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Selection of a Forklift for a Cargo Company with Fuzzy BWM and Fuzzy MCRAT Methods

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Abstract: Material handling is a cost-intensive operation for businesses. There are several alternative types of equipment for material handling, therefore it is important to select the best one among them to decrease the cost. As there are several different alternatives and criteria which are used to assess these alternatives, multi-criteria decision making (MCDM) techniques are useful to determine the optimal material handling equipment (MHE) for businesses. In this study, fuzzy BWM for determining weights of criteria and the fuzzy Multiple Criteria Ranking by Alternative Trace (MCRAT) method have been used for ranking forklift alternatives. This study's significance in the literature will be the creation of a novel fuzzy MCDM technique with the application of fuzzy MCRAT. Furthermore, there are relatively few studies employing the MCRAT approach in the literature; therefore, this study will provide additional data and outcomes from this method to the literature. The findings present that the forklift with the code FLT-3 performed the best, whereas the forklift with the code FLT-2 had the worst performance, according to the fuzzy MCRAT technique. According to the comparison analysis, the fuzzy MCRAT produced the same results as the fuzzy ARAS and had a few subtle differences to fuzzy MARCOS.

Keywords: forklift selection; fuzzy BWM; fuzzy MCRAT; MCDM

MSC: 03E72; 47S40; 90B50; 94D05

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1. Introduction

Material handling makes up 30–75% of the overall cost of a product, and effective material handling may cut the cost of operating a production system by 15%–30% [1]. The equipment used for material handling is considered an important issue for companies as logistics and production operations might increase efficiency, enhance the quality of goods, and save operational costs with the support of well-designed material handling equipment (MHE) [2].

There are several types of MHE available to companies, such as cranes, forklifts, conveyers, robots, automated guided vehicles (AGVs), automated intelligent vehicles (AIVs), and hand trucks. However, not all MHE are suitable for a particular industrial process. Inappropriate material handling practices might result in higher material handling costs and longer production times. Thus, it is important to choose the right MHE. In addition to the several alternatives, there are also various criteria that need to be considered during the selection of MHE. Although choosing MHE is a challenging and knowledge-intensive operation, a variety of mathematical approaches may be efficiently used to resolve this issue. Yet, it is consistently noted that the assessment criteria used in MHE selection problems have conflicting impacts on the functionality of the alternatives, are flexible in character, and are often represented in distinct units with varied levels [3]. Multi-Criteria Decision Making (MCDM) methods are quite useful in terms of handling these complexities with a variety of alternatives and criteria for selection problems. MCDM helps decision makers to make wise choices and pick the best option from a wide range of accessible options. Since its creation, several MCDM strategies have been successfully applied in various subjects. Many studies demonstrate its adaptability by using it in a variety of areas, including energy [4], manufacturing [5], material selection [6], automotive [7], supplier selection [8], and location selection [9].

Several studies focusing on the selection and assignment of MHE have been carried out during recent decades. However, there are no studies using the fuzzy MCRAT method as it is a novel technique developed in recent years. Therefore, other methods used in MHE selection have been summarized below.

The Analytic Hierarchy Process (AHP) was used by Chakraborty and Banik [10] to choose the optimal MHE for a certain handling situation. Of the four MHE class groups, conveying systems are found to have the highest rank. Onut et al. [11] addressed the MHE selection decision for a manufacturing business in the steel sector with fuzzy AHP and fuzzy Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) methods. According to the findings, the rail system crane is the ideal MHE. Chatterjee et al. [12] assessed the usefulness of ELECTRE (ELimination Et Choix Traduisant la REalité) II and VIKOR (VIse KriterijumsaOptimiz acija I Kompromisno Resenje) methods to solve industrial robot decision problems in manufacturing businesses. The results showed the viability, applicability, and ease of use of both techniques in addressing this decision-making issue. Tuzkaya et al. [13] integrated the fuzzy Analytic Network Process (ANP) and fuzzy Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE) methods to choose the best industrial trucks for a warehouse. It was found that using this technique makes it simple to include the ambiguity inherent in the decision-making domain.

A novel method including the Modified Grey Relational Analysis (M-GRA) and AHP was developed by Maniya and Bhatt [14] to evaluate AGVs in a specific industrial setting. They found that the suggested method is rational, consistent, and straightforward. A novel multiplicative MCDM technique was used by Bairagi et al. [15] to tackle a robot selection problem with the TOPSIS technique. For the purpose of MHE selection among conveyor, truck, and hoist alternatives, Gaurh et al. [16] employed AHP, fuzzy AHP, and TOPSIS methods. Khandekar and Chakraborty [17] applied fuzzy axiomatic design (FAD) into two MHE problems: choosing an AVG for manufacturing businesses and choosing loading and hauling equipment for a mining business.

Nguyen et al. [18] proposed a hybrid technique including fuzzy AHP and fuzzy ARAS with ambiguous and imprecise information for the assessment and selection of conveyors. Sahu et al. [19] utilized grey Degree of Possibility (DP), grey TOPSIS, and Grey Relational Analysis (GRA) techniques to identify the ideal option for MHE. In their study, Mathew and Sahu [20] assessed conveyors and AGVs and used four MCDM techniques to resolve decision making: Multi-Objective Optimization on the basis of Ratio Analysis (MOORA), Evaluation based on Distance from Average Solution (EDAS), Combinative Distance-based Assessment (CODAS), and Weighted Aggregated Sum Product Assessment (WASPAS). Hellman et al. [21] integrated AHP with Failure Mode and Effect Analysis (FMEA) to evaluate AGVs and AIVs for a manufacturing business.

In order to evaluate and choose MHE including conveyors, AGVs, and robots, Goswami and Behera [22] conducted research on the functionality and usability of Additive Ratio Assessment (ARAS) and Complex Proportional Assessment (COPRAS) techniques. Verma et al. [23] utilized AHP and TOPSIS to choose the most optimal MHE for a small manufacturing business. It was found that a hand pallet truck is ranked first and semi-electric pallet truck second. Chakraborty and Saha [24] presented the neutrosophic Full Consistency Method (FUCOM) in order to describe and resolve the problem of choosing the appropriate forklift for a storage facility. Chodha et al. [25] proposed an integrated entropy and TOPSIS technique to identify the best industrial robot. Zolfani et al. [26] created an integrated intuitionistic fuzzy MCDM technique with the Full Consistency Method (FUCOM) and WASPAS to evaluate turret trucks which offer superior capabilities than conventional MHE when utilized for particular tasks.

