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# Multi-Criteria Decision-Making Techniques for Optimal In-House Storage Location Selection

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**Abstract:** Storage is a key task of a logistics enterprise. Effective storage processes can increase the efficiency of enterprise logistics processes and positively affect logistics costs. Therefore, it is very important to deal with selecting storage locations within the enterprise area. The present paper deals with the optimal in-house storage location. The research was realized through a Czech Republic brewing company case study which aimed to find and select the best in-house storage location. The decision-making methods chosen for this solution were the additive ratio assessment method and the combined compromised solution method. While these methods are rarely used for this kind of solution-making, they helped to find the best location for reasonable storage in the research enterprise.

**Keywords:** logistics; location; decision making; storage; warehouse



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## 1. Introduction

The warehouse plays a vital role in logistics and supply chain management. It stores goods until they are delivered to the final customers. Cruz-Reyes et al. [1] state that storage goods have a crucial role in warehouse management systems, and it is not a simple process since there is uncertainty in demands, the volume of products, shipment times, etc. Nowadays, there is an increasing number of warehouses around the world. Due to the development of e-commerce and the widespread COVID-19 crisis, customers shifted to purchasing products online. Consequently, the number of physical goods going through warehouses has increased rapidly. Therefore, dealing with the correct warehouse allocation and building an effective warehouse management system is very important.

This paper aims to present the results of the case study realized in a brewery company in the Czech Republic and the solution to the in-house storage location process issue according to the company management's defined criteria. The study was conducted to increase the effectiveness of the company's storage management and find the best solution for the storage location.

The primary motivation for this research is a discussion with the top management of a brewery company about the selection of in-hose storage locations. Since this decision is affected by numerous and often conflicting criteria, the multi-criteria decision-making (MCDM) method was selected. Among various issues related to the warehouse, this paper addresses the optimal in-house storage location selection issue in the brewing company. Four in-house locations are identified as possible alternatives and marked from A to D. Those four alternatives are further assessed according to the following criteria: warehouse-location occupation costs (CZK/pallet/day), loading/unloading costs (CZK), handling time per unit (min), and distance to the given storage location (m). Multi-criteria decision-making (MCDM) techniques such as additive ratio assessment (ARAS) and combined compromising solution (CoCoSo) have been employed to address this issue. The ARAS and CoCoSo methods obtained the same ranking order of all four alternatives.

The two main contributions of this paper are as follows:

(1) For the first time, the ARAS and CoCoSo methods have been applied to solve the inside storage location selection problem;
(2) The real-life study in a brewing company has been solved by the presented methods, which may be seen as a practical contribution and a good baseline that can facilitate and optimize logistics processes in the future.

The rest of the paper is organized as follows: Section 2 is the literature review and follows the introductory section. Section 3 presents the methods used to solve the problem mentioned. Section 4 applies the MCDM techniques to a real-life study. Section 5 concludes the paper and gives directions for future research.

## 2. Literature Review

Various issues regarding the warehouse management system should be identified in the literature. Also, several exciting studies deal with the solution of effective warehouse systems.

For example, Güntez et al. [2] examined the storage and retrieval policy for perishable food products in a cold warehouse in Izmir. The study aimed to identify an optimal storage and retrieval strategy to improve performance metrics, reduce processing times, and minimize food waste. The authors developed storage and retrieval algorithms and evaluated them using simulations. They also established warm-up periods and confidence intervals for the average cycle time using the Output Analyzer tool of the ARENA 16.0 commercial simulation software. Additionally, a sensitivity analysis was conducted to investigate the relationship between product arrivals and demand distribution of product types. Finally, they developed a user-friendly decision support system embedded the proposed simulation models. The study found that their proposed storage and retrieval policy improved performance metrics, reduced process time, and decreased food waste. The research provides valuable insights for warehouse managers and practitioners looking to optimize storage and retrieval operations for perishable food products in a cold warehouse.

Rungjaroenporn and Setthawong [3] published an article that investigates the problem of storage location assignment at a warehouse as an optimization problem. The authors found that traditional optimization algorithms do not readily apply to the unique situation of each warehouse. Thus, a specifically designed optimization algorithm is necessary for the location assignment problem at Lazada Thailand Warehouse. To address this, the authors propose Multi-objective Optimization using the Flower Pollination Algorithm (MOFPA) for Storage Location Assignment at Lazada Thailand Warehouse, which includes new operators and multi-objective fitness functions to handle more complex constraints. The experimental results on four real datasets of Lazada Thailand Warehouse indicate that MOFPA can find solutions for almost all datasets, and that it outperforms traditional generic algorithms for all datasets.

