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APPLYING A HYBRID MCDM TECHNIQUE IN WAREHOUSE MANAGEMENT

A HIBRID MCDM-TECHNIKA ALKALMAZÁSA A RAKTÁRKEZELÉSBEN

The main goal of this study is to apply Multi-Criteria Decision Making (MCDM) in managing a warehouse. One of the elements that could impact organization performance is warehouse management. Surplus inventory imposes some additional costs on the organization, and inadequate inventory stops the operation of an organization. For managing and controlling warehouse inventories, the MCDM method is recommended in this study. The inventories are categorized based on multi-criteria instead of a single criterion in ABC. To specify the criteria's weight, Best-Worst Method is used, and to reach the final score of spare parts, the Analytical Hierarchy Process, and Technique for Order of Preference by Similarity to Ideal Solution is applied. Some strategies for managing and controlling organizations' warehouse is recommended.

Keywords: **Warehouse Management, Best-Worst Method (BMW), Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Multi-Criteria Decision Making (MCDM)**

A tanulmány fő célja a Multi-Criteria Decision Making (MCDM) alkalmazásának bemutatása a raktárkezelésben. Az egyik olyan elem, amely hatással lehet a szervezet teljesítményére, a raktárkezelés. A felesleges készletek többletköltségeket rónak a szervezetre, a nem megfelelő készlet pedig leállítja a szervezet működését. Ebben a tanulmányban az MCDM-módszert javasolja a szerző a raktári készletek kezelésére és ellenőrzésére. A készletek kategorizálása több kritériumon alapszik, az egyetlen ABC-kritérium helyett. A kritériumok súlyozásának meghatározásához a legjobb-legrosszabb módszert, a pótalkatrészek végső számának eléréséhez pedig az analitikai hierarchia folyamatot és az egyszerűségtől az ideális megoldásig preferencia-sorrend technikáját alkalmazzák. A szervezetek raktárának kezeléséhez és ellenőrzéséhez néhány stratégiát javasol a szerző.

Kulcsszavak: **raktárgazdálkodás, legjobb-legrosszabb módszer (BMW), analitikai hierarchia folyamat (AHP), preferencia szerinti sorrend az ideális megoldáshoz hasonlóság alapján (TOPSIS), több szempontú döntéshozatal (MCDM)**

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Inventory management is a procedure that impacts maintenance management and, as a result, productivity (Teixeira et al., 2017). One of the main aspects of manufacturing factories is accessibility to required spare parts. To increase the efficiency of machines and decrease the time of machines' failure, the necessary spare parts must always be available in the factory's warehouse (Kundrak et al., 2018). Spare parts inventory and machine downtime can be reduced with a systematic and scientific approach to spare parts management (Gajpal et al., 1994).

Controlling all of the warehouse items by strict ordering principles is not logical in terms of cost and time constraints. (Hadi-Vencheh & Mohamadghasemi, 2011).

Kaabi et al. (2018) stated that managers can control inventory-related expenditures and increase the company's competitiveness by categorizing inventory items according to their importance. To effectively oversee inventory items, managers need to classify them (Kheybari et al., 2019). According to Syntetos et al. (2009), categorization allows managers to focus on the most "important" items and makes the decision easier. So, one of the main challenges of managers in managerial decision-making of manufacturing companies is determining the optimal inventory level of each spare part. In this study, I focus on the inventory management of the warehouse to find the optimal inventory for selected spare parts using multi-criteria.

The development of a multi-criteria classification tool assists companies in identifying key stock items, which is valuable information for managers, particularly asset and maintenance managers (Molenaers et al., 2012).

Appropriate classification of items would benefit operational aims, such as sensitive raw materials supporting, inventories' control, and managing final outputs to decrease inventory expenses to the lowest feasible level (Partovi & Anandarajan, 2002).

There have been some classification methods like HML(High, Medium, Low), ABC ("A" items are extremely important, "B" items are moderately important, "C" items are relatively unimportant), SDE (Scarce, Difficult, Easy), XYZ ("X" items are least variation in demand, "Y" items are strong variable in demand, "Z" items are highly variable in demand), FSN (Fast moving, Slow-moving, Non-moving), and VDE (Vital, Desirable, Essential) to control and manage a warehouse. One of the most common methods for categorizing spare parts in a warehouse is ABC. This method has been used in different fields of study such as health (Han et al., 2020), automobile industry (Gong et al., 2020), medicine (Chinda et al., 2018), risk factor assessment (Vujovi et al., 2017), agro-industry (Ly & Raweewan, 2016), manufacturing industry (Balaji & Kumar, 2014), and hospital (Reid, 1987).

ABC is a traditional method for inventory categorization. This method classifies spare parts concerning the annual consumption rate (monetary value) (Hatefi et al., 2014; Ye et al., 2008; Cohen & Ernst, 1988).

ABC follows Pareto's 80–20 principles. Group A includes 10% of items that accounts for approximately 80% monetary value, group B contains 20% of items that costs almost 10% monetary value, and group C includes 70% of items that go for nearly 10% monetary value (Cui et al., 2021). It means a high monetary value is allocated to a small percentage of items. The items should be precisely managed (Reid, 1987). Partovi & Burton (1993) explained that the ABC might not be suitable and precise for some inventories categorization like spare parts.

Roda et al. (2012), Ramanathan (2006), Duchessi et al. (1988), Partovi & Burton (1993) believe, that to classify inventory items several criteria like lead time, cost of lacking parts, sensitivity, price, consumption rate, order size requirement, shockability, stock-out penalty cost, failure rate, sensitivity, shortages of items, etc. are important, but ABC only considers one criterion "monetary value of annual consumption". So, multiple-criteria categorization is required for accurate strategic inventory management and practical inventory classification (Zowid et al., 2019; Balaji & Kumar, 2014).

Molenaers et al. (2012) explained that if a manufacturing factory tends to classify spare parts based on different criteria in its warehouse, employing MCDM (Multi-Criteria Decision Making) could be an appropriate solution. AHP (Analytical Hierarchy Process), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), ELECTRE (ELimination Et Choix Traduisant la REalité), BWM (Best-Worst Method), etc. are some of the MCDM techniques that can be applied in the categorization of spare parts.