The review makes it abundantly clear that many studies have investigated MHE selection issues in the past using a variety of MCDM methods. However, there is still a need to use novel techniques to guide businesses in making effective decisions in MHE selection problems.

Each industrial process is built on inner transportation which uses MHE. Therefore, optimizing the movement of the transportation modes and choosing the most practical mode of transportation will result in more effective utilization and cost savings. A remarkably popular, practical, and beneficial kind of MHE is the forklift. Forklifts are transportation work tools used for unloading, moving, storing, and loading a variety of freight. On the market, there are several forklifts with various features.

Multiple Criteria Ranking by Alternative Trace (MCRAT), developed by Urošević et al. [27], is a novel technique which uses matrix trace to order the alternatives. It has several benefits, including clarity, rationality, reasoning, versatility, and reliability. Currently, there is no study using the MCRAT technique in MHE selection. It was only used by three studies in the literature, which are related to material selection [28,29] and mining [27]. As this technique is practically new, these studies also did not consider uncertainty in the analysis. In order to take uncertainty into account and apply MCRAT in other contexts rather than only the mining and material selection problems, this study intends to extend it. Therefore, this study will introduce a novel approach to the literature by addressing the subject of the application of the fuzzy MCRAT technique with fuzzy BWM in MHE selection.

Compared to the AHP method, BWM produces more accurate results and necessitates fewer pairwise comparisons [30]. Crisp BWM, however, is unable to calculate weight in an uncertain environment, thus researchers have refined BWM and created fuzzy BWM [31]. For this reason, fuzzy BWM has been used extensively in the literature, such as for risk assessment [32,33], supplier selection [34,35], performance evaluation [36], and technology selection [37]. Compared to other MCDM methods, the MCRAT method has a simpler process for the evaluation of alternatives with various criteria and it produces reliable, universal, and rational results [27]. Unfortunately, crisp MCRAT cannot handle uncertainty, so in this study a fuzzy MCRAT method is developed. In addition, the fuzzy MCRAT method's computation steps are easier than other fuzzy MCDM (fuzzy MARCOS, fuzzy TOPSIS, fuzzy PROMETHEE, and fuzzy ELECTRE) methods. The results of the proposed method have been compared with fuzzy ARAS, fuzzy TOPSIS, fuzzy VIKOR, fuzzy MABAC, fuzzy MAIRCA, and fuzzy MARCOS. Fuzzy ARAS is a popular method used commonly in MCDM studies. For example, it has been employed for course assessment [38], 3PL selection [39], location selection [40], and supplier selection [41]. Fuzzy MARCOS has been used extensively in various topics: service assessment [42], risk assessment [43], and transportation selection [44]. A prominent technique frequently employed in MCDM investigations is fuzzy VIKOR. It has been used, for instance, in performance assessment [45], 3PL selection [46], strategy selection [47], and transport assessment [48]. Numerous areas, including supplier selection [49,50], risk assessment [51], and infrastructure selection [52], have made significant use of fuzzy MABAC. Fuzzy MAIRCA has been used in the literature in various areas, such as vaccine selection [53], assessment of tourism potential [54], investment decisions [55], sustainability assessment [56], and material selection [57]. In sum, the main aim of this study is to assess the applicability and capacity of the fuzzy MCRAT method integrated with fuzzy BWM for choosing the best forklift, which is a type of material handling equipment commonly used by businesses.

The motivations for this study are as follows:

- The MHE selection problem is important for businesses. Using the wrong MHE can cause serious costs to companies. In addition, the wrong MHE choice can cause unnecessary free time and unnecessary delays in transportation. Therefore, in this study, a new fuzzy MCDM model is proposed to solve the MHE selection problem.

- The fuzzy BWM method gives more accurate results than the fuzzy AHP method and requires less pairwise comparison. Therefore, in this study, the fuzzy BWM method was used to weight the criteria.
- As mentioned above, the MCRAT method has a simpler process for the evaluation of alternatives with various criteria and it produces reliable, universal, and rational results. However, this method cannot handle uncertainty since it is crisp. Therefore, a fuzzy MCRAT method is developed in this study.

The study's remaining parts are organized as follows: The methodological foundation for the suggested approach is presented in Section 2. A real-world case of the suggested technique is offered in Section 3 to help with comprehension, and concluding notes are provided in Section 4.

2. Materials and Methods

Two MCDM methods have been used in this study. Fuzzy BWM has been used for determining the criteria weights while fuzzy MCRAT has been utilized to identify ranks of alternatives.

2.1. Fuzzy BWM

Fuzzy BWM is utilized to determine criteria weights in this study. The steps of this method are explained below [31,58].

Step 1-1: In the first step, selection criteria are determined.

Step 1-2: The worst (C_W) and best (C_B) criteria are identified.

Step 1-3: After the identification of the worst and the best criteria, the best and worst criteria with other criteria are compared pairwise. The fuzzy Best-to-Others (BOT) vector ($\widetilde{D}_B = (\widetilde{d}_{B1}, \widetilde{d}_{B2}, \ldots, \widetilde{d}_{Bn})$) is obtained by comparing the best criterion with the other criteria. The fuzzy preference of C_B over the jth criterion is indicated by $\widetilde{d}_{Bj}$ in this vector, and $\widetilde{d}_{BB}$ is (1, 1, 1). The fuzzy Others-to-Worst (OW) vector is created by comparing the other criteria to the worst criterion ($\widetilde{D}_W = (\widetilde{d}_{1W}, \widetilde{d}_{2W}, \ldots, \widetilde{d}_{nW})$). The fuzzy preference of the jth criterion over C_W is indicated by $\widetilde{d}_{jW}$ in this vector, and $\widetilde{d}_{WW}$ is (1, 1, 1). Decision makers will perform the stated pairwise evaluations using the linguistic phrases listed in Table 1. This table also shows the CI values.