Zhang et al. [4] published a paper that addresses a real-world issue in a food company where the available warehouse space for finished goods constrains production planning. They proposed a novel integrated strategy that combines production planning with a randomized storage assignment policy, taking advantage of the greater visibility and traceability of items provided by IoT-enabled tracking systems to improve space utilization. They formulated the strategy as an integer linear programming model to minimize production and warehouse operations costs. They proposed a heuristic algorithm for a near-optimal solution for large-scale real-world problems. Based on numerical experiments, the results showed that the integrated strategy with a randomized storage policy could significantly reduce the total cost (up to 16.84% with an average of 9.95%) and increase space utilization (up to 26.1% with an average of 14.8%), compared to the strategy with a dedicated policy. The results demonstrate the cost-effectiveness of implementing new technologies, such as IoT-enabled tracking systems, in warehouse management.

Cardona and Gue [5] described a method for developing layouts for unit-load warehouses that use multiple slot heights to enhance warehouse area utilization. The task was divided into two parts: putting slots into rack bays and arranging rack bays into a pattern. Depending on whether the warehouse has directed picking and put-away, the authors presented two strategies for the first subproblem. They described a simulation model and a greedy approach based on the duration-of-stay storage strategy for the second. They discovered considerable advantages to adopting varied slot heights in unit-load warehouses regarding footprint, estimated trip time, and racking cost. For a typical warehouse, they expected space savings between 25% and 35%, depending on the number of slot types, and savings of between 15% and 25% in annual operating costs.

Zhao et al. [6] proposed a warehouse layout design based on a mix of systematic layout planning (SLP) and an ant colony genetic algorithm fusion scheme (GA-ACO). They noted that the modern logistics process necessitates a warehouse performing numerous activities such as storage, processing, and order administration, increasing the number of functional regions within the warehouse. The traditional SLP approach did not yield an optimal layout plan. As a result, they recommended combining SLP with the GA-ACO algorithm. Because the genetic algorithm uses local optimization, the produced layout is not the best solution. The proposed solution improves the layout plan's overall relationship. The experimental results showed the layout plan obtained by the method proposed in this paper had a higher comprehensive relationship.

Hou [7] proposed optimizing an automated product dynamic allocation and warehousing model. He emphasized the growing significance of automated cargo warehousing in advancing modern logistics, which is required for the autonomous distribution of goods. He presented an autonomous site allocation model and the particle swarm optimization (PSO) algorithm utilized to optimize the model. He proposed the notion of genetic operator and multi-group co-evolution to improve the algorithm further. MATLAB software was used to do simulation analysis of standard PSO and enhanced PSO. The results showed that the modified PSO method iterated fewer times and produced better solution sets; when compared to the manual allocation scheme, the enhanced PSO computation reduced warehousing time, decreased center of gravity height, and increased shelf stability.

The solution and design of optimal in-house storage location is one of the most important decision issues for logistics experts. A suitable solution is presented by applying the decision-making method, especially multi-criteria decision-making methods, which can solve adequate storage and warehouse management issues.

Rezaei [8] mentioned that multi-criteria decision-making is a significant branch of decision-making theory. It is possible to use this approach to solve different issues, but several studies have dealt with MCDM in warehouse management.

For example, Amrani et al. [9] used a decision-making system to solve container storage management in a seaport. The authors developed a software tool for identifying the best location for a container integrated into a decision model.

The connection of comparative analysis of multi-criteria decision-making methodology and their implementation in the warehouse location selection problem was presented by the authors Özcan et al. [10].

Chen [11] presented an approach to the solution of the selection of distribution center location with the help of a fuzzy multiple criteria group decision-making. The authors Korpela and Lehmusvaara [12] presented an analytic hierarchy process application for analyzing customer-specific requirements for logistics service and evaluating alternative warehouse operators. The authors provided a systematic framework for the selection of a warehouse network. Fontana and Nepomuceno [13] used a multi-criteria approach for product classification and storage location assignment. The authors proposed a multi-criteria decision model to perform the product classification and solve the storage location assignment problem in a multi-layer warehouse.