In my study, a new hybrid method (BWM-AHP-TOPSIS) is suggested to categorize items in a company's warehouse. Applying BWM, which is the main part of the novelty of the suggested method, could be an easy and practical solution to obtain the weights of criteria in the inventory management problems. Using the hybrid MCDM technique will contribute decision-makers (managers) specify the optimal amount of spare parts and control inventories properly.

The main goal of this study is to classify spare parts by applying the hybrid MCDM technique. The secondary goals in this study are 1- specifying some strategies to manage warehouse inventories. 2- Determining the benefits of spare parts multi-criteria categorization compared to the single-criterion categorization. 3- Merging the results of AHP and TOPSIS by applying a new conflation method.

Using the hybrid (BWM-AHP-TOPSIS) technique would help managers to make precise managerial decisions for reaching optimum inventories in a warehouse. BWM provides the criteria weights immediately only by determining the best and worst criteria. Pairwise comparisons in BWM are more consistent and the results are more reliable for managerial decision-making. Although applying AHP, when there are too many alternatives for prioritization, would be complex and time-consuming, it is a practical technique since it provides the opportunity for managerial decision-makers to consider both qualitative and quantitative criteria and convert quickly qualitative criteria to quantitative. Using expert choice software will solve the complexity and time-consumption problem of this technique if one encounters too many alternatives. Besides simplicity, the rationality of the TOPSIS concept, easy calculation, suitable computational performance, and especially visualization possibility, would help managers to make a pragmatic decisions. The proposed method was executed for a warehouse in an Iranian petrochemical company to help managers to make the precise decision for inventory management in the warehouse of the company. The suggested technique provides an appropriate solution for optimal control and management of inventories in the warehouse.

The remainder of this article is organized as follows. Section 2 represents the literature background of AHP, TOPSIS application in the multi-criteria classification of inventories, and the application of BWM in different studies. The methodology is explained in section 3. In section 4, the results are shown. Discussion is provided in section 5. Conclusion and suggestions are described in section 6.

Literature review

The literature in this study contains the application of AHP and TOPSIS for inventory classification. Also, the literature on BWM is studied as a newly developed method to drive the criteria weights.

AHP

Partovi and Burton (1993) categorized items by applying the AHP method. Quantitative and qualitative criteria are taken into account to classify inventory items. Items are categorized into A, B, and C classes. Braglia et al. (2004) recommended a multi-criteria method to determine a proper strategy for spare parts inventory management. The AHP is applied to categorize inventory in terms of sensitivity. Some strategies (A. no storage, B. one-piece storage, C. Ordering when required, D. multi-item storage) for spare parts management are defined.

Antosz and Ratnayake (2019) used AHP to categorize spare parts based on critical evaluation criteria (logistic and maintenance requirements). Also, a practical classification of inventories based on spare parts sensitivity,

Table 1.

Limitations and points in the previous studies

Authors	Method	Limitations	Points
Flores & Whybarak (1986)	A joint criteria matrix	The methodology is difficult to implement.	Consider only quantitative criteria
Partovi & Anandarajan (2002)	Artificial neural network	Limitations in the number of criteria, and difficulty in entering many qualitative criteria.	Consider various criteria (quantitative and qualitative)
Ramanathan (2006)	Weighted Linear Optimization and DEA-like Model	Items with high value may classify in category A as an unimportant criterion.	Using different criteria weights
Ng (2007); Zhou & Fan (2007),	Weighted Linear Model	The weights of an item might be ignored. It is not easy to rank all criteria if there are too many criteria in a problem. Critical factors cannot be based on non-continuous categorical data.	Simplicity in execution
Hadi-Vencheh (2010),	Non-linear programming model (Ng improved model)	Critical factors cannot be based on non-continuous categorical data.	Determining criteria weights, using non-linear programming
Bhattacharya et al. (2007)	TOPSIS	Uncertainty and vagueness are not considered	Considering a variety of contradictory criteria
Chen (2012)	Multiple criteria inventory classification and TOPSIS	The models must be solved for each item separately.	Provide comprehensive performance and unique inventory categorization
Shahin & Gholami (2014)	TOPSIS	In an extension of results for other spare parts, decision-makers have to be cautious.	Risk Priority Number is considered as a categorization criterion.
Kaabi et al. (2018)	Genetic Algorithm, Weighted Sum and TOPSIS	Only quantitative criteria could be considered.	Classify inventory items without control policy.
Partovi & Burton (1993)	AHP	The subjectivity of decision-makers in the pairwise comparisons	Consider all qualitative and quantitative criteria
Gajpal et al. (1994); Braglia et al. (2004); Antosz & Ratnayak (2019); Nurcahyo & Malik (2017)	AHP	Subjectivity amount in the pairwise comparison.	Transparency in evaluating alternatives based on criteria and sub-criteria
Rezaei (2007); Cakir & Canbolat (2008); Zeng et al.(2012)	Fuzzy AHP	Not easy to use in the real world.	Using fuzzy numbers to overcome subjective judgment in AHP
Molenaers et al. (2012)	AHP and logic of decision diagrams	Up to date item information is necessary	Transparency and user-friendliness
Lolli et al. (2014)	AHP-K-Veto	It is unable to deliver an effective and realistic analysis due to its underlying assumptions	Prevent an item rated as high/bad on at least one criterion to be top/bottom ranked in global aggregation
Duran, 2015	Fuzzy AHP	The calculation is time-consuming and complex if there are too many criteria, sub-criteria, and alternatives	Simplicity and the possibility of combining subjective parameters and linguistic words

Source: own compilation

the possibility of item failure, restoration time, potential suppliers, availability of technical characteristics, and maintenance type was done by applying AHP in a petrochemical factory (Molenaers et al., 2012). Gajpal et al. (1994) provided an AHP model for assessing the sensitivity of spare parts. They presented a practical application of the model in a large manufacturing organization. The stock-out implication, type of item, and lead time are selected as the criteria for evaluation. A multi-criteria inventory classification by integrating the AHP method and K-Means algorithm is recommended by Lolli et al. (2014). This method classifies inventories more precisely and less subjectively. Fuzzy AHP could be an appropriate solution when factories classify spare parts in terms of uncertain factors (Duran, 2015; Zeng et al., 2012; Cakir & Canbolat, 2008). To manage maintenance spare parts, Ferreira et al. (2018) employed fuzzy-AHP. Sensitivity, demand forecast, unit value, lead time, and the number of potential suppliers are taken into account as the main criteria.