Step 1-4: Each criterion's fuzzy weight is acquired.

$$\min \tau^*$$
$$s.t.\begin{cases} \left|\dfrac{(w^l_B, w^m_B, w^u_B)}{(w^l_j, w^m_j, w^u_j)} - (B^l_j, B^m_j, B^u_j)\right| \le (k^*, k^*, k^*) \\ \left|\dfrac{(w^l_j, w^m_j, w^u_j)}{(w^l_W, w^m_W, w^u_W)} - (W^l_j, W^m_j, W^u_j)\right| \le (k^*, k^*, k^*) \\ \sum\limits_{j=1}^{n} \dfrac{w^l_j + 4w^m_j + w^u_j}{6} = 1 \\ w^l_j \le w^m_j \le w^u_j \\ w^l_j \ge 0 \end{cases} \tag{1}$$

Table 1. Linguistic phrases and fuzzy numbers for BWM [31,58].

Linguistic Phrases	Fuzzy Numbers	CI
Equally Significant (ES)	(1, 1, 1)	3.00
Weakly Significant (WS)	(2/3, 1, 3/2)	3.80
Fairly Significant (FS)	(3/2, 2, 5/2)	5.29
Very Significant (VS)	(5/2, 3, 7/2)	6.69
Absolutely Significant (AS)	(7/2, 4, 9/2)	8.04

The fuzzy weights of the worst criterion, best criterion, jth criterion, and τ^* fuzzy coefficient are denoted in Equation (1) by $\widetilde{w}_W = \left(w^l_W, w^m_W, w^u_W\right)$, $\widetilde{w}_B = \left(w^l_B, w^m_B, w^u_B\right)$, $\widetilde{w}_j = \left(w^l_j, w^m_j, w^u_j\right)$, and $\tau^* = (k^*, k^*, k^*)$, respectively. The consistency ratio (CR) is calculated using the equation $CR = \tau^*/CI$. The consistency index, which is depicted in Table 1, is shown in this equation as CI.

After fuzzy weights for every decision maker are acquired, these weights are aggregated with arithmetic mean. Arithmetic mean is calculated by Equation (2).

$$\widetilde{w}_j^* = \frac{\sum_{p=1}^{P} \widetilde{w}_j^p}{P} = \left(\frac{\left(w_j^{l1} + w_j^{l2} + \ldots w_j^{lP}\right)}{P}, \frac{\left(w_j^{m1} + w_j^{m2} + \ldots w_j^{mP}\right)}{P}, \frac{\left(w_j^{u1} + w_j^{u2} + \ldots w_j^{uP}\right)}{P} \right) \tag{2}$$

Step 1-5: to obtain crisp weights (w_j^*) of criteria, the fuzzy weights $(\widetilde{w}_j^* = (w^l_j, w^m_j, w^u_j))$ of criteria are transformed by using Equation (3) [31].

$$w_j^* = \frac{w_j^l + 4w_j^m + w_j^u}{6} \tag{3}$$

2.2. Fuzzy MCRAT

In this study, forklifts will be evaluated with the fuzzy MCRAT method. The steps of the fuzzy MCRAT technique are presented as follows:

Step 2-1: First, a fuzzy decision matrix is created. Using the linguistic data from Stanković et al. [43], decision makers assess how well each alternative performs under each criterion. The linguistic values assigned by Stanković et al. [43] are transferred to fuzzy numbers. Then, the fuzzy values given by each decision maker are integrated with arithmetic mean to form the aggregated fuzzy decision matrix. Equation (4) presents the aggregated fuzzy decision matrix.

$$\widetilde{E} = \left[\widetilde{e}_{ij}\right]_{m \times n} \tag{4}$$

Step 2-2: The values in the aggregated fuzzy decision matrix are normalized by utilizing Equation (5) (for benefit criteria) and Equation (6) (for non-benefit criteria). The fuzzy form of the normalization technique used in the crisp MCRAT method is presented in Equations (5) and (6).

$$\widetilde{f}_{ij} = \left(f^l_{ij}, f^m_{ij}, f^u_{ij}\right) = \frac{\widetilde{e}_{ij}}{max_i e^u_{ij}} = \left(\frac{e^l_{ij}}{max_i e^u_{ij}}, \frac{e^m_{ij}}{max_i e^u_{ij}}, \frac{e^u_{ij}}{max_i e^u_{ij}} \right) \tag{5}$$

$$\widetilde{f}_{ij} = \left(f^l_{ij}, f^m_{ij}, f^u_{ij}\right) = \frac{min_i e^l_{ij}}{\widetilde{e}_{ij}} = \left(\frac{min_i e^l_{ij}}{e^u_{ij}}, \frac{min_i e^l_{ij}}{e^m_{ij}}, \frac{min_i e^l_{ij}}{e^l_{ij}} \right) \tag{6}$$

Step 2-3: The fuzzy weights of the criteria are multiplied by the fuzzy normalized values to obtain fuzzy weighted normalized values.

$$\widetilde{g}_{ij} = \left(g_{ij}^{l}, g_{ij}^{m}, g_{ij}^{u}\right) = w_j^* \times \widetilde{f}_{ij} = \left(w_j^* \times f_{ij}^{l}, w_j^* \times f_{ij}^{m}, w_j^* \times f_{ij}^{u}\right) \quad (7)$$

Step 2-4: Fuzzy optimal alternative is determined.

$$\widetilde{q}_j = max\left(\widetilde{g}_{ij} \middle| 1 \leq j \leq n\right) \quad (8)$$

$$\widetilde{Q} = \left\{\widetilde{q}_1, \widetilde{q}_2, \ldots \widetilde{q}_n\right\} \quad (9)$$

Step 2-5: Fuzzy optimal alternatives are decomposed.

