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Optimization of facility layout design in furniture manufacturing using fuzzy AHP and fuzzy EDAS and comparison with fuzzy ARAS

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ABSTRACT: Efficient facility layout design is crucial for optimizing operations, reducing costs, and enhancing productivity in manufacturing environments. This study focuses on evaluating and prioritizing layout alternatives for a furniture manufacturing facility in Türkiye. An integrated decision-making methodology combining fuzzy AHP (analytic hierarchy process) and fuzzy EDAS (evaluation based on distance from average solution) is employed to solve the problem. The fuzzy AHP procedure is applied to assess the importance of criteria influencing facility layout decisions. The fuzzy EDAS procedure is used to evaluate and rank facility layout alternatives. To support the model results, a comparative analysis using fuzzy ARAS and a sensitivity analysis based on weight variations are conducted. Flexibility emerges as the most important criterion with a weight of 35.56%. Among the alternatives, layout option A3 demonstrates the best performance with a score of 0.9872, corresponding to a 68.28% share. The study results demonstrate significant operational improvements, including reduced production distances, enhanced energy efficiency, minimized bottlenecks, and accelerated assembly processes. This research serves as a valuable reference for addressing similar optimization challenges across various industries.

Keywords: Furniture facility design, AHP, EDAS, ARAS, Fuzzy set

Mobilya üretiminde bulanık AHP ve bulanık EDAS kullanılarak tesis yerleşim tasarımının optimizasyonu ve bulanık ARAS ile karşılaştırma

ÖZ: Üretim ortamlarında operasyonların optimize edilmesi, maliyetlerin azaltılması ve verimliliğin artırılması açısından etkili bir tesis yerleşim tasarımı büyük önem taşır. Bu çalışma, Türkiye'deki bir mobilya üretim tesisine yönelik yerleşim alternatiflerini değerlendirmeye ve önceliklendirmeye odaklanmaktadır. Problemin çözümünde, bulanık AHP (analitik hiyerarşi süreci) ve bulanık EDAS (ortalama çözüme uzaklığa dayalı değerlendirme) yöntemlerini birleştiren entegre bir karar verme metodolojisi kullanılmaktadır. Bulanık AHP yöntemi, tesis yerleşim kararlarını etkileyen kriterlerin önem derecesini değerlendirmek için uygulanmaktadır. Bulanık EDAS yöntemi ise tesis yerleşim alternatiflerini değerlendirmek ve sıralamak amacıyla kullanılmaktadır. Model sonuçlarını desteklemek amacıyla, bulanık ARAS kullanılarak bir karşılaştırmalı analiz ve ağırlık değişimlerine dayalı bir duyarlılık analizi gerçekleştirilmektedir. Esneklik %35,56 ağırlık ile en önemli kriter olarak öne çıkmaktadır. Alternatifler arasında, A3 yerleşim seçeneği 0,9872 puanla en iyi performansı sergilemekte olup, bu değer %68,28'lik bir paya karşılık gelmektedir. Çalışma sonuçları; üretim mesafelerinin azaltılması, enerji verimliliğinin artırılması, darboğazların en aza indirilmesi ve montaj süreçlerinin hızlandırılması gibi önemli operasyonel iyileşmeleri ortaya koymaktadır. Bu araştırma, çeşitli endüstrilerde benzer optimizasyon sorunlarının ele alınmasında değerli bir kaynak niteliği taşımaktadır.

Anahtar kelimeler: Mobilya tesisi tasarımı, AHP, EDAS, ARAS, Bulanık küme

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1 Introduction

Facility layout planning plays a crucial role in the design and optimization of manufacturing systems, service organizations, and logistics operations. It is a strategic endeavor aimed at arranging physical resources, including equipment, workstations, and storage areas, within a facility to maximize efficiency, safety, and operational effectiveness (Besbes et al., 2020). Facility layout planning directly influences productivity, costs, material flow, energy consumption, and overall organizational performance. A well-designed layout minimizes transportation and handling costs, improves communication and workflow, and supports scalability and adaptability in dynamic environments (Zha et al., 2020).

Facility layout planning has been approached through various methodologies, including systematic layout planning, mathematical optimization, and heuristic techniques. Traditionally, the focus has been on single-objective optimization, often prioritizing cost or space utilization (Al-Zubaidi et al., 2021). However, modern industries operate in complex and competitive environments, where decision-making involves balancing multiple, and sometimes conflicting, criteria. This shift has highlighted the need for multicriteria decision-making (MCDM) approaches in facility layout planning. A structured and systematic approach that integrates multiple criteria into the decision-making process is essential for effective facility layout planning (Nenzhelele et al., 2023).

MCDM is a branch of operations research that focuses on evaluating a set of alternatives based on a predefined set of criteria. These criteria can be either quantitative or qualitative, depending on the context of the decision-making problem. MCDM involves analyzing and comparing various options to assist decision-makers in selecting the most appropriate solution. The key components of MCDM include goals, alternatives, criteria, weights, and decision-makers' preferences (Mofarrah, 2008; Kumar et al., 2017). MCDM encompasses a variety of methods aimed at aiding decision-makers in scenarios where multiple decision elements must be considered simultaneously. Some of the most popular MCDM methods include the analytic hierarchy process (AHP), the technique for order of preference by similarity to ideal solution, the weighted aggregated sum product assessment, the evaluation based on distance from average solution (EDAS), and the decision-making trial and evaluation laboratory.

