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A FUZZY QFD-BASED APPROACH FOR CUTTING MACHINE SELECTION IN THE FURNITURE INDUSTRY

Melike Nur İNCE [*]
Çağatay TAŞDEMİR [**]
Aytaç YIDIZ [***]

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Abstract: To survive in an increasingly competitive business environment, companies are placing a greater emphasis on customer demands. Demand-driven manufacturing has become a key business priority in light of these developments. Furthermore, customer demand has emerged as a pivotal consideration in strategic decision-making processes within the business sector. Adopting a customer-oriented approach to decision-making in various operational areas, including purchasing, logistics, and production, could increase business profitability. In this study, a fuzzy AHP-based fuzzy QFD approach was developed for a cutting machine that a medium-sized furniture company sought to procure. This analysis identified eight customer requests and determined their relative importance using the Fuzzy AHP methodology. The results indicated that Precision (CR 3) was the most critical customer request, with a weight of 0.300, followed by Cutting Quality, which was identified as the second most crucial customer request, with a weight of 0.229. Subsequently, these weighted customer requests were input into the Fuzzy QFD methodology. Subsequently, ten technical requirements for machine selection were identified. The study results showed that the best-performing alternative was the laser cutting machine, with a percentage value of 28.00. In contrast, the worst-performing alternative was the autogenous flame-cutting machine, with 19.40%. Although the employed methodology was explicitly focused on machine selection for metal components in the furniture industry, the findings offer significant insights with broader applicability. These insights provide a reference point for addressing complex decision-making problems of a similar nature, making the research valuable to practitioners and academics working in furniture manufacturing, machine selection, and multi-criteria decision-making.

Keywords: Multi-Criteria Decision Making, Machine Selection, Furniture Industry, Fuzzy AHP, Fuzzy QFD

Mobilya Sektöründe Kesim Makinesi Seçimi İçin Bulanık QFD Tabanlı Bir Yaklaşım

Öz: Rekabetin giderek arttığı bir iş ortamında ayakta kalabilmek için şirketler müşteri isteklerine daha fazla önem vermektedir. Bu gelişmeler ışığında, talep odaklı üretim önemli bir iş önceliği haline gelmiştir. Ayrıca, müşteri isteği, iş sektöründeki stratejik karar alma süreçlerinde çok önemli bir husus olarak ortaya çıkmıştır. Satın alma, lojistik ve üretim de dahil olmak üzere çeşitli operasyonel alanlarda karar alma süreçlerinde müşteri odaklı bir yaklaşımın benimsenmesi, işletme karlılığını artırabilir. Bu çalışmada, mobilya sektöründe faaliyet gösteren orta ölçekli bir şirketin tedarik etmek istediği bir kesim makinesi için AHP tabanlı bulanık bir QFD yaklaşımı geliştirilmiştir. Bu analizde sekiz müşteri isteği

[*] Department of Industrial Engineering, Graduate School, Bursa Technical University, Bursa 16310
[**] Department of Forest Industry Engineering and Department of Industrial Engineering, Bursa Technical University, Bursa 16310
[***] Department of Industrial Engineering, Bursa Technical University, Bursa, 16310
Corresponding Author: Çağatay Taşdemir (cagatay.tasdemir@btu.edu.tr)

belirlenmiş ve Bulanık AHP metodolojisi kullanılarak bunların göreceli önemleri tespit edilmiştir. Sonuçlar, Hassasiyetin (CR 3) 0,300 ağırlıkla en kritik müşteri isteği olduğunu, bunu 0,229 ağırlıkla ikinci en önemli müşteri isteği olarak belirlenen Kesim Kalitesinin izlediğini göstermiştir. Daha sonra, bu ağırlıklı müşteri istekleri Bulanık QFD metodolojisine girilmiştir. Bu adımı takiben, makine seçimi için on teknik gereksinim belirlenmiştir. Çalışmanın sonuçları, en iyi performans gösteren alternatifin yüzde 28,00 ile lazer kesim makinesi olduğunu, en kötü performans gösteren alternatifin ise %19,40 ile otojen alevli kesim makinesi olduğunu göstermiştir. Kullanılan metodoloji özellikle mobilya endüstrisindeki metal bileşenler için makine seçimi konusuna odaklanmasına rağmen, bulgular daha geniş uygulanabilirliğe sahip önemli bilgiler sunmaktadır. Bu içgörüler, benzer nitelikteki karmaşık karar verme problemlerine çözüm sunabilecek bir referans noktası sağlamakta, dolayısıyla araştırmayı mobilya üretimi, makine seçimi problemleri ve çok kriterli karar verme konularında çalışan uygulayıcılar ve akademisyenler için değerli kılmaktadır.

Anahtar Kelimeler: Çok Kriterli Karar Verme, Makine Seçimi, Mobilya Endüstrisi, Bulanık AHP, Bulanık QFD

1. INTRODUCTION

Furniture has been a fundamental human need since the dawn of civilization, and demand for it continues to persist (Ratnasingam, 2003). Given its pervasive role in daily life, the furniture sector is expected to maintain its significant scale and importance. Numerous studies have analyzed the size and growth trends of this industry. For instance, Nandi (2021) projected a compound annual growth rate (CAGR) of 3.02%, estimating the global furniture market's value at USD 932.1 billion by 2032 (Nandi, 2021). In contrast, Precedence Research (2023) predicts a higher CAGR of 5.2% between 2024 and 2034, forecasting a market valuation of USD 1,160.84 billion by 2034 (Precedence Research, 2023). Similarly, Grand View Research (2023) anticipates a CAGR of approximately 5.9% from 2023 to 2030, with a projected market size of USD 1,070.87 billion by 2030 (Grand View Research, 2023). Additionally, Statista (2024) expects the global furniture market to expand at a CAGR of 3.79% until 2029, while Singh and Singh (2024) estimate a CAGR of 5.1%, projecting the market to reach USD 1 trillion by 2032 (Statista, 2024; Singh and Singh, 2024). Furthermore, a study by Fortune Business Insights (2024) forecasts the market value at USD 780.43 billion by 2030, with a CAGR of 5.36% (Fortune Business Insights, 2024).