Dimas da Silva et al. [14] emphasized in their research that the storage of products has a strategic role in the supply chain. Also, an efficient production organization increases the effectiveness of the warehouse and the entire warehouse management. It proposes a multicriteria decision support model for ranking products and assigning them to warehouse storage locations.

Fontana and Cavalcante [15] presented an application of the evaluation multicriteria method to the solution of the best alternative for assigning a product to a warehouse storage location. The authors reported in their research that by using the multi-criteria method, warehouse managers can learn of all the possible non-dominated allocation of the products and realize changes in the allocation when needed.

Karmaker and Saha [16] presented a possible way to optimize warehouse locations through multi-criteria decision-making. The authors applied the analytic hierarchy process and fuzzy TOPSIS method (technique for order preference by similarity to ideal solution) as practical tools for selecting the most suitable warehouse location.

Özmen and Aydoğan [17] presented an application of the selected multi-criteria decision-making methods in the solution of logistics center location. The authors determined the logistics center's location by considering modern city planning and logistics principles. They applied a three-stage methodology for selecting the mentioned center: determination of criteria, weighting of determining criteria using linear best-worst method, and ranking of locations using the evaluation based on distance from average solution method.

Ehsanifar et al. [18] used the UTASTAR method and its application in multi-criteria warehouse location selection. The study's authors presented an application of this method in a case study relating to the choice of several alternatives and the best location for construction in the research company's central warehouse.

Also, we can mention several related studies in the field of multi-criteria decision-making and its method application for the solution and optimization of allocation issues in warehouses.

According to the previous research activities of the authors of this study in the field of MCDM methods application the authors solve the optimal warehouse storage location problem using multi-criteria decision-making techniques such as ARAS and CoCoSo. It may be noticed from the literature that the mentioned methods have not been previously applied to this kind of problem. The steps of the ARAS and CoCoSo methods are explained in the next section.

## 3. Methodology

### *3.1. Additive Ratio Assessment (ARAS) Method*

The Additive Ratio Assessment (ARAS) method is created by Kamer and Saha [16]. This method can be presented through the five steps [16]:

Step 1. Define a decision-making matrix Z

$$Z = \begin{bmatrix} z_{01} & \cdots & z_{0j} & \cdots & z_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{i1} & \cdots & z_{ij} & \cdots & z_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mj} & \cdots & z_{mn} \end{bmatrix}; \; i = \overline{0,m}, \; j = \overline{1,n}. \tag{1}$$

where: $m$—number of alternatives, $n$—number of criteria describing each alternative, $z_{ij}$—a value representing the performance value of the $i$-th alternative in terms of the $j$-th criterion, $z_{0j}$—the optimal value of $j$-th criterion.

If the optimal value of the $j$-th criterion is unknown, then:

$$\begin{aligned} z_{0j} &= max_i z_{ij}, \text{ if } max_i z_{ij} \text{ is preferable.} \\ z_{0j} &= min_i z^*_{ij}, \text{ if } min_i z^*_{ij} \text{ is preferable.} \end{aligned} \tag{2}$$

Usually, the performance values $z_{ij}$ and the criteria weights $W_j$ are considered entries in a DMM. The system of criteria, as well as values and initial weights of criteria, is determined by experts. The interested parties can correct the information by considering their goals and opportunities.

Step 2. Normalize the data form Step 1.

In this step, the initial values of all the criteria are normalized—defining values $\overline{z_{ij}}$ of normalized decision-making matrix $\overline{Z}$.

$$\overline{Z} = \begin{bmatrix} \overline{z}_{01} & \cdots & \overline{z}_{0j} & \cdots & \overline{z}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{z}_{i1} & \cdots & \overline{z}_{ij} & \cdots & \overline{z}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{z}_{m1} & \cdots & \overline{z}_{mj} & \cdots & \overline{z}_{mn} \end{bmatrix}; \ i = \overline{0,\ m},\ j = \overline{1, n}; \tag{3}$$

For the criteria with the maximal preferable numbers, the normalization is calculated by the following equation:

$$\overline{z_{ij}} = \frac{z_{ij}}{\sum_{i=0}^{m} z_{ij}}; \tag{4}$$

For minimal type of criteria, the normalization is performed through two steps, by the following equation:

$$z_{ij} = \frac{1}{z_{ij}^{*}}, \quad \overline{z_{ij}} = \frac{z_{ij}}{\sum_{i=0}^{m} z_{ij}}. \tag{5}$$

Step 3. Formulate normalized-weighted matrix—$\hat{Z}$.

