. Rahmani et al. (2013) studied a two-stage, real-world capacity production system where some parameters such as production costs and customer demand are uncertain. To model the problem, an optimization model is developed in which the minimization of total costs including setup costs, production costs, labor costs, inventory costs and labor replacement costs is considered as the performance measure. Kostin et al. (2012), in their study, focused on supply chain planning and financial risk management. In this model, they used stochastic programming and MILP method, assuming that demand is stochastic. Atalay and Apaydın (2011) made a deterministic analysis of stochastic programming models with chance constraints and gave a hypothetical example. Ejikeme-Ugwu et al. (2011) made the production and distribution plan of a refinery plant and considered the demand as stochastic. They used stochastic linear programming and sample average approximation methods. In their study, Çetindere et al. (2010) emphasized the importance of production planning for enterprises and applied linear programming, one of the techniques used in solving problems in this field, in a garment enterprise. In his study, Yücel (2008) argues that most of the existing approaches take production times as deterministic and emphasizes that production times behave randomly in practice. In this study, he considered the traditional part machine placement problem and proposed a stochastic programming model in which production times are modeled as a random variable. Mei-Shiang Chang et al. (2006) aims to develop a decision-making tool that can be used in flood emergency planning of government agencies. In this paper, the problem of food emergency logistics with uncertainty is formulated as two-stage stochastic programming. Shapiro et al. (2005), in their paper, propose a stochastic programming model and solution algorithm to solve realistic scale supply chain network design problems. They mention that the existing approaches to such problems in the literature are limited to deterministic settings, and they make an application on a real supply chain network to emphasize the efficiency of the proposed solution strategy as well as the stochastic model. In Esen and Cetin (2004), based on the Konno & Yamazzaki model, which is a risk minimization model based on absolute deviations and proposed for portfolio optimization, a static model that minimizes the risk at certain confidence levels is developed. A stochastic programming model is used for this purpose. Warren and Topaloglu (2003) in their study stated that long distance freight transportation is subject to random delays and has many uncertainties such as equipment failures and last minute changes; in the light of this, they showed that planning can be done by using a stochastic programming model in this field. Taha Hamdi A. (1997), in his book, explained in detail many mathematical methods used in operations research, including stochastic programming models, and explained them with case studies and real life examples.

METHOD

Stochastic programming is a method that encompasses mathematical programming models that can be used to make decisions under uncertainty (Warren & Topaloglu, 2003). When one or more components of mathematical programs can be expressed with stochastic parameters, these models can only be modeled as stochastic programs. In fact, stochastic programming is an approach that combines mathematical programming and decision-making models since it can incorporate uncertainty into the mathematical model (Çetindere, 2010). The general linear programming model is a linear system consisting of the objective function and constraints, as shown in model (2.1), on the solution set as follows:

Objective function

$$\max(\min)\ z(x) = \sum_{j=1}^{n} c_j x_j$$

Constraints (2.1)

$$\sum_{j=1}^{n} a_{ij} x_j \leq b_i \qquad i = 1, \dots, m$$

$$x_j \geq 0, \qquad j = 1, \dots, n$$

Stochastic programming is divided into two categories: two (multistage) stochastic programming and stochastic programming with chance constraints. The most common application and study of stochastic programming models is two-stage linear stochastic programming (Shapiro et al., 2005).

Linear two- and multi-stage stochastic programming was first studied by Dantzig (1955) and Beale (1955). The idea underlying two-stage stochastic programming is the concept of recourse. Certain decisions can be two-stage; sometimes decisions are made in the first stage, but these decisions may need to be corrected in the next stage as additional information and future uncertainty are removed. (Rahmani et al. 2013) İki aşamalı problem olarak adlandırılan bu problemde, önce başlangıç tahsisleri yapılır, sonrasında stokastik olaylar) In this so-called two-stage problem, initial allocations are made first, stochastic events are observed and then the remaining resources are reallocated within the constraints imposed by the initial allocations or the stochastic event. As can be seen, some decisions are taken before the stochastic event occurs, while some decisions are taken in the second stage depending on the decisions taken in the first stage and the stochastic events (Esen and Çetin, 2010). Classical two-stage linear stochastic programming is expressed as model (2.2):

$$Min\ z = c^T X + E_{\xi}[\min q(w)^T y(w)]$$
$$s.t\ Ax \geq b, \tag{2.2}$$
$$T(\omega)x + Wy(\omega) = h(\omega),$$
$$x \geq 0, y(\omega) \geq 0.$$

Another approach used to transform a stochastic programming problem into a deterministic programming problem is stochastic programming with chance constraints. (Aksaraylı et al. ,2015) Stochastic programming with chance constraints involves random data and allows constraint perturbations up to specified probability limits. An ordinary linear programming model is called chance constrained if the linear constraints are combined with a set of probability measures that specify the width of the perturbations of the constraints. In the method that allows partial perturbation of constraints, the chance-constrained programming approach can be seen as a technique for achieving approximate reliability. This method has been generalized and applied to many industrial and economic problems (Taha et al, 1997). An ordinary linear programming model, as presented in Model (2.3), is expressed as follows.

$$\max(\min)\ \mathrm{z(x)} = \sum_{j=1}^{n} c_j x_j$$
$$\textstyle\sum_{j=1}^{n} a_{ij} x_j \leq b_i \qquad i = 1, \dots., m \tag{2.3}$$
$$x_j \geq 0, \qquad j = 1, \dots., n$$

Where cj , j =1,.... n are prices, bi, i=1.....m are right-hand side values and aij , j=1,....n , i =1....m are elements of the coefficient vector. The stochastic programming model with chance constraints, as formulated in Model (2.4), is defined as follows.

$$\max(\min)\ z(x) = \sum_{j=1}^{n} c_j x_j$$

$$P\left[\sum_{j=1}^{n} a_{ij} x_j \le b_i\right] \ge 1 - u_i\ ,\ i = 1, \ldots, m \quad (2.4)$$

$$x_j \ge 0, \qquad j = 1, \ldots, n$$

$$u_i \in (0,1), \qquad i = 1, \ldots, m$$

Here, are random variables and are selected probabilities. Here, the decision variable is assumed to be deterministic. are random variables with known variances and means (Taha et al. 1997). In this study, a stochastic programming model with chance constraints will be used.

APPLICATION

Production planning is a complex process that involves many parameters and variables such as materials, equipment, labor, raw materials, raw materials, time and capacity, aiming to deliver the product desired by the customer at the desired time and to use the available resources to the optimum extent. Considering that production systems have an uncertain demand structure in real conditions, in order to make an effective and efficient planning, the production process should be planned by using optimization techniques under uncertainty.

Stochastic programming is one of the important approaches to model optimization problems under uncertainty. In this study, the stochastic programming model with chance constraints will be used.

Composite pipes in Turkey meet the needs of some regions in Turkey and abroad for irrigation, sewage, sewage treatment, etc. pipes. The composite pipe factory in practice is producing "on order" to meet the demands of domestic and foreign customers and tries to keep as little stock as possible. There are basically three technologies used for pipe production in this factory. These technologies are continuous fiber winding (FW), centrifugal casting (CC) and helical fiber winding. The FW section produces in the range of 300 - 4000 mm, the CC section produces in the range of 350 - 1400 mm and the helical section produces in the range of 100 - 250 mm. In this study, the efficiency of helical fiber winding production will be examined in basic terms. Glass fiber reinforced and thermosetting resin helical coiled tubing offers a combination of superior corrosion resistance and high mechanical and physical properties, proven in the most demanding operating conditions in the world

In the study carried out in the factory with 100 - 150 - 200 - 250 mm diameter pipe manufacturing molds, the pressure class is assumed to be 10 bar, stiffness class 10000 and pipe lengths 6 meters. Below, a stochastic programming mathematical model of the problem created according to the relevant conditions is given:

Data Set

Data such as production quantities, labor times, cost elements and demand uncertainties are taken from CANIAS, the ERP program used by the factory. Based on these data, the decision variables, constraints and objective function were determined and the basic mathematical model was created. The decision variables corresponding to the one-month data are formulated through the equations provided in Section (3.1.1)

X1 = quantity of DN 100 mm pipe to be produced (mt)

X2 = quantity of DN 150 mm pipe to be produced (mt)

X3 = quantity of DN 200 mm pipe to be produced (mt) (3.1.1)

X4 = quantity of DN 250 mm pipe to be produced (mt)

$M_1 = DN\ 100\ mold$

$M_2 = DN\ 150\ mold$

$M_3 = DN\ 200\ mold$

$M_4 = DN\ 250\ mold$

$Mi \geq 0 \quad (i = 1, 2, 3 \ldots\ldots, n)$

The selling prices ($), unit cost ($), unit labor (min/m), actual production quantity (meters) and maximum order demand (meters) for the products are given in Table 1.

Table 1. Üretim, Maliyet ve Talep Miktarları

Products	Unit Selling Price	Unit Cost	Unit Labor (min/m)	Actual Production Quantity (m)	Maximum Order Demand
DN100	11,86	9,12	10	330	500
DN150	17,76	13,66	11,4	480	500
DN200	23,29	17,84	12,08	1200	1200
DN250	31,64	24,34	13,3	1080	1500

Unit profit values are also given in Table 2.

Table 2. Unit profit Table

Products	Unit Profit ($)
DN100	2,74
DN150	4,1
DN200	5,45
DN250	7,3

According to the 30-day production schedule of this factory; the results of the calculation of the relevant production schedule for the 6 days per week and 26 days per month work schedule with labor times are in Table 3.

Table 3. Working Hours Table

Products	Number of Employees	Daily Working Hours (min)	Total Daily Work	Monthly Work (min)
DN100	3	120	360	9360
DN150	3	210	630	16380
DN200	3	600	1800	46800
DN250	3	510	1530	39780
		1440	**4320**	**112320**

3.2. Modeling the Problem with Lineer Programming

The objective function corresponding to the linear programming model is provided in Section (3.2.1).

$$Zmax\ cj * xi \ \ (Making\ a\ 1 - month\ production\ plan\ to\ maximize\ profit)$$

$$(cj = Unit\ Selling\ Price - Unit\ Cost) \tag{3.2.1}$$

$$Zmax = (11{,}86 * X1 + 17{,}76 * X2 + 23{,}29 * X3 + 31{,}64 * X4) - (9{,}12 * X1 + 13{,}66 * X2 + 17{,}84 * X3 + 24{,}34 * X4)$$

= 2,74.X1 + 4,1.X2 + 5,45.X3 + 7,3.X4

Labor working Constraints shows how many workers can be employed in the production of one meter of pipe or how we can distribute the workers per unit meter. Time constrainst is the minimum time constraint required to produce 6 meters (1 piece) of each type of pipe. The constraints are defined in Section (3.2.2)

$$DN\ 100\ için\ üretim\ süresi\ 1\ adet\ (6mt) \geq 60\ dk$$
$$DN\ 150\ için\ üretim\ süresi\ 1\ adet\ (6mt) \geq 68{,}4\ dk$$
(3.2.2)
$$DN\ 200\ için\ üretim\ süresi\ 1\ adet\ (6mt) \geq 72{,}5\ dk$$
$$DN\ 250\ için\ üretim\ süresi\ 1\ adet\ (6mt) \geq 79{,}8\ dk$$

After the pipe production is completed with each mold, 60 minutes of preparation time is required to prepare the mold for new production. For example, the manufacturing time of DN 100 is 60 minutes. This does not mean that 1440/60 = 24 units are produced in one day. Due to the mold preparation time, it should be calculated as 1440 / 60 + 60 = 12 pipes. Since M3 and M4 molds are two pieces each, mold preparation time is not taken into account in DN 200 and DN 250 production. Because there are two molds when these products enter the production line, there will be no need for separate mold preparation time for each product that can be used alternately. The mould-related constraints are presented in Section (3.2.3)

$mi =$ Number of molds required for the production of Xi

$$m1 = 1\ ,\ m2 = 1\ ,\ m3 = 2\ \ ,\ m4 = 2 \tag{3.2.3}$$

The capacity constraints, as provided in Section (3.2.4)are specified on a daily basis, and it is the constraint that shows the maximum number of pipes that can be produced in a day considering the mold and labor constraints.

$$X1 \leq 12\,pieces$$
$$X2 \leq 11{,}2\,pieces \tag{3.2.4}$$
$$X3 \leq 19{,}8\,pieces\ (Because\ there\ are\ two\ molds)$$
$$X4 \leq 18{,}04\,pieces\ (Because\ there\ are\ two\ molds)$$
$$(60+60)X1 + (68.4+60)X2 + (72{,}5)X3 + (79{,}8)X4 \leq 1440$$
$$120X1 + 128{,}4\,X2 + 72{,}5\,X3 + 79{,}8X4 \leq 1440$$

Finally ,"demand" is not strictly certain, but can be random within a given distribution. That is, the demand for each product may fluctuate within a certain range and these constraints aim to plan taking this fluctuation into account. The demand constraints are considered stochastic in the model and are presented in Section (3.2.5)

$$D1 \leq 500$$
$$D2 \leq 500$$
$$D3 \leq 1200 \tag{3.2.5}$$
$$D4 \leq 1500$$
$$X1 + X2 + X3 + X4 \leq 3700$$

Modeling the Problem with Chance Constrained Stochastic Programming

Such problems involving stochastic situations, such as the production planning problem, are based on the existence of random variables and their being under a certain distribution, as presented in model (3.2.1), and are expressed in the following form:

$$Maksimize\ min_{p\in P}\ \{z^T x\} \tag{3.3.1}$$

It's here, "x" represents the decision variables, "z" represents the coefficients of the objective function (coefficients of the objective function), and "P" represents the set of possible values of probabilistic variables. The constraints are defined as follows, as shown in Section (3.3.2).

$$a_i^T x \leq b_i,\ i = 1, \dots, m \tag{3.3.2}$$

These constraints are expressed as follows in a deterministic (uncertainty-free) linear programming problem, as presented in Section

(3.3.3).

$$max_x c^T x$$

Subjct to; (3.3.3)

$$Ax \leq b$$

It's here, "c" represents the coefficients of the objective function, Matrix "A" contains the coefficients on the left hand side of the constraints,"b" represents the boundaries on the right-hand side of the constraints.

In order to relate the deterministic linear programming problem to the stochastic model, it is necessary to express the constraints of the probabilistic linear programming problem in a deterministic form, which can be expressed as outlined in Section (3.3.4).

$$\mathbb{E}\left[a_{\mathrm{i}}^T x\right] \leq b_i + \sqrt{Var\left(a_{\mathrm{i}}^T x\right)}.K,\ i = 1, \ldots., m \qquad (3.3.4).$$

It's here,"E[·]" represents the expected value, "Var(·)" represents variance, "K" is a constant representing a confidence level. These definitions represent the situation where random variables are under a certain distribution. When this structure is translated into a deterministic model, these constraints are fixed using the expected value and variance, resulting in a deterministic problem.

In the production planning problem, in order to transform probabilistic linear programming problems into deterministic models, it is necessary to rearrange the mathematical expressions by fixing the expected values and variances of random variables. Thus, it is possible to obtain an optimal solution with deterministic solution methods. In the analysis, demand values were taken from CANIAS, the ERP program used by the factory, and the distribution of these values was examined in SAS Enterprise program and it was determined that they conform to the Normal Distribution. In addition, "Monte Carlo Simulation" was used to generate random values for the stochastic demand constraints (D1, D2, D3, D4 respectively). Monte Carlo Simulation was performed with 1000 iterations for the problem. In this analysis, random demand values were generated at each iteration and the linear programming model was solved again with these values.

With the simulation application, the distribution and probabilities of maximum profit under the uncertainty of demand variables for decision makers were obtained. In this direction, by considering the case where demand constraints are random variables, it is possible to mathematically define the steps of transforming the chance constrained model into a deterministic model as follows:

The demand constraints of the products are defined as D1, D2, D3, and D4. Let these demand constraints be treated as random variables, as presented in Section (3.3.5).

$$D1 \sim N(\mu D1, \sigma D12)$$
$$D2 \sim N(\mu D2, \sigma D22) \qquad (3.3.5).$$
$$D3 \sim N(\mu D3, \sigma D32)$$
$$D4 \sim N(\mu D4, \sigma D42)$$

Accordingly, the decision variables are as shown in Section (3.3.6), the objective function in Section (3.3.7), the labor constraints in Section (3. 3.8), the time constraints in Section (3.3.9), and the mould constraints in Section (3.3.10).

The deterministic form of the demand constraints is provided in Section (3.2.10). With this step, we fix the demands, which are random variables, to a given value with (3.3.11). The total production constraint is defined as presented in Section (3.3.12)

$X1$: The quantity of DN 100 mm pipe to be produced (meters)

$X2$: The quantity of DN 150 mm pipe to be produced (meters)

(3.2.6)

$X3$: The quantity of DN 200 mm pipe to be produced (meters)

$X4$: The quantity of DN 250 mm pipe to be produced (meters)

Each decision variable must be positive: $X1, X2, X3, X4 \geq 0$

$$Max\ Z = 2.74X1 + 4.1X2 + 5.45X3 + 7.3X4 \qquad (3.2.7)$$

$DN\ 100:\ 10X1 \leq 9360$

$$DN\ 150:\ 11.4X2 \leq 16380 \qquad (3.2.8)$$
$$DN\ 200:\ 12.08X3 \leq 46800$$
$$DN\ 250:\ 13.3X4 \leq 39780$$

$$DN\ 100:\ 120X1 \leq 1440$$
$$DN\ 150:\ 128.4X2 \leq 1440 \qquad (3.2.9)$$
$$DN\ 200:\ 72.5X3 \leq 1440$$
$$DN\ 250:\ 79.8X4 \leq 1440$$

$$DN\ 100:\ X1 \leq 12$$
$$DN\ 150:\ X2 \leq 11.2 \qquad (3.2.10)$$
$$DN\ 200:\ X3 \leq 19.8$$
$$DN\ 250:\ X4 \leq 18.04$$

$$X1 \leq \mu D1$$
$$X2 \leq \mu D2 \qquad (3.2.11)$$
$$X3 \leq \mu D3$$
$$X4 \leq \mu D4$$
$$X1 + X2 + X3 + X4 \leq 3700 \qquad (3.2.12)$$

In this solution, the maximum profit was found to be 22,410 USD. This value indicates the production plan that can generate the maximum profit under the given constraints.

Thus, random demand constraints are defined by transforming them into a deterministic model. These steps will help us to build a model in which the demand constraints are defined according to a random distribution and a given mean. Accordingly, a stochastic model with chance constraints is transformed into a deterministic model and optimal results are obtained.

RESULTS

In the Results section, the results of the analyses carried out for the optimization of production planning are presented. The problem was solved using linear programming and stochastic programming with chance constraints approaches. The result of the linear programming model is presented in Section (4.1.1)

$X1 = 500 \quad (DN\ 100\ mm\ pipe\ quantity.)$
$X2 = 0 \quad (DN\ 150\ mm\ pipe\ quantity.)$
$X3 = 1200 \quad (DN\ 200\ mm\ pipe\ quantity.)$
$X4 = 2000 \quad (DN\ 250\ mm\ pipe\ quantity.)$

$\boldsymbol{Maximum\ Profit}$:

$$= 2.74 \times 500 + 4.1 \times 0 + 5.45 \times 1200 + 7.3 \times 2000$$
$$= 1370 + 0 + 6540 + 14600 = 22.410\ USD \qquad (4.1.1)$$

In this solution, the maximum profit was found to be 22,410 USD. This value indicates the production plan that can generate the maximum profit under the given constraints.

On the other hand, while the values generated by the Monte Carlo simulation for the chance-constrained stochastic programming model are presented in Section (4.1.2), the solution results are shown in Section (4.1.3).

$$\begin{array}{ll} DN\ 100\ için: \mu D1 = 800 & \sigma D1 = 50 \\ DN\ 150\ için: \mu D2 = 1500 & \sigma D2 = 100 \\ DN\ 200\ için: \mu D3 = 1200 & \sigma D3 = 80 \\ DN\ 250\ için: \mu D4 = 1200 & \sigma D4 = 70 \end{array} \qquad (4.1.2)$$

Based on these values, the problem was transformed into a deterministic model and the following optimal solution was obtained:

$X1 = 800 \quad (Production\ quantity\ for\ DN\ 100)$
$X2 = 1500 \quad (Production\ quantity\ for\ DN\ 150)$
$X3 = 1200 \quad (Production\ quantity\ for\ DN\ 200)$
$X4 = 200 \quad (Production\ quantity\ for\ DN\ 250)$

$$\textbf{Maximum Profit} = 16.342\ USD \qquad (4.1.3)$$

The linear programming model calculated the maximum profit as 22,410 USD under the assumption that demand is certain and constant.

However, since this method does not take into account uncertainties, it presents an approach that may carry risks in real production conditions.The stochastic programming model with chance constraints created a more realistic production plan by taking into account the uncertainties in demand. In line with the production quantities determined by Monte Carlo Simulation, it was determined that the maximum profit was 16.342 USD.

CONCLUSION AND EVALUATION

Traditional production planning models, especially by using linear programming (Hax & Meal, 1975; Bitran & Yanasse, 1984), have been built on the idea that every parameter is fixed and certain in the model. Our study argue that although deterministic approaches in production planning may offer higher profit values in short-term, but ignoring uncertainities significantly causes increasing risks in the long run.Nevertheless, these traditional production planning models with deterministic parameters like linear programming approaches in particular have been widely applied in industry for a long time (Hax & Meal, 1975; Bitran & Yanasse, 1984). Whereas many variables such as customer demand, supply lead times, machine breakdowns, and labor productivity may iclude uncertainty.