A sectoral analysis of the furniture sector reveals its substantial size. Organizations operating within such a significant sector must implement strategic initiatives to achieve a competitive advantage. In this regard, a pivotal strategy for companies is to demonstrate agility in addressing customer requirements and to adapt to evolving customer needs (Faydalı and Erkan, 2020; Gülçiçek Tolun and Tümtürk, 2020). The machinery and equipment organizations require to enhance their responsiveness and flexibility manifest several distinctive characteristics. Consequently, to respond expeditiously to customer demands, it is imperative to select flexible machines that can satisfy all customer requirements for machinery and equipment (Ertuğrul and Güneş, 2007; Organ, 2013). However, the multitude and intricacy of the decision criteria involved in this process present a substantial challenge for managers in determining the optimal machine.

Machine selection is a multifaceted decision-making process (Perçin, 2012). To address these challenges, a systematic evaluation of multiple options is imperative, taking into account a comprehensive set of criteria (Akın, 2019; Özdağoğlu, 2013). Multi-criteria decision-making (MCDM) techniques are employed to address these challenges (Emhan, 2007). For instance, Temiz and Calis (2017) employed AHP and PROMETHEE methods for excavation machine selection in the construction industry, and similarly, Hagag et al. (2023) examined MCDM methods used for machine selection problems in the construction industry (Hagag et al., 2023; Temiz and Calis, 2017).

The textile industry is another sector where machine selection is a commonly encountered issue. Organ (2018) employed the fuzzy DEMATEL method to assess the criteria that influence the machine selection process in this sector. Akın (2019) used the ENTROPY-ROV and CRITIC-ROV methods to select sewing machines for a company producing beds and sleep equipment. Finally, Faydalı and Erkan (2020) employed the Fuzzy VIKOR Method in the selection of packaging machines (Akın, 2019; Faydalı and Erkan, 2020; Organ, 2013).

A survey of the MCDM methods used in the extant literature on machine selection reveals that the PROMETHEE method is among the most frequently used approaches. To illustrate, Tuzkaya et al. (2010) employed the ANP and PROMETHEE methods in a fuzzy environment, taking uncertainties into account during the selection of material-handling equipment (Tuzkaya et al., 2010). In addition, Ozdagoglu (2013) employed the PROMETHEE method for laser cutting machine selection, and Kabadayi and Dag (2017) utilized Fuzzy DEMATEL and Fuzzy PROMETHEE methods for machine selection in cable production (Kabadayi and Dağ, 2017; Özdağoğlu, 2013). In a related study, Ozgen et al. (2011) employed a combination of modified Delphi, AHP, and PROMETHEE methods for the selection of press machines (Ozgen et al., 2011). Taha and Rostam (2012) employed MATLAB-based Fuzzy AHP and PROMETHEE methods in CNC lathe machine selection (Taha and Rostam, 2012).

Another frequently used method in machine selection is TOPSIS. In this context, Kaya et al. (2008) were the first to employ the Fuzzy TOPSIS method in CNC machine selection (Kaya et al., 2008). Perçin (2012) used the Fuzzy AHP and Fuzzy TOPSIS methods to select machine equipment in the metal industry (Perçin, 2012). In a subsequent study, Aloini et al. (2014) employed the IF-TOPSIS method for the selection of packaging machines (Aloini et al., 2014). Finally, Uzun and Kazan employed an integrated approach, combining AHP, TOPSIS, and PROMETHEE methods, to select the optimal machine for a fishing vessel project in the shipbuilding sector (Uzun and Kazan, 2016).

A review of the extant literature reveals the prevalence of another MCDM method that is widely used in machine selection: AHP. In this field, Ayag and Ozdemir (2006) employed the Fuzzy AHP method in machine tool selection (Ayağ and Özdemir, 2006). Taha and Rostam (2011) integrated the Artificial Neural Networks (ANN) and Fuzzy AHP methods for machine selection in flexible manufacturing cells (Taha and Rostam, 2011). Phung et al. (2019) employed the Fuzzy AHP method in the context of cutting tool selection, while Gulcicek Tolun and Tumturk (2020) integrated the Fuzzy AHP and Gray Relational Analysis (GRA) methods in the selection of machinery utilized in agricultural machinery and farm equipment production (Gülçiçek Tolun and Tümtürk, 2020; Phung et al., 2019).

In addition, Gok Kısa and Percin (2017) employed the Fuzzy DEMATEL and Fuzzy VIKOR methods for machine selection in the natural stone industry (Gök Kısa and Perçin, 2017). In a similar vein, Li et al. (2020) employed the Fuzzy DEMATEL and LDVIKOR methods for the selection of machine tools in the manufacturing industry (Li et al., 2020). Soltan et al. (2023) employed the FAQT-2 Method for industrial robot selection in the pharmaceutical industry (Soltan et al., 2023). Efe (2019) employed an innovative integrated QFD and IFVIKOR method, leveraging fuzzy numbers and an FCM approach for the selection of dishwashers (Efe, 2019). Similarly, in the electronics sector, an integrated DANP and Fuzzy VIKOR approach was adopted to evaluate end-of-life product recovery options. This study identified 'Social Responsibility' as the most critical criterion and determined 'Recycling' as the optimal alternative, demonstrating the method's capability to handle trade-offs in sustainable decision-making (Erdogan Aktan and Karayun, 2018).