The criteria with weights are structured between intervals $0 < W_j < 1$. The values of weight $W_j$ are usually computed by the experts' assessment. The sum of weights $W_j$ is to be equal to 1, as follows:

$$\sum_{j=1}^{n} w_j = 1; \tag{6}$$

$$\hat{Z} = \begin{bmatrix} \hat{z}_{01} & \cdots & \hat{z}_{0j} & \cdots & \hat{z}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{z}_{i1} & \cdots & \hat{z}_{ij} & \cdots & \hat{z}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{z}_{m1} & \cdots & \hat{z}_{mj} & \cdots & \hat{z}_{mn} \end{bmatrix}; \ i = \overline{0, m},\ j = \overline{1, n}; \tag{7}$$

Normalized-weighted values are found:

$$\hat{z}_{ij} = \overline{z}_{ij} \cdot \mathrm{W_j};\ i = \overline{0, m}; \tag{8}$$

where $\mathrm{W_j}$ is the significance of the *j*-th criterion, and $\overline{z}_{ij}$ is the normalized rating of the *j*-th criterion.

Step 4. Find the value of the optimality function.

$$S_i = \sum_{j=1}^{n} \hat{z}_{ij}, i = \overline{0, m}. \tag{9}$$

where: $S_i$—the value of the optimality function of *i*-th alternative.

The higher value of $S_i$ is the best one, while the lowest is the worst. Therefore, the greater the value of the optimality function $S_i$, the more influential the alternative. The priorities of other alternatives can be determined according to the value $S_i$.

Step 5. Calculate the degree of the alternative utility.

To calculate the degree of the alternative utility, it is necessary to compare the variants with the ideally best one subscript base, one $S_0$. The calculation of the utility degree $K_i$ of an alternative $a_i$ is given in Equation (10):

$$K_i = \frac{S_i}{S_0};\ i = \overline{0, m}; \tag{10}$$

where $S_i$ and $S_0$ are the optimality criterion values. The calculated values $K_i$ are between 0 and 1.

### 3.2. Combined Compromised Solution (CoCoSo) Method

A Combined Compromise Solution (CoCoSo) method was presented by Karmaker and Saha [16]. This method applies the aggregation strategies. The authors considered a distance measure that originates from the grey relational coefficient and targets to enhance the flexibility of the results. The CoCoSo method is coupled with the simple additive weighting (SAW) method and the exponentially weighted product (EWP) method. The CoCoSo method can be described through the following steps [17]:

Step 1. Determine the initial input-data matrix.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{12} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{21} & \cdots & x_{22} & \cdots & x_{2n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix},\ i = 1, 2, \ldots, m, j = 1, 2, \ldots, \text{n}; \tag{11}$$

Step 2. Normalize the data.

If the criterion is a beneficial (B), the following equation for normalization is used:

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}},\ i = 1, 2, \ldots, m, j = 1, 2, \ldots, \text{n}; \tag{12}$$

If the criterion is non-beneficial, i.e., cost (C), the following equation for normalization is applied:

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}},\ i = 1, 2, \ldots, m, j = 1, 2, \ldots, \text{n}; \tag{13}$$

Step 3. Calculate the $S_i$ and $P_i$ values for all alternatives.

$$S_i = \sum_{j=1}^{n} \left(w_j \cdot r_{ij}\right),\ i = 1, 2, \ldots, m; \tag{14}$$

$$P_i = \sum_{j=1}^{n} \left(r_{ij}\right)^{w_j},\ i = 1, 2, \ldots, m; \tag{15}$$

Step 4. Calculate the total utility strategies for each alternative.

The first strategy of total utility ($K_{ia}$) expresses the arithmetic mean of the sum of $S_i$ and $P_i$ values:

$$K_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)},\ i = 1, 2, \ldots, m; \tag{16}$$

The second strategy of total utility ($K_{ib}$) expresses the sum of the relative relations $S_i$ and $P_i$ with their worst values:

$$K_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i},\ i = 1, 2, \ldots, m; \tag{17}$$

The third strategy of total utility ($K_{ic}$) expresses a balanced compromise of $S_i$ and $P_i$ values:

$$K_{ic} = \frac{\lambda S_i + (1-\lambda)P_i}{(\lambda \max_i S_i + (1-\lambda) \max_i P_i)}, \ 0 \le \lambda \le 1; \tag{18}$$

Step 5. Calculate the final rank of alternatives.