Stochastic programming approaches provide powerful tools for these uncertainity cases. Chance-constrained programming, specifically, is a great technique for achieving reliable solution that guarantee certain goals like meeting demand or staying under budget with a specific probability. Birge and Louveaux (2011) emphasize that although this approach may result in lower profits compared to deterministic models, it protects against constraint violations and missing opportunitirs in the long term. Also Ahmed and Sahinidis (2003) say that stochastic models integrate risk aversion into production strategies, so providing a more robust planning framework for decision makers.

For real production conditions, a total order of 20,000 meters of composite pipe—consisting of four different diameters of 5,000 meters each—was evaluated by both deterministic and chance-constrained stochastic models. So the results of these two solution approaches were compared in terms of capacity, profitability, and operational feasibility. Based on actual order data, the total workload was calculated as 233,900 minutes by using the unit labor times of the four diameters (10–13.3 min/m). This value corresponds to approximately 2.08 times the monthly production capacity assumed in the model (112,320 minutes). Therefore, completing the 20 km order within a single month under the current labor force, shift structure, and production capacity is mathematically impossible; the production necessarily has to be distributed for at least two months. The deterministic model, prioritizing DN200 and DN250 according to their profit-to-cost ratios, yielded a theoretical maximum profit of 22,410 USD. However, concentrating on these high-labor products would cluster most of the total workload in the first month, creating a bottleneck and resulting in a production schedule inconsistent with real factory capacity. For this reason, the profitability suggested by the deterministic model is not operationally sustainable once capacity constraints are taken into account.

The results of the chance-constrained stochastic model, on the other hand, show much higher coherence with the real production calculations. The model's tendency to increase the production of DN100 and DN150 while relatively reducing DN200 and DN250 indicates a more balanced and sustainable product mix under uncertainty. A similar pattern emerged in the two-month plan created using the actual order: the first month was allocated to DN100 and DN150, which require lower labor time (approximately 6 km in total), while the second month was allocated to DN200 and DN250, which require higher labor time (another 6 km). This distribution balances the total workload on the production line, mitigates the impact of risks such as machine failures, maintenance needs, or raw material delays, and improves delivery reliability. The stochastic model's lower yet safer profit level of 16,342 USD aligns with this real production plan, demonstrating that it provides a more feasible approach in terms of long-term sustainability, capacity management, and operational risk reduction.

In real factory practice, producing larger diameters first imposes a much heavier labor load per meter, overwhelming the production line in the early phase and consuming capacity prematurely, thereby increasing the risk of delays. Moreover smaller diameters, require less labor, can be produced more quickly, and completing them at the beginning of the production period balances capacity usage while enabling partial deliveries to customers in case of unexpected disruptions. Therefore, producing large diameters first increases operational risk, whereas prioritizing smaller diameters creates a more reliable, sustainable, and manageable production flow.

This comparative analysis shows that although the deterministic model yields a higher short-term profit, it does not fully reflect real production limitations; in contrast, the chance-constrained stochastic model offers a more realistic and sustainable plan due to its capacity-compliant production distribution and its contribution to risk management under uncertainty.

Overall, the findings of the study are consistent with these perspectives in the literature. As the deterministic mathematical model forecasts a higher profit of USD 22,410, the chance-constrained stochastic model provides a lower but better profit of USD 16,342. Notably, the suggestion to increase production quantities for DN 100 and DN 150 pipes while decreasing those for DN 200 and DN 250 pipes illustrates how accounting for demand distributions under uncertainty can significantly alter the balance of production planning. This emphasises an important fact often overlooked by deterministic models that uncertainties affect not only profitability levels but also the product mix and capacity utilization structure.

Furthermore, recent studies in the literature indicate that uncertainties extend beyond demand fluctuations. Supply chain breakdowns (Snyder & Shen, 2011), fluctuations in labor turnover and productivity (Pinedo, 2016), and volatility in energy and material prices are also critical sources of uncertainty in production planning. So stochastic approaches such as chance-constrained programming to incorporate multiple types of uncertainty shows a critical and valuable way for both theoretical and applied research.

In conclusion, while deterministic models may provide higher profit expectations in the short run, stochastic models offer greater advantages for long-term sustainability and risk management. As emphasized in the literature (Birge & Louveaux, 2011; Shapiro et al., 2009), considering uncertainties in production planning does not only let the development of more realistic models but also supply more robust, flexible, and reliable production strategies for decision makers. Future research should explore the application of such models under uncertainty scenarios, the integration with simulation-based optimization techniques and machine learning-based forecasting models for contributing to both academic literature and industrial practice.

REFERENCES

1. Basar, R., & Eyupoglu, Y. (2023). A study on the use of linear programming in contract production planning: The case of automotive supply industry. *Istanbul.*

2. Meydan, B. (2023). A review on the use of quantitative methods in production planning under uncertainty. *Journal of Business and Entrepreneurship Research, 2*(2), 15-30.

3. Moret, S., Gironès, V., Bierlaire, M., & Maréchal, F. (2017). Characterization of input uncertainties in strategic energy planning models. *Applied Energy, 195*, 597-617.

4. Chatterjee, S., Sethi, M., & Asad, M. (2016). Production phase and ultimate pit limit design under commodity price uncertainty. *European Journal of Operational Research, 249*(2), 658-667.

5. Chen, Z., & Sarker, B. (2015). Aggregate production planning with learning effect and uncertain demand: A case-based study. *Journal of Modeling in Management, 10*(3), 296-324.

6. Aksaraylı, M., & Pala, O. (2015, October). Office products production system modeling with chance constrained stochastic programming approach. In *Production Research Symposium* (pp. 1-10).

7. Silva, A. F., & Marins, F. (2014). A fuzzy goal programming model for solving aggregate production planning problems under uncertainty: A case study in a Brazilian sugar mill. *Energy Economics, 45*, 196-204.

8. Lee, J. H. (2014). Energy supply planning and supply chain optimization under uncertainty. *Journal of Process Control, 24*(3), 323-331.

9. White, S. W. (2013). An experimentally confirmed resource planning model of services under uncertainty. *International Journal of Production Economics, 141*(2), 484-490.

10. Rahmani, D., Ramezanian, R., Fattahi, P., & Heydari, M. (2013). A robust optimization model for multi-product two-stage capacitated production

planning under uncertainty. *Applied Mathematical Modelling, 37*(6), 8957-8971.

11. Kostin, A., Guillén-Gosálbez, G., Mele, F., Bagajewicz, M., & Jiménez, L. (2012). Design and planning of infrastructures for bioethanol and sugar production under demand uncertainty. *Chemical Engineering Research and Design, 90*(3), 359-376.

12. Atalay, K. D., & Apaydin, A. (2011). Deterministic equivalents of chance constrained stochastic programming problems. *Anadolu University Journal of Science and Technology B-Theoretical Sciences, 1*(1), 1-18.

13. Ejikeme-Ugwu, E., Liu, S., & Wang, M. (2011). Integrated refinery planning under product demand uncertainty. In *21st European Symposium on Computer Aided Process Engineering* (pp. 950-954). Amsterdam: Elsevier.

14. Çetindere, A., Sevim, Ş., & Duran, C. (2010). The use of linear programming technique in production planning problems: Application in a garment business. *Erciyes University Journal of Faculty of Economics and Administrative Sciences, 35*(1), 271-300.

15. Yücel, Y. (2008). Chance constrained programming from methods used in production planning and optimization. *Trakya University Journal of Science, 9*(2), 2-10.

16. Chang, M. S., Tseng, Y. L., & Chen, J. W. (2006). A scenario planning approach for the flood emergency logistics preparation problem under uncertainty. *Transportation Research Part A, 40*(8), 597-616.

17. Shapiro, A., Santoso, T., Ahmed, S., & Goetschalckx, M. (2005). A stochastic programming approach for supply chain network design under uncertainty. *European Journal of Operational Research, 167*(1), 96-115.

18. Esen, Ö., & Çetin, E. (2004). Development of a portfolio optimization model with stochastic programming method. (Unpublished doctoral dissertation). Istanbul University, Institute of Social Sciences, Department of Numerical Methods, Istanbul.

19. Warren, B., & Topaloglu, H. (2003). Stochastic programming in

transportation and logistics. In S. W. Wallace & W. Ziemba (Eds.), *Handbooks in operations research and management science* (Vol. 10, pp. 555-636). Amsterdam: Elsevier.

20. Taha, H. A. (1997). *Operations research: An introduction* (6th ed., pp. 115-250). Upper Saddle River, NJ: Prentice Hall.

21. Dantzig, G. B. (1955). Linear programming under uncertainty. *Management Science, 1*(3-4), 197-206.

22. Beale, E. M. L. (1955). On minimizing a convex function subject to linear inequalities. *Journal of the Royal Statistical Society: Series B (Methodological), 17*(2), 173-184.

Chapter

3

DEPLOYING ENGINEERING DECISION MAKING METHODS IN THE SPORTS INDUSTRY: A CROSS-DISCIPLINARY ANALYTICAL FRAMEWORK FOR ELITE VOLLEYBALL PLAYER SELECTION

Nur Filiz Ulutas[1]

Buse Cetin[2]

Cagatay Tasdemir[3]

1 Department of Industrial Engineering, Bursa Technical University, Bursa, Türkiye
2 Department of Forest Industry Engineering, Bursa Technical University, Bursa, Türkiye.
3 Department of Industrial Engineering, Bursa Technical University, Bursa, Türkiye, Department of Forest Industry Engineering, Bursa Technical University, Bursa, Türkiye.

Introduction

Volleyball is a team sport characterized by its dynamic structure and fast pace. As a discipline that has rapidly developed and garnered widespread global attention, the significance of international tournaments has correspondingly increased. In particular, national team tournaments serve as critical platforms that reflect a country's athletic achievements and competitive strength. Success in such tournaments is not solely determined by individual talent but is also closely related to team cohesion and the accuracy of player selection.

In volleyball, each player’s role is defined by their position on the court, with each position bearing distinct responsibilities. The libero, a defensive specialist, enhances the team's backcourt defense. The outside hitter (also known as a "wing spiker") must be effective in both offensive and defensive roles. The opposite hitter, typically the highest scorer, plays diagonally opposite the setter and carries much of the team’s offensive load. The middle blocker specializes in blocking and plays a crucial role in countering the opponent's attacks. Finally, the setter serves as the team's playmaker, orchestrating all offensive plays. Consequently, the success of a volleyball team is not only a function of individual talent but is also directly linked to the strategic arrangement of players and accurate position assignments. Each position demands specific skills and evaluation criteria. For example, reception and defensive statistics are more significant for liberos, while offensive effectiveness and block performance are key indicators for outside hitters.

The increasing adoption of analytical methods in modern sports science has rendered their application in player selection both necessary and beneficial. Among these, Multi-Criteria Decision-Making (MCDM) methods have gained particular attention. MCDM is defined as a decision-making process in which a decision-maker selects the best alternative from a finite or infinite set of options based on two or more criteria (Ersöz & Kabak, 2010). The application of MCDM methods to volleyball player selection enables a systematic and objective evaluation of players based on various performance metrics. Techniques such as TOPSIS, VIKOR, and PROMETHEE enable comparative assessments across multiple performance dimensions, significantly aiding the selection of optimal candidates. The TOPSIS

(Technique for Order Preference by Similarity to an Ideal Solution) method ranks alternatives based on their distances to the ideal and negative-ideal solutions. VIKOR (Vlse Kriterijumska Optimizacija I Kompromisno Resenje) identifies compromise solutions among conflicting criteria. PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) generates a ranking by comparing alternatives' strengths and weaknesses. The simultaneous application of these methods enhances the comprehensiveness and reliability of the selection process. Furthermore, these methods are well-established in the literature and have been widely validated in studies of athlete evaluation and performance assessment.

The principal benefits of using analytical methods for athlete selection include enhanced objectivity and data-driven decision-making, more balanced team composition, and comprehensive performance analyses. These methods not only facilitate a deeper understanding of individual performance but also support the achievement of broader strategic goals at the team level. Therefore, adopting and implementing analytical approaches in modern volleyball constitutes a significant step toward success.

Literature Review

To provide depth to the study and to guide the research framework, previous studies on player selection across various sports and on the use of Multi-Criteria Decision-Making (MCDM) methods were examined. Key examples from the literature are summarized below.

In their study, Karaatlı et al. (2014) evaluated the performance of football players in the Turkish Super League during the 2012–2013 season who scored at least 15 goals. The analysis applied AHP, TOPSIS, and VIKOR methods. While goal count and seven other performance metrics were used as evaluation criteria, the ranking results generated by the MCDM methods differed from those based solely on goal statistics. The findings suggested that MCDM techniques could also be effectively applied to evaluate player and club performance in other sports such as basketball and volleyball.

Dadelo et al. (2014) conducted a study involving eighteen professional basketball players from the Lithuanian Basketball League, all of whom were healthy and had no injury history. Using the TOPSIS method, the researchers evaluated players across 23 physical performance criteria. The proposed model effectively captured complex factors influencing game performance, demonstrating its potential applicability across multiple sports disciplines.

Nikjo et al. (2015) proposed a new model for selecting top players in sports clubs using MCDM methods. The model incorporates the Analytic Hierarchy Process (AHP) to assign weights to criteria based on expert judgments and applies an extended TOPSIS method to rank alternatives. The study highlighted the model's potential to enhance the efficiency and effectiveness of player selection processes in sports organizations.

In another study, Özceylan (2016) proposed a two-stage decision-making model for selecting football players. In the first stage, player attributes were prioritized by playing position using the AHP method. In the second stage, a 0–1 integer linear programming model was developed using these weighted criteria to identify the most suitable players for inclusion in the team. The model was applied to the Turkish football club Fenerbahçe to validate its practical utility.

Qader et al. (2017) presented a new methodology for evaluating and ranking football players based on multi-criteria analysis. The study used a sample of twenty-four middle school players in Malaysia and grouped them for validation. The TOPSIS method was used, and results showed its effectiveness in solving player selection problems. A statistical comparison between group scores and rankings confirmed its applicability for school-level sports selection by focusing on specific performance criteria.

Karaatlı and Dağ (2018) focused on player selection for the Turkish National Men's Football Team using MCDM techniques. Methods such as AHP, TOPSIS, GRA, COPRAS, and the Borda Count Method were employed to determine the weights of criteria and analyze multi-season performance data. The study offers a reference framework for future research on player selection in national teams and across different sports, emphasizing multi-criteria evaluations. In another study, Blanco et al. (2018) utilized the PROMETHEE methodology to rank basketball players based on criteria such as scoring, playing time, and number of attempts. The study proposed a performance ranking method that applies a multi-criteria preference framework, offering a quantitative tool to evaluate athlete performance and contributing significantly to the literature.

Flegl et al. (2018) proposed a new personnel selection methodology based on MCDM for the Mexican national football team in preparation for the 2018 FIFA World Cup in Russia. The model was validated using data from the 2014 FIFA World Cup in Brazil, where 13 of the 23 players selected by the model also appeared on the final national roster. Although the match rate was slightly below 60%, the model proved its feasibility and practical applicability. The study emphasized the importance of decision-making tools in managing the complexities of personnel selection when multiple criteria are involved.

Esen and Uslu (2020) conducted a study using AHP and TOPSIS to evaluate the athletic abilities of 20 primary school boys with a mean age of 9.64 ± 0.37 years. Tests included balance, reaction, agility, jumping, endurance, and flexibility. Since few studies have integrated AHP and TOPSIS with qualitative assessments in talent selection, the criteria weights determined via pairwise comparisons in this study may serve as a reference for future research.

Anamisa et al. (2021) aimed to support coaches in determining the most suitable positions for football players through objective decision-making. In this study, the AHP method was used to assign weights to 12 criteria, and the TOPSIS method was applied to conduct precise evaluations. Using data from 112 players, the study assessed suitability across positions, including defensive midfielders, goalkeepers, midfielders, and defenders. The system achieved an accuracy of 83.9% across these four roles, demonstrating its effectiveness.

Zulfikar et al. (2020) implemented a decision support system to identify the best players in the English football league during the 2020/21 season. Seven evaluation criteria were used: number of goals, assists, shots, wins, passes, fouls, and playing time. The study employed three MCDM techniques—AHP, PROMETHEE, and TOPSIS. The combination of methods improved the reliability and fairness of the evaluations and emphasized the importance of using concrete and accurate assessments in the decision-making process.

Aydın et al. (2021) applied the VIKOR method to evaluate and select players for the Turkish National Football Team based on data from the 2018–2019 season. The objective was to eliminate subjectivity from the selection process. The study relied on historical performance data and demonstrated that similar evaluations could also guide future transfers between clubs.

Ati et al. (2024) conducted a systematic literature review based on Kitchenham's guidelines to compile studies on the use of MCDM and machine learning in player selection and performance prediction. The review aimed to support the development of decision support systems and integrated machine learning algorithms to facilitate more objective and accurate decisions in football.

The literature review confirms that MCDM methods are widely and effectively used in various sports disciplines. However, the review also reveals a noticeable gap in the application of these methods to volleyball player selection. This indicates that the use of analytical techniques in volleyball remains underexplored and underutilized. Given the unique performance evaluation needs of each playing position, future studies applying MCDM methods to volleyball are expected to yield significant contributions.

The objectives of this study are threefold: (1) to construct a team that will maximize the performance of the Turkish Women's National Volleyball Team, (2) to apply MCDM techniques to systematically and objectively evaluate player performance criteria, and (3) to address the gap in the literature on volleyball player selection by demonstrating the applicability and effectiveness of MCDM methods, thereby contributing to future research and practice in this domain.

Material and Methods

In this study, player selection for the Turkish Women's National Volleyball Team was conducted based on playing positions, using the 30-player preliminary roster announced for the 2024 Volleyball Nations League (VNL), organized by the Fédération Internationale de Volleyball (FIVB), as the foundation. To evaluate player performance during the selection process, official performance statistics from the 2023–2024 season were collected from the websites of the Turkish Volleyball Federation (2024), China Volleyball Association (2024), Russian Volleyball Federation (2024), German Volleyball Federation (2024), Japan Volleyball Association (2024), and Polish Volleyball Federation (2024). These statistics served as the primary data source to analyze each player's seasonal performance objectively. Table 1 presents the league and team affiliations of players included in the 30-player extended roster.

Table 1. Turkish Women's National Volleyball Team – 2024 VNL Preliminary Roster

	No	Player	Volleyball League	Team
LIBERO	1	Gizem Orge	Türkiye Vodafone Sultans League	Fenerbahce
	2	Simge Akoz	Türkiye Vodafone Sultans League	Vakifbank
	3	Ayca Aykac	Türkiye Vodafone Sultans League	Vakifbank
	4	Melis Yılmaz	Türkiye Vodafone Sultans League	Turk Hava Yollari
OUTSIDE HITTER	5	Hande Baladin	Türkiye Vodafone Sultans League	Eczacibasi
	6	Meliha Diken	Türkiye Vodafone Sultans League	Fenerbahce
	7	Ilkin Aydin	Türkiye Vodafone Sultans League	Galatasaray
	8	Tugba Senoglu Ivegin	Türkiye Vodafone Sultans League	Kuzeyboru
	9	Idil Naz Bascan	Türkiye Vodafone Sultans League	Vakifbank (first half)
				Besiktas (second half)
	10	Bianka Ilayda Mumcular	Türkiye Women's Volleyball 1st League	Edremit Bld. Altınoluk
	11	Derya Cebecioglu	Japan 1st V. League	Kurobe AquaFairies (first half)
			Türkiye Vodafone Sultans League	Vakıfbank (second half)
	12	Saliha Sahin	Poland Tauron Liga	Chemik Police
	13	Ebrar Karakurt	Russian Volleyball Super League	Lokomotiv Kaliningrad
O PPOSI	14	Alexia Carutasu	Türkiye Vodafone Sultans League	Vakıfbank
	15	Defne Basyolcu	Türkiye Vodafone Sultans League	Eczacibasi

	16	Melissa Vargas	China Women's Volleyball Super League	Tianjin Bohai Bank (first half)
			Türkiye Vodafone Sultans League	Fenerbahce (second half)
	17	Tutku Burcu Yuzgenc	German Women's 1. Bundesliga League	SSC Palmberg Schwerin
MIDDLE BLOCKER	18	Eda Erdem Dundar	Türkiye Vodafone Sultans League	Fenerbahce
	19	Zehra Gunes	Türkiye Vodafone Sultans League	Vakifbank
	20	Aslı Kalac	Türkiye Vodafone Sultans League	Fenerbahce
	21	Beyza Arıcı	Türkiye Vodafone Sultans League	Eczacibasi
	22	Kubra Akman	Türkiye Vodafone Sultans League	Turk Hava Yollari
	23	Yasemin Guveli	Türkiye Vodafone Sultans League	Cukurova Belediyespor
	24	Bahar Akbay	Türkiye Vodafone Sultans League	Vakifbank
	25	Bengisu Aygun	Türkiye Vodafone Sultans League	Besiktas
	26	Deniz Uyanık	Türkiye Vodafone Sultans League	Nilufer Belediyespor
SETTER	27	Cansu Ozbay	Türkiye Vodafone Sultans League	Vakifbank
	28	Elif Sahin	Türkiye Vodafone Sultans League	Eczacibasi
	29	Sıla Calıskan	Türkiye Vodafone Sultans League	Turk Hava Yollari
	30	Dilay Ozdemir	Türkiye Vodafone Sultans League	Karayollari

Due to the unavailability of performance statistics from Türkiye's First Division Women's Volleyball League, Bianka İlayda Mumcular was excluded from this analysis. To facilitate comparisons among alternatives, players were categorized into five groups by position: Libero (4 players), Outside Hitter (8 players), Opposite Hitter (4 players), Middle Blocker (9 players), and Setter (4 players). Figure 1 illustrates the typical court positioning of these roles.