A literature review reveals that using Multi-Criteria decision-making (MCDM) methodologies in machine selection effectively reduces decision-making complexity. Furthermore, methods devised for fuzzy environments have been observed to eliminate uncertainty and incorporate linguistic considerations. In addition to considering both qualitative and quantitative criteria, the studies also focus on evaluating the perspectives of multiple decision-makers and solving decision-making challenges in manufacturing environments. In this context, the applicability of MCDM methodologies in production planning and operations is emphasized, and it is concluded that they provide flexibility, ease of use, and time savings for decision-makers.

MCDM techniques facilitate the identification of optimal solutions in scenarios involving multiple decision alternatives and criteria. Consequently, MCDM techniques have many applications in all strategic decision-making problems (Gök Kısa and Perçin, 2017; Kaya et al., 2008). A notable illustration of this application is the study by Ayag (2010), who employed the fuzzy analytic hierarchy process (AHP) methodology in the context of selecting CAD software (Ayağ, 2010). In a subsequent study, Apak et al. (2012) employed the AHP method to assess the preferences of luxury car consumers (Apak et al., 2012). The fuzzy AHP method, a prominent MCDM approach, has also been employed in studies assessing wastewater facilities and technologies (Hu et al., 2016; Jing et al., 2013).

Multi-criteria decision-making (MCDM) methods are the predominant solution methods for resolving facility site selection problems. In this field, Hanine et al. (2016) integrated the Fuzzy TODIM and Fuzzy AHP methods for landfill site selection (Hanine et al., 2016). Similarly, AI Mohamed et al. (2023) employed the Fuzzy AHP and Fuzzy TOPSIS methods for the selection of a hospital site (Al Mohamed et al., 2023). Finally, Abdullah et al. (2023) employed the Fuzzy AHP methodology in site selection for a nuclear power plant (Abdullah et al., 2023).

A similar trend is observed in supplier selection, where MCDM methodologies are frequently employed. For instance, Bevilacqua et al. (2006) used the Fuzzy QFD methodology in supplier selection (Bevilacqua et al., 2006). In a similar vein, Lima-Junior and Carpinetti (2016) employed the Fuzzy QFD methodology for supplier selection in the automotive industry (Lima-Junior and Carpinetti, 2016). Babbar and Amin (2018) employed a two-stage Fuzzy QFD and a stochastic multi-objective mathematical model for green supplier selection and order allocation in the beverage industry (Babbar and Amin, 2018). In a recent study addressing uncertainty in green supplier selection, a hybrid decision-making model was proposed. This study utilized the Fuzzy Analytic Hierarchy Process (F-AHP) to determine criterion weights—identifying 'Environmental Competencies and Certifications' as the most critical factor—and employed the Fuzzy Weighted Aggregated Sum Product Assessment (F-WASPAS) method to rank alternatives, ultimately providing a robust framework for sustainable supply chain management (Daldır and Tosun, 2018). Beyond QFD applications, the AHP method has also been utilized to prioritize supplier selection criteria quantitatively in mechanical material procurement. The findings highlighted 'Quality' as the dominant factor (0.52) over price and delivery, validating AHP’s effectiveness in structuring complex purchasing decisions (Sonmez and Tandogan Oney, 2021).

The utilization of QFD methodology in decision-making processes is imperative to ensure the prioritization of customer desires and product design (Chan and Wu, 2002). Kuo et al. (2009) developed an enhanced Eco-QFD methodology for the design of environmentally friendly products (Kuo et al., 2009). Furthermore, Liu (2011) employed the Fuzzy QFD methodology in the context of prototype product design (Liu, 2011). Furthermore, Ping et al. (2020) developed a novel QFD methodology for product design that integrates the evaluation of product features based on PFLSs and EDAS (Ping et al., 2020).

A review of the extant literature indicates that when evaluating multiple alternatives against multiple criteria, implementing MCDM techniques can be advantageous. In essence, engineering methodologies enhance the effectiveness of decisions made with MCDM techniques, particularly in strategic contexts. A thorough examination of the extant literature reveals that while QFD methodology has been extensively employed in product design, it also extends to strategic decision-making with equal efficacy.

The substantial number of studies published in academic literature evidences the extant body of research in the field of MCDM. Figure 1 illustrates the structure of the focus groups in these studies. The reviewed studies encompass a range of subjects, including machine/equipment selection, fuzzy AHP, and fuzzy QFD. Additionally, these studies explore the interconnections and synergies among these domains.

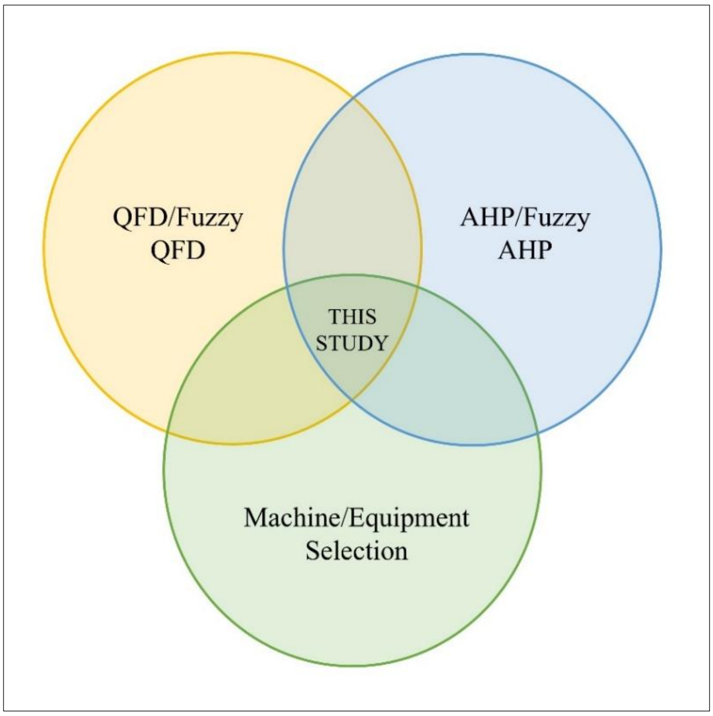

Figure 1.
Target contribution zone of the study.