The final ranking of the alternatives is determined based on $K_i$:

$$K_i = (K_{ia} \cdot K_{ib} \cdot K_{ic})^{\frac{1}{3}} + \frac{1}{3}(K_{ia} + K_{ib} + K_{ic}). \tag{19}$$

## 4. Results and Discussion

This paper addresses an optimal warehouse storage location problem in a brewing company in the Czech Republic. After discussing this with the top management of a brewing company, I found that its name is not mentioned for internal policy reasons. However, it is one of the leaders in producing and distributing alcoholic drinks in the Czech market. The company's significant advantages include high production, service quality, customer satisfaction, professional staff, etc. The case study was realized based on the optimal warehouse storage location in Figure 1.

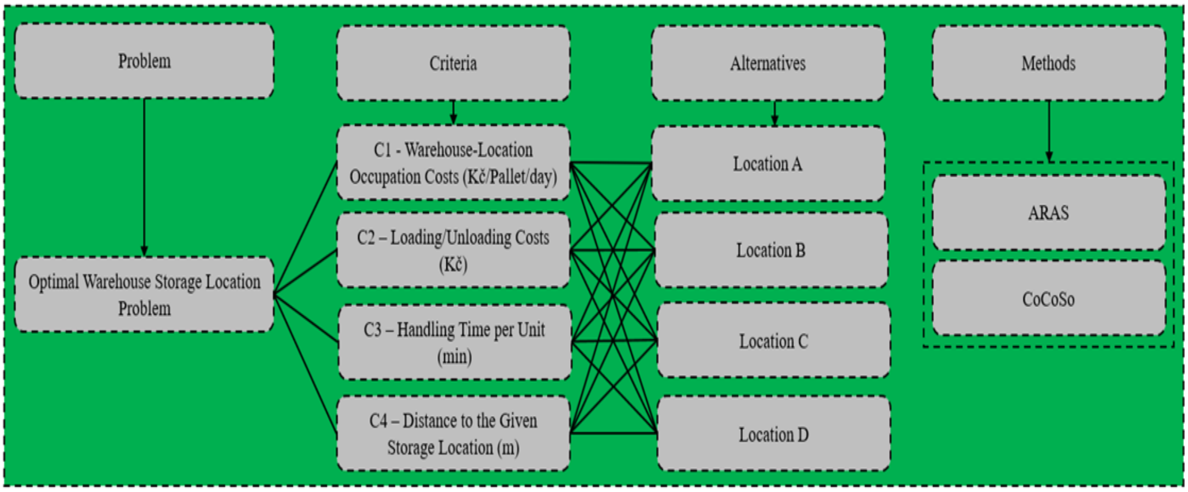


**Figure 1.** Optimal warehouse storage location problem description.

To address the previously mentioned issue, four criteria have been chosen as crucial: C1—Warehouse-Location Occupation Costs (CZK)—Cost of one pallet in CZK per day; C2—Loading/Unloading Cost (CZK); C3—Handling Time per Unit (min), and C4—Distance to the given storage location (m). In addition, four possible inside storage locations have been considered as alternatives. The locations are marked as Location A, Location B, Location C, and Location D. When it comes to methods, two of the multi-criteria decision-making (MCDM) methods are employed to tackle the optimal storage location issue—the additive ratio assessment (ARAS) method and the combined compromised solution (CoCoSo) method.

Before applying the abovementioned methods, it is necessary to formulate an input data matrix where the alternatives will be compared according to the four previously mentioned criteria. The input data matrix is presented in Table 1.

After the initial decision-making matrix is formulated, the next step is to apply the ARAS and the CoCoSo methods. The following results of the ARAS method have been reached (Tables 2–7).