Multi-criteria ABC categorization integrated with fuzzy AHP and data envelopment analysis is provided by Hadi-Vencheh and Mohamadghasemi (2011) to efficiently manage the inventory items and define the appropriate ordering policies. Yearly dollar usage, storage space constraint, average lot cost, and lead time are the appraisal criteria for classifying inventories. Nurcahyo and Malik (2017) recommended the AHP approach for precise multi-criteria classification of aircraft spare parts to decrease unessential downtime such as delay and cancelation because of spare part damage. AHP is used by Balaji and Kumar (2014) to classify the inventory of an automobile rubber components manufacturing industry and by Molnar and Horvath (2017) to demonstrate the interaction issues between the attributes included in the decision hierarchy.

TOPSIS

Shahin and Gholami (2014) employed TOPSIS to classify spare parts of a warehouse in an Iranian petrochemical company. Cost, sensitivity, lead time, and consumption rate are considered to categorize the spare parts. TOPSIS is proposed as the preferred methodology for classifying inventory items in a pharmaceutical company in India (Bhattacharya et al., 2007). Cost of Unit, lead time, rate of consumption, items' perishability, and raw materials storing cost are considered in categorizing the inventories.

TOPSIS is used for classifying inventory and calculating item value in the study of Chen (2012), Kaabi et al. (2018), and Kheybari et al. (2019).

BWM

To gain the optimum weights of alternatives with fewer pairwise comparisons and higher consistency ratios, Rezaei (2015); Rezaei et al. (2016) recommended the Best Worth Method.

BMW has been widely used in different fields of studies like supplier development (Aboutorab et al., 2018), supplier segmentation (Rezaei et al., 2015), supply chains (Sharma et al., 2021), healthcare waste management (Pamučar, 2021).

Several scholarly articles integrated BWM with other techniques. For example, triangle fuzzy numbers (Maghsoodi et al., 2019; Ecer & Pamucar, 2020; Amiri et al., 2020), TOPSIS (You et al., 2017), fuzzy TOPSIS (Gupta, 2018b; Gupta & Barua, 2017), fuzzy-cumulative prospect theory (Zhao et al., 2019), BWM under probabilistic hesitant fuzzy sets (Li et al., 2019), fuzzy TOPSIS and fuzzy multi-objective linear programming (Lo et al., 2018). Mou et al. (2016; 2017) applied an intuitionistic fuzzy set in BWM to calculate the criteria weights.

Torkayesh et al. (2021) used BWM to find the weights of criteria in evaluating healthcare performance. Rough-fuzzy BWM is proposed to calculate the relative weights of sustainability criteria to choose sustainable hydrogen production technologies (Mei & Chen, 2021).

Table 1 represents limitations and points in some previous studies.

Contribution and novelty

Focusing on the literature review, one can find that managing and controlling warehouses could be done by inventories' classification. It has been proved that multi-criteria classification outperforms single-criterion classification. In this study, a hybrid method (BWM-AHP-TOPSIS) is recommended to classify spare parts to manage the warehouse. To the best of my knowledge, such a hybrid model has never been recommended for classifying inventories.

Reviewing the literature Molenaers et al. (2012) Balaji and Kumar (2014), Antosz and Ratnayake's (2016), Hadi-Vencheh and Mohamadghasemi (2011), Bhattacharya et al. (2007), and Chen (2012) Kheybari et al. (2019), AHP and TOPSIS are used for items classification. Since both of the methods are practical, AHP-TOPSIS integration could give managers more confidence to make managerial decision-making in the context of spare parts classification. To gain criteria weights, some researchers have used AHP but Rezaei (2015) suggested the BWM outperforms the AHP in terms of minimizing pairwise comparisons and consistency ratio. Therefore, the hybrid (BWM-AHP-TOPSIS) method not only provides decision-makers (managers) with reliable criteria weights but also contributes to the managerial decision-making in classifying spare parts and keeping optimal inventories.

Classifying all inventories in a warehouse takes too much time and would be a complex task. Previous research has recommended that a limited number of inventories could be selected and then classified based on the provided model. If the model was helpful, the procedure can be expanded.

In this study, 12 crucial spare parts of a gas turbine in the warehouse of a petrochemical company are selected to be classified based on the criteria (Critical, Cost, Consumption Rate, and Lead Time). Criteria weights are calculated by applying BWM. After that, by using AHP and TOPSIS methods, the score of each spare part is gained. Then, the max-min square method (Ajripour et al., 2019) is recommended to combine the score of spare parts. Finally, using the Pareto principle, the spare parts are categorized into the ABC groups.

Methodology

The proposed integrated techniques are drawn in a flowchart (Figure 1). First, the goal of the study is determined. Decision-makers selected 4 criteria based on the previous studies. They appointed the value of alternatives based on each criterion. The data relating to the 12 strategic spare parts of the gas turbine are represented by interviewing eight experts. The criteria's weights are calculated by BWM since it provides fewer pairwise comparisons and higher consistency ratios. The score of alternatives could be gained by employing TOPSIS, which is capable of handling various, competing criteria, and AHP, which allows converting the qualitative criterion "critical" to a quantitative one (Bhattacharya et al., 2007). The final score of alternatives is integrated by applying the max-min square method. Then, spare parts will be classified based on the Pareto principle. Finally, inventory control strategies are provided to manage the warehouse.

most important criterion over the other criteria. Applying a 5-point scale where 1 shows equal importance and 5 reflects strongly more importance. The comparison matrix of most favorable-to-other is as follows: $A_B = (a_{B1}, a_{B2},\ldots, a_{Bn})$ where a_{Bj} shows the preference of the most important (best) criterion B over the criterion j. It would be evident that $a_{BB} = 1$.