$$\widetilde{Q} = \widetilde{Q}^{max} \cup \widetilde{Q}^{min} \quad (10)$$

$$\widetilde{Q} = \left\{\widetilde{q}_1, \widetilde{q}_2, \ldots \widetilde{q}_k\right\} \cup \left\{\widetilde{q}_1, \widetilde{q}_2, \ldots \widetilde{q}_h\right\}; k + h = j \quad (11)$$

Step 2-6: Alternatives are decomposed.

$$\widetilde{V} = \widetilde{V}^{max} \cup \widetilde{V}^{min} \quad (12)$$

$$\widetilde{V} = \left\{\widetilde{v}_1, \widetilde{v}_2, \ldots \widetilde{v}_k\right\} \cup \left\{\widetilde{v}_1, \widetilde{v}_2, \ldots \widetilde{v}_h\right\}; k + h = j \quad (13)$$

Step 2-7: Fuzzy magnitude of components are calculated.

$$\widetilde{Q}_k = \left(q_k^l, q_k^m, q_k^u\right) = \left(\sqrt{\left(q_1^l\right)^2 + \left(q_2^l\right)^2 + \ldots + \left(q_k^l\right)^2}, \sqrt{\left(q_1^m\right)^2 + \left(q_2^m\right)^2 + \ldots + \left(q_k^m\right)^2}, \sqrt{\left(q_1^u\right)^2 + \left(q_2^u\right)^2 + \ldots + \left(q_k^u\right)^2}\right) \quad (14)$$

$$\widetilde{Q}_h = \left(q_h^l, q_h^m, q_h^u\right) = \left(\sqrt{\left(q_1^l\right)^2 + \left(q_2^l\right)^2 + \ldots + \left(q_h^l\right)^2}, \sqrt{\left(q_1^m\right)^2 + \left(q_2^m\right)^2 + \ldots + \left(q_h^m\right)^2}, \sqrt{\left(q_1^u\right)^2 + \left(q_2^u\right)^2 + \ldots + \left(q_h^u\right)^2}\right) \quad (15)$$

The same process is used for each alternative.

$$\widetilde{V}_k = \left(v_k^l, v_k^m, v_k^u\right) = \left(\sqrt{\left(v_1^l\right)^2 + \left(v_2^l\right)^2 + \ldots + \left(v_k^l\right)^2}, \sqrt{\left(v_1^m\right)^2 + \left(v_2^m\right)^2 + \ldots + \left(v_k^m\right)^2}, \sqrt{\left(v_1^u\right)^2 + \left(v_2^u\right)^2 + \ldots + \left(v_k^u\right)^2}\right) \quad (16)$$

$$\widetilde{V}_h = \left(v_h^l, v_h^m, v_h^u\right) = \left(\sqrt{\left(v_1^l\right)^2 + \left(v_2^l\right)^2 + \ldots + \left(v_h^l\right)^2}, \sqrt{\left(v_1^m\right)^2 + \left(v_2^m\right)^2 + \ldots + \left(v_h^m\right)^2}, \sqrt{\left(v_1^u\right)^2 + \left(v_2^u\right)^2 + \ldots + \left(v_h^u\right)^2}\right) \quad (17)$$

Step 2-8: $\widetilde{Y}$ and $\widetilde{B}_i$ matrices are created. The first one is composed of optimal alternative components and the latter one is composed of each alternative.

$$\widetilde{Y} = \begin{bmatrix} \widetilde{Q}_k & 0 \\ 0 & \widetilde{Q}_h \end{bmatrix} \quad (18)$$

$$\widetilde{B}_i = \begin{bmatrix} \widetilde{V}_{ik} & 0 \\ 0 & \widetilde{V}_{ih} \end{bmatrix} \quad (19)$$

Step 2-9: $\widetilde{Y}$ and $\widetilde{B}_i$ matrices are multiplied to obtain $\widetilde{Z}_i$ matrix shown in Equation (20).

$$\widetilde{Z}_i = \widetilde{Y} \times \widetilde{B}_i = \begin{bmatrix} \widetilde{z}_{11;i} & 0 \\ 0 & \widetilde{z}_{22;i} \end{bmatrix} \tag{20}$$

Step 2-10: The fuzzy trace of the matrix $\widetilde{Z}_i$ is obtained as follows.

$$tr(\widetilde{Z}_i) = \widetilde{z}_{11;i} + \widetilde{z}_{22;i} = \left(z^l_{11,i} + z^l_{22,i}, z^m_{11,i} + z^m_{22,i}, z^u_{11,i} + z^u_{22,i}\right) \tag{21}$$

In Equation (21), $tr(\widetilde{Z}_i) = \left(Z^l_i, Z^m_i, Z^u_i\right)$ indicates the fuzzy trace of Z_i matrix and this value is defuzzied to obtain $tr(Z_i)$ by using $Z_i = \frac{Z^l_i + 4Z^m_i + Z^u_i}{6}$. The most favorable alternative is the one with the highest $tr(Z_i)$ value.

3. Application

A logistics warehouse would like to purchase a forklift that laborers can use in the warehouse. Six managers working in the logistics warehouse were asked to identify the criteria to be used in the assessment and the forklift alternatives they were considering. Managers identified eight criteria and six forklifts as alternatives. Among the forklifts, the FLT-1 and FLT-4 forklifts are forklifts of the same brand, while the others are forklifts of different brands. The criteria determined by the managers are listed below:

- Purchasing Price (PP);
- Lifting Height (LH);
- Lowering Speed (LS);
- Lifting Speed (LIS);
- Loading Capacity (LOC);
- Movement Area Requirement (MAR);
- Image of the Manufacturer Company (IMC);
- Supply of Spare Parts (SUSP).

Only two of the criteria (PP and MAR) shown above are non-benefit criteria and the others are benefit criteria.

First, each manager was asked to identify the best and worst criteria, and then each manager was asked to assign linguistic phrases to compare the criteria, as shown in Table 1. These linguistic phrases were translated into fuzzy numbers by means of Table 1. Then, the criteria weights were calculated for each manager by applying the steps of fuzzy BWM. The calculated fuzzy weights of the criteria and CR values are shown in Table 2.

Table 2. The weights of the criteria for each manager (EXP).