Traditional MCDM methods utilize crisp numerical inputs, which may not adequately represent real-world conditions. Fuzzy logic provides a framework for incorporating human-like reasoning into MCDM. Fuzzy set theory allows elements to have partial membership in a set, represented by membership functions ranging from 0 to 1. This capability makes fuzzy MCDM well-suited for problems involving human judgment. Fuzzy MCDM is an advanced decision-support technique that integrates the principles of fuzzy set theory into multicriteria decision analysis (Keshavarz Ghorabaee et al., 2018). In a typical fuzzy MCDM process, decision-makers first define decision elements. The ratings for criteria and alternatives are expressed using linguistic terms and fuzzy numbers (connected set of possible values). Fuzzy MCDM is particularly useful in situations where decision-making involves multiple, often conflicting criteria, and where the input data or preferences are imprecise, uncertain, or subjective (Petrović et al., 2019).

An integrated fuzzy decision-making methodology, consisting of AHP and EDAS, is employed in this study for modeling and analyzing the facility layout problem. AHP solves complex problems by structuring them into a hierarchical framework. By using pairwise comparisons and a numerical scale to assess the importance of decision elements, AHP assigns priority weights to criteria and ranks alternatives (Özşahin et al., 2019; Kuşcuoğlu and

Dilik, 2023). AHP offers numerous advantages, making it a valuable tool for decision-making. One of its key strengths is its ability to structure complex problems into a clear hierarchy, enabling systematic analysis of each component. AHP includes a consistency check to ensure that pairwise comparisons are reliable. Its emphasis on both qualitative and quantitative factors enhances the overall quality and defensibility of decisions (Moeinaddini et al., 2010). In this study, fuzzy AHP is used to prioritize facility layout selection criteria. EDAS is designed to rank alternatives based on their proximity to an ideal solution. This method calculates positive and negative distances for each criterion, aggregates them, and uses these values to determine the overall performance score of each alternative (Keshavarz Ghorabaee et al., 2015). EDAS offers several advantages. One of its primary strengths is its ability to balance positive and negative deviations from the average solution. This dual consideration minimizes bias and ensures that all aspects of performance are considered. Additionally, EDAS is computationally straightforward, making it accessible and easy to implement across various decision-making scenarios. Its reliance on the average solution as a reference point makes it particularly suitable for situations where extreme values or outliers might distort the results of other MCDM methods (Torkayesh et al., 2023). In this study, fuzzy EDAS is used to prioritize facility layout alternatives.

The purpose of this study is to evaluate and prioritize facility layout alternatives for a furniture manufacturing facility by integrating the AHP and EDAS methods within a fuzzy environment. The motivation stems from the significant impact of facility layout decisions on operational efficiency and resource optimization in furniture manufacturing. The fuzzy AHP procedure is used to determine the importance of criteria influencing facility layout decisions, while the fuzzy EDAS procedure is applied to rank facility layout alternatives. This study provides a reliable and flexible tool to support strategic facility layout decisions.

2 Materials and Methods

2.1 Fuzzy sets and fuzzy numbers

Fuzzy set theory extends the classical concept of sets by allowing elements to have partial membership rather than a binary inclusion or exclusion. In classical set theory, an element either belongs to a set (membership value of 1) or does not belong (membership value of 0). However, in many real-world scenarios, boundaries between categories or sets are not clear-cut, leading to uncertainty and vagueness. Fuzzy sets provide a mathematical framework to handle this imprecision by assigning a membership grade to each element in the range [0, 1]. The degree of membership reflects the extent to which an element belongs to the fuzzy set. A triangular fuzzy number is defined by three parameters (l, m, u), where l is the lower limit, m is the middle value, and u is the upper limit. The membership function of a triangular fuzzy number is defined using Equation (1). The triangular fuzzy number is graphically represented as a triangle on a two-dimensional plane, where the base spans from l to u and the peak occurs at m with a membership value of 1. This simple structure makes it a popular choice in fuzzy modeling (Akdag et al., 2014).

$$\mu_{\widetilde{M}}(x) = \begin{cases} 0, & x < l \text{ or } x > u \\ (x-l)/(m-l), & l \le x \le m \\ (u-x)/(u-m), & m \le x \le u \end{cases} \tag{1}$$

If $\widetilde{M}_1 = (l_1, m_1, u_1)$ and $\widetilde{M}_2 = (l_2, m_2, u_2)$ represent two triangular fuzzy numbers, their common mathematical operations are defined as follows:

$$\widetilde{M}_1 \oplus \widetilde{M}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

$$\widetilde{M}_1 \ominus \widetilde{M}_2 = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{3}$$

$$\widetilde{M}_1 \otimes \widetilde{M}_2 = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (4)$$
$$\alpha\widetilde{M}_1 = (\alpha l_1, \alpha m_1, \alpha u_1) \quad (5)$$
$$\widetilde{M}_1^{-1} = (1/u_1, 1/m_1, 1/l_1) \quad (6)$$