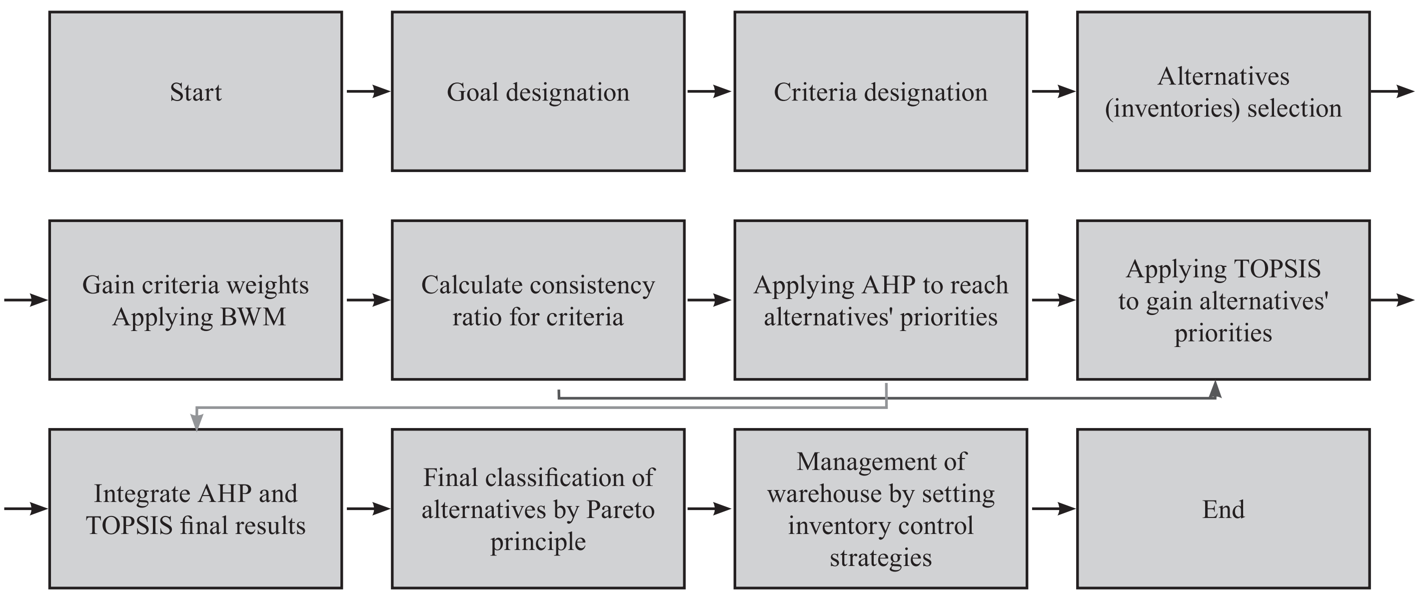
Step 4 – Decision-makers should make a pairwise comparison between other criteria and the least important (worst) criterion by applying a 5-point scale. The comparison matrix of other-to-least desirable is as follows: $A_W = (a_{1W}, a_{2W},\ldots, a_{nB})^T$ where a_{jW} represents the preference of criterion j over the least desirable (worst) criterion. It would be obvious that $a_{ww} = 1$.

Step 5 – Calculation of criteria's optimal weights (w_1^*, $w_2^*,\ldots,w_n^*$).

The optimal weight for each pair of $\frac{W_B}{W_j}$ and $\frac{W_j}{W_w}$ should fulfill the requirement $\frac{W_B}{W_j} = a_{jW}$ and $\frac{W_j}{W_w} = a_{jW}$. A proper solution should be found where the maximum absolute differences $\left|\frac{W_B}{W_j} - a_{Bj}\right|$, and $\left|\frac{W_j}{W_w} - a_{jW}\right|$ for all j are minimized. Taking into account the weights' non-negativity and sum conditions, the following problem can be formularized:

Figure 1.

Research methodology



Source: author's drawing

Best Worst Method

To compute the most favorable criteria weights, BWM provides a linear mathematical model. The steps of BWM are as follows:

Step 1 – Decision-makers (DMs) should define a set of criteria $\{c_1, c_2,\ldots, c_n\}$

Step 2 – DMs should determine the most important (best) and the least important (worst) criteria.

Step 3 – DMs should determine the preference of the

$$\min \max \left\{\left|\frac{W_B}{W_j} - a_{Bj}\right|, \left|\frac{W_j}{W_w} - a_{jW}\right|\right\}$$

s.t.

$$\sum_j W_j = 1 \qquad W_j \geq 0, \text{ for all j} \tag{1}$$

Model (1) can be converted as follows:

$$\min \xi$$

s.t.

$$\left|\frac{W_B}{W_j} - a_{Bj}\right| \leq \xi \quad \text{for all j}$$

$$\left|\frac{W_j}{W_w} - a_{jW}\right| \leq \xi \quad \text{for all j}$$

$$\sum_j W_j = 1 \qquad W_j \geq 0, \text{ for all j} \tag{2}$$

By solving model (2), the optimum weights of criteria (w_1^*, w_2^*,…,w_n^*) and the value of ξ will be gained.

Applying and the corresponding Consistency Index (max) values (Table 2), the Consistency Ratio (CR) of BWM can be calculated as follows (Rezaei, 2015):

$$CR = \frac{\xi^*}{Consistency\ Index} \quad (3)$$

The more the value of CR close to zero, the more consistent the vectors are.

$$IR = \frac{II}{IRI} \quad (5)$$

$$II = \frac{\lambda_{max} - n}{n-1} \quad (6)$$

n: number of alternatives/criteria

Inconsistency Random Index can be extracted from Table 4.

Table 2

Best Worst Method Consistency Index

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency Index	0	0.44	1	1.63	2.30	3	3.37	4.47	5.23

Source: own compilation based on Rezaei (2015)

Analytic Hierarchy Process

AHP was introduced by Saaty in the 1970s. The four simple steps in AHP are as follow (Sedghiyan et al., 2021):

Step 1 – Drawing decision-making hierarchical structure including goals, criteria, sub-criteria, and alternatives.

Step 2 – Making Pairwise comparisons for all criteria, sub-criteria, and alternatives by DMs based on the measurement scale (Table 3). If there is more than one decision-maker, a geometric could be used (Ajripour, 2020). The final pairwise comparison matrices would be organized as follow: A= (a_{ij}), *where* i, j=1, 2, 3,…., n.

Step 3 – Normalize all pairwise matrices by applying equation (1). The arithmetic mean should be calculated in each row for all pairwise comparison matrices to gain the relative weights of criteria and alternatives.