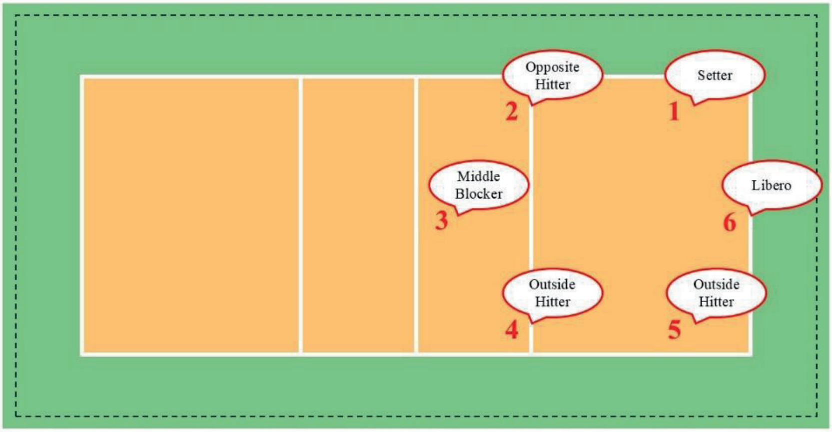


Figure 1. Standard Volleyball Court Positions of the Players

The study focused on the five fundamental volleyball positions—outside hitter, setter, opposite hitter, middle blocker, and libero—illustrated in Figure 1. Each position's specific responsibilities and roles were analyzed in detail. Accordingly, distinct performance criteria were established for each role. The performance data used for evaluation were obtained from the official websites of the respective volleyball leagues, ensuring data reliability. For players who transferred between teams mid-season, cumulative performance statistics were used to reflect their complete seasonal output. Position-specific performance statistics for each player are presented in the following tables.

Table 2. Performance Statistics for Libero Position

Player	Games	Sets	Excellent Reception	Positive Reception	Poor Reception	Very Poor Reception	Reception Errors	Ace Against
Gizem Orge	33	116	150	22	75	32	116	112
Simge Akoz	30	95	110	25	51	27	67	71
Ayca Aykac	22	71	125	19	55	19	74	67
Melis Yılmaz	27	90	94	17	54	16	80	64

Table 2 presents the performance statistics for four libero players over the season, including the number of games and sets played, reception quality, reception errors, and the number of aces conceded.

Table 3. Performance Statistics for Outside Hitter Position

Player	Games	Sets	Aces	Blocks	Attacks	Attacks Errors	Successful Attack	Reception
Hande Baladin	31	89	16	42	206	52	46	121
Meliha Diken	31	101	18	29	116	23	27	99
Ilkin Aydin	31	116	36	30	394	67	98	172
Idil Naz Bascan	21	61	25	12	92	25	21	85

Derya Cebecioglu	24	73	8	18	261	52	5	193
Saliha Sahin	26	63	10	17	332	23	30	72
Ebrar Karakurt	38	133	42	70	686	192	99	60

Table 3 provides the seasonal performance statistics for seven outside hitters, including games and sets, service aces, blocks, attacks, attack errors, successful attacks, and receptions.

Table 4. Performance Statistics for Opposite Hitter Position

Player	Games	Sets	Aces	Service Errors	Blocks	Attacks	Attack Errors
Alexia Carutasu	30	98	22	50	43	221	38
Defne Basyolcu	5	9	2	2	1	6	1
Melissa Vargas	35	111	60	82	45	497	52
Tutku Burcu Yuzgenc	20	60	12	7	35	152	43

Table 4 presents performance statistics for four opposite hitters. Variables include games and sets played, service aces, service errors, blocks, total attacks, and attack errors. For Defne Başyolcu, whose values for blocks and attack errors were zero, the value “1” was used to maintain consistency in the evaluation process.

Table 5. Performance Statistics for Middle Blocker Position

Player	Games	Sets	Total Serves	Successful Serves	Service Errors	Total Blocks	Successful Blocks	Block Errors	Total Attacks	Successful Attacks	Attack Errors
Eda Erdem Dundar	27	94	20	47	30	64	12	76	169	24	21
Zehra Gunes	24	85	26	36	13	66	18	76	119	29	26
Aslı Kalac	31	108	19	43	21	89	14	89	123	20	15
Beyza Arici	29	82	18	24	13	61	8	65	80	14	9
Kubra Akman	28	97	9	23	15	56	9	78	88	7	13
Yasemin Guveli	15	53	13	26	11	60	25	66	87	14	15
Bahar Akbay	25	67	14	26	16	33	6	57	58	9	2
Bengisu Aygun	26	91	17	36	11	71	20	107	65	11	11
Deniz Uyanik	29	107	17	30	11	69	15	113	150	33	16

Table 5 summarizes the performance of nine middle blockers throughout the season, based on match data, serving and blocking metrics, and attacking statistics.

Table 6. Performance Statistics for Setter Position

Player	Games	Sets	Excellent Setter Ball	Opponent's Ace	Net Fault
Cansu Ozbay	22	77	270	34	32
Elif Sahin	26	70	263	29	30
Sıla Caliskan	27	79	245	28	28
Dilay Ozdemir	23	80	259	33	52

Table 6 presents the seasonal performance data for four setters, including the number of games and sets played, the number of excellent sets, the number of opponents' aces conceded, and the number of net violations.

Based on the compiled data, a multi-phase analytical process was followed to identify the most suitable players for the Turkish Women's National Volleyball Team. First, the Analytic Hierarchy Process (AHP) was used to determine the weights of performance criteria. Next, player performances were evaluated using the TOPSIS, VIKOR, and PROMETHEE methods independently. Finally, these rankings were integrated using the Borda Count Method, allowing for the objective and systematic selection of the best players for each position.

Analytical Hierarchy Process (AHP)

Developed by Thomas L. Saaty in the 1970s, the Analytic Hierarchy Process (AHP) is a fundamental decision-making methodology. It is designed to aid decision-makers in selecting the optimal alternative among a set of options evaluated according to multiple criteria by addressing both rational and intuitive aspects. In this process, the decision-maker conducts pairwise comparisons to establish an overall prioritization of alternatives (Saaty & Vargas, 2012).

In AHP, Saaty's 1–9 fundamental scale is employed to facilitate pairwise comparisons between alternatives and criteria. The values 2, 4, 6, and 8 serve as intermediate levels of preference. This scale is presented in Table 7 (Hoş & Demirer, 2020).

Table 7. Saaty's 1–9 Fundamental Scale (Level of Importance)

Importance Level	Definition	Description
1	Equally Important	No dominance between two elements being compared.
3	Moderately More Important	One element is slightly more important than the other.
5	Strongly More Important	One element is significantly more important than the other.
7	Very Strongly Important	One element is very strongly favored over the other.
9	Extremely Important	One element is absolutely more important than the other.
2,4,6,8	Intermediate Values	Used when a compromise is needed between two judgments.

The AHP method comprises the following steps for problem-solving (Saaty, 1990):

Step 1: Constructing the Hierarchical Structure

The AHP technique establishes a hierarchical structure comprising multiple alternatives and criteria. This structure simplifies complex problems by decomposing them into manageable subcomponents, thereby enhancing comprehensibility. An example of a hierarchical model for player selection is illustrated in Figure 2.

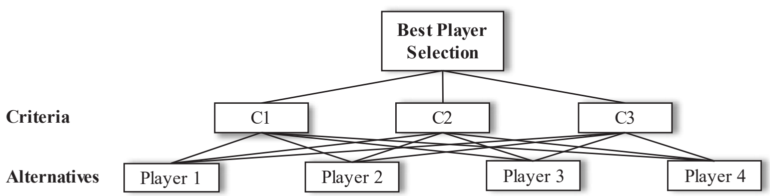


Figure 2. Hierarchical Structure for Optimal Player Selection (Three-Level Model)

Step 2: Forming the Pairwise Comparison Matrix

After defining the hierarchy, the criteria and alternatives are compared pairwise by experts. In the resulting square matrix (Equation 1), diagonal elements (i = j) take a value of "1" as each criterion is compared to itself. The values in the upper triangle of the matrix are assigned according to Saaty's scale (Table 7), and the corresponding reciprocal values are placed in the lower triangle using Equation 2.

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} = 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} = 1/a_{1n} & a_{n2} = 1/a_{2n} & \dots & 1 \end{bmatrix} \quad (1)$$

$$a_{ij} = \frac{1}{a_{ji}} \quad (2)$$

Step 3: Calculating the Relative Importance Vector (Eigenvector)

The entries in the pairwise comparison matrix are used to compute the relative importance vector, which indicates the importance of each criterion relative to others. This is calculated using Equation 3.

$$w_i = \frac{(a_{ij})^{1/n}}{\sum_{i=1}^{n}(a_{ij})^{1/n}} \quad (3)$$

The resulting relative importance vector *w* is:

$$w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ \vdots \\ w_n \end{bmatrix} \quad (4)$$

Step 4: Consistency Ratio Calculation

To verify the consistency of expert judgments in the pairwise comparison matrix, the Consistency Ratio (CR) is computed. A CR value greater than 0.10 indicates inconsistent judgments, necessitating a review of the matrix. The process begins by calculating the maximum eigenvalue (λ_{max}) using Equation 5.

$$\lambda_{max} = \frac{Aw}{w} \quad (5)$$

where *A* is the pairwise comparison matrix, and *w* is the eigenvector.

The Consistency Index (CI) is then calculated as:

$$CR = \frac{\lambda_{max} - n}{(n-1)} \tag{6}$$

The Consistency Ratio is computed by dividing CI by the Random Index (RI) (Equation 7), which varies with the number of criteria, *n*. Table 8 provides RI values for various matrix sizes.

$$CR = \frac{CI}{RI} \tag{7}$$

Table 8. Random Index (RI) Values (Saaty, 1990)

							0	**1**	**2**	**3**	**4**	**5**
I .58	.9	.12	.24	.32	.41	.45	.49	.51	.48	.56	.57	.59
If the calculated CR ≤ 0.10, the level of consistency is considered acceptable.												

TOPSIS Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a widely used method in Multi-Criteria Decision-Making (MCDM), developed by Yoon and Hwang (1981). It is based on the principle that the most preferable alternative should have the shortest geometric distance from the Positive Ideal Solution (PIS) and the farthest distance from the Negative Ideal Solution (NIS). In this context, the PIS maximizes beneficial attributes and minimizes cost-related ones, whereas the NIS does the opposite, minimizing benefits and maximizing costs (Huang & Peng, 2012).

According to Yoon and Hwang (1995), the steps of the TOPSIS method are as follows:

Step 1: Constructing the Decision Matrix

The decision matrix *A* (Equation 8) is constructed with alternatives listed in rows and evaluation criteria listed in columns:

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \tag{8}$$

Where a_{ij} represents the performance score of the i^th^ alternative under the j^th^ criterion.

Step 2: Normalizing the Decision Matrix

Each element of the decision matrix is normalized using Equation 9.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{9}$$

This yields the normalized decision matrix $R=[r_{ij}]$ shown in Equation 10.

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad \text{for } i = 1,2,3,\dots,m \text{ ve } j = 1,2,3,\dots,n$$

(10)

Step 3: Constructing the Weighted Normalized Decision Matrix

Weights (w_j) determined in the AHP process are assigned to each criterion. The normalized values are multiplied by their respective weights (Equation 11) to form the weighted normalized matrix $V=[v_{ij}]$ (Equation 12).

$$v_{ij} = w_j \times r_{ij} \tag{11}$$

$$V_{ij} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \tag{12}$$

Step 4: Determining the Positive Ideal Solution (A^+) and Negative Ideal Solution (A^-)

For each criterion, the highest value corresponds to the PIS and the lowest to the NIS, are computed through Equations 13 and 14 (Arıbaş & Özcan, 2016).

$$A^+ = \left\{\left(\max_i v_{ij} \,\middle|\, j \in J\right), \left(\min_i v_{ij} \,\middle|\, j \in J'\right)\right\} \tag{13}$$

$$A^- = \left\{\left(\min_i v_{ij} \,\middle|\, j \in J\right), \left(\max_i v_{ij} \,\middle|\, j \in J'\right)\right\}$$

(14)

Where J is the set of benefit criteria and J' is the set of cost criteria.

Step 5: Calculating the Separation Measures

The Euclidean distance is used to calculate the separation of each alternative from the ideal and negative-ideal solutions as given in Equations 15 and 16.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2} \tag{15}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \tag{16}$$

Step 6: Calculating the Relative Closeness to the Ideal Solution

The relative closeness of each alternative to the ideal solution is calculated as:

$$C_i^+ = \frac{S_i^-}{S_i^- + S_i^+} \tag{17}$$

The value of C_i^+ lies between 0 and 1. Alternatives are ranked in descending order based on C_i^+, with the highest score indicating the most preferable option.

VIKOR Method

The VIKOR method (VlseKriterijumska Optimizacija I Kompromisno Resenje), developed by Serafim Opricovic in 1998, is an optimization and compromise-ranking method used for solving Multi-Criteria Decision-Making (MCDM) problems. VIKOR aims to identify a compromise solution that maximizes group utility and minimizes individual regret when conflicting criteria are present (Opricovic & Tzeng, 2007). The methodological steps of the VIKOR technique are as follows:

Step 1: Determination of the Best (fi^*) and Worst (fi^-) Values for Each Criterion

For $i = 1,2,\dots,n;$

If the i^{th} criterion represents a benefit:

$$f_i^* = \max_j f_{ij}, \quad f_i^- = \min_j f_{ij}, \tag{18}$$

If the i^{th} criterion represents a cost:

$$f_i^* = \min_j f_{ij}, \quad f_i^- = \max_j f_{ij}, \tag{19}$$

Step 2: Calculation of S_j (Group Utility Measure) and R_j (Individual Regret Measure)

Using the weights w_i assigned to each criterion, the following measures are computed:

For j = 1,2, … , J;

$$S_j = \sum_{i=1}^{n} w_i(f_i^* - f_i^-)/(f_i^* - f_i^-), \tag{20}$$

$$R_j = \max_i\left[w_i\left(f_i^* - f_{ij}\right)/(f_i^* - f_i^-)\right], \tag{21}$$

Where S_j represents the aggregated gap from the ideal solution (group benefit), while R_j identifies the maximum individual regret for each alternative.

Step 3: Computation of Q_j (Compromise Measure)

A compromise ranking index Q_j is calculated for each alternative:

For j = 1,2, … , J;

$$Q_j = v(S_j - S^*)/(S^- - S^*) + (1 - v)(R_j - R^*)/(R^- - R^*), \tag{22}$$

Where:

- $S^* = \min\ S_j, S^- = \max\ S_j$
- $R^* = \min\ R_j, R^- = \max\ R_j$
- v is the weight of the decision-making strategy emphasizing "the majority rule" (commonly taken as $v = 0.5$); $1 - v$ emphasizes "individual regret" (Tzeng et al., 2005).

Step 4: Ranking Alternatives Based on S, R, and Q Values

Three separate rankings are generated: one each for S_j, R_j, and Q_j, arranged from best (smallest value) to worst (largest value).

Step 5: Proposing the Compromise Solution

The alternative with the lowest $Q_j$value is proposed as the best compromise solution if the following two conditions are simultaneously satisfied:

- *Condition 1 (Acceptable Advantage):*

$$Q\left(A^{(2)}\right) - Q(A^{(1)}) \geq DQ \tag{23}$$

$$DQ = 1/(J-1) \tag{24}$$

Where $A^{(1)}$and $A^{(2)}$represent the first and second-ranked alternatives, respectively, and J is the number of evaluated alternatives.

- *Condition 2 (Acceptable Stability in Decision-Making):*

The top-ranked alternative $A^{(1)}$ must also be ranked first in at least one of the Sor R rankings.

If either condition is not met:

- If only Condition 2 fails, both $A^{(1)}$and $A^{(2)}$ are considered as compromise solutions.
- If Condition 1 fails, all alternatives $A^{(1)}$, $A^{(2)}$, ..., $A^{(M)}$ satisfying the following condition are included in the compromise set (Equation 25):

$$Q(A^M) - Q(A^1) < DQ \tag{25}$$

PROMETHEE Method

PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations), developed in 1982 by Jean-Pierre Brans, is one of the multi-criteria decision-making methods used to analyze and rank alternatives. Unlike other MCDM methods, PROMETHEE considers not only the importance weights that indicate the relational structure among criteria but also the internal relationships within each evaluation factor (Özlemiş & Eren, 2024).

The steps of the PROMETHEE method are as follows (Aslan & Bağ, 2021):

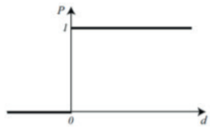
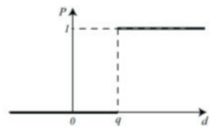
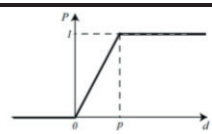
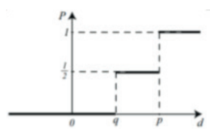
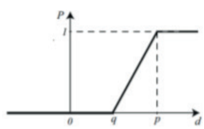
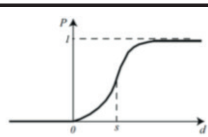
Step 1: Identification of Alternatives, Criteria, and Criterion Weights

For the decision problem, the alternatives, the criteria to be considered in selecting and/or ranking these alternatives, and the weights of these criteria are identified.

Step 2: Definition of Preference Functions for Each Criterion

Preference functions are mathematical tools used to determine decision-makers' preferences among options, helping identify the most suitable choices in a given situation or decision. Table 9 presents six types of preference functions. In this study, the Type 5 (Linear) Preference Function was used, based on expert opinion. The Linear Preference Function assesses preferences linearly and proportionally reflects differences between alternatives.

Table 9. Types of Preference Functions.

Type	Graphic	Definition	Parameter
Type 1: Usual		$P(d) = \begin{Bmatrix} 0 & d \leq 0 \\ 1 & d > 0 \end{Bmatrix}$	-
Type 2: U-Shape		$P(d) = \begin{Bmatrix} 0 & d \leq q \\ 1 & d > q \end{Bmatrix}$	q
Type 3: V-Shape		$P(d) = \begin{Bmatrix} 0 & d \leq 0 \\ \dfrac{d}{p} & 0 \leq d \leq p \\ 1 & d > p \end{Bmatrix}$	p
Type 4: Level		$P(d) = \begin{Bmatrix} 0 & d \leq q \\ \dfrac{d-q}{p-q} & 0 \leq d \leq p \\ 1 & d > p \end{Bmatrix}$	p,q
Type 5: Linear		$P(d) = \begin{Bmatrix} 0 & d \leq q \\ \dfrac{d-q}{p-q} & q \leq d \leq p \\ 1 & d > p \end{Bmatrix}$	p,q
Type 6: Gaussian		$P(d) = \begin{Bmatrix} 0 & d \leq 0 \\ 1 - e^{-\frac{d^2}{2s^2}} & d > 0 \end{Bmatrix}$	s

Step 3: Calculation of Preference Values for Each Criterion

For each criterion, a pairwise comparison of alternatives is conducted, and the degree of preference is computed using the corresponding preference function (type 5 linear).

Step 4: Determination of Aggregated Preference Indices

The preference values obtained for each criterion are multiplied by the criterion's weight, and aggregated preference indices are calculated for each pair of alternatives.

Step 5: Calculation of Positive and Negative Preference Flows

Positive preference flow Phi$^+$ (Φ^+) represents the extent to which an alternative is preferred over all others. In contrast, negative preference flow Phi$^-$ (Φ^-) indicates the extent to which others dominate an alternative.

Step 6: Determination of Partial Preferences with PROMETHEE I

According to partial preferences, if any of the conditions expressed in Equations 26, 27, or 28 is satisfied, alternative *a* is preferred over alternative *b*:

$$\Phi^+(a) > \Phi^+(b) \text{ and } \Phi^-(a) < \Phi^-(b) \tag{26}$$

$$\Phi^+(a) = \Phi^+(b) \text{ and } \Phi^-(a) < \Phi^-(b) \tag{27}$$

$$\Phi^+(a) > \Phi^+(b) \text{ and } \Phi^-(a) = \Phi^-(b) \tag{28}$$

If the condition in Equation 29 is satisfied, *a* and *b* are considered indifferent:

$$\Phi^+(a) = \Phi^+(b) \text{ and } \Phi^-(a) = \Phi^-(b) \tag{29}$$

If either of the conditions in Equations 30 or 31 is satisfied, *a* and *b* are considered incomparable:

$$\Phi^+(a) > \Phi^+(b) \text{ and } \Phi^-(a) > \Phi^-(b) \tag{30}$$

$$\Phi^+(a) < \Phi^+(b) \text{ and } \Phi^-(a) < \Phi^-(b) \tag{31}$$

Step 7: Determination of Complete Preferences with PROMETHEE II

The complete preference of an alternative is determined by the difference between its positive and negative preference flows, as shown in Equation 32. When alternatives are ranked in descending order according to their complete preference values, the final preference ranking is obtained:

$$\Phi(a) = \Phi^+(a) - \Phi^-(a) \tag{32}$$

Borda Count Method

The Borda Count Method was introduced in 1784 by Jean-Charles de Borda as a voting technique. The Borda Count, which played an essential role in the development of modern election systems, is a technique that ranks candidates (alternatives) based on the sum of the individual preferences of voters (decision-makers) (Cerrahoğlu, 2021).

