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Spare Parts Criticality Evaluation Using Hybrid Mcdm Technique

KEYWORDS

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ABSTRACT *Spare parts constitute a significant portion of the inventory in any manufacturing organization. A systematic and scientific approach to spare parts management can result in minimizing spare parts inventory and machine downtime. Present work uses the combination of Fuzzy Analytical Hierarchy process (FAHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to evaluate the criticality of spare parts for oxygen lance assembly. This approach is demonstrated with a real world case study involving six main evaluation criteria that the company has determined to choose the most priority spare part.*

1. Introduction

Spare parts management plays a crucial role in any manufacturing organization. A systematic and scientific approach to spare parts management can result in minimizing spare parts inventory and machine downtime. Spare parts inventory systems are mostly concerned with the determination of reorder levels and order/production quantities as in the case of other inventory systems - raw materials, semi-finished goods, finished goods and consumables. A key distinguishing feature of the spare parts inventory system is the need to evaluate and specify the criticality of items in the inventory, keeping in mind the specific uses of different spares. Factors such as cost of spares, availability, storage considerations, probability of requirement of a spare, machine downtime costs, etc., are generally considered while managing spare parts inventories. In the literature many analytical models of different inventory control systems have been discussed (Taha, 1990 & Starr et al., 1990). However, there is no evidence that any of the works have attempted to raise the question of evaluating the criticality of spare parts using systematic and well-structured procedures. Moreover, the various models described in the literature feature many assumptions that remain violated in real life.

Mathematical models and Classification approaches are the two main approaches followed to develop a possible spares provisioning decision model (Huiskonen, 2001). A vast number of mathematical models have been developed by several researchers. Most of their works are generally concentrated on the mathematical optimization of the inventory costs and service levels associated with a potential spares inventory policy in terms of economic order quantity, reorder point, safety stocks, and so on. Unfortunately, most of these methodologies are too complex, abstract or oversimplified, thus reducing their usefulness for a maintenance manager. In addition, these models do not consider several intangible factors such as obsolescence, standard characteristics of the item etc.

The use of classification schemes as a spare parts management tool represents a popular approach in industrial world. Unfortunately, these approaches are based on a one-dimensional (e.g. the classical ABC-analysis) or a two-dimensional classification scheme that does not make it possible to discriminate all the potential control parameters of different types of items. Duchessi et al. (1988) used a two-dimensional classification scheme with many limitations for combining inventory cost and part criticality as criteria. To overcome these types of limitations, some authors have developed new multi-attribute classification models, which are able to manage multiple factors that conflict with each other and heterogeneous units.

Flores and Whybark (1989) are the first persons to use multiple criteria ABC classification in maintenance inventory control with the aid of a matrix-based methodology. However, the methodology is relatively difficult to implement when more criteria have to be considered. Petrovic et al. (1992) designed an expert system model for advising on spare part inventory control. Gajpal et al. (1994) elaborated the criticality analysis of spare parts by using the analytic hierarchy process for classifying the spare parts. Cohen and Ernst (1988) presented a general grouping method that can be used to define group-based operational control policies. Partovi and Burton (1993) presented a multi criteria approach to the ABC classification problem in inventory control. The proposed method based on Saaty's Analytic Hierarchy Process, rates items on both qualitative and quantitative criteria. Puente et al. (2002) presented a fuzzy model of classifying the different productive items of a company. Their model contrasts with the classic Pareto classification (ABC), which ranks productive items according to their importance in terms of frequency and costs. Jafar Rezaei (2007) presented a new approach using fuzzy set theory and fuzzy AHP. This approach is applicable to any multi criteria classification problem with any number of classes. Ching (2008) proposed an inventory control approach called ABC-fuzzy classification, which can handle variables with either nominal or non-nominal attribute, incorporating manager's experience and judgment into inventory classification. Mladen (2010) proposed multi criteria inventory model which is based on ranking and classifying the spare parts in groups according to similar attributes. It is observed from the review of the past researches that plenty of research works have already been carried out on spare parts criticality evaluation using various techniques, referred. Also, there is no evidence in the literature that any of them were prepared with the aim of the criticality evaluation of spare parts for a specific equipment using TOPSIS in which the weights of criteria obtained using fuzzy AHP.