$n_i = \frac{a_i}{\sum_{i=1}^{n} a_i}$ for all alternative pairwise comparison matrices based on each criterion (1)

$n_j = \frac{a_j}{\sum_{j=1}^{n} a_j}$ for criteria pairwise comparison matrix

Step 4 – Applying equation (2) to calculate the final score of alternatives.

$$W = W_A . W_c \quad (2)$$

where W_A and W_c are the matrices of relative weights for alternatives and criteria, respectively.

Step 5 – To calculate the biggest eigenvalue λ_{max}, first, equation (3) for calculating the weighted sum vector (WSV) must be used. Then using equation (4) provide the consistency vector value. Finally, the arithmetic mean is used to find λ_{max}.

$$WSV = A.\ W \quad (3)$$

$$CV = \frac{WSV}{W_c\ or\ W_A} \quad , \quad \lambda_{max} = \frac{CV}{n} \quad (4)$$

n: number of alternatives/criteria

Step 6 – To calculate the Inconsistency Ratio (IR) for all pairwise comparison matrices, first, the inconsistency Index (II) should be computed by equation (6), then by applying equations (5), IR value will be gained. The inconsistency Ratio should be ≤ 0.1; otherwise, decision-makers should change their preferences in the decision matrices.

Table 3

Measurement scale

Intensity of importance	*Description*
1	Equal importance: A is equally preferred to B
3	Moderate importance: A is moderately more preferred than B
5	Strong importance: A is strongly more preferred than B
7	Very strong importance: A is very strongly more preferred than B
9	Extreme importance: A is extremely more preferred than B
2,4,6,8	Intermediate preferences

Source: own compilation based on Chatzimouratidis & Pilavachi (2009)

Table 4

Inconsistency Random Index table

n	1	2	3	4	5	6	7	8	9	10
IRI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.51

Source: own compilation based on Sindhu et al. (2017), Aragonés-Beltrán et al. (2014)

TOPSIS

TOPSIS was first introduced by Hwang and Yoon (1981). The principle logic of this method is to obtain the ideal and the ant-ideal solution. The ideal solution maximizes positive criteria and minimizes negative criteria. In TOPSIS, alternatives are ranked based on their similarity to the ideal solution. This method chooses the best alternative based on the maximum distance from negative ideal solutions and minimum distance from positive ideal solutions.

The advantages TOPSIS technique are: simple, rational, easy to understand, simplicity in the calculation procedure (Roszkowska, 2011).

The main steps of the TOPSIS method are as follows (Ajripour et al., 2019; Sedghiyan et al., 2021; Ajripour & Alamian, 2021):

Step 1 – Establish the decision matrix and the weights of each criterion ((the criteria weights are calculated by BMW in this study).

A= (a_{ij}) where i= 1,2,…, n; j= 1,2,…,m

Step 2 – Normalize the decision matrix by applying equation (7) and calculate the weighted normalized decision matrix as equation (8):

$$n_{ij}=\frac{a_{ij}}{\sqrt{\sum_{i=1}^{n} a_{ij}^2}} \quad \text{where i= 1,2,…, n ; j= 1,2,…,m} \quad (7)$$

$$V=w_j \cdot A_N \quad \text{where i= 1,2,…, n ; j= 1,2,…,m;} \quad (8)$$

w_j is the weights of criteria

Step 3 – Find positive A_j^+ and negative A_j^- ideal solutions:

The positive ideal solution (A_j^+) is the vector of the best value of each criterion in the matrix $V|V_j^+$

The negative ideal solution (A_j^-) is the vector of the best value of each criterion in the matrix $V|V_j^-$

The best value in the positive criterion is the maximum value, and the worst is the minimum. It would be vice versa in the negative criteria.

Step 4 – Applying equations (9) and (10) to calculate Euclidean distances from the positive ideal solution and the negative ideal solution.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^+)^2} \quad (9)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2} \quad (10)$$

Step 5 – Using equations (11), the relative closeness (to the positive ideal solution will be gained.

$$Cl_i^* = \frac{S_i^-}{S_i^- + S_i^+}$$

The greater the relative closeness is, the higher the rank of alternative is.

Results

To support the maintenance process and protect machines against failure, the optimum required amount of spare parts should be stored at the warehouse. Sometimes factories encounter the issue of keeping a large volume of inventories and sometimes lack essential parts. Classification of inventories could help the factories to control and balance the inventories. This study aims to manage a warehouse with the help of classifying spare parts in an Iranian petrochemical company. Optimizing and controlling inventories in warehouses is an important strategic issue in the factory. Keeping all the inventories always in the warehouse is not necessary. So categorizing the inventories and using various strategies for inventory control is recommended. A multi-criterion hybrid MCDM technique is recommended to classify some of the inventories in a petrochemical factory. If the method provides valuable results, it will be expanded to categorize all the rest of the inventories.

A team of decision-makers, including eight experts, was formed. They reached an agreement to choose only 12 critical spare parts of the gas turbine as the alternatives in classification. Based on the literature review and availability of data in the factory, cost, critical, consumption rate, and lead time (Table 5) are selected as the criteria for classifying the alternatives.

Table 5

Criteria

Names of Criteria	Description
C1: Cost	The last price of an inventory in the factory purchasing database.
C 2:Lead Time	The time between the orders of an inventory until reaching the factory warehouse.
C3:Consumption	The annual consumption rate of an inventory.
C4:Critical	The sensitivity of an inventory in three aspects of (production, safety, and environment)

Source: own compilation

Decision-makers are asked to determine the best and the worst criterion. Then, they should make a pairwise comparison between the best to the other criteria (Table 6-left) and the others to the worst (Table 6- right) using 5-point scale.