2.2 Fuzzy AHP method

AHP is designed to address complex MCDM problems by organizing them into a hierarchical structure. The core concept of AHP involves breaking down a problem into a hierarchy of levels, typically starting with the goal at the top, followed by criteria and subcriteria in the middle, and alternatives at the bottom. Decision-makers perform pairwise comparisons of decision elements at each level using a scale of importance ranging from 1 (equal importance) to 9 (extreme importance). AHP incorporates a built-in consistency ratio that evaluates the coherence of pairwise comparisons. Pairwise comparison matrices are constructed and analyzed to obtain weights. These weights reflect the importance of each decision element (Darko et al., 2019). Traditional AHP relies on precise numerical values for pairwise comparisons, but in many real-world scenarios, decision-makers may find it difficult to express their judgments with exact numbers due to the complexity of the problem. Fuzzy AHP addresses this limitation by using fuzzy logic to model these judgments. Some notable studies that have utilized the fuzzy AHP method can be listed as follows: conveyor selection (Nguyen et al., 2016), flood vulnerability assessment (Duan et al., 2022), nuclear power plant selection (Abdullah et al., 2023), third-party logistics provider selection (Wang et al., 2024), and prioritization of renewable energy sources (Luhaniwal et al., 2025). The current study uses the Buckley AHP method to prioritize facility layout selection criteria. This method consists of the following steps (Buckley, 1985; Budak and Ustundag, 2015):

Step 1: A fuzzy pairwise comparison matrix is created according to Equation (7).

$$D = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & \tilde{a}_{nn} \end{bmatrix} \quad (7)$$

where n refers to the number of criteria, and $\tilde{a}_{ij}$ is a triangular fuzzy number representing the importance between two criteria.

Step 2: Geometric means of fuzzy comparison values are calculated using Equation (8).

$$\tilde{r}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \dots \otimes \tilde{a}_{in})^{1/n} \quad (8)$$

Step 3: Fuzzy weight values are calculated using Equation (9).

$$\widetilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{-1} \quad (9)$$

Step 4: Weight vectors are obtained using Equation (10).

$$w_{Fj} = \frac{\widetilde{w}_{Fj}'}{\sum_{j=1}^{n} \widetilde{w}_{Fj}'} = \frac{w_{Fjl} + w_{Fjm} + w_{Fju}}{\sum_{j=1}^{n} \widetilde{w}_{Fij}'} \quad (10)$$

2.3 Fuzzy EDAS method

EDAS serves as an effective tool for assessing and ranking alternatives based on their performance relative to a set of criteria. The central idea of EDAS revolves around the comparison of each alternative with an average solution, which is derived by calculating the mean value of each criterion across all alternatives. For each alternative, two measures are computed: the positive distance from average (PDA) and the negative distance from average (NDA). The final performance score of each alternative is computed by integrating the weighted PDA and NDA values (Keshavarz Ghorabaee et al., 2015). Fuzzy EDAS is a powerful extension of classical EDAS. It is designed to address the challenges of uncertainty and vagueness in decision-making. Fuzzy EDAS is particularly suitable for scenarios where precise data are challenging to obtain. The following are some prominent studies that have employed the fuzzy EDAS method: hospital site selection (Yilmaz and Atan, 2021), energy consumption planning (Demirtas et al., 2021), material selection (Singer and Över Özçelik, 2022), strategy analysis (Le and Nhieu, 2022), and wind turbine selection (Tüysüz and Kahraman, 2023). The current study uses the fuzzy EDAS method to prioritize facility layout alternatives. The steps of this method are as follows (Ghorabaee et al., 2016; Hasheminasab et al., 2019):

Step 1: A decision matrix is structured with m alternatives and n criteria. This matrix contains the performance values ($\tilde{x}_{ij}$) of each alternative across various criteria.

$$A = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}; i = 1,\ldots,m; j = 1,\ldots,n \tag{11}$$

Step 2: Average solutions are obtained using Equation (12).

$$\widetilde{av}_j = \frac{1}{m} \bigoplus_{i=1}^{m} \tilde{x}_{ij} \tag{12}$$

Step 3: PDA and NDA matrices are constructed according to the following equations:

$$\widetilde{pda}_{ij} = \begin{cases} \dfrac{\psi\left(\tilde{x}_{ij} \ominus \widetilde{av}_j\right)}{\kappa(\widetilde{av}_j)} & \text{if } j \in \text{set of benefit criteria} \\ \dfrac{\psi\left(\widetilde{av}_j \ominus \tilde{x}_{ij}\right)}{\kappa(\widetilde{av}_j)} & \text{if } j \in \text{set of cost criteria} \end{cases} \tag{13}$$

$$\widetilde{nda}_{ij} = \begin{cases} \dfrac{\psi\left(\widetilde{av}_j \ominus \tilde{x}_{ij}\right)}{\kappa(\widetilde{av}_j)} & \text{if } j \in \text{set of benefit criteria} \\ \dfrac{\psi\left(\tilde{x}_{ij} \ominus \widetilde{av}_j\right)}{\kappa(\widetilde{av}_j)} & \text{if } j \in \text{set of cost criteria} \end{cases} \tag{14}$$