The traditional AHP requires crisp judgments. However due to the complexity and uncertainty involved in real world decision problems, a Decision Maker (DM) may sometimes feel more confident to provide fuzzy judgments than crisp comparisons. This makes fuzzy logic a more natural approach to this kind of problems. A number of methods fuzzy LLSM (Laarhoven et al., 1983), a modified fuzzy LLSM (Wang et al., 2006), the geometric mean method (Buckley, 1985), an extent analysis method (Chang, 1996), fuzzy Preference Programming Method (Mikhailov, 2003), Lambda-Max method (Csutora et al., 2001) have been developed to handle fuzzy comparison matrices. Among the above approaches, the extent analysis method has been employed in quite a number of applications (jajimoggala et al., 2011, Bozbura & Beskese, 2007, Bozdag, 2003, Chan & Kumar, 2007, Ertay, 2005, Er-

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ensal, 2006, Kahraman, 2004, Kahraman, 2006, Kulak, 2005, Kwong, 2003, Tang, 2005, Tolga, 2005, Zhu, 1999.) due to its computational simplicity. Hence, in the present work, an extent analysis method (Chang, 1996) which derives crisp priority weights for fuzzy comparison matrices is used.

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is one of the well known classical MCDM methods. TOPSIS is a widely accepted multi criteria decision making technique due to its sound logic, simultaneous consideration of the ideal and the anti-ideal solutions, and easily programmable computation procedure. This technique is based on the concept that the ideal alternative has the best level for all criteria, whereas the negative ideal is the one with all the worst criteria values. It is quite clear that spares required for a given manufacturing application involves a large number. The use of TOPSIS method is quite capable and computationally easy to evaluate and to rank the spares so that inventory cost can be decreased.

There are many weight calculation procedures, but the AHP has some advantages. One of the most important advantages of the AHP is based on pair-wise comparison. However, sometimes large number of pair wise comparisons performed by DMs can cause impractical usage of the AHP process, especially in fuzzy AHP. To cope with this problem, TOPSIS technique can be used to reduce the number of pair wise comparisons and to rank the alternatives.

2. Application of Proposed Method for Oxygen lance assembly

In this paper, a combined fuzzy AHP and TOPSIS approach for critical spare parts selection for a specific machine/ equipment is proposed. After determining the importance of given equipment in a line, the required spares alternatives for the equipment under consideration are identified. Then the evaluation criteria of the specified spares that the related managers and engineers consider most important are determined. According to these criteria, the required data utilized in the comparisons are collected from the related DMs again. After constructing the evaluation criteria hierarchy, the criteria weights are calculated by applying the fuzzy AHP method. Finally TOPSIS is employed to achieve the final ranking results.

The proposed methodology is applied for the equipment, i.e., steel making oxygen lance assembly, which is used for feeding oxygen into converter in steel plant. The spare parts of oxygen lance assembly under consideration are platform moving gear box, brake assembly, brake shoes, oxygen lance assembly, lance tip assembly and packing ring which are represented as A1, A2, A3, A4, A5 and A6 respectively. By using group-discussion and anonymous questionnaire methods at the same time, necessary information is gathered and the 15 experts' ideas are analyzed. Furthermore a detailed questionnaire related with the data regarding the qualitative and quantitative criteria that affect the criticality class of the spares was prepared. Then a lot of face-to-face interviews were held to develop solid information on the selected criteria and alternatives. After a set of interviews, six criteria were determined to perform the analysis. The six criteria are: The specificity of a SP, Status of availability of the production facility, Lead-time of procurement, Reparability character, the stage of lifecycle and Supply market which are denoted C1, C2, C3, C4, C5 and C6 respectively.

Factors that affects the criticality of spare parts:

- The specificity of a spare part (C1): Among the wide spectrum of spare parts are typically both standard parts, which are widely used by many users, and a certain amount of parts specifically tailored for and used by a particular user only. For standard parts the availability is usually good, so the criticality of a spare part is less. For non standard part the availability is less, so the criticality of a spare part is more.
- Status of availability of the production facility (C2): When an original part fails and a spare part is required, status is as follows: If alternative production facility available: Criticality of a spare part is less. If Alternative production facility available if suitable modifications are made in machine or process: Criticality of a spare part is less. If no alternative production facility available. So, a spare part may have more criticality.
- Lead-time of procurement (C3): The difficulty to obtain a spare part has something with lead-time of procurement. When the lead time is long, Criticality is more. When the lead time is less, Criticality is less.
- Reparability character (C4): If a spare part can't be repaired or the time for repair is so long for enterprise, the difficulty to manage a SP is high so, the criticality of spare part is high.
- The stage of lifecycle (C5): If a spare part is in initial or decay stage, the difficulty to obtain a spare part in a short time will become higher so, the criticality is more.
- Supply market (C6): When a spare part is always readily available from several suppliers, criticality is less. When a spare part is not readily available from several suppliers, criticality is more.