Within the method, which is based on selecting the decision alternative that best serves the purpose, Borda points are calculated by assigning (n−1) points to the most preferred alternative among *n* alternatives, (n−2) points to the second most preferred alternative, and so on, with 0 points assigned to the least preferred alternative. The best alternative is determined by ranking the obtained Borda points from highest to lowest (Gök Kısa & Perçin, 2020; Lumini & Nanni, 2006). The Borda score for each alternative is calculated using Equation 33.

For $i = 1,2,3, \ldots, m$ and $j = 1,2,3, \ldots, n$;

$$b_i = \sum_{j=1}^{n} (m - r_{ij}) \qquad (33)$$

Where:

r_{ij}: the ranking of the i^{th} alternative under the j^{th} criterion
m: total number of alternatives

Results and Discussion

In this section, the data and analyses obtained as a result of the application of Multi-Criteria Decision-Making (MCDM) methods are presented. In the performance evaluation, the criterion weights determined by the AHP method were applied to rank the players using TOPSIS, VIKOR, and PROMETHEE, respectively, and the resulting rankings were then combined using the Borda count method. As a result of these analyses, the goal is to identify the best player by position and to construct the most suitable squad for the Turkish Women's National Volleyball Team.

Criterion Weighting with the Analytic Hierarchy Process (AHP)

Since each position in volleyball has its own unique duties and responsibilities, the criteria for evaluating player performance differ by position. In this study, expert opinions were used to determine the criteria for each position and their weights. In line with the contributions of these experts, the criteria considered essential for each position were identified, and their weights were calculated using the AHP (Analytic Hierarchy Process) method. In this way, the aim was to perform the most accurate and comprehensive evaluation for each position. The criteria and criterion weights for the respective positions are presented in Tables 10-14.

Table 10. Libero Criteria Weights

Criteria	Games	Sets	Excellent Reception	Positive Reception	Poor Reception	Very Poor Reception	Reception Errors	Ace Against
Criteria Weights	0.03618	0.03618	0.3066	0.17289	0.07933	0.11605	0.10115	0.15162

Table 11. Outside Hitter (Spiker) Criteria Weights

Criteria	Games	Sets	Aces	Blocks	Attacks	Attacks Errors	Successfu l Attack	Receptio n
Criteria Weights	0.03106	0.03587	0.07911	0.22289	0.20113	0.13721	0.18774	0.10018

Table 12. Opposite Hitter Criteria Weights

Criteria	Games	Sets	Aces	Service Errors	Blocks	Attacks	Attack Errors
Criteria Weights	0.29884	0.18638	0.13721	0.09693	0.11679	0.07164	0.09222

Table 13. Middle Blocker Criteria Weights

Criteria	Games	Sets	Total Serves	Successful Serves	Service Errors	Total Blocks	Successful Blocks	Block Errors	Total Attacks	Successful Attacks	Attack Errors
Criteria Weights	0.17045	0.17045	0.10768	0.09123	0.08551	0.0764	0.06812	0.06498	0.05718	0.04999	0.05803

Table 14. Setter Criteria Weights

Criteria	Games	Sets	Excellent Setter Ball	Opponent's Ace	Net Fault
Criteria Weights	0.06898	0.06898	0.17057	0.26906	0.42241

TOPSIS Method Player Selection Results

First, the decision matrix for the libero position, consisting of four alternatives and eight criteria (Table 2), was normalized using Equation 9. As a result of this procedure, the normalized decision matrix presented in Table 15 was obtained.

Table 15. Normalized Decision Matrix for the Libero Position

Player	Games	Sets	Excellent Reception	Positive Reception	Poor Reception	Very Poor Reception	Reception Errors	Ace Against
Gizem Orge	0.58318	0.61461	0.61722	0.52455	0.63012	0.65732	0.67173	0.69233
Simge Akoz	0.53016	0.50334	0.45263	0.59608	0.42848	0.55461	0.38798	0.43889
Ayca Aykac	0.38879	0.37618	0.51435	0.45302	0.46209	0.39028	0.42852	0.41416
Melis Yılmaz	0.47715	0.47685	0.38679	0.40534	0.45369	0.32866	0.46326	0.39562

In the normalized decision matrix, each value was multiplied by the criterion weights provided in Table 10 to obtain the Weighted Normalized Decision Matrix. By applying Equations 13 and 14 to each column of the weighted normalized matrix, the A^+ and A^- values were calculated. The results of these computations are provided in detail in Table 16.

Table 16. Weighted Normalized Decision Matrix for the Libero Position

Player	Games	Sets	Excellent Reception	Positive Reception	Poor Reception	Very Poor Reception	Reception Errors	Ace Against
Gizem Orge	0.02110	0.02224	0.18924	0.09069	0.04999	0.07628	0.06795	0.10497
Simge Akoz	0.01918	0.01821	0.13877	0.10306	0.03399	0.06436	0.03924	0.06655
Ayca Aykac	0.01407	0.01361	0.15770	0.07832	0.03666	0.04529	0.04334	0.06280
Melis Yılmaz	0.01726	0.01725	0.11859	0.07008	0.03599	0.03814	0.04686	0.05999
A^+	0.02110	0.02224	0.18924	0.10306	0.03399	0.03814	0.03924	0.05999
A^-	0.01407	0.01361	0.11859	0.07008	0.04999	0.07628	0.06795	0.10497

Using Equations 15 and 16, the Si^+ and Si^- values given in Table 17 were obtained to determine each alternative's distance from the ideal solution. Then, the Ci^+ value obtained through Equation 17 was used to identify the best option within the group.

Table 17. Ci^+ Values for the Libero Position

Player	Si^+	Si^-	Ci^+	Ranking
Gizem Orge	0.06864	0.07443	12.84954	**1**
Simge Akoz	0.05742	0.06512	8.45588	**2**
Ayca Aykac	0.04258	0.07155	2.47003	**3**
Melis Yılmaz	0.07862	0.06436	-4.51626	**4**

Based on the ranking results, Gizem Örge (Ci^+ = 12.84954) was selected as the best alternative. The remaining players ranked as follows: Simge Aköz (Ci^+ = 8.45588), Ayça Aykaç (Ci^+ = 2.47003), and Melis Yılmaz (Ci^+ = –4.51626). The decision matrix in Table 3, consisting of eight alternatives and eight criteria for the outside hitter position, was normalized using Equation 9. The resulting normalized matrix is given in Table 18.

Table 18. Normalized Decision Matrix for the Outside Hitter Position

Player	Games	Sets	Aces	Blocks	Attacks	Attacks Errors	Successful Attack	Reception
Hande Baladin	0.37582	0.33239	0.23025	0.41870	0.21349	0.22767	0.28922	0.33548
Meliha Diken	0.37582	0.37720	0.25903	0.28911	0.12022	0.10070	0.16976	0.27449
Ilkin Aydın	0.37582	0.43323	0.51805	0.29907	0.40833	0.29335	0.61616	0.47689
Tugba Senoglu Ivegin	0.33945	0.36227	0.28781	0.29907	0.25909	0.26708	0.25778	0.41866
Idil Naz Bascan	0.25459	0.22782	0.35976	0.11963	0.09535	0.10946	0.13203	0.23567
Derya Cebecioglu	0.29096	0.27263	0.11512	0.17944	0.27049	0.22767	0.03144	0.53511
Saliha Sahin	0.31520	0.23529	0.14390	0.16948	0.34408	0.10070	0.18862	0.19963
Ebrar Karakurt	0.46068	0.49671	0.60439	0.69784	0.71095	0.84064	0.62244	0.16636

Each value in the normalized decision matrix was multiplied by the criterion weights given in Table 11 to obtain the Weighted Normalized Decision Matrix. Equations 13 and 14 were applied to each column to determine A^+ and A^- values. The results are shown in Table 19.

Table 19. Weighted Normalized Decision Matrix for the Outside Hitter Position

Player	Games	Sets	Aces	Blocks	Attacks	Attacks Errors	Successful Attack	Reception
Hande Baladin	0.09305	0.08230	0.05701	0.05318	0.00698	0.00744	0.00946	0.01097
Meliha Diken	0.09305	0.09340	0.06413	0.03672	0.00393	0.00329	0.00555	0.00898
Ilkin Aydın	0.09305	0.10727	0.12827	0.03798	0.01335	0.00959	0.02015	0.01559
Tugba Senoglu Ivegin	0.08405	0.08970	0.07126	0.03798	0.00847	0.00873	0.00843	0.01369
Idil Naz Bascan	0.06304	0.05641	0.08908	0.01519	0.00312	0.00358	0.00432	0.00771
Derya Cebecioglu	0.07204	0.06750	0.02850	0.02279	0.00885	0.00744	0.00103	0.01750
Saliha Sahin	0.07804	0.05826	0.03563	0.02152	0.01125	0.00329	0.00617	0.00653
Ebrar Karakurt	0.11406	0.12299	0.14965	0.08863	0.02325	0.02749	0.02035	0.00544
A^+	0.11406	0.12299	0.14965	0.08863	0.02325	0.00329	0.02035	0.01750
A^-	0.06304	0.05641	0.02850	0.01519	0.00312	0.02749	0.00103	0.00544

Using Equations 15 and 16, the Si^+ and Si^- values were calculated (Table 20). Then, the Ci^+ values obtained from Equation 17 enabled ranking the alternatives.

Table 20. Ci^{+} Values for the Outside Hitter Position

Player	Si^{+}	Si^{-}	Ci^{+}	Ranking
Meliha Diken	0.10949	0.11642	16.80082	**1**
Hande Baladin	0.11126	0.12351	10.08193	**2**
Tugba Senoglu Ivegin	0.10547	0.13414	4.67837	**3**
Ilkin Aydın	0.06206	0.17411	1.55387	**4**
Ebrar Karakurt	0.02703	0.18247	1.17393	**5**
Saliha Sahin	0.15315	0.08658	-1.30047	**6**
Idil Naz Bascan	0.12983	0.10922	-5.29776	**7**
Derya Cebecioglu	0.15637	0.13478	-6.24087	**8**

According to the ranking, Meliha Diken (Ci^{+} = 16.80082) was selected as the best alternative. The remaining rankings were: Hande Baladın (Ci^{+} = 10.08193), Tuğba Şenoğlu İvegin (Ci^{+} = 4.67837), İlkin Aydın (Ci^{+} = 1.55387), Ebrar Karakurt (Ci^{+} = 1.17393), Saliha Şahin (Ci^{+} = –1.30047), İdil Naz Başcan (Ci^{+} = –5.29776), and Derya Cebecioğlu (Ci^{+} = –6.24087). The decision matrix in Table 4, consisting of four alternatives and seven criteria for the opposite hitter position, was normalized using Equation 9. The resulting normalized matrix is presented in Table 21.

Table 21. Normalized Decision Matrix for the Opposite Hitter Position

Player	Games	Sets	Aces	Service Errors	Blocks	Attacks	Attack Errors
Alexia Karutasu	0.59409	0.61243	0.33818	0.51912	0.60212	0.39129	0.49066
Defne Basyolcu	0.09901	0.05624	0.03074	0.02076	0.01400	0.01062	0.01291
Melissa Vargas	0.69310	0.69367	0.92231	0.85135	0.63013	0.87997	0.67143
Tutku Burcu Yuzgenc	0.39606	0.37496	0.18446	0.07268	0.49010	0.26913	0.55522

Each value was multiplied by the criterion weights given in Table 12 to construct the Weighted Normalized Decision Matrix. A^+ and A^- values were computed using Equations 13 and 14. The results are detailed in Table 22.

Table 22. Weighted Normalized Decision Matrix for the Opposite Hitter Position

Player	Games	Sets	Aces	Service Errors	Blocks	Attacks	Attack Errors
Alexia Karutasu	0.17754	0.11414	0.04640	0.05032	0.07032	0.02814	0.04525
Defne Basyolcu	0.02959	0.01048	0.00422	0.00201	0.00164	0.00076	0.00119
Melissa Vargas	0.20713	0.12928	0.12655	0.08252	0.07360	0.06328	0.06192
Tutku Burcu Yuzgenc	0.11836	0.06988	0.02531	0.00704	0.05724	0.01935	0.05120
A^+	0.20713	0.12928	0.12655	0.00201	0.07360	0.06328	0.00119
A^-	0.02959	0.01048	0.00422	0.08252	0.00164	0.00076	0.06192

Using Equations 15 and 16, the Si^+ and Si^- values were calculated and presented in Table 23. Ranking was determined using Ci^+ values computed via Equation 17.

Table 23. Ci^+ Values for the Opposite Hitter Position

Player	Si^+	Si^-	Ci^+	Ranking
Aleksia Karutasu	0.11423	0.20297	2.28725	**1**
Melissa Vargas	0.10084	0.26398	1.61815	**2**
Defne Basyolcu	0.26398	0.10084	-0.61815	**3**
Tutku Burcu Yuzgenc	0.16242	0.14527	-8.46732	**4**

According to the ranking, Aleksia Karutasu ($Ci^+ = 2.28725$) was identified as the best alternative, followed by Melissa Vargas ($Ci^+ = 1.61815$), Defne Başyolcu ($Ci^+ = -0.61815$), and Tutku Burcu Yüzgenç ($Ci^+ = -8.46732$). The decision matrix for the middle blocker position in Table 5, consisting of nine alternatives and eleven criteria, was normalized using Equation 9. The normalized matrix is given in Table 24.

Table 24. Normalized Decision Matrix for the Middle Blocker Position

Player	Games	Sets	Total Serves	Successful Serves	Service Errors	Total Blocks	Successful Blocks	Block Errors	Total Attacks	Successful Attacks	Attack Errors
Eda Erdem Dundar	0.34131	0.35306	0.37898	0.46984	0.59726	0.32953	0.26217	0.30620	0.51036	0.40286	0.44793
Zehra Gunes	0.30338	0.31926	0.49268	0.35987	0.25881	0.33982	0.39326	0.30620	0.35937	0.48679	0.55457
Aslı Kalac	0.39187	0.40564	0.36003	0.42985	0.41808	0.45825	0.30587	0.35858	0.37145	0.33572	0.31995
Beyza Arici	0.36659	0.30799	0.34108	0.23992	0.25881	0.31408	0.17478	0.26188	0.24159	0.23500	0.19197
Kubra Akman	0.35395	0.36433	0.17054	0.22992	0.29863	0.28833	0.19663	0.31426	0.26575	0.11750	0.27729
Yasemin Guveli	0.18962	0.19907	0.24634	0.25991	0.21899	0.30893	0.54620	0.26591	0.26273	0.23500	0.31995
Bahar Akbay	0.31603	0.25165	0.26529	0.25991	0.31854	0.16991	0.13109	0.22965	0.17515	0.15107	0.04266
Bengisu Aygun	0.32867	0.34179	0.32213	0.35987	0.21899	0.36557	0.43696	0.43110	0.19629	0.18465	0.23463
Deniz Uyanik	0.36659	0.40189	0.32213	0.29990	0.21899	0.35527	0.32772	0.45527	0.45298	0.55394	0.34128

Each value was weighted according to Table 13, forming the Weighted Normalized Decision Matrix. A^+ and A^- values were obtained using Equations 13 and 14, presented in Table 25.

Table 25. Weighted Decision Matrix for the Middle Blocker Position

Player	Games	Sets	Total Serves	Successful Serves	Service Errors	Total Blocks	Successful Blocks	Block Errors	Total Attacks	Successful Attacks	Attack Errors
Eda Erdem Dundar	0.05817	0.06018	0.04081	0.04286	0.05107	0.02517	0.01786	0.01990	0.02918	0.02014	0.02599
Zehra Gunes	0.05171	0.05442	0.05305	0.03283	0.02213	0.02596	0.02679	0.01990	0.02055	0.02434	0.03218
Aslı Kalac	0.06679	0.06914	0.03877	0.03921	0.03575	0.03501	0.02083	0.02330	0.02124	0.01678	0.01857
Beyza Arici	0.06248	0.05250	0.03673	0.02189	0.02213	0.02399	0.01191	0.01702	0.01381	0.01175	0.01114
Kubra Akman	0.06033	0.06210	0.01836	0.02098	0.02554	0.02203	0.01339	0.02042	0.01519	0.00587	0.01609
Yasemin Guveli	0.03232	0.03393	0.02653	0.02371	0.01873	0.02360	0.03720	0.01728	0.01502	0.01175	0.01857
Bahar Akbay	0.05387	0.04289	0.02857	0.02371	0.02724	0.01298	0.00893	0.01492	0.01001	0.00755	0.00248
Bengisu Aygun	0.05602	0.05826	0.03469	0.03283	0.01873	0.02793	0.02976	0.02801	0.01122	0.00923	0.01361
Deniz Uyanik	0.06248	0.06850	0.03469	0.02736	0.01873	0.02714	0.02232	0.02958	0.02590	0.02769	0.01980
A^{+}	0.06679	0.06914	0.05305	0.04286	0.01873	0.03501	0.03720	0.01492	0.02918	0.02769	0.00248
A^{-}	0.03232	0.03393	0.01836	0.02098	0.05107	0.01298	0.00893	0.02958	0.01001	0.00587	0.03218

Si^+ and Si^- values were computed using Equations 15 and 16 and are shown in Table 26. Ranking was completed using Ci^+ values.

Table 26. Ci^+ Values for the Middle Blocker Position

Player	Si^+	Si^-	Ci^+	Ranking
Eda Erdem Dundar	0.04956	0.05720	7.49058	**1**
Beyza Arici	0.04842	0.05666	6.88162	**2**
Bengisu Aygun	0.04167	0.06020	3.24920	**3**
Zehra Gunes	0.04171	0.06332	2.92980	**4**
Deniz Uyanik	0.03749	0.06870	2.20155	**5**
Aslı Kalac	0.03586	0.06715	2.14647	**6**
Yasemin Guveli	0.06594	0.04928	-2.95929	**7**
Bahar Akbay	0.06287	0.04821	-3.28903	**8**
Kubra Akman	0.05867	0.05198	-7.75973	**9**

Eda Erdem Dündar (Ci^+ = 7.49058) was identified as the best alternative. The following best were Beyza Arıcı (Ci^+ = 6.88161) and Bengisu Aygün (Ci^+ = 3.24920). The last three players were Yasemin Güveli (Ci^+ = –2.95929), Bahar Akbay (Ci^+ = –3.28903), and Kübra Akman (Ci^+ = –7.75973). The decision matrix for the setter position in Table 6 was normalized using Equation 9. The normalized matrix is given in Table 27.

Table 27. Normalized Decision Matrix for the Setter Position

Player	Games	Sets	Excellent Setter Ball	Opponent's Ace	Net Fault
Cansu Ozbay	0.44740	0.50261	0.52041	0.54654	0.43498
Elif Sahin	0.52874	0.45692	0.50692	0.46617	0.40780
Sıla Caliskan	0.54908	0.51567	0.47222	0.45009	0.38061
Dilay Ozdemir	0.46773	0.52220	0.49921	0.53047	0.70685

After multiplying these values by the criterion weights, the Weighted Decision Matrix was obtained, and A^+ and A^- values were calculated using Equations 13 and 14 (Table 28).

Table 28. Weighted Decision Matrix for the Setter Position

Player	Games	Sets	Excellent Setter Ball	Opponent's Ace	Net Fault
Cansu Ozbay	0.03086	0.03467	0.08876	0.14705	0.18374
Elif Sahin	0.03647	0.03152	0.08646	0.12543	0.17226
Sıla Caliskan	0.03788	0.03557	0.08055	0.12110	0.16077
Dilay Ozdemir	0.03227	0.03602	0.08515	0.14273	0.29858
A^+	0.03788	0.03602	0.08876	0.12110	0.16077
A^-	0.03086	0.03152	0.08055	0.14705	0.29858

Si^+ and Si^- values were computed using Equations 15 and 16; Ci^+ values were calculated using Equation 17 (Table 29).

Table 29. Ci^+ Values for the Setter Position

Player	Si^+	Si^-	Ci^+	Ranking
Cansu Ozbay	0.03538	0.11517	1.44345	**1**
Elif Sahin	0.01335	0.12842	1.11598	**2**
Sıla Caliskan	0.00823	0.14046	1.06225	**3**
Dilay Ozdemir	0.13965	0.00788	-0.05982	**4**

As per Table 29, Cansu Özbay ($Ci^+ = 1.44345$) was selected as the best setter, followed by Elif Şahin ($Ci^+ = 1.11598$), Sıla Çalışkan ($Ci^+ = 1.06225$), and Dilay Özdemir ($Ci^+ = -0.05982$).

VIKOR Method Player Selection Results

For the libero position, the four alternatives and eight criteria specified in Table 2 were evaluated using the VIKOR method. First, the best (fi^*) and worst (fi^-) values were calculated using Equations 18 and 19, and these values are presented in Table 30.

Table 30. Best and Worst Values for the Libero Position

Criteria	Games	Sets	Excellent Reception	Positive Reception	Poor Reception	Very Poor Reception	Reception Errors	Ace Against
f_i^*	33	116	150	25	51	16	67	64
f_i^-	22	71	94	17	75	32	116	112

Using the criterion weights provided in Table 10 and Equations 20 and 21, the Si (group utility measure) and Ri (individual regret measure) values in Table 31 were calculated. Then, based on the Qi (compromise ranking measure) values computed through Equation 22, the alternatives were evaluated. The alternative with the smallest Qi value was identified as the best option within the group. According to the ranking, Ayça Aykaç (Qi = 0.120) was selected as the best alternative. The other alternatives ranked as follows: Simge Aköz (Qi = 0.242), Gizem Örge (Qi = 0.439), and Melis Yılmaz (Qi = 1.000).