A comprehensive review of the extant literature reveals numerous examples of strategic decision-making across a myriad of scenarios. Nevertheless, the predominant emphasis in these decision problems is on selecting machinery and equipment and implementing Fuzzy AHP and Fuzzy QFD, either as standalone methods or in conjunction. A review of the extant literature reveals that Fuzzy QFD is predominantly used in product design. While the number of examples is limited, it has been employed in selection studies. The review further reveals that Fuzzy AHP and AHP methods have been used in many strategic decision-making problems. In these cases, the utilization of fuzzy AHP has been observed to encompass the determination of criteria weights or the guidance of selection processes. The extant literature documents the use of diverse MCDM methodologies in machinery equipment selection. A comprehensive literature review reveals a paucity of studies that have employed a holistic approach to integrate fuzzy AHP and QFD methodologies in machinery selection. The objective of this study is twofold: first, to identify the most suitable cutting machine for use in the furniture industry, and second, to demonstrate the effectiveness of using Fuzzy AHP and Fuzzy QFD methodologies together in MCDM applications for selection problems.

2. MATERIALS AND METHODS

In today's global industrial setting, organizations are regularly confronted with many critical decisions. These vital decisions have significant implications for companies' futures. Due to the high costs typically associated with such decisions, reversing them once they have been made is not feasible. For this reason, MCDM methods are employed to support critical decision-making. One such critical decision is selecting the machinery for a specific purpose.

This study aims to determine the most suitable cutting machine for producing metal furniture parts in a medium-sized furniture industry enterprise. Four alternative cutting machines were identified for evaluation. A total of eight criteria were identified to assist decision-makers in selecting among the four alternative machines. The literature was reviewed in the first stage of the study to determine the relevant selection criteria. Then, three rounds of Delphi surveys were conducted with the participation of four experts in the field. The selection criteria were considered established when there was 75% or more consensus regarding their relevance. The selection criteria were subjected to a fuzzy AHP analysis and evaluated in the context of customer demands, which was the "what" question in the fuzzy QFD method. Using the Delphi technique, similar to that used for the selection criteria, the expert engineers identified ten technical requirements to meet the customer requirements. Finally, the most suitable alternative was selected from four different alternatives using the Fuzzy QFD methodology. These alternative cutting machines, customer requirements, and technical requirements are given in Table 1.

Table 1. Alternatives, Customer Requirements, and Technical Requirements

Alternatives	Customer Requirements	Technical Requirements
Water Cutting (A1) Laser Cutting (A2) Plasma Cutting (A3) Autogenous Flame Cutting (A4)	Flexibility (C1) Cutting Quality (CR2) Precision (CR3) Cutting Speed (CR4) Energy Efficiency (CR5) Ease of Use (CR6) Ease Of Maintenance and Repair (CR7) Safety (CR8)	Replaceable Tool Unit (TR1) Machining Control (TR2) Machine Power (TR3) Drive Systems (TR4) Number of Axes (TR5) Programmability Solutions (TR6) LCD Displays (TR7) Continuously Available Tools (TR8) Ergonomic Design (TR9) Built-in Safety Function (TR10)

2.1. Fuzzy AHP Method

Buckley proceeded to develop an additional extension of Saaty's AHP method, incorporating fuzzy comparison ratios a_{ij}. Buckley introduced a new algorithm, highlighting two primary issues in Van Laarhoven and Pedrycz's methods (Buckley, 1985). Buckley employed the geometric mean to address the abovementioned issues and calculate performance scores.

The following section outlines the process steps of Buckley's algorithm (Teng et al., 2010).

Step 1: Following consultation with the decision maker(s), a comparison matrix comprising triangular fuzzy numbers, represented by the elements $\tilde{a}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, $\forall i, j$, as shown in Equation 2, is created. A positive pairwise comparison matrix is constructed using the data in Table 2, which presents the relative importance of each criterion to the others.

$$A = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{a}_{m1} & \tilde{a}_{m2} & \cdots & \tilde{a}_{mn} \end{bmatrix} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ 1/\tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ 1/\tilde{a}_{m1} & 1/\tilde{a}_{m2} & \cdots & \tilde{a}_{mn} \end{bmatrix} \tag{1}$$

$$\tilde{a}_{ij} = \begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} & relative\ importance\ of\ criterion\ i\ to\ criterion\ j \\ 1, \quad i = j & \\ \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1} & inverse\ relative\ importance\ of\ criterion\ i\ to\ criterion\ j \end{cases} \tag{2}$$

Table 2. Fuzzy Scale and Linguistic Expression of Relative Importance between Two Criteria

Fuzzy Number	Linguistic Scale	Scale of Fuzzy Number
$\tilde{1}$	Very Low (VL)	(1, 1, 3)
$\tilde{3}$	Low (L)	(1, 3, 5)
$\tilde{5}$	Medium (M)	(3, 5, 7)
$\tilde{7}$	High (H)	(5, 7, 9)
$\tilde{9}$	Very High (VH)	(7, 9, 9)

Step 2: The geometric average of each row is calculated using Equation 3 below.

$$\tilde{a}_{ij} = (\tilde{a}_{ij} \otimes \ldots \otimes \tilde{a}_{ij})^{1/n}, \quad \forall i \tag{3}$$

Step 3: The fuzzy vector $\widetilde{W}_i$ of each criterion is calculated using equation 4.

$$\widetilde{W}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \ldots \oplus \tilde{r}_n)^{-1} \tag{4}$$

Step 4: Equation 5 is employed to calculate the BNP score for each criterion.

$$BNP\widetilde{W}_i = \frac{[(uw_i - lw_i) + (mw_i - lw_i)]}{3} + lw_i \tag{5}$$

Step 5: The BNP scores for each criterion are then normalized using Equation 6.

$$N\widetilde{W}_i = \frac{BNP\widetilde{W}_i}{\sum BNP\widetilde{W}_i} \tag{6}$$

2.2. Fuzzy QFD Method

The Quality Function Deployment (QFD) method employs a matrix known as the "quality house." The rows of the quality house represent customer requirements; the columns represent technical requirements; the body contains the relationships between the two; and the roof includes the relationships within the technical requirements. The quality house is a four-stage model, or matrix of matrices, arranged in the following order: product, product part, production process, and production planning.