The function $\kappa(\tilde{A})$ is used to obtain the defuzzified value of a triangular fuzzy number, while the function $\psi(\tilde{A})$ identifies the maximum value between the triangular fuzzy number and zero. Equations (15) and (16) are used to calculate these functions.

$$\kappa(\tilde{A}) = \frac{l + 2m + u}{4} \tag{15}$$

$$\psi(\tilde{A}) = \begin{cases} \tilde{A} & \text{if } \kappa(\tilde{A}) > 0 \\ 0 & \text{if } \kappa(\tilde{A}) \leq 0 \end{cases} \tag{16}$$

Step 4: The weighted sum of PDA and weighted sum of NDA are calculated using Equations (17) and (18).

$$\widetilde{sp}_i = \bigoplus_{j=1}^{n} (\tilde{w}_j \otimes \widetilde{pda}_{ij}) \tag{17}$$

$$\widetilde{sn}_i = \bigoplus_{j=1}^{n} (\widetilde{w}_j \otimes \widetilde{nda}_{ij}) \tag{18}$$

Step 5: The summed values are normalized using Equations (19) and (20).

$$\widetilde{nsp}_i = \frac{\widetilde{sp}_i}{\max_i(\kappa(\widetilde{sp}_i))} \tag{19}$$

$$\widetilde{nsn}_i = 1 - \frac{\widetilde{sn}_i}{\max_i(\kappa(\widetilde{sn}_i))} \tag{20}$$

Step 6: Fuzzy performance scores are obtained using Equation (21).

$$\widetilde{as}_i = \frac{\widetilde{nsp}_i \oplus \widetilde{nsn}_i}{2} \tag{21}$$

Step 7: Crisp performance scores are revealed using Equation (15).

3 Application

3.1 Problem definition

This study focuses on identifying and addressing inefficiencies in the production processes of child bed components within a furniture manufacturing facility in Türkiye. An integrated fuzzy AHP-EDAS methodology is proposed to handle the problem. The current operations face significant challenges that adversely impact operational efficiency, productivity, and customer satisfaction. These issues primarily stem from suboptimal facility layout and production flow, highlighting an urgent need for waste reduction and process optimization. Specifically, the study examines the MOBAKS line within the facility. Figure 1 illustrates the existing operations on the MOBAKS line.

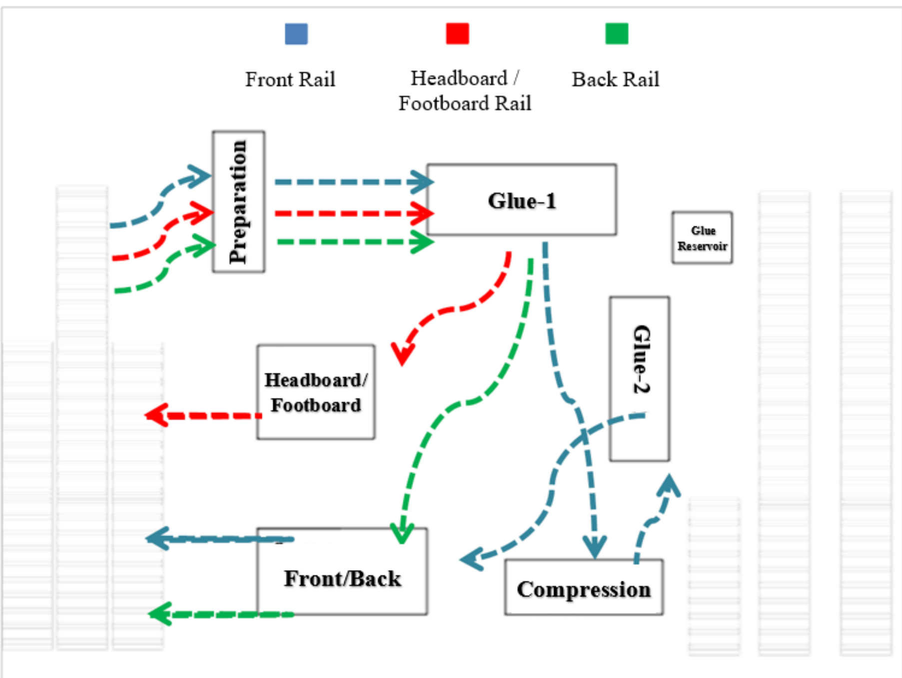

Figure 1. Current operations of the MOBAKS line

The current facility layout limits the effective utilization of both the workforce and production space. This structure results in the unnecessary transportation of parts over long distances, leading to wasted time, increased energy consumption, and heightened material handling costs. Moreover, the expansion of product variety and the rising demand from customers have outpaced the current capacity of the facility. This mismatch creates delays, backlogs, and reduced responsiveness to orders. Interruptions in production flow caused by bottlenecks and process inefficiencies further exacerbate the situation. An additional challenge lies in the use of high-power machinery for simple tasks. Meanwhile, the components of newly developed modules require prolonged machining times on standard CNC machines. This contributes to extended cycle times, delays in the production line, and reduced overall throughput. Deviations from standard work definitions, coupled with a lack of streamlined processes, lead to defects and increased customer dissatisfaction. The growing number of customer complaints highlights the pressing need for improvement initiatives.