Table 6

Pairwise comparison between the best criterion to others (upper) – others to the worst (lower)

Best to Others	Cost	Lead Time	Consumption	Critical
Critical	3	5	3	1

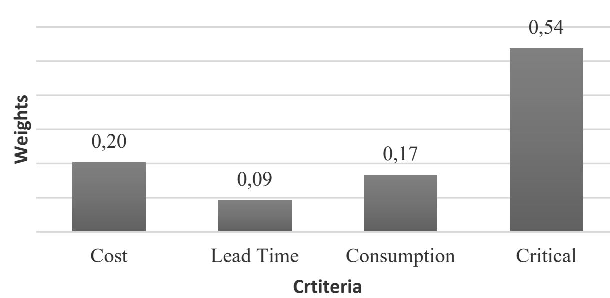
Others to the Worst	Lead Time
Cost	3
Lead Time	1
Consumption	1
Critical	5

Source: own compilation

To calculate the final weights of the criteria, I used the BWM solver recommended by Rezaei (https://bestworstmethod.com/software/). The weights of the criteria are shown in Graph 1.

Graph 1

Criteria weights



Source: own compilation

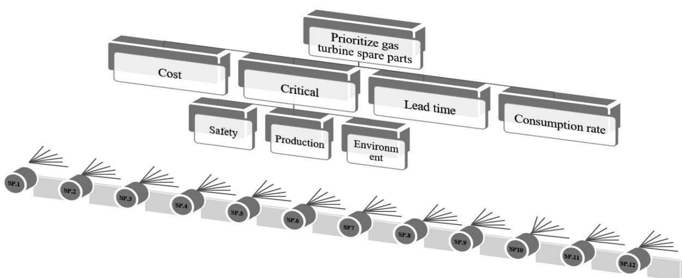
As shown in Graph 1, the most important criterion is “critical”, which gained 0.54 weight, and the least desirable is “lead time” with 0.09 weight.

The next step is to gain the alternatives score by applying AHP techniques.

Figure 2 shows the hierarchical structure of the problem.

Figure 2.

The hierarchical structure of the issue



Source: Author's drawing

The decision-makers provided detailed technical information for calculating the alternatives score in the AHP method. The relative weights of criteria are gained by the use of BWM (C_1: 0.20; C_2:0.09; C_3: 0.17; C_2 = 0.54).

Four criteria are taken into account in this study. Cost, consumption rate, lead time, and critical. Except for critical, the three other criteria are quantitative ones. To convert the qualitative criterion “critical” to a quantitative one, Table 7 is defined with the help of decision-makers.

Table 8

Alternative values based on criteria

Spare part No.	Price (USD)	Lead Time (Working day)	Consumption Rate (year)	Production Critical	Safety Critical	Environment Critical
8	1854.69 $	7	1	3	1	3
10	1341.25 $	30	2	3	1	3
11	953.13 $	30	3	3	3	1
13	903.13 $	45	2	3	3	1
16	343.75 $	50	3	2	1	1
21	231.25 $	30	5	2	1	3
24	175 $	2	12	2	1	1
25	156.25 $	2	8	2	1	1
27	121.88 $	30	8	2	1	1
28	112.50 $	25	24	2	1	1
29	103.13 $	20	8	2	1	1
38	15.63 $	3	60	1	1	1

Source: Data retrieved from the warehouse system

Momeni (2010) has proposed that no need to do pairwise comparisons between alternatives based on each criterion and assess the inconsistency rate if all criteria are quantitative. Except “critical” criterion, all the other criteria are quantitative. By converting the qualitative criterion to quantitative one by using Table 7, no need

Table 7

Convert qualitative scale to quantitative “critical” criterion

	Critical in Production			Critical in Safety		Critical in Environmental	
Qualitative Score	High	Medium	Low	High	Low	High	Low
Quantitative Score	3	2	1	3	1	3	1
Inventories lack causes	stop	partial stop	does not affect	death or injury	does not affect	pollution or violates its laws	does not affect

Source: Author's work based on decision makers' opinion

Let's describe the sub-criteria of critical criterion. Critical in production means lack of a part makes an interruption in factory productions. Critical in safety means a shortage of a part may rise some dangers and cause death or injury. Critical in the environment means the absence of a part may endanger the environment.

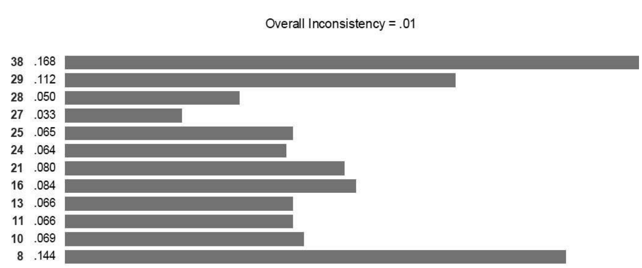
To assess alternatives based on the criteria, the values related to cost, lead times, and annual consumption rates are provided by the decision-makers concerning the last recorded information in the factory's warehouse database (Table 8). Considering Table 7, decision-makers determined the values for the production, safety, and environmental sub-criteria.

The weights of sub-criteria are determined by the factory's top manager. The safety, environmental, and production sub-criteria weights are 0.4, 0.35, 0.25, respectively.

to do a pairwise comparison between all alternatives. By applying expert choice software, the final score of alternatives is obtained (Figure 3).

Figure 3

Final score of alternatives



Source: Authors' data using expert choice calculation

Figure 3 shows that spare part No.38 got the highest score, and the minimum score is assigned to spare part No.27. The overall inconsistency is 0.01, which represents a good consistency of the pairwise comparisons.

The next step is finding alternative scores by applying the TOPSIS method. Considering Table 8 as the decision-making matrix, Graph 1 (criterion weights), and equations (7) and (8), the weighted normalized decision matrix is displayed in Table 9.

Table 9

Weighted normalized decision matrix

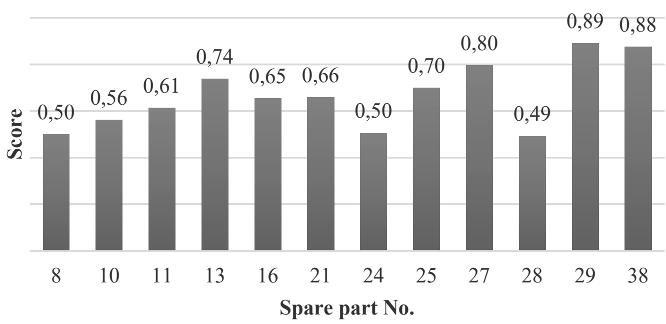
Criteria type	–	–	–	–
SP No.	Cost	Lead time	Consumption rate	Critical
8	0.000	0.02	0.70	0.32
10	0.338	0.19	0.04	0.32
11	0.240	0.19	0.06	0.31
13	0.018	0.19	0.04	0.31
16	0.002	0.03	0.44	0.28
21	0.003	0.03	0.50	0.26
24	0.583	0.64	0.00	0.20
25	0.197	0.64	0.02	0.20
27	0.009	0.06	0.08	0.28
28	0.670	0.19	0.00	0.25
29	0.026	0.13	0.16	0.17
38	0.000	0.01	0.20	0.20
w_j	0.20	0.09	0.17	0.54