Table 31. Libero Position Ranking

Player	Si	Ri	Qi	Ranking
Ayca Aykac	0.40	0.14	0.120	**1**
Simge Akoz	0.35	0.22	0.242	**2**
Gizem Orge	0.51	0.15	0.439	**3**
Melis Yılmaz	0.56	0.31	1.000	**4**

When the best alternative is evaluated in terms of acceptable advantage and acceptable stability, using Equations 23 and 24, the acceptable advantage (C1) was calculated, and the DQ value was determined to be 0.3333. Since the C1 value (0.3662) is greater than 0.3333, the acceptable advantage condition is satisfied. The best alternative was also found to rank first according to the S and/or R values, indicating that the acceptable stability condition (C2) is satisfied.

For the outside hitter position, the eight alternatives and eight criteria specified in Table 3 were evaluated using the VIKOR method. First, the best (fi*) and worst (fi⁻) values calculated using Equations 18 and 19 are presented in Table 32.

Table 321. Best and Worst Values for the Outside Hitter Position

Criteria	Games	Sets	Aces	Blocks	Attacks	Attacks Errors	Successful Attack	Reception
f_i^*	38	133	42	70	686	23	99	193
f_i^-	21	61	8	12	92	192	5	60

Using the criterion weights given in Table 11 and Equations 20 and 21, the Si (group utility) and Ri (individual regret) in Table 33 were calculated. Then, based on the Qi values from Equation 22, the alternatives were evaluated. The alternative with the smallest Qi value was identified as the best option. According to the ranking, Ebrar Karakurt (Qi = 0) was selected as the best alternative. The remaining rankings were: İlkin Aydın (Qi = 0.33800), Tuğba Şenoğlu İvegin (Qi = 0.62369), Meliha Diken (Qi = 0.63478), Hande Baladın (Qi = 0.68892), Saliha Şahin (Qi = 0.98400), Derya Cebecioğlu (Qi = 0.98539), and İdil Naz Başcan (Qi = 0.99224).

Tablo 332. Outside Hitter Position Ranking

Player	Si	Ri	Qi	Ranking
Ebrar Karakurt	0.09740	0.03270	0.00000	**1**
Ilkin Aydın	0.35369	0.10195	0.33800	**2**
Tugba Senoglu Ivegin	0.57123	0.16021	0.62369	**3**
Meliha Diken	0.53820	0.17478	0.63478	**4**
Hande Baladin	0.56754	0.18934	0.68892	**5**
Saliha Sahin	0.82188	0.24072	0.98400	**6**
Derya Cebecioglu	0.80071	0.24760	0.98539	**7**
Idil Naz Bascan	0.81064	0.24760	0.99224	**8**

Evaluating the best alternative in terms of acceptable advantage and acceptable stability: Using Equations 23 and 24, the acceptable advantage (C1) was calculated, and the DQ value was found to be 0.1429. Since the C1 value (2.3660) is greater than 0.1429, the acceptable advantage condition is satisfied. The best alternative was also identified as the top-ranked option based on S and/or R values; thus, the acceptable stability condition (C2) is satisfied.

For the opposite hitter (pasör çaprazı) position, the four alternatives and seven criteria specified in Table 4 were evaluated using the VIKOR method. First, using Equations 18 and 19, the best (fi*) and worst (fi⁻) values were calculated, and these values are presented in Table 34.

Table 343. Best and Worst Values for the Opposite Hitter Position

Criteria	Games	Sets	Aces	Service Errors	Blocks	Attacks	Attack Errors
f_i^*	35	111	60	2	45	497	1
f_i^-	5	9	2	82	1	6	52

Using the criterion weights provided in Table 12 and Equations 20 and 21, the Si (group utility measure) and Ri (individual regret measure) values shown in Table 35 were calculated. Then, based on the Qi values obtained using Equation 22, the alternatives were evaluated. The alternative with the smallest Qi value was identified as the best option within the group. As a result of the ranking, Melissa Vargas (Qi = 0.01683) was selected as the best alternative. The remaining alternatives ranked as follows: Alexia Karutasu (Qi = 0.11664), Tutku Burcu Yüzgenç (Qi = 0.40458), and Defne Başyolcu (Qi = 1.00000).

Table 35. Ranking for the Opposite Hitter Position

Player	Si	Ri	Qi	Ranking
Melissa Vargas	0.18915	0.09693	0.01683	**1**
Alexia Karutasu	0.33425	0.08989	0.11664	**2**
Tutku Burcu Yuzgenc	0.51523	0.14942	0.40458	**3**
Defne Basyolcu	0.81113	0.29884	1.00000	**4**

When the best alternative is evaluated in terms of acceptable advantage and acceptable stability, using Equations 23 and 24, the acceptable advantage (C1) was calculated, and the DQ value was determined to be 0.3333. The C1 value was found to be 0.0998, which is smaller than 0.3333; this indicates that the condition of acceptable advantage was not satisfied. It was determined that the best alternative ranked first according to the Si value, and therefore, the acceptable stability condition (C2) was satisfied. Since the C1 condition was not met, the situation described in Equation 25 was examined. In this case, alternatives satisfying the condition $Q(A^M) - Q(A^1) \geq DQ$ are included in the compromise solution set.

$Q(A^2) - Q(A^1) = 0.0998$

$Q(A^3) - Q(A^1) = 0.3877$

Because 0.3877 > 0.3333, Melissa Vargas and Alexia Karutasu were identified as the compromise solutions. Either candidate may be selected. In this study, Melissa Vargas was chosen as the first alternative.

In Table 5, the nine alternatives and eleven criteria defined for the middle blocker position were evaluated using the VIKOR method. First, the best (fi*) and worst (fi⁻) values calculated using Equations 18 and 19 were identified, and these values were presented in Table 36.

Table 36. Best and Worst Values for the Middle Blocker Position

Criteria	Games	Sets	Total Serves	Successful Serves	Service Errors	Total Blocks	Successful Blocks	Block Errors	Total Attacks	Successful Attacks	Attack Errors
f_i^*	31	108	26	47	11	89	25	57	169	33	2
f_i^-	15	53	9	23	30	33	6	113	58	7	26

Using the criterion weights provided in Table 13 and Equations 20 and 21, the Si (average group utility) and Ri (maximum individual regret) values in Table 37 were calculated. Subsequently, the alternatives were evaluated based on the Qi (compromise ranking index) values obtained using Equation 22. The alternative with the lowest Qi value was identified as the best option within the group. According to the ranking, Aslı Kalaç (Qi = 0) was selected as the best alternative. The remaining alternatives ranked as follows: Deniz Uyanık (Qi = 0.14996), Zehra Güneş (Qi = 0.24895), Bengisu Aygün (Qi = 0.25294), Eda Erdem Dündar (Qi = 0.30356), Beyza Arıcı (Qi = 0.41220), Kübra Akman (Qi = 0.58161), Bahar Akbay (Qi = 0.76971), and Yasemin Güveli (Qi = 1).

Table 37. Ranking for the Middle Blocker Position

Player	Si	Ri	Qi	Ranking
Aslı Kalac	0.26124	0.04500	0.00000	**1**
Deniz Uyanik	0.31779	0.06498	0.14996	**2**
Zehra Gunes	0.36665	0.07457	0.24895	**3**
Bengisu Aygun	0.42290	0.05802	0.25294	**4**
Eda Erdem Dundar	0.37551	0.08551	0.30356	**5**
Beyza Arici	0.45671	0.08743	0.41220	**6**
Kubra Akman	0.52802	0.10768	0.58161	**7**
Bahar Akbay	0.61715	0.12706	0.76971	**8**
Yasemin Guveli	0.66327	0.17045	1.00000	**9**

When the best alternative is evaluated in terms of acceptable advantage and acceptable stability, using Equations 23 and 24, the acceptable advantage (C1) was calculated, and the DQ value was determined to be 0.1250. The C1 value was found to be 1.1997, which is greater than 0.1250; this indicates that the acceptable advantage condition has been satisfied. It was also determined that the best alternative ranked first based on the S and/or R values, indicating that the acceptable stability condition (C2) was satisfied as well. In Table 6, the nine alternatives and five criteria defined for the setter position were evaluated using the VIKOR method. First, the best (fi*) and worst (fi⁻) values calculated using Equations 18 and 19 were identified, and these values were presented in Table 38.

Table 384. Best and Worst Values for the Setter Position

Criteri a	Games	Sets	Excellent Setter Ball	Opponent's Ace	Net Fault
f_i^*	27	80	270	28	28
f_i^-	22	70	245	34	52

Using the criterion weights provided in Table 14 and Equations 20 and 21, the Si (average group utility) and Ri (maximum individual regret) values in Table 39 were calculated. Subsequently, the alternatives were evaluated based on the Qi (compromise ranking index) values obtained using Equation 22. The alternative with the lowest Qi value was identified as the best option within the group. According to the ranking, Elif Şahin (Qi = 0.02763) was selected as the best alternative. The remaining alternatives ranked as follows: Sıla Çalışkan (Qi = 0.14371), Cansu Özbay (Qi = 0.49300), and Dilay Özdemir (Qi = 1).

Table 39. Ranking for the Setter Position

Player	Si	Ri	Qi	Ranking
Elif Sahin	0.21058	0.06898	0.02763	**1**
Sıla Caliskan	0.17746	0.17057	0.14371	**2**
Cansu Ozbay	0.42914	0.26906	0.49300	**3**
Dilay Ozdemir	0.77686	0.42241	1.00000	**4**

When the best alternative is evaluated in terms of acceptable advantage and acceptable stability, using Equations 23 and 24, the acceptable advantage (C1) was determined, and the DQ value was found to be 0.3333. The condition C1 = 0.3483 ≥ 0.3333 is satisfied. Using Equations 23 and 24, the acceptable advantage (C1) was calculated again, and the DQ value was determined to be 0.3333. The C1 value was found to be 0.3483, which is greater than 0.3333; this indicates that the acceptable advantage condition has been satisfied. It was also determined that the best alternative ranked first according to the Ri value, and thus the acceptable stability condition (C2) was satisfied.

PROMETHEE Method Player Selection Results

PROMETHEE was selected as another Multi-Criteria Decision-Making (MCDM) method in this study. In the analysis conducted with the Visual PROMETHEE software, the criterion weights determined by the AHP method were used, and, based on expert opinion, the Type V (linear) preference function was selected. The linear preference function enabled the evaluation of preferences among criteria through a linear relationship and allowed the ranking of alternatives to be performed objectively. The final ranking obtained using the PROMETHEE method for the libero position is presented in Figure 3.

Rank	action	Phi	Phi+	Phi-
1	Simge Akoz	0,1127	0,2479	0,1352
2	Ayca Aykac	0,0665	0,2139	0,1474
3	Gizem Orge	-0,0794	0,3170	0,3964
4	Melis Yilmaz	-0,0998	0,1736	0,2734

Figure 3. Ranking Obtained with Visual PROMETHEE for the Libero Position

Figure 3 presents the overall performance scores (Phi), positive performance scores (Phi+), and negative performance scores (Phi–) of the players in the libero position. Simge Aköz, with the highest overall performance score (Phi = 0.1127), was identified as the best libero. She is followed by Ayça Aykaç (Phi = 0.0665). Gizem Örge (Phi = –0.0794) and Melis Yılmaz (Phi = –0.0998) ranked third and fourth, respectively. The final ranking obtained using the PROMETHEE method for the outside hitter position is presented in Figure 4.

Rank	action	Phi	Phi+	Phi-
1	Ebrar Karakurt	0,4686	0,6538	0,1852
2	Ilkin Aydin	0,2732	0,3252	0,0520
3	Hande Baladin	-0,0282	0,0949	0,1231
4	Tugba Senoglu Ivegin	-0,0502	0,0739	0,1241
5	Derya Cebecioglu	-0,1061	0,0886	0,1946
6	Meliha Diken	-0,1500	0,0380	0,1881
7	Saliha Sahin	-0,1813	0,0385	0,2198
8	Idil Naz Bascan	-0,2259	0,0304	0,2563

Figure 4. Ranking Obtained with Visual PROMETHEE for the Outside Hitter Position

Figure 4 displays the overall performance scores (Phi), positive performance scores (Phi+), and negative performance scores (Phi–) of the players in the outside hitter position. Ebrar Karakurt (Phi = 0.4686) was identified as the best outside hitter based on her overall performance score. İlkin Aydın (Phi = 0.2732) ranked second, followed by Hande Baladın (Phi = –0.0282), Tuğba Şenoğlu İvegin (Phi = –0.0502), and Derya Cebecioğlu (Phi = –0.1061). Meliha Diken (Phi = –0.1500), Saliha Şahin (Phi = –0.1813), and

İdil Naz Başcan (Phi = –0.2259) were identified as the lowest-performing players in this group.

The final ranking obtained using the PROMETHEE method for the opposite hitter position is presented in Figure 5.

Rank	action	Phi	Phi+	Phi-
1	Melissa Vargas	0,2648	0,4143	0,1495
2	Alexia Karutasu	0,0452	0,1766	0,1314
3	Tutku Burcu Yuzgenc	-0,0376	0,1375	0,1751
4	Defne Basyolcu	-0,2724	0,1969	0,4693

Figure 5. Ranking Obtained with Visual PROMETHEE for the Opposite Hitter Position

Figure 5 presents the overall performance scores (Phi), positive performance scores (Phi+), and negative performance scores (Phi–) of the players in the opposite hitter position. Melissa Vargas, with the highest overall performance score (Phi = 0.2648), was identified as the best opposite hitter. She is followed by Alexia Karutasu (Phi = 0.0452). Tutku Burcu Yüzgenç (Phi = –0.0376) and Defne Başyolcu (Phi = –0.2724) ranked third and fourth, respectively.

The final ranking obtained using the PROMETHEE method for the middle blocker position is presented in Figure 6.

Rank	action	Phi	Phi+	Phi-
1	Aslı Kalac	0,1981	0,2680	0,0699
2	Zehra Gunes	0,1722	0,2498	0,0777
3	Eda Erdem Dundar	0,1021	0,2313	0,1291
4	Deniz Uyanik	0,1015	0,2024	0,1009
5	Bengisu Aygun	0,0402	0,1522	0,1120
6	Beyza Arici	-0,0251	0,1100	0,1351
7	Kubra Akman	-0,0911	0,0973	0,1884
8	Bahar Akbay	-0,1874	0,1070	0,2945
9	Yasemin Guveli	-0,3105	0,1014	0,4118

Figure 6. Ranking Obtained with Visual PROMETHEE for the Middle Blocker Position

Figure 6 presents the overall performance scores (Phi), positive performance scores (Phi$^+$), and negative performance scores (Phi$^-$) of the players in the middle blocker position. Aslı Kalaç, with the highest overall performance score (Phi = 0.1981), was identified as the best middle blocker. Similarly, Zehra Güneş ranked second with an overall performance score of Phi = 0.1722. Yasemin Güveli, on the other hand, had the lowest overall performance score (Phi = –0.3105) and a relatively high negative performance score (Phi$^-$ = 0.4118), indicating that she is at a greater disadvantage compared to the other players.

The final ranking obtained using the PROMETHEE method for the setter position is presented in Figure 7.

Rank	action	Phi	Phi+	Phi-
1	Elif Sahin	0,2786	0,3409	0,0623
2	Sıla Caliskan	0,2340	0,3693	0,1352
3	Cansu Ozbay	0,0010	0,2065	0,2056
4	Dilay Ozdemir	-0,5136	0,0539	0,5675

Figure 7. Ranking Obtained with Visual PROMETHEE for the Setter Position

Figure 7 presents the overall performance scores (Phi), positive performance scores (Phi$^+$), and negative performance scores (Phi$^-$) of the players in the setter position. Elif Şahin, with the highest overall performance score (Phi = 0.2786), was identified as the best setter. She is followed by Sıla Çalışkan (Phi = 0.2340). Cansu Özbay (Phi = 0.0010) and Dilay Özdemir (Phi = –0.5136) ranked third and fourth, respectively.

Integration of Rankings Using the Borda Count Method

The rankings obtained from the three methods (TOPSIS, VIKOR, and PROMETHEE) were integrated using the Borda Count method, and the best players for each position were identified. As a result of this comprehensive evaluation, the players who should be selected to form the optimal team are listed in Tables 40-44. These players, who stand out with their superior skills and performance in each position, are the key athletes who make a significant impact on the volleyball court.

Table 40. Ranking for the Libero Position

Players	TOPSIS		VIKOR		PROMETHEE		BORDA	
	Ranking	Score	Ranking	Score	Ranking	Score	Score	Ranking
Simge Akoz	2	2	2	2	1	3	7	**1**
Ayca Aykac	3	1	1	3	2	2	6	**2**
Gizem Orge	1	3	3	1	3	1	5	**3**
Melis Yılmaz	4	0	4	0	4	0	0	**4**

In the libero position, different players ranked first across the three methods (TOPSIS, VIKOR, and PROMETHEE): Gizem Örge in TOPSIS, Ayça Aykaç in VIKOR, and Simge Aköz in PROMETHEE. The reason different players emerged as the top choice across the three methods is that each technique evaluates player performance from a distinct analytical perspective. However, based on the integration performed using the Borda Count Method, Simge Aköz was determined to be the best overall choice.

Table 41. Ranking for the Outside Hitter Position

Players	TOPSIS		VIKOR		PROMETHEE		BORDA	
	Ranking	Score	Ranking	Score	Ranking	Score	Score	Ranking
Ebrar Karakurt	5	3	1	7	1	7	17	**1**
Ilkin Aydın	4	4	2	6	2	6	16	**2**
Hande Baladin	2	6	5	3	3	5	14	**3**
Tugba Senoglu Ivegin	3	5	3	5	4	4	14	**3**
Meliha Diken	1	7	4	4	6	2	13	**5**
Saliha Sahin	6	2	6	2	7	1	5	**6**
Derya Cebecioglu	8	0	7	1	5	3	4	**7**
Idil Naz Bascan	0	1	4	0	8	0	1	**8**

In the outside hitter position, while Meliha Diken ranked first according to the TOPSIS method, Ebrar Karakurt was evaluated as the top player in both the VIKOR and PROMETHEE methods. As a result of the integration process that combines the outcomes of these different methods, Ebrar Karakurt emerged as the best outside hitter. This finding highlights Ebrar Karakurt's superior performance when the results of multiple evaluation methods are considered together.

Table 42. Ranking for the Opposite Hitter Position

Players	TOPSIS		VIKOR		PROMETHEE		BORDA	
	Ranking	Score	Ranking	Score	Ranking	Score	Score	Ranking
Melissa Vargas	2	2	1	3	1	3	8	**1**
Alexia Karutasu	1	3	2	2	2	2	7	**2**
Tutku Burcu Yuzgenc	4	0	3	1	3	1	2	**3**
Defne Basyolcu	3	1	4	0	4	0	1	**4**

In the opposite hitter position, the TOPSIS method ranked Alexia Karutasu in first place, whereas the VIKOR and PROMETHEE methods identified Melissa Vargas as the top-ranked player. The integration process, which consolidates the results of these different methods, has demonstrated that Melissa Vargas is the best option for this position and should be included on the team. This evaluation clearly shows that the combined outcomes of multiple methods highlight Melissa Vargas's superior performance and confirm her as the most appropriate choice for the team.

Table 43. Ranking for the Setter Position

Players	TOPSIS		VIKOR		PROMETHEE		BORDA	
	Ranking	Score	Rankin g	Score	Ranki ng	Score	Sco re	Ranking
Elif Şahin	2	2	1	3	1	3	8	1
Cansu Özbay	1	3	3	1	3	1	5	2
Sıla Çalışkan	3	1	2	2	2	2	5	2
Dilay Özdemir	4	0	4	0	4	0	0	4

In the setter position, while the TOPSIS method ranked Cansu Özbay first, the VIKOR and PROMETHEE methods ranked Elif Şahin first. Based on the overall evaluation conducted using the Borda method, Elif Şahin was identified as the best setter and the most suitable choice to be included in the team.

Table 44. Ranking for the Middle Blocker Position

Players	TOPSIS		VIKOR		PROMETHEE		BORDA	
	Rank ing	Score	Ran king	Score	Rank ing	Score	Score	Ranking
Aslı Kalac	6	3	1	8	1	8	19	1
Zehra Gunes	4	5	3	6	2	7	18	2
Eda Erdem Dundar	1	8	5	4	3	6	18	2
Deniz Uyanik	5	4	2	7	4	5	16	4
Bengisu Aygun	3	6	4	5	5	4	15	5
Beyza Arici	2	7	6	3	6	3	13	6
Kubra Akman	9	0	7	2	7	2	4	7
Yasemin Guveli	7	2	9	0	8	1	3	8
Bahar Akbay	8	1	8	1	9	0	2	9

In the final evaluation of the middle blockers, the TOPSIS method ranked Eda Dündar Erdem first, while the VIKOR and PROMETHEE methods identified Aslı Kalaç as the top player. The overall analysis conducted using the Borda method revealed that Aslı Kalaç is the most suitable choice for the middle blocker position.

Based on the results of the study, it was observed that, except for Derya Cebecioğlu, Beyza Arıcı, and Dilay Özdemir, the rankings obtained were highly consistent with the actual performance outcomes during the player selection period stated in the purpose of the study. Apart from these three players, the alignment between the performance-based rankings and the players on the main roster demonstrates that the MCDM methods were applied effectively and yielded objective results. This, in turn, confirms the study's overall success and validity.

The main objective of the study was to form a core roster of six players who demonstrated the highest performance among the 30-player extended squad. In this context, Simge Aköz exhibited the best performance in the libero position. Aköz, who plays for Eczacıbaşı, ranked first across all methods and secured the top position in the overall performance ranking. In the 2024 VNL, Aköz played in 7 of Türkiye’s 13 games, while the other libero, Gizem Örge, appeared in 9 games, resulting in comparable playing time for both.