As part of this study, a needs analysis is conducted by evaluating the current production plans for child beds alongside medium- and long-term strategies for future growth. A detailed assessment of the production efficiency of machines and workstations is carried out to identify areas for improvement. Based on the processing steps of the production components, alternative layouts are evaluated. Interactions between the machines are examined. Figure 2 presents the current route analysis of the considered line and a relationship diagram for the machines. The left side of the figure (⟵) shows the defined routes and the total Kanban quantity for each route. The most frequently used routes are B-B-C (540) and B-D-E (459), indicating critical material flows within the system. The right side of the figure (⟶) shows a relationship matrix detailing the number of direct transitions between the machines. The highest values are observed in the flows between B-C (954), D-E (465), and B-D (465). These figures point to a highly intensive workflow among these machines, underscoring the importance of positioning them in close physical proximity to ensure an efficient layout design. With the addition of a new area to the layout, alternative layout configurations are identified.

Route	Kanban Quantity
B-B-C	540
B-D-E	459
B-C-G	155
B-C	122
P-G	111
B-F	82
B-B-C-C-F	85
B-C-F	52
F-C	48
B-G	35
I-F	30
M-F	25
F	17
K-E	8
P-F	7
L-F	6
O-H-E	6
J-D-E	6
N-E	6
K-F	6
P-E	4
B-B-F	4
B-B	4
B-D-K-K-C-E	3
B-D-K-E	3
R-H-E	3

Machine	A	B	C	D	E	F	G	H	I	J	K
A						17					
B			**954**	**465**		86	35				
C					3	137	155				
D					**465**						6
E											
F			48								
G											
H					9						
I						30					
J				6			47				
K			3		11	6					
L						6					
M						25					
N					6						
O							6	6			
P					4	7	**220**				
R								3			

Figure 2. Current route analysis and machine relationship diagram for the MOBAKS line

3.2 Decision-making framework

This study employs a two-phase decision-making methodology to handle the facility layout problem. In the first phase, the fuzzy AHP procedure is applied to assess the importance of criteria influencing facility layout decisions. Fuzzy AHP generates criteria weights that reflect their significance in achieving the facility's operational objectives. Building on these weights, the second phase utilizes the fuzzy EDAS procedure to prioritize facility layout alternatives. Fuzzy EDAS evaluates each alternative's performance by analyzing its distance from the average solution, accounting for both positive and negative deviations. Sensitivity analysis is performed by varying the criteria weights to observe the stability of ranking outcomes. Additionally, comparative analysis is conducted using the fuzzy ARAS method.

An expert team is established to evaluate the decision elements of the model. The selection of experts is based on their domain-specific knowledge and prior experience in relevant decision-making processes. Three alternatives (denoted as A1, A2, and A3) are analyzed to identify the most effective solution. The criteria defined for evaluating the alternatives are total walking distance (C1), distance for cutting and drilling (C2), distance for roofless bedframe (C3), total rail savings (C4), compatibility with other machines (C5), and flexibility (C6).

3.3 Prioritization of evaluation criteria

Prioritizing evaluation criteria is a critical step to ensure that decisions align with operational goals and long-term efficiency. This study uses fuzzy AHP to prioritize the criteria influencing layout selection decisions. The fuzzy AHP process involves the pairwise comparisons of the criteria. The experts assess the importance of each criterion using linguistic terms provided in Table 1. These linguistic terms are subsequently converted into triangular fuzzy numbers for mathematical calculations.

Table 1. Linguistic terms and fuzzy numbers to evaluate the criteria (Ali Sadat et al., 2021)

Code	Linguistic term	Fuzzy number
1	Equally important	(1, 1, 1)
2	Equally to slightly more important	(1, 2, 3)
3	Fairly more important	(2, 3, 4)
4	Fairly more important to highly important	(3, 4, 5)
5	Highly important	(4, 5, 6)
6	Highly important to very highly important	(5, 6, 7)
7	Very highly important	(6, 7, 8)
8	Very highly important to absolutely more important	(7, 8, 9)
9	Absolutely more important	(8, 9, 10)

The pairwise comparisons are arranged in a fuzzy matrix (Table 2). To ensure consistency and reliability, the consistency ratio of the pairwise comparisons is calculated using the classical AHP consistency check procedure (Saaty 1977). Since the calculated value is below the threshold of 0.1, the evaluations are considered consistent and acceptable. Fuzzy AHP calculates the weights of the criteria based on the created matrix. These weights are then used to rank the criteria and guide the subsequent evaluation of the layout alternatives. The resulting weights are presented in Figure 3.