Source: author's calculation

The values in the "critical" column are reached by integrating weighted normalized values of production, safety, and environment. Calculation example for the value 0.31 (spare part No.11): (*0.34**0.25+*0.42**0.40+*0.17**0.35= 0.31). The values 0.34, 0.42, and 0.17, respectively, are the normalized values of production, safety, and environment. The 0.25, 0.40, and 0.35 are the weights of production, safety, and the environment, respectively, determined by the top management.

Graph 2

Final score of alternatives in TOPSIS



Source: author's drawing

Following the TOPSIS steps in section 3.3 and using Excel 2016, the final score of alternatives is gained, as illustrated in Graph 2.

Spare parts No.29 and 28 got the maximum and minimum scores, respectively. If we compare the final scores of alternatives provided by AHP and TOPSIS, there are some differences in the priority of alternatives. To reach a precise final score of alternatives, an integration method is used. Ajripour et al. (2019) provide an integration method called max-min square mean. Following the simple below steps to combine the final scores of alternatives.

Applying equations (12) and (13) to calculate the maximum and minimum value of alternatives, respectively. The final alternatives' combined scores will be calculated by using equation (14).

$$s_{max} = \frac{MAX\, s_i{}^2}{n} \quad \text{where } S_i \text{ is the maximum score of alternative i} \qquad (12)$$

n: number of methods (AHP, TOPSIS)

$$s_{min} = \frac{Min\, s_i{}^2}{n} \quad \text{where } S_i \text{ is the minimum score of alternative i} \qquad (13)$$

n: number of methods (AHP, TOPSIS)

$$S = \frac{s_{max} + s_{min}}{2}$$

Table 10 displays the final score of alternatives.

Table 10

Final alternatives' scores

Spare Part No.	**Score**		S_{max}	S_{min}	**S**	**Final Ranks**
	AHP	**TOPSIS**				
38	0.168	0.875	0.383	0.014	0.199	2
29	0.112	0.891	0.397	0.006	0.201	1
28	0.050	0.492	0.121	0.001	0.061	12
27	0.033	0.795	0.316	0.001	0.158	3
25	0.065	0.699	0.244	0.002	0.123	5
24	0.064	0.505	0.127	0.002	0.065	11
21	0.080	0.659	0.217	0.003	0.110	6
16	0.084	0.654	0.214	0.004	0.109	7
13	0.066	0.738	0.272	0.002	0.137	4
11	0.066	0.613	0.188	0.002	0.095	8
10	0.069	0.562	0.158	0.002	0.080	9
8	0.144	0.499	0.125	0.010	0.068	10

Source: author's calculation

In the real world, companies may have hundreds of parts in their warehouse for categorization. In this case, I recommend that the companies categorize the parts in different sections. For example, in a petrochemical company, parts related to the gas turbine, vessel, auxiliary equipment, etc. could be categorized separately in different sections.

Discussion

The final ranks of alternatives are obtained in Table 9. To categorize alternatives based on the ABC method and Pareto principle, one-fifth percentage of the spare parts gained the highest point, put in the A category, the next two-fifth percentage placed in the B group, and the C class contains the rest (two-fifth percentage) with the lowest score.

To find the optimal amount of each spare part in the warehouse, decision-makers used Antosz and Ratnayake's (2016) storage and control strategies in addition to their opinions (Table 11).

Table 11

Inventory storage and control strategies

Class	A	B	C
Strategies	I. • Spare parts must be kept. • Precise inventory control • Precedence in purchasing • Keeping 5-times average consumption over lead time	II. • Keeping spare parts is not compulsory but is advised • Second precedence in purchasing • Keeping 3-times average consumption over lead time	III. • Reconsider keeping spare parts • Buy if it is needed • If lack of spare parts causes critical implications, keeping 2-times average consumption over lead time

Source: Antosz & Ratnayake (2016) and experts' opinion

Based on the strategies provided in Table 11, and the final scores in Table 10, spare parts are classified and the storage and control strategies are determined for all the alternatives (Table 12).

The spare parts are categorized not only based on ABC multi-criteria classification but also ABC single-criterion classification (ABCSC). As it is shown, the multi-criteria classification method placed most of the spare parts in a different category than the single criterion. For example, spare parts No.38 and 29 are grouped in category A with regards to the ABCMC but based on ABCSC, they are categorized in group C. Implementing storage and control strategies for the spare parts, the minimum spare parts which must be kept in the warehouse, the adjusted inventory level, and the adjusted inventories incomes or expenses could be calculated. In column seventh (Table12), the minimum parts that must be kept in the warehouse plus one more as a safety stock are calculated. For instance, the strategy "I" is assigned to spare part No. 38 with A categorization. The lead time for spare part No.38 is three working days, and its' annual consumption is 60. The average number used during the lead time is ($\frac{60*3}{365}$ = 0.49). Considering strategy "I", the minimum spare parts 38 that must be kept is (0.49*5= 2.47). A safety stock must be considered, so the final amount of spare part No.38 for keeping in the warehouse would be 2.47 +1= 3.4 ≈ 3 but ABCSC classification illustrates that spare part No.38 is categorized in group C.

Column eighth Table 12 displays the adjusted inventory level. It would be calculated by subtracting the current inventory from the minimum parts that must be kept in the warehouse (e.g., spare part No.24: 1 (current inventory)-1(Minimum parts must be kept in warehouse+1) = 0 (adjusted inventory). A positive number shows the extra spare parts in the warehouse, while a negative one represents the lack of spare parts in the warehouse.