Criteria	EXP 1	EXP 2	EXP 3
PP	(0.15, 0.18, 0.18)	(0.111, 0.128, 0.154)	(0.227, 0.248, 0.248)
LH	(0.121, 0.152, 0.157)	(0.111, 0.128, 0.154)	(0.091, 0.111, 0.131)
LOS	(0.121, 0.152, 0.157)	(0.111, 0.121, 0.157)	(0.091, 0.111, 0.131)
LIS	(0.121, 0.152, 0.157)	(0.111, 0.128, 0.154)	(0.091, 0.111, 0.131)
LOC	(0.121, 0.152, 0.157)	(0.189, 0.189, 0.228)	(0.091, 0.111, 0.131)
MAR	(0.065, 0.087, 0.1)	(0.078, 0.078, 0.098)	(0.091, 0.111, 0.131)

Table 2. *Cont.*

Criteria	EXP 1	EXP 2	EXP 3
IMC	(0.056, 0.066, 0.068)	(0.075, 0.077, 0.092)	(0.075, 0.090, 0.100)
SUSP	(0.065, 0.087, 0.1)	(0.111, 0.128, 0.154)	(0.091, 0.111, 0.131)
CR	0.043	0.084	0.035
Criteria	**EXP 4**	**EXP 5**	**EXP 6**
PP	(0.065, 0.079, 0.084)	(0.202, 0.233, 0.233)	(0.065, 0.079, 0.084)
LH	(0.101, 0.140, 0.157)	(0.078, 0.099, 0.101)	(0.150, 0.181, 0.181)
LOS	(0.101, 0.140, 0.157)	(0.078, 0.099, 0.101)	(0.101, 0.140, 0.157)
LIS	(0.101, 0.140, 0.157)	(0.078, 0.099, 0.101)	(0.101, 0.140, 0.157)
LOC	(0.150, 0.181, 0.181)	(0.078, 0.099, 0.101)	(0.101, 0.140, 0.157)
MAR	(0.101, 0.140, 0.157)	(0.058, 0.066, 0.067)	(0.101, 0.140, 0.157)
IMC	(0.056, 0.065, 0.068)	(0.134, 0.166, 0.174)	(0.056, 0.065, 0.068)
SUSP	(0.101, 0.140, 0.157)	(0.134, 0.166, 0.174)	(0.101, 0.140, 0.157)
CR	0.043	0.063	0.043

Equation (2) and the fuzzy criterion weights are merged. Then, these combined fuzzy weights are made crisp weights with the help of Equation (3). Fuzzy combined weights and crisp criteria weights are shown in Table 3.

Table 3. Fuzzy combined weights and crisp weights of criteria.

Criteria	Combined Fuzzy Weights	Combined Crisp Weights
PP	(0.137, 0.158, 0.164)	0.156
LH	(0.109, 0.135, 0.147)	0.133
LOS	(0.101, 0.127, 0.143)	0.125
LIS	(0.101, 0.128, 0.143)	0.126
LOC	(0.122, 0.145, 0.159)	0.144
MAR	(0.082, 0.104, 0.118)	0.103
IMC	(0.075, 0.088, 0.095)	0.087
SUSP	(0.101, 0.129, 0.146)	0.127

According to Table 3, the criteria are ordered from the most significant to the least significant: PP, LOC, LH, SUSP, LIS, LOS, MAR, and IMC. Accordingly, the most important criterion is determined as the PP criterion, while the least significant criterion is determined as the IMC.

After the criteria weights were determined, the fuzzy MCRAT method was used. First, it asked managers to evaluate the performance of forklifts under each criterion using the linguistic phrases shown in Stanković et al. [43]. With the help of these linguistic phrases, weights were translated into fuzzy numbers. Then, these fuzzy values given by each manager were integrated with the arithmetic mean to form the aggregated fuzzy decision matrix. The aggregated fuzzy decision matrix is presented in Table 4.

Table 4. The aggregated fuzzy decision matrix.

Alternatives	PP	LH	LOS	LIS
FLT-1	(4, 5.667, 6)	(5.333, 6.333, 7.333)	(2, 3, 4)	(5.667, 6.667, 7.667)
FLT-2	(5, 5.667, 7)	(5.333, 6.333, 7.333)	(3.667, 5, 5.667)	(4, 5, 6)
FLT-3	(5.667, 7.333, 7.667)	(6.667, 7.333, 8.667)	(4, 5.667, 6)	(5.667, 6.667, 7.667)
FLT-4	(5.667, 7.333, 7.667)	(5.667, 6.667, 7.667)	(4, 5.667, 6)	(5.667, 6.667, 7.667)
FLT-5	(5, 6, 7)	(5.667, 6.667, 7.667)	(4, 5.667, 6)	(4, 5, 6)
FLT-6	(5, 6, 7)	(5.667, 6.333, 7.667)	(4, 5.667, 6)	(4, 5, 6)
Alternatives	**LOC**	**MAR**	**IMC**	**SUSP**
FLT-1	(4.333, 5.333, 6.333)	(5.333, 6.333, 7.333)	(5.333, 6, 7.333)	(4.667, 5.667, 6.667)
FLT-2	(4.333, 5.333, 6.333)	(6.333, 7.333, 8.333)	(6, 6.667, 8)	(5.667, 6, 7.667)
FLT-3	(6, 7, 8)	(6.333, 7.333, 8.333)	(6, 7, 8)	(5, 6, 7)
FLT-4	(6, 7, 8)	(6.333, 7.333, 8.333)	(5.333, 6, 7.333)	(4.667, 5.667, 6.667)
FLT-5	(4.333, 6, 6.333)	(5.333, 6.333, 7.333)	(5.667, 6, 7.667)	(5, 6, 7)
FLT-6	(4.333, 5.667, 6.333)	(5, 5.667, 7)	(5, 5.667, 7)	(5.667, 6.333, 7.667)

Equations (5) and (6) have been used to create the aggregated fuzzy decision matrix with normalization. Table 5 shows the fuzzy normalized matrix.

Table 5. The fuzzy normalized matrix.