Table 2. Fuzzy pairwise comparison matrix

Criterion	C1	C2	C3	C4	C5	C6
C1	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)	(1, 1, 1)	(0.25, 0.33, 0.50)	(0.25, 0.33, 0.50)
C2		(1, 1, 1)	(1, 1, 1)	(0.25, 0.33, 0.50)	(0.17, 0.20, 0.25)	(0.17, 0.20, 0.25)
C3			(1, 1, 1)	(0.25, 0.33, 0.50)	(0.17, 0.20, 0.25)	(0.17, 0.20, 0.25)
C4				(1, 1, 1)	(0.33, 0.50, 1.00)	(0.33, 0.50, 1.00)
C5					(1, 1, 1)	(0.25, 0.33, 0.50)
C6						(1, 1, 1)

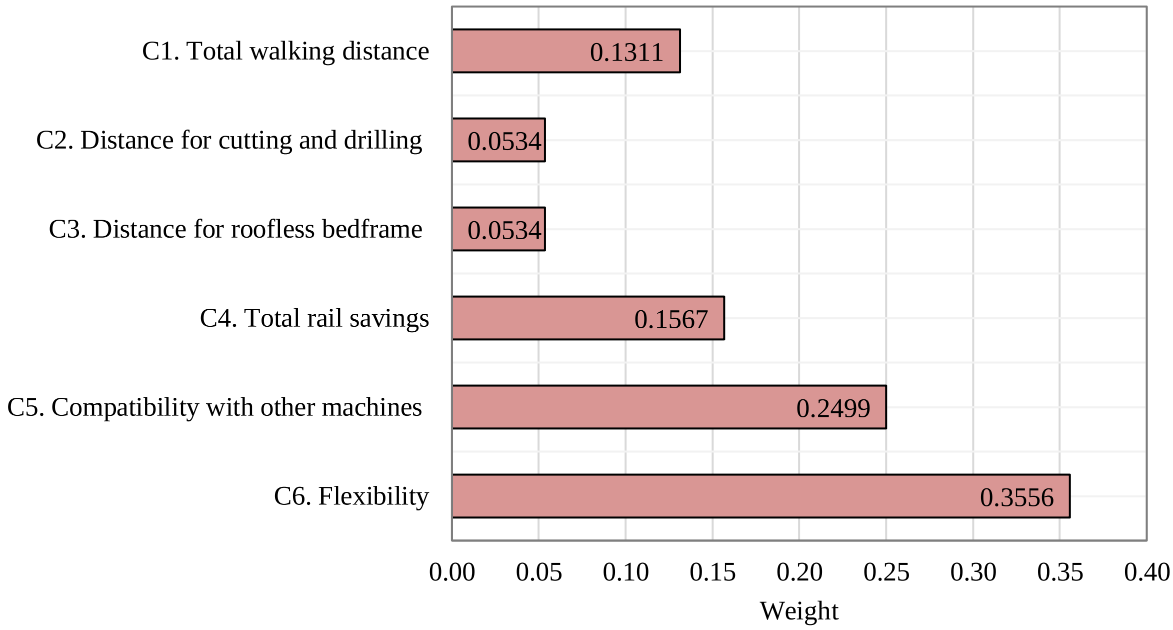

Figure 3. Importance weights of the criteria

The calculated weights reveal the importance of each criterion in the facility layout decision-making process. Flexibility emerges as the most critical criterion, accounting for 35.56% of the total weight. This result underscores the importance of a layout that can adapt to changing production demands. The high priority given to flexibility highlights the facility's need to remain agile and responsive to future operational changes. The second most significant criterion is compatibility with other machines, with a weight of 24.99%. Proper machine alignment and interaction prevent workflow bottlenecks, minimize downtime, and improve overall operational efficiency. These insights guide the selection of the optimal layout alternative to meet the facility's strategic objectives.

3.4 Prioritization of alternatives

The selection of the optimal facility layout requires a systematic evaluation of alternatives based on predefined criteria. The study employs fuzzy EDAS to prioritize three layout alternatives. The experts evaluate the performance of each alternative against all the criteria using linguistic terms provided in Table 3. These qualitative assessments are subsequently converted into fuzzy numbers for use in the fuzzy EDAS calculations. The resulting decision matrix for the alternatives is presented in Table 4.

Table 3. Linguistic terms and fuzzy numbers to evaluate the alternatives (Ali Sadat et al., 2021)

Code	Linguistic term	Fuzzy number
1	Very bad	(1, 1, 3)
2	Bad	(1, 3, 5)
3	Medium	(3, 5, 7)
4	Good	(5, 7, 9)
5	Very good	(7, 9, 11)

Table 4. Decision matrix for the alternatives

Criterion	A1	A2	A3
C1	(1, 3, 5)	(1, 1, 3)	(1, 3, 5)
C2	(3, 5, 7)	(1, 1, 3)	(1, 3, 5)
C3	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)
C4	(1, 1, 3)	(3, 5, 7)	(1, 3, 5)
C5	(1, 1, 3)	(1, 3, 5)	(3, 5, 7)
C6	(1, 1, 3)	(1, 3, 5)	(5, 7, 9)

For each criterion, the average performance score across all the alternatives is computed in fuzzy and crisp forms. This average serves as the reference point for calculating the distances. After determining the average solution for each criterion, the PDA and NDA matrices are formed. These matrices provide a structured representation of how each alternative performs relative to the average values for all the criteria. Specifically, the PDA matrix highlights the degree to which each alternative exceeds the average performance, while the NDA matrix captures the extent to which alternatives fall short. For each alternative, the individual PDA and NDA values across all the criteria are summed and normalized, as outlined in Steps 4 and 5 of the fuzzy EDAS procedure. These results are then used to determine the final performance of each alternative. The outcomes of the fuzzy EDAS analysis are presented in Table 5.