In the outside hitter position, Ebrar Karakurt of Lokomotiv Kaliningrad was the highest-performing player. Known for her powerful attacks and effective blocking, Karakurt is expected to contribute significantly to the team's offensive strength. She appeared in 12 of Türkiye’s 13 games in the 2024 VNL. In a lineup such as the one illustrated in Figure 1, the team takes the court with six players. Accordingly, İlkin Aydın, who ranked second in the performance evaluation for the second outside hitter role, was included in the six-player core roster. However, due to an injury sustained during the 2024 VNL, she was able to participate in only 5 of the 13 games.

In the opposite hitter position, Melissa Vargas, who spent half of the season with Tianjin Bohai Bank and the other half with Fenerbahçe, was identified as the highest-performing player. Noted for her powerful attacks and strong serving performance, Vargas played in all 13 of Türkiye’s games in the 2024 VNL. Similarly, in the setter position, Elif Şahin from Eczacıbaşı showed the highest level of performance and also appeared in all 13 games.

Finally, in the middle blocker position, Aslı Kalaç, who demonstrated the best overall performance, was included in the six-player core roster. She played in 11 of the 13 games, receiving more court time than the other middle blockers. The on-court arrangement of the selected six-player core roster is shown in Figure 8.

Figure 8. On-Court Formation of the Selected Main Roster

Based on the analyses, the six selected players were included in the VNL 2024 roster, confirming the accuracy of the selection process. The six-player core lineup, determined by performance rankings, consisted of the players who received the most playing time in Türkiye's games during VNL 2024. This demonstrates that the selected players exhibited both high performance and strong durability, highlighting the effectiveness and precision of the selection procedure.

These athletes, chosen from the broader 30-player squad, were evaluated through a rigorous assessment process and according to specific performance criteria, ensuring that only those who demonstrated the highest performance levels were identified. Below, Table 9 presents the detailed composition of the 30-player extended roster, the 18-player VNL 2024 roster, and the six-player core lineup determined through the analyses. These selections play a critical role in the Turkish Women's National Volleyball Team's success.

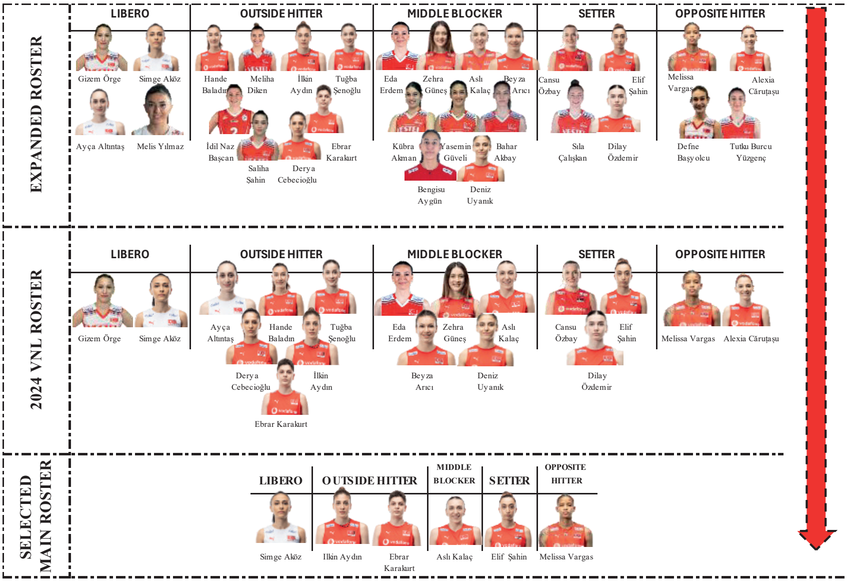


Figure 9. Expanded Roster, VNL 2024 Roster, and Selected Main Roster

The findings of this study offer valuable insight into how structured analytical tools can meaningfully support player selection for elite national teams. One of the most important contributions of this research is its ability to bring together performance data from six major international volleyball leagues and evaluate them on a common platform. Because Turkish national team players compete in leagues that differ in speed, tactical complexity, and competitive culture, comparing their performances fairly is often challenging. By standardizing the data and applying a consistent set of position-specific criteria, this study shows that players can be evaluated systematically and equitably across diverse competitive environments. This provides a stronger foundation for identifying athletes who can perform at a high level on the international stage.

From an academic standpoint, the study fills a clear gap in the volleyball analytics literature. While sports analytics continues to grow, research that uses multi-criteria decision-making techniques for volleyball player selection remains surprisingly limited. By applying TOPSIS, VIKOR, and PROMETHEE side by side, this study highlights how different analytical perspectives can generate a more comprehensive understanding of player performance. The comparison of methods enriches the scholarly conversation by showing how each technique responds to trade-offs among criteria and how model behavior shifts when evaluating players with distinct performance profiles. The integrated approach, combining AHP for weighting and Borda Count for final ranking, demonstrates a thoughtful and rigorous analytical structure that can inspire further methodological innovation in sports science research.

For managers, coaches, and national team administrators, the practical implications of this study are particularly compelling. The substantial overlap between the model-generated rankings and the actual roster selected for VNL 2024 suggests that data-driven tools can reinforce expert judgment rather than compete with it. In a context where roster decisions are highly scrutinized by athletes, clubs, and the public, an analytical framework provides transparency and a defensible rationale for selections. Position-specific findings also help coaching staff plan training sessions more effectively, identify strengths and weaknesses within the roster, and develop tactical strategies that align with the capabilities of the chosen athletes. Beyond immediate selection decisions, this type of analysis can support longer-term talent development by identifying potential successors for key positions or highlighting areas where the national pipeline may need reinforcement.

There are also broader organizational benefits to adopting such systematic approaches. National federations can use models like the one presented in this study to monitor player development over multiple seasons, assess readiness for international competition, and evaluate the impact of club-level performance on national team outcomes. As performance data becomes increasingly accessible through digital tracking systems, adopting structured evaluation processes becomes not only possible but essential for maintaining competitive advantage. In addition, integrating analytical tools into selection decisions helps cultivate a culture of evidence-based management within sports organizations, thereby enhancing professionalism and strategic planning.

The societal implications of this research extend beyond the volleyball court. As the Turkish Women's National Volleyball Team continues to inspire significant public interest, transparent, merit-based roster decisions help build trust among fans and stakeholders. Demonstrating that national representation results from objective, carefully evaluated performance reinforces the principles of fairness and accountability in sports governance. The study also illustrates the growing importance of data-driven thinking across all areas of sport, potentially encouraging younger generations to pursue fields that combine athletic passion with analytical skills. Finally, by focusing on women's volleyball, the study contributes to the growing recognition of women's sports in academic research. This increased visibility supports ongoing efforts to elevate professional standards, encourage investment, and promote gender equity in sports analytics.

Limitations of the Study

Although the study provides meaningful insights into objective player selection using MCDM methods, several limitations should be acknowledged. First, the analysis relied on performance statistics drawn from a single season and from multiple leagues with differing competitive structures, which may introduce variability in data comparability. Player performance metrics were limited to quantifiable, publicly available statistics, excluding qualitative factors such as leadership, psychological readiness, tactical adaptability, or injury history, which may also influence overall suitability for national team selection. Additionally, the decision-making criteria and their weights were determined based on expert judgment, which, although valuable, may still involve subjective bias. Finally, the study evaluated performance in women's volleyball in Türkiye, and the findings may not be directly generalizable to other national teams, competitive contexts, or mixed-gender analyses.

Future Research Directions

Future studies may expand upon the current work in several meaningful ways. First, longitudinal analyses incorporating multi-season performance data would enable monitoring of player development, consistency, and improvement over time. Integrating biomechanical data, physical fitness measurements, and psychological performance indicators into MCDM frameworks could provide a more holistic assessment of player suitability. Combining video analytics, artificial intelligence–based performance tracking, and machine learning algorithms with traditional MCDM methods may also enhance predictive accuracy in player selection.

Furthermore, future research may compare the effectiveness of different MCDM techniques, such as ELECTRE, MACBETH, or fuzzy-based approaches, to assess their robustness in complex selection environments. Cross-sport applications, including basketball, handball, or soccer, could broaden the generalizability of the findings and contribute to the development of standardized decision-support systems for national team selection. Finally, mixed-methods approaches that incorporate both quantitative metrics and expert qualitative evaluations could offer more balanced, contextually rich insights into elite athlete selection.

Conclusions

This study provided a detailed, position-focused assessment of player selection for the Turkish Women's National Volleyball Team, using the 30-player extended roster announced for the 2024 Volleyball Nations League as its basis. To create a reliable basis for comparison, performance statistics from the 2023 to 2024 season were gathered from six major volleyball leagues, including Türkiye, China, Russia, Germany, Japan, and Poland. Bringing these league statistics together within a common analytical framework made it possible to compare athletes fairly, even though they competed in different environments. This approach ensured that each player's international performance level could be analyzed more clearly and accurately.

A set of position-specific performance criteria was developed, and experts contributed to determining their importance using the Analytic Hierarchy Process. This step added structure and transparency to the evaluation process and helped ensure that the selection of players was grounded in well-considered priorities. Player performances were then evaluated using three well-established multi-criteria decision-making methods: TOPSIS, VIKOR, and PROMETHEE. While the three methods follow different analytical logics, VIKOR and PROMETHEE produced noticeably more consistent results in this context. Their ability to evaluate performance variations and balance multiple criteria appeared to contribute to their stability. Although TOPSIS occasionally produced rankings that differed from those of the other two methods, its inclusion enriched the overall evaluation by providing an additional analytical perspective. Ultimately, the Borda Count method was used to integrate the three sets of rankings, ensuring that the final results reflected all available viewpoints.

Because the study was conducted during the same period as VNL 2024, it was possible to compare the model-based rankings with the roster actually selected for the tournament. The national team competed with an 18-player roster drawn from the extended list, and the majority of the top-ranked athletes in the analysis were also chosen for the tournament squad. Accordingly, the Turkish Women's National Volleyball Team participated in the tournament with an 18-player roster consisting of 2 liberos, six outside hitters, five middle blockers, three setters, and two opposite hitters selected from the 30-player extended list. Based on the performance rankings generated in this study:

- For the libero position, the top three performers, namely, Simge Aköz, Ayça Aykaç, and Gizem Örge, were all included in the 18-player roster. However, despite being listed as a libero in the extended squad, Ayça Aykaç was deployed as an outside hitter in the tournament.

- In the outside hitter position, the top four performers, namely, Ebrar Karakurt, İlkin Aydın, Hande Baladın, and Tuğba Şenoğlu İvegin, were selected for the 18-player roster. Additionally, Derya Cebecioğlu, who ranked seventh in the performance evaluation, was also included.

- For the opposite hitter position, the two top-performing players, Melissa Vargas and Alexia Karutasu, were both part of the 18-player roster.

- In the middle blocker position, the top four performers, namely Aslı Kalaç, Zehra Güneş, Eda Erdem Dündar, and Deniz Uyanık, were included in the 18-player roster. Beyza Arıcı, who ranked sixth, was also selected.

- For the setter position, the top two performers, namely, Elif Şahin and Cansu Özbay, were included in the roster. Additionally, Dilay Özdemir, ranked fourth, was also selected.

This substantial overlap between analytical outcomes and real-world coaching decisions suggests that data-driven selection tools can meaningfully support expert judgment. Such convergence reinforces the value of structured evaluation methods, especially in settings where decisions must be both fair and performance-oriented.

In a broader sense, the study demonstrates how multi-criteria decision-making techniques can contribute positively to elite athlete selection. By combining systematic data analysis with domain expertise, national teams can improve the transparency and accuracy of their roster decisions. The framework developed here provides a solid starting point for integrating analytical decision support tools into volleyball and other team sports. As competitive environments become increasingly complex, approaches that combine evidence and expertise will likely play an even more critical role in shaping effective and competitive national teams.

References

Anamisa, D. R., Kustiyahningsih, Y., Yusuf, M., Rochman, E. M. S., Putro, S. S., Syakur, M. A., & Bakti, A. S. (2021). A selection system for the position ideal of football players based on the AHP and TOPSIS methods. *IOP Conference Series: Materials Science and Engineering*, *1125*(1), 012044. https://doi.org/10.1088/1757-899X/1125/1/012044

Arıbaş, M., & Özcan, U. (2016). Akademik Araştırma Projelerinin AHP ve TOPSIS Yöntemleri Kullanılarak Değerlendirilmesi. *Politeknik Dergisi*, *19*(2), 163–173.

ASLAN, E., & BAĞ, M. E. (2021). Çok Kriterli Karar Verme Yöntemleri AHP ve PROMETHEE ile Bursiyer Seçimi. *MANAS Sosyal Araştırmalar Dergisi*, *10*(4), 2301–2313. https://doi.org/10.33206/mjss.748963

Ati, A., Bouchet, P., & Ben Jeddou, R. (2024). Using multi-criteria decision-making and machine learning for football player selection and performance prediction: a systematic review. *Data Science and Management*, *7*(2), 79–88. https://doi.org/10.1016/j.dsm.2023.11.001

Aydin, M., Avci, S., & Aladağ, Z. (2021). Futbolcu Performanslarının VIKOR Yöntemi ile Değerlendirilmesi ORİJİNAL ARAŞTIRMA. *Mediterranean Journal of Sport Science*, *4*(1). https://doi.org/10.37021/asbid873554

Blanco, V., Salmerón, R., & Gómez-Haro, S. (2018). A Multicriteria Selection System Based on Player Performance: Case Study—The Spanish ACB Basketball League. *Group Decision and Negotiation*, *27*(6), 1029–1046. https://doi.org/10.1007/s10726-018-9583-9

Cerrahoğlu, S. (2021). Sosyal medya etkileşiminin turizm pazarlamasındaki rolünün değerlendirilmesi. *Turizm Ekonomi ve İşletme Araştırmaları Dergisi*, *3*(1), 21–44.

China Volleybol Association. (2024). *2022-2023 China Women's Volleyball Super League Technical Statistics Ranking*. http://www.volleychina.org/

Dadelo, S., Turskis, Z., Zavadskas, E. K., & Dadeliene, R. (2014). Multi-criteria assessment and ranking system of sport team formation based on objective-measured values of criteria set. *Expert Systems with Applications*, *41*(14), 6106–6113. https://doi.org/10.1016/j.eswa.2014.03.036

Ersöz, F., & Kabak, M. (2010). Savunma Sanayi Uygulamalarında Çok Kriterli Karar Verme Yöntemlerinin Literatür Araştırması. *Savunma Bilimleri Dergisi*, *9*(1), 97–125. https://doi.org/10.17134/sbd.85950

Esen, S., & Uslu, T. (2020). Futbolda Yetenek Seçiminin Analitik Hiyerarşi Süreci ve TOPSIS Yöntemi Aracılığıyla Değerlendirilmesi. *Türkiye Spor Bilimleri Dergisi*, *4*(2), 111–123. https://doi.org/10.32706/tusbid.821124

Flegl, M., Jiménez-Bandala, C. A., Lozano, C., & Andrade, L. (2018). Personnel selection in complex organizations: A case of Mexican football team for the 2018 World Cup in Russia. *Revista Del Centro de Investigación de La Universidad La Salle*, *13*(49), 43–66. https://doi.org/10.26457/recein.v13i49.1510

German Volleyball Federation. (2024). *2023-2024 1. Bundesliga Women's Technical Statistics Ranking*. https://www.volleyball-bundesliga.de/

GÖK KISA, A. C., & PERÇİN, S. (2020). BULANIK ÇOK KRİTERLİ KARAR VERME YAKLAŞIMI İLE TÜRKİYE İMALAT SANAYİİ'NDE PERFORMANS ÖLÇÜMÜ. *Uluslararası İktisadi ve İdari İncelemeler Dergisi*, 31–56. https://doi.org/10.18092/ulikidince.522799

Hoş, S., & Demirer, Ö. (2020). Talaşlı İmalat Sektöründe AHP İle Tedarikçi Seçimi. *Turkuaz Uluslararası Sosyo-Ekonomik Stratejik Araştırmalar Dergisi*, *2*(2), 27–41.

Huang, J.-H., & Peng, K.-H. (2012). Fuzzy Rasch model in TOPSIS: A new approach for generating fuzzy numbers to assess the competitiveness of the tourism industries in Asian countries. *Tourism Management*, *33*(2), 456–465. https://doi.org/10.1016/j.tourman.2011.05.006

Japan Volleyball Association. (2024). *2023-2024 Women's 1st V League Technical Statistics Ranking*. https://www.vleague.jp/

Karaatlı, M., & Dağ, O. (2018). Türk Milli Erkek Futbol Takımına Çok Kriterli Karar Verme Yöntemleri İle Futbolcu Seçimi. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *23*(4), 1433–1454.

Karaatlı, M., Ömürbek, N., & Köse, G. (2014). Analitik Hiyerarşi Süreci Temelli TOPSIS ve VIKOR Yöntemleri İle Futbolcu Performanslarının Değerlendirilmesi. *Dokuz Eylül Üniversitesi İktisadi İdari Bilimler Fakültesi Dergisi*, *29*(1), 25–61.

Lumini, A., & Nanni, L. (2006). Detector of image orientation based on Borda Count. *Pattern Recognition Letters*, *27*(3), 180–186. https://doi.org/10.1016/j.patrec.2005.08.023

Nikjo, B., Rezaeian, J., & Javadian, N. (2015). Decision Making in Best Player Selection: An Integrated Approach with AHP and Extended TOPSIS Methods Based on Wefa Freamwork in MAGDM Problems. *Int. J. Res. Ind. Eng*, *4*(4), 1–14. https://doi.org/10.22105/riej.2017.49166

Opricovic, S., & Tzeng, G.-H. (2007). Extended VIKOR method in comparison with outranking methods. *European Journal of Operational Research*, *178*(2), 514–529. https://doi.org/10.1016/j.ejor.2006.01.020

Ozceylan, E. O. (2016). A Mathematical Model Using AHP Priorities For Soccer Player Selection: A Case Study. *South African Journal of Industrial Engineering*, *27*(2). https://doi.org/10.7166/27-2-1265

Özlemiş, Ş., & Eren, T. (2024). Afet Sonrası Kullanılacak Geçici Barınma Alanlarının Çok Kriterli Karar Verme Yöntemleri Kullanılarak Seçilmesi Üzerine Bir Uygulama. *Uluslararası Muhendislik Arastirma ve Gelistirme Dergisi*. https://doi.org/10.29137/umagd.1469270

Polish Volleyball Federation. (2024). *2023-2024 Tauron League Women's Technical Statistics Ranking*. https://www.tauronliga.pl

Qader, M. A., Zaidan, B. B., Zaidan, A. A., Ali, S. K., Kamaluddin, M. A., & Radzi, W. B. (2017). A methodology for football players selection problem based on multi-measurements criteria analysis. *Measurement*, *111*, 38–50. https://doi.org/10.1016/j.measurement.2017.07.024

Russian Volleyball Federation. (2024). *PARI Super League Russia Championship 2024: Women Technical Statistics Ranking.* https://volley.ru/

Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, *48*(1), 9–26. https://doi.org/10.1016/0377-2217(90)90057-I

Saaty, T. L., & Vargas, L. G. (2012). *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process* (Vol. 175). Springer US. https://doi.org/10.1007/978-1-4614-3597-6

Turkish Volleyball Federation. (2024). *Turkish Volleyball Federation 2024 Report.* https://tvf.org.tr/

Tzeng, G.-H., Lin, C.-W., & Opricovic, S. (2005). Multi-criteria analysis of alternative-fuel buses for public transportation. *Energy Policy*, *33*(11), 1373–1383. https://doi.org/10.1016/j.enpol.2003.12.014

Yoon, K. P., & Hwang, C.-L. (1995). Multiple attribute decision making: An introduction. In *Multiple attribute decision making: An introduction.* Sage Publications, Inc.

Zulfikar, R., Andryana, S., & Gunaryati, A. (2020). *Selection of the Best EPL Players Using AHP, PROMETHEE, and TOPSIS Methods with a Pairwise Comparison Scale* (Vol. 4, Issue 3). https://iocscience.org/ejournal/index.php/mantik

Chapter 4

CONCEPTUALIZING WORK-RELATED HEALTH ISSUES FOR COMPUTER ENGINEERING OCCUPATION LINKING ERGONOMIC RISK FACTORS WITH PHYSICAL AND PSYCHOSOCIAL DISORDERS

Burcu YILMAZ KAYA[1]

1 Assoc. Prof. Dr., Industrial Engineering Department, Faculty of Engineering, Gazi University, Türkiye, burcuyilmaz@gazi.edu.tr, 0000-0002-5088-5842

1. INTRODUCTION

Occupational diseases are illnesses specific to workplace conditions and working life, where the antecedents factor is present in daily working environment and since exposure is continuous are among the leading health problems in working life and induce colossal economic burdens to both companies and governments.

The rapid digitalization of work processes has led to a substantial increase in occupations characterized by prolonged computer use, where, computer engineers (CEs) constituting one of the most exposed professional groups. CE is a knowledge-intensive profession characterized by continuous sitting, repetitive hand–wrist movements, sustained neck–shoulder postures, high cognitive workload, time pressure, and increasingly blurred work–life boundaries due to remote and hybrid working models. Software development, system administration, data engineering, cybersecurity, and DevOps activities require sustained cognitive effort combined with extended periods of sedentary work, and intensive visual engagement. As a result, CEs face a unique constellation of occupational diseases due to ergonomic risk factors that could end to negatively affect their physical health, psychological well-being, and work performance.