Alternatives	PP	LH	LOS	LIS
FLT-1	(0.667, 0.706, 1)	(0.615, 0.731, 0.846)	(0.333, 0.5, 0.667)	(0.739, 0.87, 1)
FLT-2	(0.571, 0.706, 0.8)	(0.615, 0.731, 0.846)	(0.611, 0.833, 0.945)	(0.522, 0.652, 0.783)
FLT-3	(0.522, 0.545, 0.706)	(0.769, 0.846, 1)	(0.667, 0.945, 1)	(0.739, 0.87, 1)
FLT-4	(0.522, 0.545, 0.706)	(0.654, 0.769, 0.885)	(0.667, 0.945, 1)	(0.739, 0.87, 1)
FLT-5	(0.571, 0.667, 0.8)	(0.654, 0.769, 0.885)	(0.667, 0.945, 1)	(0.522, 0.652, 0.783)
FLT-6	(0.571, 0.667, 0.8)	(0.654, 0.731, 0.885)	(0.667, 0.945, 1)	(0.522, 0.652, 0.783)
Alternatives	**LOC**	**MAR**	**IMC**	**SUSP**
FLT-1	(0.542, 0.667, 0.792)	(0.682, 0.79, 0.938)	(0.667, 0.75, 0.917)	(0.609, 0.739, 0.87)
FLT-2	(0.542, 0.667, 0.792)	(0.6, 0.682, 0.79)	(0.75, 0.833, 1)	(0.739, 0.783, 1)
FLT-3	(0.75, 0.875, 1)	(0.6, 0.682, 0.79)	(0.75, 0.833, 1)	(0.652, 0.783, 0.913)
FLT-4	(0.75, 0.875, 1)	(0.6, 0.682, 0.79)	(0.667, 0.75, 0.917)	(0.609, 0.739, 0.87)
FLT-5	(0.542, 0.75, 0.792)	(0.682, 0.79, 0.938)	(0.708, 0.75, 0.958)	(0.652, 0.783, 0.913)
FLT-6	(0.542, 0.708, 0.792)	(0.714, 0.882, 1)	(0.625, 0.708, 0.875)	(0.739, 0.826, 1)

With Equation (7), the fuzzy weighted normalized matrix is obtained. This matrix is shown in Table 6.

Table 6. The fuzzy weighted normalized matrix.

Alternatives	PP	LH	LOS	LIS
FLT-1	(0.104, 0.11, 0.156)	(0.082, 0.097, 0.113)	(0.042, 0.063, 0.083)	(0.093, 0.11, 0.126)
FLT-2	(0.089, 0.11, 0.125)	(0.082, 0.097, 0.113)	(0.076, 0.104, 0.118)	(0.066, 0.082, 0.099)
FLT-3	(0.081, 0.085, 0.11)	(0.102, 0.113, 0.133)	(0.083, 0.118, 0.125)	(0.093, 0.11, 0.126)
FLT-4	(0.081, 0.085, 0.11)	(0.087, 0.102, 0.118)	(0.083, 0.118, 0.125)	(0.093, 0.11, 0.126)
FLT-5	(0.089, 0.104, 0.125)	(0.087, 0.102, 0.118)	(0.083, 0.118, 0.125)	(0.066, 0.082, 0.099)
FLT-6	(0.089, 0.104, 0.125)	(0.087, 0.097, 0.118)	(0.083, 0.118, 0.125)	(0.066, 0.082, 0.099)
Alternatives	**LOC**	**MAR**	**IMC**	**SUSP**
FLT-1	(0.078, 0.096, 0.114)	(0.07, 0.081, 0.097)	(0.058, 0.065, 0.08)	(0.077, 0.094, 0.11)
FLT-2	(0.078, 0.096, 0.114)	(0.062, 0.07, 0.081)	(0.065, 0.072, 0.087)	(0.094, 0.099, 0.127)
FLT-3	(0.108, 0.126, 0.144)	(0.062, 0.07, 0.081)	(0.065, 0.076, 0.087)	(0.083, 0.099, 0.116)
FLT-4	(0.108, 0.126, 0.144)	(0.062, 0.07, 0.081)	(0.058, 0.065, 0.08)	(0.077, 0.094, 0.11)
FLT-5	(0.078, 0.108, 0.114)	(0.07, 0.081, 0.097)	(0.062, 0.065, 0.083)	(0.083, 0.099, 0.116)
FLT-6	(0.078, 0.102, 0.114)	(0.074, 0.091, 0.103)	(0.054, 0.062, 0.076)	(0.094, 0.105, 0.127)

With Equations (8) and (9), the fuzzy optimal alternatives are determined first, and these alternatives are decomposed by Equations (10) and (11). With Equations (12) and (13), the alternatives are decomposed. Equations (14) and (15) calculate the fuzzy magnitude of components. The fuzzy magnitude of components' values are presented in Table 7.

Table 7. The fuzzy magnitude of components' values.

	Magnitude
$\widetilde{Q}_k$	(0.225, 0.267, 0.306)
$\widetilde{Q}_h$	(0.128, 0.143, 0.187)

By means of Equations (16) and (17), the same process is performed for the alternatives. Then, with Equations (18)–(20), the values of $\widetilde{z}_{11;i}$ and $\widetilde{z}_{22;i}$, which are the elements of the $\widetilde{Z}_i$ matrix, are found. Equation (21) is used to obtain the fuzzy trace ($tr(\widetilde{Z}_i)$) of the matrix $\widetilde{Z}_i$. Finally, this fuzzy value is defuzzified. Table 8 shows these values and the results of the fuzzy MCRAT technique.

Table 8. The findings of fuzzy MCRAT technique.