After determining all selection criteria and alternative spares, the paired comparisons were made by using the TFNs (Table 1) to tackle the ambiguities involved in the process of the linguistic assessment of the data.

Linguistic scale for importance	Fuzzy numbers for fuzzy AHP	Membership function $\mu_M(x)$	Domain	Triangular fuzzy number (l. m. u)
Just equal Equal importance	1			(1.1.1)
Weak importance of one over another	3	3 - x/3 - 1 x - 1/3 - 1	1 ≤ x ≤ 3 1 ≤ x ≤ 3	(1.1.3) (1.3.5)
Essential or strong importance	5	5 - x/5 - 3 x - 3/5 - 3	3 ≤ x ≤ 5 3 ≤ x ≤ 5	(3.5.7)
Very strong importance	7	7 - x/7 - 5 x - 7/7 - 5	5 ≤ x ≤ 7 5 ≤ x ≤ 7	(5.7.9)
Extremely preferred	9	9 - x/9 - 7 x - 9/9 - 7	7 ≤ x ≤ 9 7 ≤ x ≤ 9	(7.9.9)

Table1 Linguistic variables describing weights of the criteria and values of ratings

Note: If criterion i has one of the above numbers assigned to it when compared to criterion j, then j has the reciprocal value when compared with i. Reciprocals of TFN (l, m, u) is.

The project team filled this pair wise comparision matrix (Table 2) by reaching a general agreement on questions related to the importance of the criteria and alternatives via Delphi technique as a group decision making tool. Moreover, to include the multiple preferences from several decision makers, we modify AHP by taking the geometric mean of the measures of individuals.

Table2 Pairwise Comparision Matrix

	C1	C2	C3	C4	C5	C6	Weights
C1	(1,1,1)	(1,3,5)	(1/7,1/5,1/3)	(3,5,7)	(1/5,1/3,1)	(1/9,1/7,1/5)	0.1142
C2	(1/5,1/3,1)	(1,1,1)	(1/7,1/5,1/3)	(3,5,7)	(3,5,7)	(1/9,1/7,1/5)	0.1430

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C3	(3,5,7)	(3,5,7)	(1,1,1)	(1/9,1/9,1/7)	(1/9,1/7,1/5)	(1/9,1/7,1/5)	0.1326
C4	(1/7,1/5,1/3)	(1/7,1/5,1/3)	(7,9,9)	(1,1,1)	(1/5,1/3,1)	(1/5,1/3,1)	0.0978
C5	(1,3,5)	(1/7,1/5,1/3)	(5,7,9)	(1,3,5)	(1,1,1)	(1,3,5)	0.2227
C6	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)	(1/5,1/3,1)	(1,1,1)	0.2897

V(S1> S2, S3, S4, S5, S6) = 0.3941; V(S2 > S1, S3, S4, S5, S6) = 0.4935;

V(S3 > S1, S2, S4, S5, S6) = 0.4577; V(S4 > S1, S2, S3, S5, S6) = 0.3375

V(S5 > S1, S2, S3, S4, S6) = 0.7689; V(S6 > S1, S2, S3, S4, S5) = 1

Table 2 depicts the pair wise comparison matrix set by TFNs that matches linguistic statements of data. The fuzzy values of paired comparison were converted to crisp values via the Chang's extent analysis.