Table 5. Fuzzy EDAS results

Variable	A1	A2	A3
$\widetilde{sp}_i$	(-0.23, 0.09, 0.36)	(-0.10, 0.10, 0.26)	(-0.39, 0.50, 1.25)
$\widetilde{sn}_i$	(-0.23, 0.50, 0.95)	(-0.66, 0.19, 1.05)	(-0.22, 0.00, 0.27)
$\widetilde{nsp}_i$	(-0.49, 0.19, 0.78)	(-0.21, 0.21, 0.57)	(-0.85, 1.08, 2.69)
$\widetilde{nsn}_i$	(-1.20, -0.17, 1.54)	(-1.45, 0.57, 2.53)	(0.38, 1.00, 1.51)
$\widetilde{as}$	(-0.85, 0.01, 1.16)	(-0.83, 0.39, 1.55)	(-0.23, 1.04, 2.10)
as	0.0844	0.3742	0.9872
Ranking	3	2	1

A3 is identified as the best-performing option among the evaluated alternatives. The performance of A3 aligns closely with the decision-making objectives, making it the most suitable choice for implementation. The decision-makers should proceed with the implementation of A3 (Figure 4), as it demonstrates the best potential for improving production efficiency and meeting operational objectives.

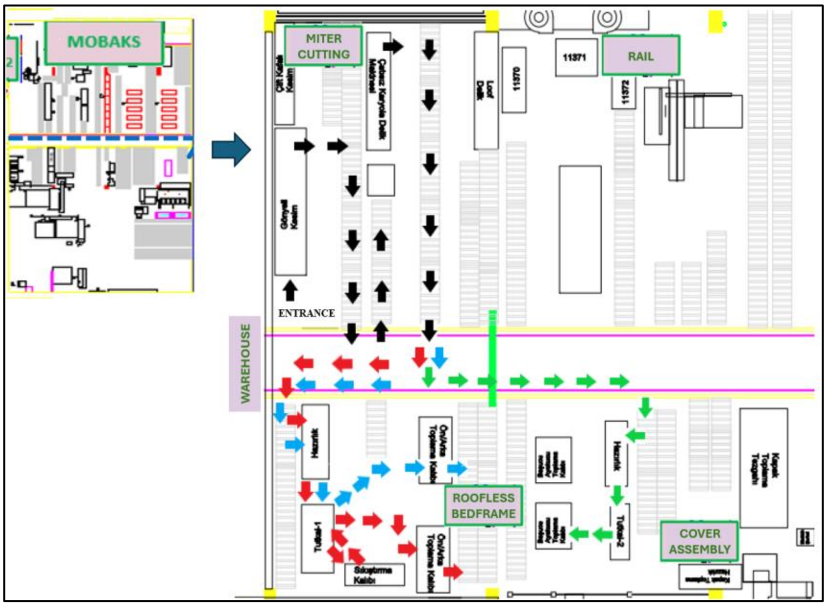

Figure 4. Optimal layout option

3.5 Sensitivity analysis

Sensitivity analysis is an essential process for evaluating the reliability of decision-making outcomes. By modifying the weights of evaluation criteria, this analysis examines how such changes influence the ranking of alternatives. In this study, sensitivity analysis is performed by interchanging the weights of two criteria while keeping the weights of all other criteria constant. The weights assigned to two criteria are swapped, and the fuzzy EDAS procedure is reapplied to assess whether the alternative rankings are affected. Each scenario represents a weight adjustment between two criteria. As shown in Figure 5, A3 consistently ranks as the best-performing option. This outcome confirms the reliability of the obtained ranking.