**Table 1.** An Input data matrix.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| 0—Optimal Value | 4.5 | 23 | 2 | 50 |
| Location A | 7.5 | 23 | 2 | 50 |
| Location B | 6 | 48 | 4 | 150 |
| Location C | 9 | 32 | 3 | 180 |
| Location D | 4.5 | 40 | 5 | 400 |
| Criteria Weights | 0.2857 | 0.2551 | 0.2142 | 0.2448 |
| min/max type | min | min | min | min |
| $\sum$ | 0.8556 | 0.1640 | 1.7833 | 0.0547 |

**Table 2.** Initial Decision-Making Matrix (DMM).

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| Location A | 7.5 | 23 | 2 | 50 |
| Location B | 6 | 48 | 4 | 150 |
| Location C | 9 | 32 | 3 | 180 |
| Location D | 4.5 | 40 | 5 | 400 |
| Criteria Weights | 0.2857 | 0.2551 | 0.2142 | 0.2448 |
| min/max type | min | min | min | min |

**Table 3.** Normalized DMM.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| 0—Optimal Value | **0.2597** | **0.2650** | **0.2804** | **0.3655** |
| Location A | 0.1558 | 0.2650 | 0.2804 | 0.3655 |
| Location B | 0.1948 | 0.1270 | 0.1402 | 0.1218 |
| Location C | 0.1299 | 0.1905 | 0.1869 | 0.1015 |
| Location D | 0.2597 | 0.1524 | 0.1121 | 0.0457 |
| Criteria Weights | 0.2857 | 0.2551 | 0.2142 | 0.2448 |
| min/max type | min | min | min | min |

**Table 4.** Weighted DMM with the final rank.

| **Weighted D-M Matrix** | $C_1$ | $C_2$ | $C_3$ | $C_4$ | **S** | **K** | **Rank** |
|---|---|---|---|---|---|---|---|
| 0—Optimal Value | **0.0742** | **0.0676** | **0.0601** | **0.0895** | **0.2913** | | |
| Location A | 0.0445 | 0.0676 | 0.0601 | 0.0895 | 0.2617 | 0.8981 | 1 |
| Location B | 0.0557 | 0.0324 | 0.0300 | 0.0298 | 0.1479 | 0.5077 | 4 |
| Location C | 0.0371 | 0.0486 | 0.0400 | 0.0249 | 0.1506 | 0.5169 | 2 |
| Location D | 0.0742 | 0.0389 | 0.0240 | 0.0112 | 0.1483 | 0.5090 | 3 |
| min/max type | **min** | **min** | **min** | **min** | | | |

**Table 5.** Initial (DMM).

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| Location A | 7.5 | 23 | 2 | 50 |
| Location B | 6 | 48 | 4 | 150 |
| Location C | 9 | 32 | 3 | 180 |
| Location D | 4.5 | 40 | 5 | 400 |
| Criteria value 1 | 4.5 | 23 | 2 | 50 |
| Criteria value 2 | 9 | 48 | 5 | 400 |
| min/max type | **min** | **min** | **min** | **min** |

**Table 6.** Normalized Decision-Making Martix if the Input Data.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| Location A | 0.3333 | 1.0000 | 1.0000 | 1.0000 |
| Location B | 0.6667 | 0.0000 | 0.3333 | 0.7143 |
| Location C | 0.0000 | 0.6400 | 0.6667 | 0.6286 |
| Location D | 1.0000 | 0.3200 | 0.0000 | 0.0000 |
| Criteria Weights | 0.2857 | 0.2551 | 0.2142 | 0.2448 |

**Table 7.** Total Utility Strategies.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | Si | Pi | SiPi | Kia | Kib | Kic |
|---|---|---|---|---|---|---|---|---|---|---|
| Location A | 0.0952 | 0.2551 | 0.2142 | 0.2448 | 0.8093 | 3.7306 | 4.5399 | 0.3532 | 4.3378 | 1.0000 |
| Location B | 0.1905 | 0.0000 | 0.0714 | 0.1749 | 0.4367 | 2.6019 | 3.0386 | 0.2364 | 2.6776 | 0.6693 |
| Location C | 0.0000 | 0.1633 | 0.1428 | 0.1539 | 0.4599 | 2.7018 | 3.1617 | 0.2459 | 2.7979 | 0.6964 |
| Location D | 0.2857 | 0.0816 | 0.0000 | 0.0000 | 0.3673 | 1.7478 | 2.1151 | 0.1645 | 2.0000 | 0.4659 |

The range of storage locations obtained by the ARAS method is presented in Figure 2. It may be noticed that the ARAS method ranked Location A as the best possible solution for storing goods, followed by Location C, Location B, and Location D, respectively.