The objective of combining QFD applications with fuzzy logic is to eliminate subjectivity and uncertainty in evaluating "what" and "how" questions.

The Fuzzy QFD method comprises nine stages. The following section provides a comprehensive overview of these nine steps.

Step 1: Defining customer requirements.

Step 2: Determination of technical requirements.

Step 3: Determination of the relative importance of customer requirements.

The normalized weights obtained through the Fuzzy AHP approach are employed.

Step 4: Construction of the relationship matrix between customer requests and technical requirements.

Table 3. Linguistic Variables for Relationships between Customer Demands and Service Requirements

Linguistic Variable	Symbol	Triangular Fuzzy Number	Membership Function	Range
Strong Relationship (SR)	Θ	(6, 8, 10)	$\mu(x) = (x-6)/(8-6)$ $\mu(x) = (10-x)/(10-8)$	$6 \le x \le 8$ $8 \le x \le 10$
Moderate Relationship (MR)	O	(2, 5, 8)	$\mu(x) = (x-2)/(5-2)$ $\mu(x) = (8-x)/(8-5)$	$2 \le x \le 5$ $5 \le x \le 8$
Weak Relationship (WR)	∇	(0, 2, 4)	$\mu(x) = (x-0)/(2-0)$ $\mu(x) = (4-x)/(4-2)$	$0 \le x \le 2$ $2 \le x \le 4$

Step 5: Calculating the importance weights of technical requirements with Equation 7.

$$W_i^* = \sum_{i=1}^{n} [W_i \times d_{ij}] \qquad i = 1, 2, \dots, n \qquad j = 1, 2, \dots, m \tag{7}$$

n: Number of customer requests

m: number of technical requests

W_i^*: Fuzzy importance level of i'th technical requirement

W_i: Fuzzy importance level of I'th customer request

d_{ij}: Fuzzy relationship value between the i'th customer request and the j'th technical requirement

Step 6: For each alternative, a relationship matrix is created for the levels of meeting the technical requirements criteria.

Table 4. Linguistic Variables for Relationships between Technical Requirements and Alternatives

Linguistic Variables	Fuzzy Numbers	Membership Function	Range
Very Low Important (VLI)	(0, 0, 2.5)	$\mu(x) = (2.5-x)/(2.5-0)$	$0 \le x \le 2.5$
Low Important (LI)	(0, 2.5, 5)	$\mu(x) = (x-0)/(2.5-0)$ $\mu(x) = (5-x)/(5-2.5)$	$0 \le x \le 2.5$ $2.5 \le x \le 5$
Moderately Important (MI)	(2.5, 5, 7.5)	$\mu(x) = (x-2.5)/(5-2.5)$ $\mu(x) = (7.5-x)/(7.5-5)$	$2.5 \le x \le 5$ $5 \le x \le 7.5$
Important (I)	(5, 7.5, 10)	$\mu(x) = (x-5)/(7.5-5)$ $\mu(x) = (10-x)/(10-7.5)$	$5 \le x \le 7.5$ $7.5 \le x \le 10$
Very Important (VI)	(7.5, 10, 10)	$\mu(x) = (x-7.5)/(10-7.5)$	$7.5 \le x \le 10$

Step 7: Calculation of the weights of the alternatives with Equation 8.

$$RI_j = \sum_{i=1}^{n} \left[W_i^* \otimes R_{ij} \right] \quad i = 1, \dots, n; \quad j = 1, \dots, m \tag{8}$$

n: Number of technical requirements

m: Number of alternatives

RI_j: Fuzzy importance weight of the jth alternative

W_i^*: Fuzzy importance level of the jth technical requirement

R_{ij}: Fuzzy relationship between the i'th technical requirement and the j'th alternative

Step 8: Calculating the stabilized fuzzy alternative importance weight values is performed using Equation 9.

$$X^* = \frac{l + 2m + u}{4} \tag{9}$$

X^*: Crips Value

Step 9: Calculation of normalized importance weights via Equation 10.

$$NRI_j = \frac{RI_j}{\sum_{j=1}^{i} RI_j} \times 100 \tag{10}$$

NRI_j: Normalized value of the importance weight of the j'th alternative

R_{ij}: Fuzzy relationship between the i'th technical requirement and the j'th alternative

After normalizing the weights, the alternatives are ranked, and the best alternative is selected.

3. RESULTS

A medium-sized enterprise operating in the furniture industry is seeking to procure the optimal cutting machine to meet internal and external customer requirements. Accordingly, a Fuzzy AHP-based fuzzy-QFD method was employed to determine the optimal cutting machine among four distinct types (Water Cutting, Laser Cutting, Plasma Cutting, and Autogenous Flame Cutting).

First, four academics determined the customer requirements for selecting the cutting machine, and the weights of these requirements were calculated using the Fuzzy AHP method. A pairwise comparison matrix was constructed to represent the customer requests. The linguistic evaluations utilized in the constructed matrix are presented in Table 5.