Alternatives	$\widetilde{V}_{ik}$	$\widetilde{V}_{ih}$	$\widetilde{z}_{11;i}$	$\widetilde{z}_{22;i}$
FLT-1	(0.18, 0.219, 0.259)	(0.125, 0.137, 0.184)	(0.0405, 0.0585, 0.0793)	(0.016, 0.0196, 0.0344)
FLT-2	(0.19, 0.226, 0.271)	(0.108, 0.13, 0.149)	(0.0428, 0.0603, 0.0829)	(0.0138, 0.0186, 0.0279)
FLT-3	(0.221, 0.265, 0.302)	(0.102, 0.11, 0.137)	(0.0497, 0.0708, 0.0924)	(0.0131, 0.0157, 0.0256)
FLT-4	(0.21, 0.256, 0.291)	(0.102, 0.11, 0.137)	(0.0473, 0.0684, 0.089)	(0.0131, 0.0157, 0.0256)
FLT-5	(0.189, 0.238, 0.27)	(0.113, 0.132, 0.158)	(0.0425, 0.0635, 0.0826)	(0.0145, 0.0189, 0.0295)
FLT-6	(0.191, 0.235, 0.272)	(0.116, 0.138, 0.162)	(0.043, 0.0627, 0.0832)	(0.0148, 0.0197, 0.0303)

Table 8. *Cont.*

Alternatives	$tr(\widetilde{Z}_i)$	$tr(Z_i)$	Rankings
FLT-1	(0.0565, 0.0781, 0.1137)	0.0564	5
FLT-2	(0.0566, 0.0789, 0.1108)	0.0555	6
FLT-3	(0.0628, 0.0865, 0.118)	0.0606	1
FLT-4	(0.0604, 0.0841, 0.1146)	0.0586	2
FLT-5	(0.057, 0.0824, 0.1121)	0.0567	4
FLT-6	(0.0578, 0.0824, 0.1135)	0.0573	3

According to Table 8, forklifts are listed as follows: FLT-3, FLT-4, FLT-6, FLT-5, and FLT-1. According to the findings of the fuzzy MCRAT technique, the forklift with the best performance was determined as the forklift with the code FLT-3, while the forklift with the worst performance was determined as the forklift with the code FLT-2. The fuzzy MCRAT method was compared with the fuzzy ARAS, fuzzy TOPSIS, fuzzy MABAC, fuzzy VIKOR, fuzzy MAIRCA, and fuzzy MARCOS methods to confirm whether the developed method achieved accurate results. Table 9 presents the findings of the fuzzy MCDM methods.

Table 9. The findings of fuzzy MCDM techniques.

Alternatives	Fuzzy ARAS	Fuzzy MARCOS	Fuzzy MCRAT	Fuzzy TOPSIS	Fuzzy MABAC	Fuzzy VIKOR	Fuzzy MAIRCA
FLT-1	5	6	5	6	5	6	5
FLT-2	6	5	6	5	6	5	6
FLT-3	1	1	1	1	1	1	1
FLT-4	2	2	2	2	2	2	2
FLT-5	4	4	4	4	4	4	4
FLT-6	3	3	3	3	3	3	3

According to Table 9, the fuzzy MCRAT method developed with the fuzzy ARAS, fuzzy MABAC, and fuzzy MAIRCA methods reached the same results. There are slight differences between the fuzzy MARCOS method and the fuzzy MCRAT method. The fuzzy MARCOS method found the forklift with the code FLT-1 to be in sixth place and the forklift with the code FLT-2 in fifth place, while the fuzzy MCRAT method found the forklift with the code FLT-1 to be in fifth place and the forklift with the code FLT-2 in sixth place. The Pearson correlation coefficient between the results of these two methods was found to be 0.94. The results of the fuzzy MARCOS method, the fuzzy TOPSIS, and fuzzy VIKOR methods are the same. Therefore, the Pearson correlation coefficients between the fuzzy TOPSIS, the fuzzy VIKOR methods, and the fuzzy MCRAT method are 0.94.

The developed fuzzy MCRAT method was compared with six fuzzy MCDM methods and it was tried to determine whether it obtained correct results. According to the comparison results, the Pearson correlation coefficient between the fuzzy MCRAT method and the fuzzy MARCOS, fuzzy TOPSIS, and fuzzy VIKOR methods was found as 0.94, while the Pearson correlation coefficient between the fuzzy ARAS, fuzzy MABAC, and fuzzy MAIRCA methods, which are other fuzzy MCDM methods, and the fuzzy MCRAT method was found to be 1. Based on this, it is concluded that the fuzzy MCRAT method developed gives accurate results.

In this study, sensitivity analysis was performed by changing the weights of the criteria. The weights of the three criteria (PP, LH, and LOC) with the highest weights were reduced in this study to create a total of thirty scenarios. Below is Equation (22), which was utilized in the scenario arrangement [59].

$$W_{n\delta} = (1 - W_{n\alpha})\frac{W_\delta}{(1 - W_n)} \quad (22)$$

In Equation (22), $W_{n\delta}$ demonstrates a new value of the weight of the criterion, while W_δ presents the original value of the criterion. Additionally, $W_{n\alpha}$ demonstrates the reduced criterion weight, and W_n presents the original weight of the criterion with a reduced value [59]. Figure 1 shows the results of sensitivity analysis.

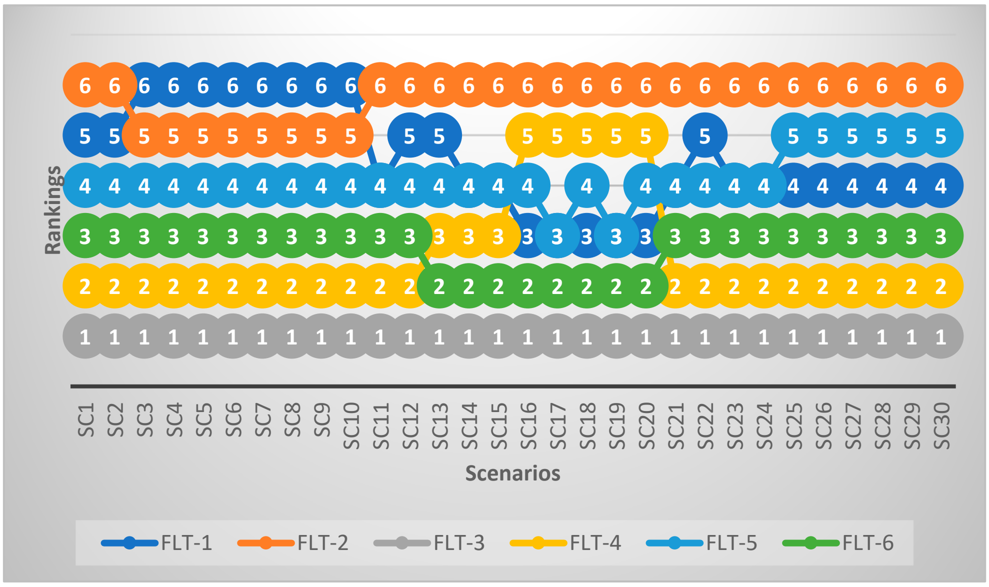

Figure 1. The results of sensitivity analysis.