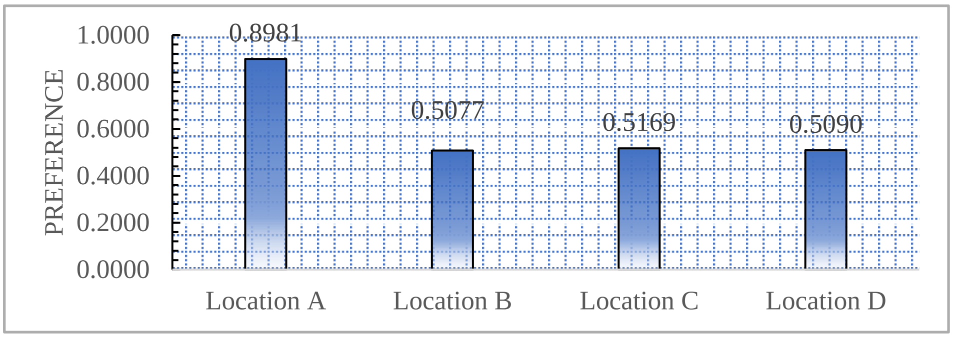


**Figure 2.** Rank of the Storage Locations obtained by the ARAS method.

To compare the results with the ARAS method, the authors applied the CoCoSo method, and the results are presented below (Tables 5–7). The rank of the storage location obtained by the mentioned method is presented in Figure 3.

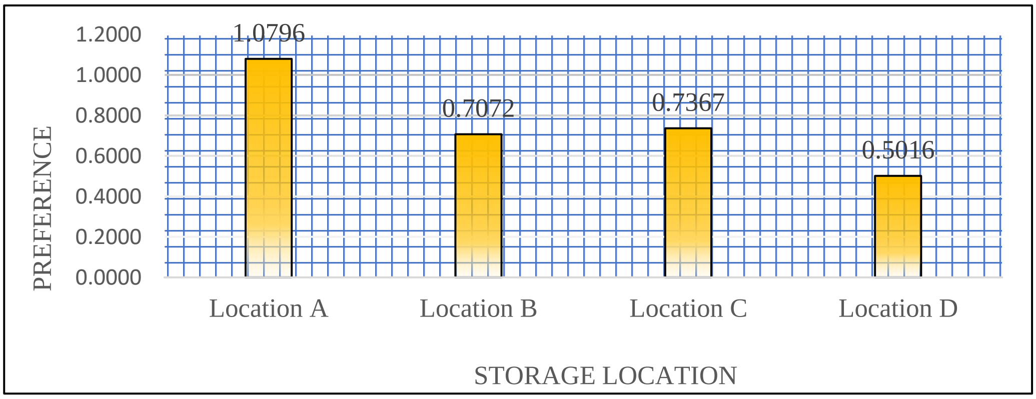


**Figure 3.** Rank of the storage locations obtained by the CoCoSo method.

In this case, the CoCoSo method confirmed Location A as the best way to store goods. Location C is the second best, followed by Location B and D, respectively. In both cases, Location A is shown as the best possible solution for storing goods in a brewing company.

A comparative analysis of the ARAS and CoCoSo methods is performed to check the results' reliability. The results are depicted in Figure 4.