Table 5. Linguistic Evaluation of Customer Requests

Customer Requirements	CR1	CR2	CR3	CR4	CR5	CR6	CR7	CR8
CR 1		1/H	1/M	1/M	H	M	VL	1/L
CR 2	H		1/L	VL	M	H	H	M
CR 3	M	L		L	M	H	VH	M
CR 4	M	1/VL	1/L		H	H	VH	L
CR 5	1/H	1/M	1/M	1/H		VL	L	1/M
CR 6	1/M	1/H	1/H	1/H	1/VL		L	VL
CR 7	1/VL	1/H	1/VH	1/VH	1/L	1/L		1/M
CR 8	L	1/M	1/M	1/L	M	1/VL	M	

The linguistic evaluations presented in Table 5 were subsequently transformed into triangular fuzzy numbers per the specifications outlined in Table 2. The transformation above is illustrated in Table 6.

Table 6. Triangular Fuzzy Number Correspondences of Linguistic Evaluations of Customer Requests

Customer Requirements	CR1			CR2			CR3			CR4		
CR 1	1.00	1.00	3.00	0.11	0.14	0.20	0.14	0.20	0.33	0.14	0.20	0.33
CR 2	5.00	7.00	9.00	1.00	1.00	3.00	0.20	0.33	1.00	1.00	1.00	3.00
CR 3	3.00	5.00	7.00	1.00	3.00	5.00	1.00	1.00	3.00	1.00	3.00	5.00
CR 4	3.00	5.00	7.00	1.00	1.00	3.00	0.20	0.33	1.00	1.00	1.00	3.00
CR 5	0.11	0.14	0.20	0.14	0.20	0.33	0.14	0.20	0.33	0.11	0.14	0.20
CR 6	0.14	0.20	0.33	0.11	0.14	0.20	0.11	0.14	0.20	0.11	0.14	0.20
CR 7	1.00	1.00	3.00	0.11	0.14	0.20	0.11	0.11	0.14	0.11	0.11	0.14
CR 8	1.00	3.00	5.00	0.14	0.20	0.33	0.14	0.20	0.33	0.20	0.33	1.00
Customer Requirements	CR5			CR6			CR7			CR8		
CR 1	5.00	7.00	9.00	3.00	5.00	7.00	9.00	3.00	5.00	7.00	9.00	3.00
CR 2	3.00	5.00	7.00	5.00	3.00	5.00	7.00	5.00	3.00	5.00	7.00	5.00
CR 3	3.00	5.00	7.00	5.00	3.00	5.00	7.00	5.00	3.00	5.00	7.00	5.00
CR 4	5.00	7.00	9.00	5.00	5.00	7.00	9.00	5.00	5.00	7.00	9.00	5.00
CR 5	1.00	1.00	3.00	1.00	1.00	1.00	3.00	1.00	1.00	1.00	3.00	1.00
CR 6	1.00	1.00	3.00	1.00	1.00	1.00	3.00	1.00	1.00	1.00	3.00	1.00
CR 7	0.20	0.33	1.00	0.20	0.20	0.33	1.00	0.20	0.20	0.33	1.00	0.20
CR 8	3.00	5.00	7.00	1.00	3.00	5.00	7.00	1.00	3.00	5.00	7.00	1.00

Subsequently, the geometric mean of each customer request was calculated using Equation 3, and the value of $\tilde{r}_i$ was determined. The calculated values are presented in Table 7.

Table 7. The calculated $\tilde{r}_i$ values are presented in

	CR1			CR2			CR3			CR4		
r_i	0.54	0.71	1.37	1.97	2.70	4.88	2.35	4.04	6.16	1.79	2.62	4.68
	CR5			CR6			CR7			CR8		
r_i	0.28	0.39	0.71	0.34	0.28	0.39	0.71	0.34	0.28	0.39	0.71	0.34

Then, the fuzzy weight associated with each customer request, denoted as $\widetilde{W}_i$, is derived through Equation 4 and subsequently presented in Table 8.

Table 8. Fuzzy Weight Values of Customer Requests

	CR1			CR2			CR3			CR4		
W_i	0.03	0.06	0.17	0.09	0.22	0.60	0.11	0.33	0.76	0.08	0.21	0.57
	CR5			**CR6**			**CR7**			**CR8**		
W_i	0.01	0.03	0.09	0.02	0.01	0.03	0.09	0.02	0.01	0.03	0.09	0.02

The BNP scores for customer requests, for which fuzzy weight values were determined, were computed using Equation 5. The resultant BNP scores are depicted in Table 9.

Table 9. BNP Scores of Customer Requests

	CR1	CR2	CR3	CR4	CR5	CR6	CR7	CR8
$BNPW_i$	0,08	0,30	0,40	0,29	0,04	0,05	0,03	0,12

Employing the BNP scores delineated in Table 9, the normalized weight values of customer requests are computed using Equation 6 and are provided in Table 10.

Table 10. Normalized Weight Values of Customer Requests

	CR1	CR2	CR3	CR4	CR5	CR6	CR7	CR8
NW_i	0,06	0,23	0,30	0,22	0,03	0,04	0,03	0,09

The normalized weight values in Table 10 served as input for the Fuzzy QFD methodology. At the same time, the technical requirements capable of meeting customer demands were identified through the Delphi technique, involving the contributions of four scholars. The linguistic evaluations regarding the correlations between customer requests and technical requirements were conducted utilizing Table 2 and are illustrated in Table 11.

Table 11. Linguistic Assessment of the Relationship between Customer Demands and Technical Requirements

		Technical Requirements									
Customer Requirements	**Importance Level**	**TR1**	**TR2**	**TR3**	**TR4**	**TR5**	**TR6**	**TR7**	**TR8**	**TR9**	**TR10**
CR1	0,06		SR		SR	SR	SR		SR		
CR2	0,23	WR	SR	WR	MR	SR			SR		
CR3	0,30	MR	SR		SR	SR	SR		MR		
CR4	0,22		SR	MR	SR		SR				
CR5	0,03		SR	SR	MR	MR			MR		
CR6	0,04	WR			MR		SR	SR		SR	SR
CR7	0,03	MR			WR			MR		SR	WR
CR8	0,09		MR					MR		SR	SR

The triangular fuzzy number equivalents corresponding to the linguistic evaluations represented in Table 11 are detailed in Table 12, as per the rules identified in Table 3.