Adjusted inventory- income/expense in column ninth indicates the income that the factory gains if it may sell the extra spare parts or the expenses that the factory must pay to purchase the required inventories. For example, the adjusted inventory level for spare part No.27 is -2 i.e., the

Table 12

Classifying spare parts – storage and control strategies

Spare Part No.	Score	ABCMC classification	Storage and control strategy	Price (USD)	Current inventory	Minimum parts must be kept in warehouse + 1	Adjust inventory level	Adjust inventory-Income / Expense (USD)	ABCSC classification
38	0.199	A	I	15.63	6	3	3	46.89	C
29	0.201	A	I	103.13	2	3	-1	-103.13	C
28	0.061	C	III	112.5	1	3	-2	-225.00	C
27	0.158	B	II	121.88	1	3	-2	-243.76	C
25	0.123	B	II	156.25	2	1	1	156.25	C
24	0.065	C	III	175	1	1	0	0	B
21	0.110	B	II	231.25	2	2	0	0	B
16	0.109	B	II	343.75	2	2	0	0	B
13	0.137	B	II	903.13	2	2	0	0	B
11	0.095	C	III	953.13	2	1	1	953.13	B
10	0.080	C	III	1341.25	1	1	0	0	A
8	0.068	C	III	1854.69	1	1	0	0	A

Source: author's calculation

factory is in lacks spare part No.27, and it is required to buy two more parts No.27. Purchasing 2 more spare part No.27 costs the factory 243.74$ = 2* 121.88$.

In summary, after implementing storage and control strategies, the inventory of one spare part (No.29) must be increased, and one (No.38) should be decreased in category A. In category B, spare parts No.21,16, and 13 stayed without any changes. But spare part No.27 must be increased, and No.25 could be decreased. Although spare parts No.10,8, and 24 in group C remained without any alters, spare part No.25 must be increased, and No.11 should be decreased.

Comparing the final results of ABCMC classification and the results of ABCSC categorization, only four spare parts (No.28, 21, 16, and 13) in the ABCMC method are put in the same category as the ABCSC. Spare parts 38 and 39 in the ABCMC are placed in category A while in ABCSC are placed in class C. Group B in ABCMC classification is included five spare parts (No.27, 25, 21, 16, 13). Three out of five have the same category as ABCSC, only spare parts No.27 and 25 in ABCSC classification are placed in category C. The spare parts categorized in group C based on the ABCMC, except spare part No.28, have gained a different class in the ABCSC classification.

These differences between the ABCMC classification and the ABCSC categorization are because the latter method just takes into account the monetary value of annual consumption as a criterion for spare parts classification while the ABCMC considers different criteria.

In my study, I used a hybrid MCDM technique. The results of items' classification in ABC single criterion and the results in ABC multi-criterion are compared. The previous studies (Bhattacharya et al., 2007; Gajpal et al.,1994; Braglia et al., 2004; Antosz & Ratnayak, 2019; Nurcahyo & Malik, 2017; Rezaei, 2007; Cakir & Canbolat, 2008; Zeng et al., 2012; Molenaers et al., 2012; Duran, 2015) have used multi-criteria in the prioritization of items, but none of them have compared the results provided from ABC traditional method (single criterion) and ABC multi-criteria for each item.

The only study that has provided the results of item classification using ABC (single criterion) besides the results provided by multi-criteria classification, is the study of Partovi and Burton (1993) which used just AHP.

Integration of AHP and TOPSIS has never been used in the former research of item categorization. The only studies that proposed an integration model are Kaabi et al. (2018) which is a hybrid model based on a genetic algorithm, weighted sum, and TOPSIS. The AHP-TOPSIS integrated method can consider a variety of quantitative and qualitative criteria at the same time. This method has a low likelihood of error and can be used to solve the real-time MCDM problem. Besides, in-depth technical knowledge of the AHP and TOPSIS methods is not required. This technique is computationally robust and straightforward, and it can handle a high number of input and output variables.

In contrast to the limitations of previous studies (Table 1-column 3), the proposed hybrid (BWM-AHP-TOPSIS) method is practical, easy to use, considers both qualitative and quantitative criteria, active, usable, and trustworthy for managerial decision making.

Conclusion and suggestions

Managing inventories in a factory's warehouse is an important issue that managers encounter. Some factories have used the ABC method to classify and manage inventories, but it may not provide the best solution. Employing multi-criteria besides applying a hybrid MCDM technique for the classification of inventories would help managers to manage and control a warehouse appropriately. In this study, the selected inventories were classified based on multi-criteria (Cost, Lead time, Consumption, and critical).

Applying integrated multi-criteria decision-making techniques could help managers control and manage inventories in a factory's warehouse. In this study, BWM-AHP-TOPSIS as a hybrid method is proposed to classify the selected inventories. To calculate the criteria weights, BWM was applied since it provides fewer comparisons and higher consistency. Having both quantitative and qualitative criteria, AHP and TOPSIS methods were employed to classify spare parts. Applying expert choice software provided quick and rational results for the AHP problem. Due to the capability of the TOPSIS approach to handling various and competing criteria, it was employed to determine the category of spare parts for optimal inventory control. So, the proposed hybrid method is practical and easy to use which helps managers to make managerial decisions regarding warehouse management as the result of inventory management.

Applying "Maximum-Minimum Square Mean" method, provided the final results of alternatives.

Based on the final integrated rank of alternatives and considering the Pareto principle, two spare parts containing the highest point are categorized in group A, the next five spare parts with descended scores are classified in group B, and finally, the five remains are grouped in category C.

Inventory storage and control strategies (Table 11) are defined to reach an optimum inventory in the factory's warehouse.

The limitation of my study: 1. The limited number of selected spare parts 2. Lack of data in the company's warehouse database.

The hybrid technique has shown its practicability in the management of warehouses by classification of inventories. So, the technique can be expanded to categorize all of the inventories in the factory's warehouse.

Inventories' multi-criteria classification based on some other criteria like reliability, deterioration, etc., is strongly suggested. Applying another hybrid method such as BWM-fuzzy AHP-fuzzy TOPSIS or other techniques like Simple Additive Weighting (SAW), VIekriterijumsko KOmpromisno Rangiranje (VIKOR), ELimination Et Choice Translating REality (ELECTRE), Preference Ranking Organization Method for Enrichment

Evaluations (PROMETHEE) is recommended. The integration methods like Borda, Copeland, and average methods could be employed to combine the final results of the MCDM techniques.

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