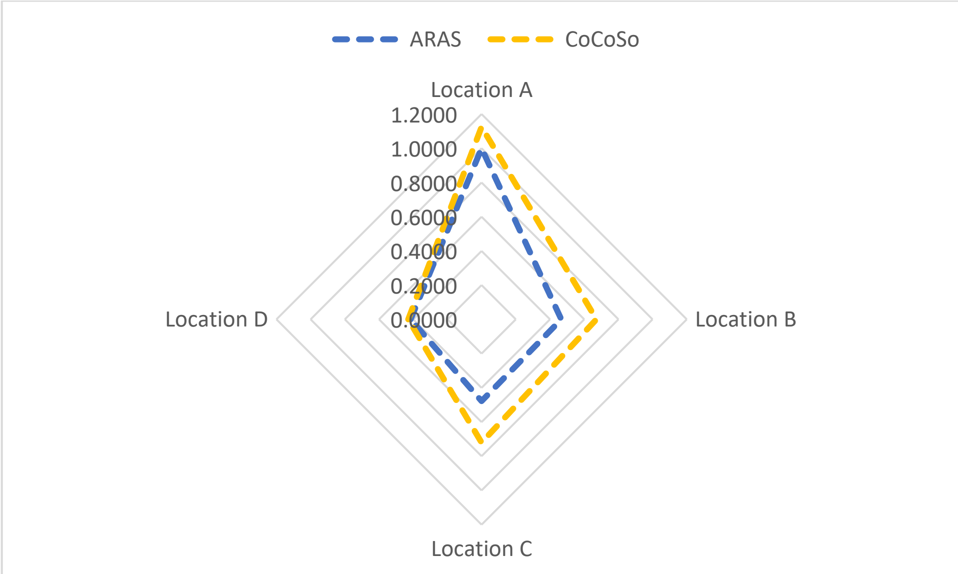


**Figure 4.** Comparative analysis.

The results of the comparative analysis reveal that both methods ranked Location A as the best solution for in-storage goods in a brewing company. According to the ARAS method, the locations are ranked as A > C > D > B. On the other hand, the CoCoSo method ranks the locations as follows: A > C > B > D. The only difference is in the locations D and B.

## 5. Conclusions

The aim of this study was twofold: to present suitable options for solving warehouse location issues, and to present the case study results realized in the specific company. The solution to warehouse location issues is very important. It is based not only on the economic effect of effective warehouse management but also on the global economic situation of the company management. Based on the literature review and the author's previous research activity, MCDMs were selected to solve the issue of warehouse location.

The problem has been solved in the context of a brewing company in the Czech Republic. After a lengthy consultation with the company about the warehouse's main issue, the authors realized that the result of the consultation was a proposal for a storage location. Based on the consultation and literature review results, the company's administrators and management selected four critical criteria and alternatives. These four criteria are C1—Warehouse-Location Occupation Costs (CZK)—Cost of one pallet in CZK per day; C2—Loading/Unloading Cost (CZK); C3—Handling Time per Unit (min), and C4—Distance to the given storage location (m). In addition, four possible inside storage locations have been considered as alternatives. The locations were marked as Location A, Location B, Location C, and Location D. To solve this problem, the authors of this paper applied multi-criteria decision-making (MCDM) techniques such as ARAS and CoCoSo. The results of both methods indicated that Location A is the best possible solution for storing goods.

This paper's significant theoretical and practical contributions are as follows:

(1) For the first time, the MCDM techniques such as ARAS and CoCoSo were applied to the in-house Storage Location Selection problem.
(2) The applied methods have been used to solve a real-life problem in a brewing company in the Czech Republic.

Possible future directions of this paper should be to apply some other MCDM methods to solve the same or similar in-house management problems.

However, it is important to emphasize in future research that the applicability of MCDM methods in location problem solutions, in general, can be enhanced by combining them with quantum computing, or at least by prioritizing some components. This includes the determination of procedures and applicable methods, the validation and evaluation of information obtained in the field of quantum computing, and the use of quantum computers with a focus on solving optimization tasks in logistics. It is mainly an examination of the possibilities of using quantum computers and quantum calculations, which are converted into technical and logical models in the following stages of the project. Part of the future research activity of the authors includes researching the possibility of using quantum concepts to solve the fuzzy model. Fuzzy logic should be implemented to solve optimization in logistics because it deals with uncertainty. Since quantum computing is an upcoming field, it should present many opportunities in terms of logistics.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| MCDM | multi-criteria decision-making |
| ARAS | additive ratio assessment |
| CoCoSo | combined compromising solution |
| MOFPA | Multi-objective Optimization using the Flower Pollination |
| SLP | systematic layout planning, |
| PSO | participle swarm optimization |
| TOPSIS | a technique for order preference by similarity to an ideal solution |
| SAW | simple additive weighting |
| EWP | exponentially weighted product |
| $m$ | number of alternatives, |
| $n$ | number of criteria describing each alternative, |
| $x_{ij}$ | a value representing the performance value of the *i*–th alternative in terms of the *j*-th criterion, |
| $x_{0j}$ | an optimal value of *j*-th criterion. |
| $\overline{X}$ | normalized decision-making matrix |
| $\mathrm{W_j}$ | the weight (importance) of the j-th criterion and |
| $\overline{x}_{ij}$ | the normalized rating of the *j-th* criterion. |
| $S_i$ | the value of the optimality function of i-th alternative. |
| $S_0$ | comparison of the variants with the ideal best one |
| C | cost |
| $S_i$ | the weighted sequences for alternatives |
| $P_i$ | the weighted sequences for alternatives |
| $K_{ia}$ | the first strategy of total utility |
| $K_{ib}$ | the second strategy of total utility |
| $K_{ic}$ | the third strategy of total utility |
| $K_i$ | the final ranking of the alternatives |

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