Table 12. Triangular Fuzzy Number Correspondents of Technical Requirements

		Technical Requirements														
Customer Requirements	**Importance Level**	**TR1**			**TR2**			**TR3**			**TR4**			**TR5**		
CR1	0,06				6	8	10				6	8	10	6	8	10
CR2	0,23	0	2	4	6	8	10	0	2	4	2	5	8	6	8	10
CR3	0,30	2	5	8	6	8	10				6	8	10	6	8	10
CR4	0,22				6	8	10	2	5	8	6	8	10			
CR5	0,03				6	8	10	6	8	10	2	5	8	2	5	8
CR6	0,04	0	2	4							2	5	8			
CR7	0,03	2	5	8							0	2	4			
CR8	0,09				2	5	8									
Customer Requirements	**Importance Level**	**TR6**			**TR7**			**TR8**			**TR9**			**TR10**		
CR1	0,06	6	8	10				6	8	10						
CR2	0,23							6	8	10						
CR3	0,30	6	8	10				2	5	8						
CR4	0,22	6	8	10												
CR5	0,03							2	5	8						
CR6	0,04	6	8	10	6	8	10				6	8	10	6	8	10
CR7	0,03				2	5	8				6	8	10	0	2	4
CR8	0,09				2	5	8				6	8	10	6	8	10

The importance weights for the technical requirements are computed using Equation 7 and shown in Table 13.

Following the computation of the importance weights for technical requirements, the subsequent phase involved assessing each cutting machine alternative based on its technical specifications. At this juncture, an expert academic evaluated each alternative using Table 4. The findings of this evaluation are presented in Table 13.

Table 13. Linguistic Evaluation of Alternatives

Technical Requirements	Importance Weight			A1	A2	A3	A4
TR1	0,65	2,17	3,69	LI	LI	MI	I
TR2	5,24	7,20	9,15	VI	VI	MI	LI
TR3	0,64	1,82	3,00	I	VI	I	MI
TR4	4,10	6,22	8,34	VI	VI	I	MI
TR5	3,62	4,90	6,19	VI	VI	I	I
TR6	3,73	4,98	6,22	VI	VI	VI	I
TR7	0,47	0,90	1,33	VI	VI	I	LI
TR8	2,42	4,00	5,59	VI	VI	I	MI
TR9	0,94	1,25	1,56	VI	VI	I	LI
TR10	0,78	1,09	1,40	I	I	MI	LI

These linguistic variables were subsequently transformed into triangular fuzzy numbers using Table 4, with the resulting values displayed in Table 14.

Table 14. Conversion of Linguistic Evaluations of Alternatives into Triangular Fuzzy Numbers

Technical Requirements	Importance Weight			A1			A2			A3			A4		
TR1	0,65	2,17	3,69	0	2.5	5	0	2.5	5	2.5	5	7.5	5	7.5	10
TR2	5,24	7,20	9,15	7.5	10	10	7.5	10	10	2.5	5	7.5	0	2.5	5
TR3	0,64	1,82	3,00	5	7.5	10	7.5	10	10	5	7.5	10	2.5	5	7.5
TR4	4,10	6,22	8,34	7.5	10	10	7.5	10	10	5	7.5	10	2.5	5	7.5
TR5	3,62	4,90	6,19	7.5	10	10	7.5	10	10	5	7.5	10	5	7.5	10
TR6	3,73	4,98	6,22	7.5	10	10	7.5	10	10	7.5	10	10	5	7.5	10
TR7	0,47	0,90	1,33	7.5	10	10	7.5	10	10	5	7.5	10	0	2.5	5
TR8	2,42	4,00	5,59	7.5	10	10	7.5	10	10	5	7.5	10	2.5	5	7.5
TR9	0,94	1,25	1,56	7.5	10	10	7.5	10	10	5	7.5	10	0	2.5	5
TR10	0,78	1,09	1,40	5	7.5	10	5	7.5	10	2.5	5	7.5	0	2.5	5

The importance weights of each cutting machine alternative were calculated using Equation 8 and subsequently normalized using Equation 9. Subsequently, the calculated normalized importance weights were used to determine the percentage importance of each alternative, and the results are presented in Table 16.

Table 15. Ranking of Alternatives

	A1			A2			A3			A4		
Alternatives Importance Weights	160,98	321,76	446,28	162,58	326,30	446,28	105,60	245,28	429,10	57,91	176,68	355,16
Crips Value	312,70			315,36			256,31			191,61		
%	0,291			0,293			0,238			0,178		
Order of Selection	2			1			3			4		

A ranking of the alternatives by their respective percentage importance showed that A2 (Laser Cutting) had the most favorable outcome. In contrast, the A4 (Autogenous Flame Cutting) alternative demonstrated the least favorable performance. It is therefore recommended that this furniture sector company purchase a laser cutting machine. It is thus anticipated that the company will be able to respond to customer requests more practically and offer a more flexible work environment.

4. DISCUSSION

By synergistically combining the Fuzzy Analytic Hierarchy Process (AHP) and Fuzzy Quality Function Deployment (QFD) methodologies, this research addresses the decision-making process for selecting a cutting machine for a medium-sized enterprise operating in the furniture manufacturing sector. In this investigation, a cutting machine was chosen through a comprehensive analysis that included a review of existing literature, evaluations from subject matter experts, and, particularly, customer demands. During the assessment phase, eight distinct customer requirements were initially identified, and the corresponding weights were derived using the Fuzzy AHP method. Upon analyzing the results, it was determined that the paramount customer requirement was "Precision" (CR3). Subsequently, the assigned weights to the identified customer requirements were incorporated into the Fuzzy QFD method, thereby enabling the selection process to continue.