Existing literature research support that with meta-analysis findings (Ul Hasanat, Ali, Rasheed & Khan, 2017; Chim & Chen, 2021) indicating a high prevalence of musco-skeletal disorders (MSDs) among office workers using computers (e.g., lower back, neck, upper back, etc.). Work-related musculoskeletal disorders (WMSDs), visual strain, and psychosocial conditions such as stress and burnout issues are among the most frequent reported occupational diseases among CEs, where, these disorders not only diminish individual quality of life but also impose significant organizational and societal costs through productivity loss, absenteeism, job-dissatisfaction and increased healthcare expenditures. This situation necessitates a systematic and transparent conceptualization of work-related health issues for CEs in scientific perspectives of ergonomics and occupational health sciences.

Since risks emerged to be in a working environment of CE are identified in diverse dimension i.e. physical, cognitive and psychosocial, one-dimensional ergonomics assessments could not be expected to fully explain the handled problem. In real organizational settings, ergonomic decision-making involves multiple actors—including engineers, occupational health specialists, ergonomists, human resources professionals, and managers—each with distinct perspectives and priorities.

Accordingly, this book chapter addresses the problem of occupational disease development among CEs due to ergonomic risks, aiming to (*i*) identify and redefine ergonomic risk factors specific to CE occupation, (*ii*) evaluate the relative significance and occurrence status of the analyzed issues based on a a group decision-making (GDM) approach to reflect the multi-stakeholder nature of the decision model and different stakeholder perspectives e.g. employees, occupational health and safety (OHS) experts, managers, and, (*iii*) employ a robust and trusted mathematical solution method, Evaluation based on Distance from Average Solution (EDAS), to dissect the problem space and constitute a secure and valid solution.

The remaining of this chapter was organized as, the theoretical background of work-related health issues and ground arguments on CE occupational diseases and ergonomic risk factors were analyzed under Section 2. The origin and computation methodology of EDAS method were introduced under Section 3, where, Section 4 presents the scientific literature review. A real-world application of addressed problem was handled and presented under Section 5. Section 6 acquaints and discusses the results and concludes the chapter.

2. ERGONOMICS, OCCUPATIONAL HEALTH, COMPUTER ENGINEERING

Ergonomics, or human factors engineering, as an interdisciplinary field, seeks to optimize the interaction between the most important element, human, and work system by aligning task demands, physical environment, and organizational structure with employee or user capabilities and limitations (Yılmaz Kaya, 2022). The universal definition of ergonomics was identified by

International Ergonomic Association (IEA, 2021) as "the scientific discipline concerned with an understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design to optimise human well-being and overall system performance." The concept of ergonomics has its roots in ancient Greek, combining the words *ergon*, meaning work, and *nomos*, meaning laws or principles (Taifa & Desai 2016; IEA, 2021; Taifa, 2022; Yılmaz Kaya, 2022).

As the core principles of ergonomics are founded on the provision of safe, comfortable, and sustainable working environments that protect employees' physical health, well-being, and safety, OHS represents a fundamental and indispensable domain within ergonomic applications across organizations operating in diverse industrial contexts. Notwithstanding the demonstrated effectiveness of advanced measurement techniques and technologically enhanced assessment tools, OHS initiatives predominantly focus on controlling individual behaviors or addressing immediate physical risks associated with environmental conditions and job design (Yılmaz Kaya, 2022).

In computer-intensive occupations, ergonomic challenges arise not only from physical work place elements but also from cognitive demands, job design and psycho-social stressors, where, diverse instances from existing ergonomics and OHS science literature underlines the vigorous bond between psycho-social work environment factors and adverse health outcomes (Yılmaz Kaya & Kılıç Delice, 2024).

From an occupational health perspective, prolonged exposure to suboptimal ergonomic conditions contributes to cumulative trauma disorders, particularly affecting the neck, shoulders, lower back, and upper extremities (Atcheson, Ward & Lowe, 1998; Giersiepen & Spallek, 2011; Riccò, Pezzetti & Signorelli, 2015; Lewanska, Grzegorzewski & Walusiak-Skorupa, 2016; Riccò, Cattani & Signorelli, 2016; Ul Hasanat et al., 2017; Moldovan, Voidazan, Moldovan, Vlasiu, Moldovan & Panaitescu, 2020; Chim & Chen, 2021). Simultaneously, sustained mental workload, time pressure, and insufficient recovery periods exacerbate fatigue, stress, and emotional exhaustion (Yılmaz Kaya & Kılıç

Delice, 2024). Importantly, physical and psychosocial risk factors do not operate independently; rather, they interact synergistically, amplifying adverse health outcomes.

CE, as an occupation, exhibits several defining characteristics that intensify ergonomic risk exposure, e.g. long uninterrupted sitting durations, high-frequency keyboard and mouse use, constrained postures, continuous screen viewing, irregular work rhythms driven by deadlines, system incidents, team-work pressure, frequent deadline changes, release cycles, etc.. Environmental conditions such as lighting quality in remote working, noise in open-plan offices, or thermal comfort in both office and remote working further influence ergonomic load. In addition, psychosocial factors such as high cognitive demands, role ambiguity, limited job control, individual working, group working, isolation feeling in remote working, and constant performance monitoring play critical role in shaping work-related health outcomes. Therefore, an integrative ergonomic risk framework for CEs must encompass various ergonomics pillars and analyze the problem space under a multi-dimensional structure of physical, environmental, organizational, and psychosocial dimensions.

Work-related diseases or occupational disorders that might be seen in CEs could be generalized by under a few main headings divided into sub-branches associated with ergonomic work environment and job design deficiencies. WMSD based diseases (neck pain, cervical strain, etc.) generally arise from monitor height and/or distance mismatch, continuous forward head position and static muscle load (frequently in arms, hands, neck), where, lower back pain and lumbar problems are connected with long sitting, inadequate lumbar support and low range of motion. Keyboard and mouse position mismatch, wrong desk height, and, static shoulder elevation cause shoulder-back (upper trapezius) tension, whereas; repetitive wrist flexion or extension, repetitive micro-movements, improper mouse and keyboard use cause carpal tunnel syndrome and tendinitis (tenosynovitis). Lightening has a significance advert impact on CE health, wrong screen brightness and contrast, and, inappropriate lighting induce eyestrain and ocular system disorders (Atcheson, Ward &

Lowe, 1998; Giersiepen & Spallek, 2011; Riccò, Pezzetti & Signorelli, 2015; Lewanska, Grzegorzewski & Walusiak-Skorupa, 2016; Riccò, Cattani & Signorelli, 2016; Moldovan, Voidazan, Moldovan, Vlasiu, Moldovan & Panaitescu, 2020).

Not only the physical environment but also the job design and psychosocial environment are highly correlated with work-related health issues particular to CEs. Visual load, team work stress, constant pressure to meet deadlines, long working hours, uncertain end-user demands, nighttime screen exposure, shift and incident mismanagement, low job control, lack of social support, changing task priorities, release pressure exacerbate both psychological and physical symptoms such as headache, migraine episodes, sleep disturbances, insomnia, burnout, anxiety, depression (Gaan & Sahoo, 2023; Ivory, Towse, Sturdee, Levine & Nuseibeh, 2023; Wong, Cheng, Oewel, Genuario, Stoeckl, Schueller, Ahmed, van der Hoek & Reddy, 2025).

Despite these insights, the literature reveals several gaps. First, most studies examine ergonomic risk factors in isolation e.g. focusing on only physical, environmental, equipment-based, etc., lacking an integrative prioritization perspective. Second, research specifically targeting CEs, rather than generic office workers, remains limited, despite the distinctive cognitive and organizational demands of engineering work. Third, the application of advanced mathematical solution techniques in ergonomic risk prioritization is scarce where matrix-based solution approaches (Failure Mode Effect Analysis, Fine-Kinney, etc.) dominates the related literature, and, group decision making perspectives are rarely incorporated lacking the current outputs having the product of a multi-dimensional point of view.

Consequently, there is a clear need for a comprehensive framework that combines ergonomic theory, empirical health outcomes, and structured decision making methods to support effective intervention planning particular to CEs.

3. EDAS

EDAS method was proposed by Keshavarz Ghorabee, Zavadskas, Olfat and Turskis (2015) to provide practical, effective and robust results to complex decision problems. EDAS method differ from its equivalents (distance-based methods) such as TOPSIS (Technique for Order Preference by Similarity to Ideal Solutions), VIKOR (Vise Kriterijumska Optimizacija I Kompromisno Resenje) and CODAS (Combinative Distance-Based Assessment) by determining the best alternative based on calculating the positive and negative distances from the average solution for each alternative. The best alternative was determined by calculating the distance from the *ideal* and *rare* solutions in TOPSIS and VIKOR methods, while EDAS finds the best alternative depending on the distance from the *average solution* (AV), providing an important computational convenience to decision makers when dealing with complex and large decision problems, also, making it robust against extreme values and suitable for problems involving qualitative judgments and group evaluations. When combined with group decision making, EDAS enables the aggregation of diverse expert opinions into a coherent prioritization framework. The application steps of the EDAS method are introduced according to Keshavarz Ghorabee (2015), hereinafter.

Step 1: Preliminary: The problem criteria set and alternatives to be evaluated are determined and the decision matrix representing these problem space elements, and, performance scores of the alternatives based on the criteria was constituted.

Step 2: Generation of the AV matrix: The average solution corresponds to the average of the performance values of all alternatives under the relevant criterion was generated (Eq. 1).

$$AV = [AV_j]_{1xm} \tag{1}$$

where AV_j represents the average solution for each criterion and is calculated by Equation (2).

$$AV_j = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{2}$$

Here, X_{ij} is the performance value of the *ith* alternative according to the *jth* criterion, and,
n is the number of alternatives.

Step 3: Construction of the positive (PDA) and negative (NDA) distance matrices: The positive and negative distances from the average solution matrices are created regarding the function type of the criteria (Eq. 3, Eq. 4).

$$PDA = [PDA_{ij}]_{nxm} \tag{3}$$

$$NDA = [NDA_{ij}]_{nxm} \tag{4}$$

Here, PDA_{ij}, represents the positive distance of the *ith* alternative from AV_i in terms of the *jth* criteria, and is calculated with Equation (5) if the *jth* criterion is a maximization criterion , and Equation (6) if it is a minimization criterion. Similarly, NDA_{ij}, represents the negative distance of the *ith* alternative from AV_i in terms of the *jth* criteria. If the *jth* criterion is a maximization criterion, it is calculated with Equation (7), and, if it is a minimization criterion then it is calculated with Equation (8).

$$PDA_{ij} = \frac{\max(0,(x_{ij} - AV_j))}{AV_j} \tag{5}$$

$$PDA_{ij} = \frac{\max(0,(AV_j - x_{ij}))}{AV_j} \tag{6}$$

$$NDA_{ij} = \frac{\max(0,(AV_j - x_{ij}))}{AV_j} \tag{7}$$

$$NDA_{ij} = \frac{\max(0,(x_{ij} - AV_j))}{AV_j} \tag{8}$$

Step 4: Calculation of the weighted sum of PDS (SP_i) and NDA (SN_i) values: Tthe weighted sum of positive and negative distances of all alternatives are determined by multiplication of the PDA_{ij} and NDA_{ij} values obtained in Step 3 by the pre-determined criteria weights. In other words, the weighted sums of the positive and negative distances from AV_i are calculated using Equations (9) and (10).

$$SP_i = \sum_{j=1}^{m} w_j PDA_{ij} \tag{9}$$

$$SN_i = \sum_{j=1}^{m} w_j NDA_{ij} \tag{10}$$

Here, w_j is the pre-determined weighting score of the *jth* criterion.

Step 5: Normalization of the SP_i and SN_i values: The normalized SP_i and SN_i values are calculated using Equations (11) and (12).

$$NSP_i = \frac{SP_i}{\max_i(SP_i)} \tag{11}$$

$$NSN_i = \frac{SN_i}{\max_i(SN_i)} \tag{12}$$

Step 6: Calculation of the assessment score for each alternative: AS_i values ($0 \le AS_i \le 1$) for all alternatives (the assessment scores) are calculated using Equation (13).

$$AS_i = {}^{1}/_{2}\,(NSP_i + NSN_i) \tag{13}$$

Step 7: Obtaining alternative ranking: The calculated AS_i values of each alternative are ranked from highest to lowest, where, the alternative with the highest AS_i value is determined as the most suitable.

4. SCIENTIFIC LITERATURE REVIEW

Work-related health issues and occupational disorders pose a vital advert impact on CE daily work; still the existing literature is unfortunately way far from having the depth to shed light on these problems. Despite the growing prevalence of these issues, existing a few ergonomic risk assessment practices for CEs often remain fragmented, focusing predominantly on isolated physical factors (e.g., workstation design), similar to any other occupation-based practices, while neglecting organizational and psychosocial dimensions. To the best of our knowledge, lamentably the CE literature is very limited regarding ergonomics applications even though within the searches by keywords "*occupational health*" and "*computer engineering*", "*occupational disorder*" and "*computer engineering*", "*occupational health and safety*" and "*computer *engineering*", "*ergonomics*" and "*computer engineering*", "*occupational disorders*" and "*computer engineering*"; which address the need for particular scientific studies focusing on CE work environment and ergonomics association. While the existing affluent OHS literature has numerous valuable instances studied on occupational disorders, the number of studies correlated with "*computers*" is again quite low. Almost all of these limited number of studies focus on the treatment of occupational disorders using computerized applications or computer software programs, or, on detection of occupational disorders using computer-added recognizing systems; hence, unfortunately, there are very few specific applications particular to occupational health and safety concerns on CE profession. As an instance, Ul Hasanat et al. (2017) investigated neck pain and its association with risk factors among software engineers in their study. As instances probed computer work but not CE occupation in particular, Giersiepen and Spallek (2011), Riccò, Pezzetti and Signorelli (2015), Lewanska et al. (2016), Riccò, Cattani and Signorelli (2016) analyzed carpal tunnel syndrome and tendinitis disorder in computer users, where, Moldovan et al. (2020) studied ocular disorders pertained to computer use.

EDAS method offers particular advantages for ergonomic analysis and applications highlighting both identification and investigation of element of a multi-dimensional problem. EDAS evaluates alternatives by measuring their positive and negative distances from an average solution, making it robust against extreme values and suitable for problems involving qualitative judgments and group evaluations. When combined with group decision-making, EDAS enables the aggregation of diverse expert opinions into a coherent prioritization framework. As a convenient and robust solution method, EDAS has a vast literature on varying application areas and problem types, however; to the best of our knowledge, there are no instances in the OHS or ergonomics application to CE occupation literature, which employed EDAS method as a solution approach. As limited instances available on ergonomics and OHS topics employed EDAS in the existing literature; Barros, Soares and Fernandes (2014) and Turskis and Juodagalvienė (2016) employed EDAS to ergonomic design problems, Şi̇mşek Keski̇n, Bahadir and Bi̇lgi̇n (2019) and Liu, Mou and Liu (2020) researched OHS topic, Soltani, Mohammadinejad, Rashnoudi and Ahmadi (2025) studied risk assessment framework. As recent instances to studies employed EDAS method to other themes, research areas of logistics (Pourmohammadreza & Akbari Jokar, 2024), energy (Brodny & Tutak, 2023; Dehshiri & Firoozabadi, 2024; Behera & Panda, 2025; GaneshKumar, Ajithkumar, Sivalingam, Divya, Oh, Pandiaraj & Al-Otaibi, 2025; Güler, Mukul & Konyalıoğlu, 2025), process and material selection (Aouag & Soltani, 2023; Chowdhury, Chatterjee & Chakraborty, 2024; Hadjira, Yallese, Chihaoui & Haddad, 2025; Kaykov, Mijalkovski & Arsova-Borisova, 2025), sustainability and environment (Mujeeb & Zafar, 2025; Thakkar, Paliwal, Prasad Gupta & Agrawal, 2025; Simsek, Koc & Gultekin Tarla, 2025) could be listed among numerous valuable works.

5. REAL WORLD APPLICATION

In this book chapter, to identify ergonomic risk factors in CE occupation associated with physical and psychological discomforts, which ultimately will breed employee inefficiency and work-related health issues, a group decision making model was developed employing EDAS method to yield a robust mathematical solution. The mathematical framework and calculation mechanism of EDAS will be demonstrated step-by-step through a real-life application. A risk catalog for conceptualization of occupational hazardous elements particular to CEs is aimed to be launched by redefining the biomechanical, physical, environmental and psychosocial risk groups within the CE context, and, scientifically recommend which ergonomic interventions should be performed first.

The criteria set is determined according to extant literature review (Atcheson, Ward & Lowe, 1998; Giersiepen & Spallek, 2011; Riccò, Pezzetti & Signorelli, 2015; Lewanska, Grzegorzewski & Walusiak-Skorupa, 2016; Riccò, Cattani & Signorelli, 2016; Ul Hasanat et al., 2017; Moldovan et al. 2020; Chim & Chen, 2021; Gaan & Sahoo, 2023; Ivory, Towse, Sturdee, Levine & Nuseibeh, 2023; Wong, Cheng, Oewel, Genuario, Stoeckl, Schueller, Ahmed, van der Hoek &

Reddy, 2025) and decision makers (DMs) experience and deliberately structured to reflect differentiated, symptom-specific influence patterns of ergonomic risk factors to CEs, ensuring that evaluation captures meaningful ergonomic causality rather than uniform exposure. In a living system, ergonomic risk factors do not influence all physical and psychological symptoms uniformly, e.g. improper monitor height primarily affects neck pain and visual strain, while cognitive workload predominantly contributes to mental fatigue and stress-related symptoms, leading us that each criterion has to be defined to theoretically and empirically affect CE occupational disorder symptoms differently than others. The identified criteria set consists of nine ergonomic risk factors; "*C_1:Prolonged static sitting* (extended periods of uninterrupted sitting combined with limited postural variation and low mobility lead to increased musculoskeletal loading)", "*C_2:Improper monitor configuration* (inappropriate monitor height, viewing distance, or screen angle, multiple monitor or laptop use place additional strain on the neck, shoulders, and visual system)", "*C_3:Inadequate keyboard and mouse ergonomics* (poorly designed or positioned input devices that force non-neutral wrist and forearm postures increase upper-extremity strain)", "*C_4:Insufficient micro-breaks* (lack of short, regular breaks for posture change, movement, and visual recovery e.g. 20-20-20 etc. results in cumulative physical and visual load)", "*C_5: Extended working hours* (night work, on-call working, sprint pressure, excessive daily or weekly working durations disrupt the balance between work and recovery and reduce overall resilience)", "*C_6: High cognitive workload* (sustained mental effort driven by complex tasks, continuous problem solving, and prolonged attentional demands)", "*C_7: Time pressure and work pace* (deadline-driven work structures, sprint cycles, and high task urgency intensify psychosocial stress)", "*C_8: Inadequate furniture ergonomics* (suboptimal home-office conditions, including unsuitable furniture, and poorly configured workstations)", "*C_9: Poor environmental conditions* (inadequate ambient lighting, glare, noise exposure, and thermal discomfort negatively affect both physical comfort and psychological well-being)". All criteria are modelled as maximization criteria, meaning that higher values correspond to higher ergonomic risk and greater potential negative impact, and, assumed to have same significance impact, meaning that having equal weighting scores.

The alternatives represent observable and self-reported physical and psychological symptoms that have strong theoretical and empirical links to ergonomic risk exposure and frequently experienced by CEs. *Neck Pain (A1)* is one of the most commonly reported WMSD among computer engineers. It is primarily associated with sustained head–neck flexion, prolonged screen viewing, inappropriate monitor positioning, and extensive laptop-based work. *Shoulder and Upper Back Pain (A2)* symptom includes discomfort, stiffness, and pain in the shoulder girdle and upper back region. It typically develops as a result of prolonged static arm positioning, inadequate arm support, and poorly arranged keyboard and mouse placement. *Lower Back Pain (A3)* represents a high-risk, often chronic condition linked to extend sitting periods, insufficient lumbar support, and limited opportunities for postural change during work. *Hand and Wrist Pain or Numbness (A4*) arise mainly from repetitive keyboard and mouse use, sustained non-neutral wrist postures, and localized contact pressure. These symptoms are frequently associated with cumulative trauma disorders, including carpal tunnel syndrome. *Eye Strain and Visual Discomfort (A5)* covers symptoms such as blurred vision, burning or dryness of the eyes and visual fatigue due to prolonged screen exposure, inadequate lighting conditions, glare, and insufficient visual rest. *General Physical Fatigue (A6)* refers to a pervasive sense of bodily exhaustion that develops due to cumulative static loading, low movement variability, and extended working hours without adequate recovery. *Mental Fatigue (A7)* manifests as diminished attention, slower cognitive processing, and difficulty in maintaining focus. It is strongly related to sustained cognitive demands, continuous problem-solving activities, and frequent task switching. *Work-Related Stress and Psychological Tension (A8)* encompasses psychological strain arising from high work intensity, time pressure, sprint-oriented workflows, elevated responsibility, and limited tolerance for errors. As the last, *Sleep Disturbances (A9)* and sleep-related problems include reduced sleep quality, irregular sleep patterns, and difficulty maintaining restorative sleep. These issues are often linked to long working hours, night-time work, and persistent digital connectivity beyond standard working times.

This chapter aims to reflect the perspectives of different parties involved to the handled decision process, CE employees, CE managers and OHS experts, hence, a group decision making based solution approach was adopted. Three DMs were contributed to the assessment process and demographics related to the DMT is presented in Table 1, hereinafter.