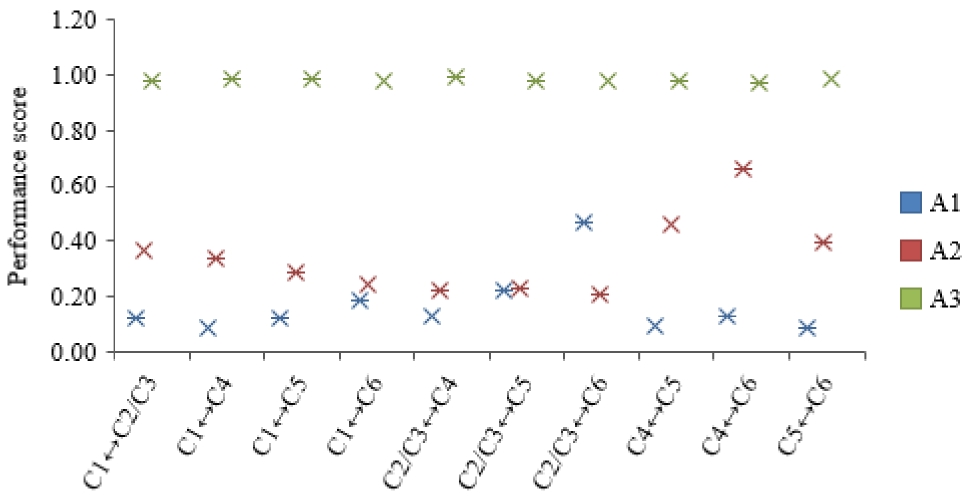

Figure 5. Sensitivity analysis results

3.6 Comparative analysis

Comparative analysis is a systematic approach used to validate the results of decision-making processes by evaluating alternatives through multiple methods. The primary goal of this analysis is to ensure the robustness, reliability, and consistency of the rankings or decisions obtained. In this study, fuzzy ARAS is used to perform the comparison analysis of the alternatives to validate the results obtained through fuzzy EDAS. Mathematical details of fuzzy ARAS can be found in the literature (Heidary Dahooie et al., 2022). The same criteria and their weights are used in this analysis to ensure consistency. As shown in Figure 6, the results of fuzzy ARAS are consistent with those obtained using fuzzy EDAS. The alignment of the results underscores the suitability of A3 as the optimal alternative.

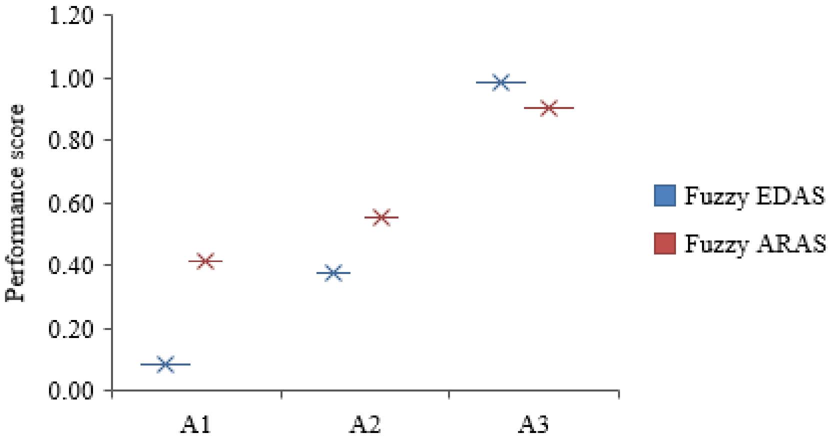

Figure 6. Comparative analysis results

4 Conclusion

This study focuses on evaluating and prioritizing layout alternatives for a furniture manufacturing facility in Türkiye. An integrated decision-making methodology combining fuzzy AHP and fuzzy EDAS is employed. The fuzzy AHP procedure is used to determine the importance of various criteria influencing facility layout decisions. The fuzzy EDAS procedure is used to evaluate and rank the identified facility layout alternatives. The results of the analysis highlight several significant improvements achieved through the selected layout configuration:

- Flexibility and compatibility with other machines are identified as the top two criteria, with weights of 35.56% and 24.99%, respectively. Layout option A3 demonstrates the highest performance, scoring 0.9872 and accounting for 68.28% of the total. Layout option A2 follows with a score of 0.3742, representing 25.88% of the total, while layout option A1 ranks last with a score of 0.0844, accounting for 5.84% of the total.
- The selected layout significantly enhances production efficiency and streamlines processes. It reduces bottlenecks in miter cutting operations and eliminates glue transportation between the roofless bedframe and cover assembly areas.
- The production distance for product components decreases by 210 meters, while active rail length increases from 55 to 90 meters. The assembly time for rail components decreases by 13.8 minutes. Reallocating tasks from CNC machines to lower-power equipment saves approximately 25,640 kWh annually. The layout also enables simultaneous production of multiple components.
- The findings of this study are consistent with prior research that employed various methods to enhance facility layouts. For instance, Erden et al. (2016) used fuzzy

axiomatic design in a furniture company to optimize layout and improve workflow. Similarly, Savsar and Aldehaim (2020) applied the CRAFT algorithm to reduce interdepartmental backflows and material handling costs. Lins et al. (2021) integrated a (re)layout strategy into a cleaner production initiative, increasing area efficiency by 33.33% and reducing waste. İnce and Taşdemir (2024) combined AHP, PROMETHEE, and CORELAP to create a layout that cut handling costs and improved flow while keeping managers close to operations. Our study aligns with these efforts in its approach and outcomes.

- This study provides a valuable contribution to the field of facility layout optimization by presenting an integrated decision-making framework. The study results demonstrate significant operational improvements, including reduced production distances, enhanced energy efficiency, minimized bottlenecks, and accelerated assembly processes. This research not only offers a robust solution for the furniture manufacturing sector but also serves as a valuable reference for other industries facing similar optimization challenges.
- Future research can expand upon this work by incorporating additional criteria. The integration of artificial intelligence could enable real-time visualization of layout configurations under varying operational scenarios.

Author Contribution

Hilal Singer: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Abdullah Cemil İlçe:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Murat Bulca:** Conceptualization, Methodology, Writing – original draft. **Erkan Bayır:** Conceptualization, Methodology, Writing – original draft.

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Conflict of Interest Statement

The author declares no conflict of interest.

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