In the study conducted by Özdağoğlu (2013), which utilized the PROMETHEE method for comparing laser cutting machines, the most critical decision-making criterion was established as "Working Accuracy," aligning the findings with those of the present study (Özdağoğlu, 2013). In the investigation by Phung et al. (2019) regarding cutting tool selection through the application of Fuzzy AHP, the criterion deemed most significant was Quality, characterized by a value of 0.289, while Cutting Quality (CR2) emerged as the second-most critical customer requirement with a value of 0.23 (Phung et al., 2019). In the research conducted by Ozgen et al. (2011) focusing on press machine selection via Fuzzy AHP, the importance weight attributed to the Safety (CR4) criterion was determined to be 0.10, whereas this study calculated the importance weight of the Safety (CR8) criterion to be 0.09 (Ozgen et al., 2011). This finding demonstrates that the present study is consistent with other investigations documented in the existing literature.

In accordance with the methodology, 10 technical requirements that align with customer requirements were identified, and their relative importance was determined. In accordance with the aforementioned technical requirements, each cutting machine alternative was subjected to a linguistic evaluation, with triangular fuzzy numbers employed for the subsequent calculations. The study's findings are presented in Table 15, including a ranking of the cutting machine alternatives. Consequently, it was determined that the Laser Cutting (A2) machine alternative yielded the optimal result.

In a study by Efe (2019), the Fuzzy QFD methodology was employed to assess the relative importance of customer requests and technical requirements in selecting dishwashers. Subsequently, the Intuitive Fuzzy VIKOR methodology was utilized to evaluate and prioritize the alternatives (Efe, 2019). In this study, the weights of customer requests for a cutting machine used in the furniture industry were determined using the Fuzzy AHP methodology, and the weights of technical requirements and the ranking of alternatives were determined using the Fuzzy QFD methodology. Similarly, the Fuzzy AHP methodology has been employed in the selection of machinery for various applications, including press machines (Ozgen et al., 2011), CNC turning machines (Taha and Rostam, 2012), fishing vessel projects (Uzun and Kazan, 2016), construction excavation machines (Temiz and Calis, 2017), and agricultural machinery (Gülçiçek Tolun and Tümtürk, 2020). A literature review reveals the use of Fuzzy AHP and AHP methodologies for machine selection, as well as the applicability of Fuzzy QFD in this context.

The value of this study to the existing literature could be evaluated from three distinct perspectives: academic, practical, and managerial. The academic implications include contributions to the existing literature, the development of new research models, and the extension of the theoretical framework. Moreover, this study has demonstrated that an integrated approach could be developed by combining multiple MCDM methods. The practical implications of this study include the potential for competitive advantage, industrial applicability, cost and performance optimization, and productivity improvement. The managerial implications of this study are evident in several areas, including strategic decision-making processes, decision-making under uncertainty, resource management, and risk management.

In conclusion, while this study focuses on selecting a cutting machine for a medium-sized company, the methodology could be applied to any decision problem with a similar structure. Furthermore, the study scope could be broadened to include additional customer and technical requirements, as well as alternatives. While customer requirements were a primary focus of the study, the organization's needs were not fully addressed. Accordingly, a more comprehensive analysis could be developed by considering this issue in future research. Furthermore, a more thorough and comparative approach could be achieved by incorporating artificial intelligence tools into the study.

5. CONCLUSION

The ability to make informed decisions is paramount in the contemporary era. A variety of methodologies could be employed to develop solutions for decision-making processes. One of the most significant techniques for resolving complex issues is the MCDM approach. The MCDM method is a productive approach to problem-solving when there are multiple decision criteria and alternative solution options. The objective of this study was to assist a medium-sized company in making an informed decision about purchasing a cutting machine. However, exercising caution and discernment throughout the decision-making process is paramount, as the selected cutting machine must meet the highest customer satisfaction standards. For this reason, the MCDM method is employed in machine selection problems.

The findings of this study could be summarized as follows:

- Although machine selection problems are inherently complex, MCDM methods have been demonstrated to address this complexity effectively.
- The Fuzzy AHP method was employed to ascertain the weights of customer requirements and identify the most pivotal customer requirements in machine selection.
- Among the customer requirements, precision (CR3) is the most important, with a weight of 0.30, followed by cutting quality (CR2), with a weight of 0.22. In contrast, Ease of Maintenance and Repair (CR7) is the least essential customer requirement, with a weight of 0.03.
- The customer requirements that are most critical to the problem are precision and cutting quality.
- Concurrently, the service requirements necessary to fulfill each customer requirement were identified, and the optimal alternative cutting machine was selected using the Fuzzy QFD method with customer requirements.
- Each machine alternative was evaluated using the Fuzzy QFD method, resulting in a preference ranking of Laser Cutting > Water Cutting > Plasma Cutting > Autogenous Flame Cutting. Consequently, the optimal machine alternative was identified as the laser cutting machine.

This study contributes to the literature on selecting cutting machines for metal components in the furniture industry by integrating two established methodologies: fuzzy AHP and fuzzy QFD. While these methods are oriented explicitly toward machine selection for metal components in the furniture industry, the findings offer significant insights with broader applicability. These insights provide a reference point for addressing complex decision-making problems of a similar nature, making the research valuable to practitioners and academics working in furniture manufacturing, machine selection, and multi-criteria decision-making.

CONFLICT OF INTEREST

The authors confirm that there are no known conflicts of interest or shared interests with any organization or individual.

AUTHOR CONTRIBUTIONS

Çağatay Taşdemir led the conceptualization and supervision of the study. Melike Nur İnce, Çağatay Taşdemir, and Aytaç Yıldız made equal contributions to the data collection, data analysis and interpretation, manuscript drafting, critical revision of the content, and final approval of the version to be published.

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