Table 1. DM Demographics

Expertise	Title	Background	Experience(years)
Backend	Expert Software Developer	CE	8
DevOps	Team Leader	CE (M.Sc.)	15
OHS	Expert	Chemical Engineering	5

Three different evaluation matrices were constructed for each DM for EDAS computations, where DM assessments were performed on a [1-9] linguistic scale. The DM assessments were gathered and presented in Table 2, hereinafter.

Table 2. DM assessments matrix

	C1			C2			C3			C4			C5		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
A1	9	9	6	9	7	7	5	7	3	7	9	4	7	9	5
A2	9	9	7	9	7	7	5	7	4	7	9	4	7	9	5
A3	9	9	7	9	7	5	5	5	4	7	9	4	7	9	5
A4	4	7	4	5	2	3	9	9	9	5	9	4	6	9	5
A5	2	7	5	9	9	9	2	2	1	7	9	6	8	9	5
A6	9	9	8	9	9	8	9	9	8	9	9	9	9	9	9
A7	5	9	6	6	2	3	3	2	2	9	9	9	9	9	9
A8	5	9	4	3	2	1	5	2	1	7	9	7	9	9	9
A9	2	7	7	2	2	1	1	2	1	7	5	7	9	9	9

	C6			C7			C8			C9		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
A1	2	2	1	4	7	3	7	7	9	4	2	1
A2	2	2	1	4	7	2	7	7	9	4	2	1
A3	2	2	1	4	7	2	8	7	9	2	2	1
A4	2	1	1	5	7	3	7	7	7	1	4	1
A5	4	5	3	3	7	4	3	3	5	9	7	7
A6	1	2	1	7	7	9	7	9	9	5	5	5
A7	9	9	9	9	9	9	1	2	1	9	5	9
A8	9	9	9	9	9	9	3	2	5	9	2	9
A9	7	9	9	9	9	9	1	5	5	7	5	7

EDAS method was applied according to the execution steps introduced in Section 3, and, AV matrix was constructed with the employment of Equation (1) and Equation (2), presented in Table 3, hereinafter.

Table 3. Avarage solution (AV_i) values

	C1	C2	C3	C4	C5	C6	C7	C8	C9
DM1	6,000	6,778	4,889	7,222	7,889	4,222	6,000	4,889	5,556
DM2	8,333	5,222	5,000	8,556	9,000	4,556	7,667	5,444	3,778
DM3	6,000	4,889	3,667	6,000	6,778	3,889	5,556	6,556	4,556

The positive (*PDA*) and negative (*NDA*) distance matrices were constructed with the employment of Equations (3 – 8), where, the weighted sum of *PDS* (SP_i) and *NDA* (SN_i) values were computed with the employment of Equation (9) and Equation (10), and, presented in Table 4, hereinafter.

Table 4. Weighted sum (SP_i and SN_i) values

	DM1		DM2		DM3	
	SPi	SNi	SPi	SNi	SPi	SNi
A1	0,142	0,143	0,129	0,124	0,089	0,307
A2	0,142	0,143	0,129	0,124	0,118	0,307
A3	0,165	0,183	0,084	0,124	0,073	0,307
A4	0,141	0,295	0,133	0,183	0,169	0,367
A5	0,107	0,247	0,192	0,144	0,153	0,211
A6	0,295	0,096	0,292	0,072	0,452	0,083
A7	0,293	0,163	0,178	0,206	0,415	0,188
A8	0,268	0,127	0,142	0,258	0,378	0,233
A9	0,173	0,333	0,164	0,208	0,348	0,196

The normalized values of NSP_i and NSN_i were calculated with the employment of Equation (11) and Equation (12) and presented in Table 5, hereinafter.

Table 5. Normalized (NSP_i and NSN_i) values

	DM1		DM2		DM3	
	NSPi	NSPi	NSPi	NSPi	NSPi	NSPi
A1	0,483	0,571	0,440	0,518	0,198	0,163
A2	0,483	0,571	0,440	0,518	0,261	0,164
A3	0,560	0,451	0,288	0,518	0,160	0,164
A4	0,480	0,113	0,455	0,291	0,374	0,000
A5	0,362	0,256	0,656	0,441	0,338	0,423
A6	1,000	0,712	1,000	0,721	1,000	0,775
A7	0,994	0,511	0,610	0,203	0,918	0,488
A8	0,910	0,619	0,487	0,000	0,837	0,365
A9	0,587	0,000	0,560	0,192	0,770	0,466

AS_i values were computed with Equation (13) for each DM and the assessment scores calculated for each alternative regarding each DM and also the overall assessment scores of alternative symptoms computed with the arithmetic mean operator were presented in Table 6, hereinafter.

Table 6. Assessment scores of alternatives

	A1	A2	A3	A4	A5	A6	A7	A8	A9
DM1	0,527	0,527	0,506	0,296	0,309	0,856	0,753	0,764	0,294
DM2	0,479	0,479	0,403	0,373	0,549	0,860	0,406	0,243	0,376
DM3	0,180	0,212	0,162	0,187	0,381	0,887	0,703	0,601	0,618
Overall	0,396	0,406	0,357	0,285	0,413	0,868	0,621	0,536	0,429

6. RESULTS AND DISCUSSION

In this chapter, identified ergonomic risk factors relevant to CEs are systematically identified and evaluated by a group of stakeholders, including engineers, ergonomics experts, and managerial decision makers. This chapter presents a multidimensional risk taxonomy particular to CEs, which simultaneously considers physical, job design, and psychosocial dimensions, aiming to fill a significance gap of the related literature. Thanks to the proposed solution framework, ergonomic risk definitions, which are based on a multi-criteria decision-making approach fueled by symptom data, and, did not remain abstract and could be addressed by relating them to common occupational disorder symptoms of CEs.

In this study, group decision making technique was applied to enable a more detailed definition of the problem space from different perspectives, and calculations were performed based on the assessments of three different DM profiles (Tables 1-6, Figure 1). As the data of Table 2 and Figure 1 indicates, each DM acted uniquely in their evaluations from their own perspective and made their profile-based decisions independently. Fluctuations in DM assessments are illustrated in Figure 1 for better analysis, hereinafter.

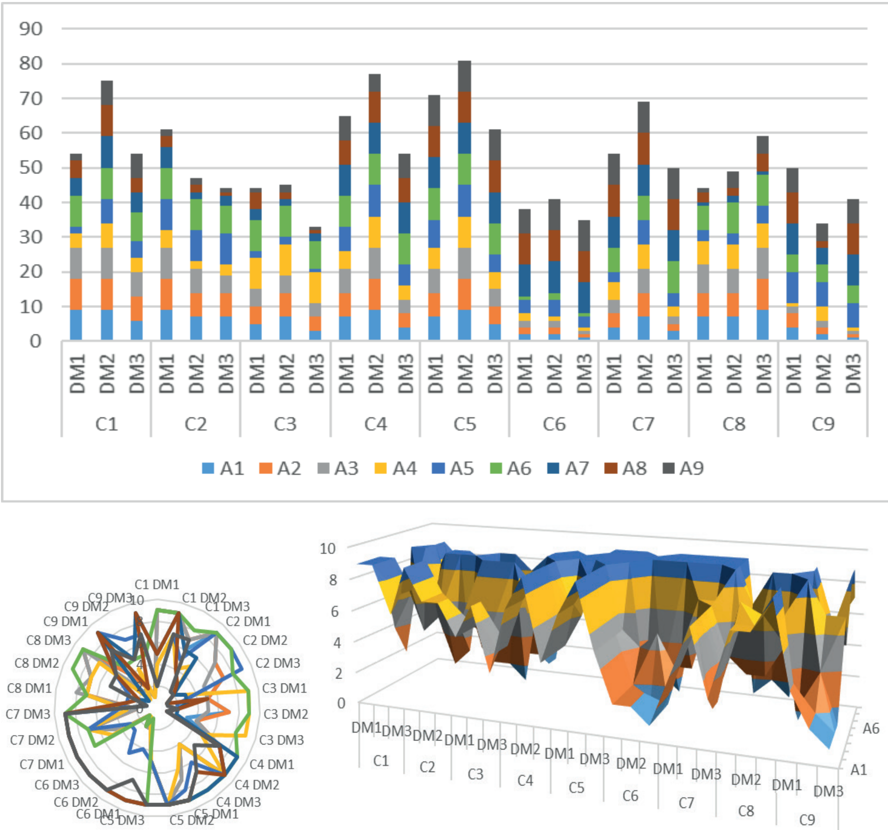


Figure 1. Delineated DM profiles and assessments analysis

According to the results, the symptoms most likely to occur according to the level of impact of delineated ergonomic risk factors are ranked as respectively A6, A7, A8, A9, A5, A4, A1, A3, and A4 (Table 6, Figure 2).

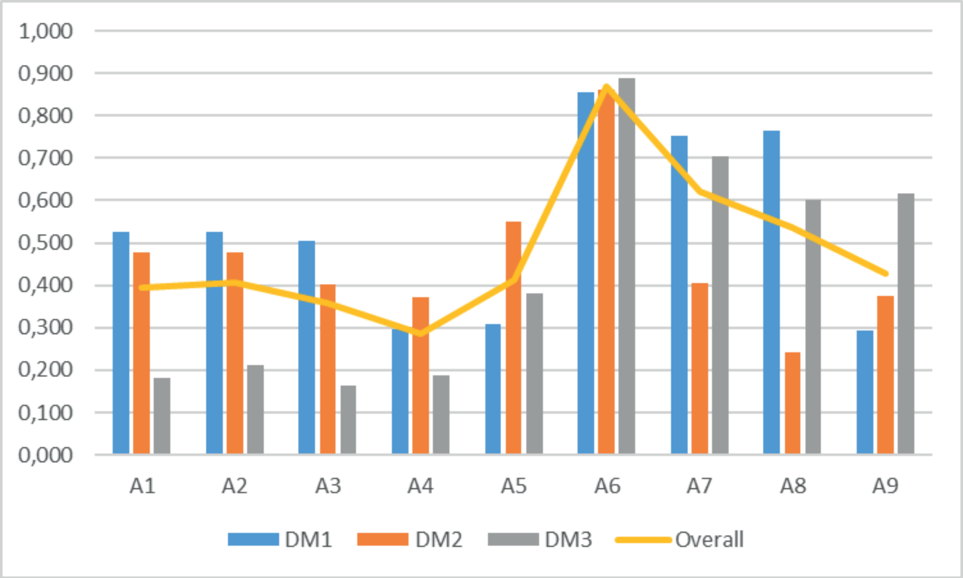


Figure 2. Delineated DM profiles and assessments analysis

The results suggest that WMSD symptoms (e.g. neck, shoulder, lower back pain, etc.) are primarily driven by physical workstation and posture-related risk factors, such as static sitting and improper monitor or input device configuration.

Considering the research volume, in contrast with the related literature, study findings revealed that cognitive workload-related symptoms "*A7: Mental fatigue and decreased concentration*" is ranked higher than limb-specific physical impairment symptoms in terms of likelihood of occurrence. This situation highlights the shortcomings of existing literature and provides opportunities for improvement in strategies that will prevent occupational disorders and decreased work efficiency caused by high cognitive workload and mental fatigue.

Through the indicated findings of this chapter, a symptom-to-intervention mapping could be ensured to develop short-, mid- and long-term ergonomic intervention strategies which are symptom-specific rather than generic and prioritized based on evidence.

As recommendations for low-or-no-cost *short-term ergonomic interventions* correcting monitor height and screen position to reduce excessive neck bending and visual strain, especially for employees heavily reliant on laptops; providing external keyboards and mouses to support upper extremity posture and reduce hand-wrist discomfort; implementing structured micro-breaks, supported by simple software reminders or shared team norms, to limit static load accumulating throughout the workday; adopting the 20-20-20 rule to promote vision improvement and reduce eye strain during prolonged screen use could be made. These actions can be reinforced with short posture awareness and guidance sessions as employee trainings aiming to observe the effects over a longer horizon.

As *mid-term ergonomic intervention strategies*, it is recommended to address persistent spinal strain and improve sitting posture by promoting the use of ergonomic furniture, integrating sit-stand desks or shared, height-adjustable workstations, conducting structured home office ergonomic assessments for remote workers to identify and correct work environment-related risk factors, reducing cumulative musculoskeletal strain by designing new jobs that reduce prolonged repetitive activities, and balancing cognitive load by implementing attention span policies that maintain uninterrupted working hours.

To introduce more durable structural improvements in CE working environment, *long-term ergonomic intervention strategies* as developing sustainable workload and sprint planning models that balance performance demands with rest needs, setting clear limits on long working hours and reducing expectations of "always being on," providing managers with psychosocial risk management and leadership training programs, and, continuously monitoring and updating the ergonomic risk and symptom modelling map prepared in this chapter can be suggested.

From a practical standpoint, the findings support the development of targeted ergonomic intervention strategies that balance health benefits, feasibility, and cost-effectiveness. Unlike traditional ergonomic checklists, the proposed framework identifies which symptoms are most sensitive to ergonomic deficiencies and highlights the dominant risk pathways contributing to each symptom.

A limitation of this study is that the DM weights were assigned equally; however, sensitivity analysis could be performed by assigning different weights to each DM based on their contribution to the evaluations. Future studies could also analyze the impact of including a larger number of DMs with different profiles (frontend, test, project owner, HR expert, project manager, etc.) in the decision-making process on the results.

REFERENCES

Aouag, H., & Soltani, M. (2023). Improvement of lean manufacturing approach based on MCDM techniques for sustainable manufacturing. *International Journal of Manufacturing Research*, *18*(1), 50-74.

Atcheson, S. G., Ward, J. R., & Lowe, W. (1998). Concurrent medical disease in work-related carpal tunnel syndrome. *Archives of Internal Medicine*, *158*(14), 1506-1512.

Barros, R. Q., Soares, M. M., & Fernandes, M. G. (2014, June). Ergonomic evaluation of manual force levels of the elderly in the handling of products: an analysis using virtual reality. In *International Conference of Design, User Experience, and Usability* (pp. 124-132). Cham: Springer International Publishing.

Behera, M., & Panda, A. C. (2025). Assessment of renewable energy systems through the integrated SWARA-LOPCOW-EDAS decision-making method with a novel Fermatean fuzzy scoring function. *Journal of the Operational Research Society*, 1-25.

Brodny, J., & Tutak, M. (2023). *Assessing the energy and climate sustainability of European Union member states: An MCDM-based approach. Smart Cities, 6 (1), 339–367.*

Chim, J.M.Y., & Chen, T. (2021). Occupational Disease Compensation and Update on the Musculoskeletal Health of Office Employees in Hong Kong. In: Black, N.L., Neumann, W.P., Noy, I. (eds) Proceedings of the 21st Congress of the International Ergonomics Association (IEA 2021). IEA 2021. Lecture Notes in Networks and Systems, vol 222. Springer, Cham. https://doi.org/10.1007/978-3-030-74611-7_97

Chowdhury, S. R., Chatterjee, S., & Chakraborty, S. (2024). Optimization of grinding processes using multi-criteria decision making methods in intuitionistic fuzzy environment. *Opsearch*, *61*(2), 709-740.

Dehshiri, S. S. H., & Firoozabadi, B. (2024). Sustainable solar energy in urban areas: A novel framework for uncertainty, reliability, and 7E analysis. *Journal of Cleaner Production*, *444*, 141136.

Gaan, N., & Sahoo, A. (2023). Adhocracy culture buffers for mindfulness outcome: A cross-level moderated mediation analysis. *Telematics and Informatics Reports*, *11*, 100071.

GaneshKumar, P., Ajithkumar, A., Sivalingam, V., Divya, S., Oh, T. H., Pandiaraj, S., & Al-Otaibi, J. S. (2025). Exploring the cost-effective and environmentally friendly energy storage materials for solar desalination: A multi-criteria decision-making framework. *Journal of Energy Storage*, *132*, 117720.

Giersiepen, K., & Spallek, M. (2011). Carpal tunnel syndrome as an occupational disease. *Deutsches Ärzteblatt International*, *108*(14), 238.

Güler, M., Mukul, E., & Konyalıoğlu, A. K. (2025). A hesitant fuzzy approach to renewable energy technology selection aligned with sustainable development goals in Turkey. *Sustainable Chemistry and Pharmacy*, *48*, 102261.

Hadjira, B., Yallese, M. A., Chihaoui, S., & Haddad, A. (2025). Optimization of cutting parameters in hard machining of AISI 52100 with wiper and conventional ceramic insert using the DF, EDAS, and VIKOR methods. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 09544062251329763.

International Ergonomics Association, "What is ergonomics?," 2021, https://iea.cc/what-is-ergonomics/

Ivory, M., Towse, J., Sturdee, M., Levine, M., & Nuseibeh, B. (2023). Recognizing the known unknowns; the interaction between reflective thinking and optimism for uncertainty among software developer's security perceptions.

Kaykov, D., Mijalkovski, S., & Arsova-Borisova, K. (2025). Mining method selection based on hierarchical clustering and correspondence analysis. *Mining Science*, *32*.

Keshavarz Ghorabaee, M., Zavadskas, E. K., Olfat, L., & Turskis, Z. (2015). Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS). *Informatica*, 26 (3), 435-451.

Lewańska, M. J., Grzegorzewski, A., & Walusiak-Skorupa, J. (2016). Bilateral hypermobility of ulnar nerves at the elbow joint with unilateral left ulnar neuropathy in a computer user-a case study. *International Journal of Occupational Medicine and Environmental Health*, *29*(3).

Liu, R., Mou, X., & Liu, H. C. (2020). Occupational health and safety risk assessment based on combination weighting and uncertain linguistic information: method development and application to a construction project. *IISE transactions on occupational ergonomics and human factors*, *8*(4), 175-186.

Moldovan, H. R., Voidazan, S. T., Moldovan, G., Vlasiu, M. A., Moldovan, G., & Panaitescu, R. (2020). Accommodative asthenopia among Romanian computer-using medical students—A neglected occupational disease. *Archives of environmental & occupational health*, *75*(4), 235-241.

Mujeeb, A., & Zafar, A. (2025). Assessing Environmental Pollution: Quality Control Using CRITIC-WASPAS Methods under Intuitionistic Fuzzy Z-Numbers Bushra Khalid Department of Mathematics, COMSATS University Islamabad, Vehari Campus, Pakistan. *Punjab University Journal of Mathematics*, *57*(02), 139-165.

Pourmohammadreza, N., & Akbari Jokar, M. R. (2024). Efficient last-mile logistics with service options: A multi-criteria decision-making and optimization methodology. *International Journal of Industrial Engineering Computations, 15*(2), 367-386.

Ricco, M., Cattani, S., & Signorelli, C. (2016). Personal risk factors for carpal tunnel syndrome in female visual display unit workers. *International Journal of Occupational Medicine and Environmental Health*, *29*(6), 927-936.

Riccò, M., Pezzetti, F., & Signorelli, C. (2015). Risk factors for Carpal Tunnel Syndrome in female visual display unit workers. In *European Journal of Neurology* (Vol. 22, pp. 791-791). 111 RIVER ST, HOBOKEN 07030-5774, NJ USA: WILEY.

Şi̇mşek Keski̇n, H., Bahadir, H., & Bi̇lgi̇n, A. C. (2019). Physıcıans attıtudes towards the elderly: Ageısm in a unıversıty hospıtal in turkey. *Türk Geriatri Dergisi*, *22*(1), 101-11.

Simsek, A. I., Koc, E., & Gultekin Tarla, E. (2025). Assessing Green Logistics and Supply Chain Resilience With Future Importance Analysis: Machine Learning and Multicriteria Decision-Making Approach. *Business Strategy and the Environment*. Article in Press.

Soltani, E., Mohammadinejad, A., Rashnoudi, P., & Ahmadi, O. (2025). A fuzzy based hybrid approach for risk assessment of anesthesiologists using OPA and EDAS methods. *Scientific Reports*, *15*(1), 32028.

Taifa, I. W. (2022). A student-centred design approach for reducing musculoskeletal disorders in India through six sigma methodology with ergonomics concatenation. Safety Science, vol. 147, Article ID 105579.

Taifa, I. W., & Desai, D. A. (2016). Student-defined quality by Kano model: a case study of engineering students in India, Int. J. Qual. Res., vol. 10, no. 3, pp. 569–582.

Thakkar, N., Paliwal, P., Prasad Gupta, N., & Agrawal, R. (2025). Sensitivity Analysis of Sustainability Dimensions in Technology Ranking in Multi-Criteria Decision-Making Approaches. *Process Integration and Optimization for Sustainability*, 1-26.

Turskis, Z., & Juodagalvienė, B. (2016). A novel hybrid multi-criteria decision-making model to assess a stairs shape for dwelling houses. *Journal of Civil Engineering and Management*, *22*(8), 1078-1087.

Ul Hasanat, M. R., Ali, S. S., Rasheed, A., & Khan, M. (2017). Frequency and associated risk factors for neck pain among software engineers in Karachi, Pakistan. *JPMA. The Journal of the Pakistan Medical Association*, *67*(7), 1009-1012.

Wong, N., Cheng, N. Y., Oewel, B., Genuario, K. E., Stoeckl, S., Schueller, S. M., Ahmed, I., van der Hoek, A. & Reddy, M. (2025). 'It's a spectrum': Exploring Autonomy, Competence, and Relatedness in Software Development Processes and Tools. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-19).

Yılmaz Kaya, B. (2022). Minimizing OHS risks with spherical fuzzy sets as a verdict to inventory management: A case regarding energy companies. *Discrete Dynamics in Nature and Society*, *2022*(1), 9511339.

Yılmaz Kaya, B., & Kılıç Delice, E. (2024). How Resilient are Lucid Motivators? Endeavoring Reforms for Effects of Psycho-social Factors on Workers Health Through Concurrent Engineering. *Safety and Health at Work*, *15*(3), 327-337.