The weights of the criteria were arranged with 30 scenarios. A change was observed in the rankings of all forklifts except the FLT-3-coded forklift. The FLT-1-coded forklift is sixth in SC3-SC10, 5th in SC1, SC2, SC12, SC13, and SC22, and fourth in SC11, SC14, SC15, SC21, and SC23-SC30. In other scenarios, this forklift took third place. The FLT-2-coded forklift is sixth in SC1, SC2, and SC11-SC30, while this forklift is fifth in other scenarios. The FLT-4-coded forklift is second in SC1-SC12 and SC21-SC30, this forklift is third in SC13-SC15, and it is fifth in SC16-SC20. The FLT-5-coded forklift is fourth in SC1-SC16, SC18, and SC20-SC24, this forklift is third in SC17 and SC19, and it is fifth in SC25-SC30. The FLT-6-coded forklift is third in SC1-SC12 and SC21-SC30; however, this forklift is second in other scenarios. According to the results obtained, it was observed that the changes in the weights of the criteria modified the results. Based on this, it can be stated that the fuzzy MCRAT method developed is sensitive to the changes in the weights of the criteria.

4. Conclusions

Numerous disciplines, including engineering, economics, management, among others, can benefit from the usage of MCDM techniques. MHE is seen as a crucial issue for businesses since it may help with logistics and manufacturing processes to boost productivity, improve the quality of goods, and reduce operating costs. Longer production delays and greater material handling expenses might be the results of improper material handling procedures. Hence, picking the appropriate MHE is significant. The selection of MHE must consider several criteria in addition to the numerous alternatives. When it comes to tackling this complexity with a multitude of options and criteria in selection issues, MCDM techniques are highly useful. In this study, forklifts which are among the pieces of material handling equipment commonly used by businesses, are assessed with fuzzy BWM and fuzzy MCRAT techniques. Fuzzy BWM has been used for calculating the weights of criteria while fuzzy MCRAT has been used to identify the ranks of alternatives.

The fuzzy BWM method found the order of importance of criteria to be PP, LOC, LH, SUSP, LIS, LOS, MAR, and IMC. As a result, the IMC is decided to be the least essential criterion while the PP is determined to be the most relevant criterion. The fuzzy MCRAT approach reveals that FLT-3 performed the best, while FLT-2 had the poorest performance. To validate the accuracy of this method, it was compared with fuzzy ARAS, fuzzy TOPSIS, and fuzzy MARCOS approaches. The comparative assessment indicates that the fuzzy MCRAT and fuzzy ARAS techniques yielded the same outcomes. However, there were minor discrepancies between fuzzy MARCOS and fuzzy MCRAT methods. Specifically, the fuzzy MARCOS approach ranked FLT-1 sixth and FLT-2 fifth, whereas fuzzy MCRAT placed FLT-1 fifth and FLT-2 sixth.

Six fuzzy MCDM methods were compared with the newly designed fuzzy MCRAT approach in an effort to ascertain if it produced accurate findings. The comparison findings demonstrated that the fuzzy MCRAT method and the fuzzy MARCOS, fuzzy TOPSIS, and fuzzy VIKOR methods had a Pearson correlation coefficient of 0.94, while the fuzzy ARAS, fuzzy MABAC, and fuzzy MAIRCA methods, which are other fuzzy MCDM methods, had a Pearson correlation coefficient of 1. This leads to the conclusion that the fuzzy MCRAT approach produces reliable outcomes.

In this study, sensitivity analysis was performed by changing the weights of the criteria. The weights of the criteria were changed in a total of thirty scenarios. According to the results of the sensitivity analysis, a change was observed in the order of all forklifts except the FLT-3-coded forklift. The FLT1-coded forklift is ranked sixth in SC3-SC10, fifth in SC1, second in SC2, third in SC12, third in SC13, and fourth in SC11, SC14, SC15, and SC21, as well as SC23-SC30. It is ranked third in other scenarios. While the FLT-2-coded forklift is ranked fifth in other scenarios, it is ranked sixth in SC1, SC2, and SC11-SC30. The FLT4 forklift is second in SC1-SC12 and SC21-SC30, third in SC13-SC15, and fifth in SC16-SC20. The FLT-5 forklift ranks fourth in SC1-SC16, SC18, and SC20-SC24, third in SC17 and SC19, and fifth in SC25-SC30. The FLT-6-coded forklift comes in third in SC1-SC12 and SC21-SC30 but comes second in all other scenarios. Based on these results, it was concluded that the fuzzy MCRAT method developed is sensitive to changes in the weights of the criteria.

Selecting the right forklift is important for ensuring safety, productivity, cost effectiveness, and environmental sustainability in the workplace. The results of this study were shared with the logistics warehouse which would like to benefit from finding the right forklift for warehouse operations, and it was recommended that the logistics warehouse purchase the forklift with the code FLT-3.

Although clarity, rationalism, logic, adaptability, and dependability are only a few advantages of the MCRAT technique, there is no study employing an MCRAT approach in MHE selection. The studies using MCRAT in different decision problems in the literature [27–29] also did not take uncertainty into account in the analysis. This study therefore contributed to the literature by creating a novel fuzzy MCDM technique.

Only forklifts were assessed in this study, despite the use of a novel MCDM technique. The suggested MCDM model in this study can be used to solve various decision problems in future studies. Additionally, the fuzzy MCRAT technique can be used with other MCDM techniques in other studies.

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