According to the method of Chang's (1992) extent analysis, each object is taken and extent analysis for each goal is performed, respectively. Therefore, m extent analysis values for each object can be obtained, with the following signs:

$$M_{gi}^{1}, M_{gi}^{2}, \ldots, M_{gi}^{m}, \quad i=1,2\ldots n \quad \text{where all the } M_{gi}^{j} (j=1,2,\ldots m) \text{ are TFNs} \tag{1}$$

The steps of Chang's extent analysis can be given as in the following

Step 1: The fuzzy synthetic extent value with respect to the ith object is defined as:

$$S_i=\sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} \tag{2}$$

To obtain, $\sum_{j=1}^{m} M_{gi}^{j}$ perform the fuzzy addition operation m extent analysis values for a particular matrix such that

$$\sum_{j=1}^{m} M_{gi}^{j}=\left(\sum_{j=1}^{m} l_j \sum_{j=1}^{m} m_j \sum_{j=1}^{m} u_j\right) \tag{3}$$

and obtain, $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1}$ perform the fuzzy addition operation of j=1, 2…m) values such that

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{i=1}^{n} l_i \sum_{i=1}^{n} m_i \sum_{i=1}^{n} u_i\right) \tag{4}$$

and then compute the inverse of the vector in Eq. 3 such that

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \tag{5}$$

Step 2: The degree of possibility of

$$M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$$

is defined as:

$$V(M_2 \geq M_1) = \sup_{y \geq x}\left[\min\left(\mu_{M1}(x), \mu_{M_2}(y)\right)\right] \tag{6}$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & \text{if } m_2 \geq m_1, \\ 0, & \text{if } l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2-u_2)-(m_1-l_1)}, & \text{otherwise} \end{cases} \tag{7}$$

where d is the ordinate of the highest intersection point D between μM_1 and μM_2. T To compare M_1 and, M_2 both the values of V ($M_1 \geq M_2$) and ($M_2 \geq M_1$) Vare required.

Step 3:
The degree possibility of a convex fuzzy number to be greater than k convex fuzzy numbers M i (i=1,2,………,k) can be defined by

V(M ≥ M_1, M_2,……M_k) = V[(M ≥ M_1)] and V[(M ≥ M_2)…(M ≥M_k)

= min V (M ≥ Mi), i=1,2,3,………,k. (8)

Assume that: (Ai) = min V(Si ≥ Sk) (9)

for k = 1, 2,….. n; k ≠i . Then, the weight vector is given by as in Eq.

W′ =(d′(A_1),d′(A_2),……,d′(An)) ^T where A_i (i=1,2,……) has n elements. (10)

Step 4: The normalized weight vectors are defined as:

W^ =(d(A_1),d(A_2),……,d(An) ^T where W is a non fuzzy number. (11)

First, the fuzzy synthetic extent values were calculated by using Eq. 2 with the help of Eqs. 3–5. Equations 6–7 were applied to express the degree of synthetic extent values. To have a weight vector, given by as in Eq. 10, Eqs. 8-9 were applied by comparing the fuzzy numbers. After normalizing weight vector defined as in Eq. 11, the obtained priority weight vector of criteria is figured out in the last column of Table 2.

Once the weights of criteria are obtained in Phase I, in Phase II a TOPSIS approach is proposed for conducting the ranking process. The full AHP, solution is usable in a realistic or sensitive way only if the number of criteria and alternatives is limited. Also, the number of pair-wise comparisons, performed by decision makers or experts, must remain below a reasonable threshold. Due to a large number of required spares in the current industrial environment, a full AHP decision process becomes impractical in some cases. To avoid an unreasonably large number of pair-wise comparisons, we choose TOPSIS as the ranking technique because of its concept's ease of use (Shih, et al., 2004). Also, fuzzy AHP is adopted simply for the acquisition of the weights of criteria.

Phase II starts with establishing fuzzy evaluations of the alternative spares (SP1, SP2, SP3, SP4, SP5 and SP6) with respect to the individual criteria by using TFNs again. This is a decision matrix for ranking alternatives and indicates the performance ratings of the alternatives according to the criteria. We use the linguistic scales and their corresponding fuzzy numbers: (1,1,1)-very poor, (1,3,5)-poor, (3,5,7)-fair, (5,7,9)-good, (7,9,9)-very good. Table 3 shows the comparison of alternatives according to the criteria.

Table 3 Decision Matrix

SPARES	C1	C2	C3	C4	C5	C6
Platform Moving Gear Box(SP1)	(3,5,7)	(3,5,7)	(5,7,9)	(1,3,5)	(5,7,9)	(1,3,5)
Brake Assembly (SP2)	(1,3,5)	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)
Break Shoes (SP3)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)
Oxygen Lance Assembly (SP4)	(7,9,9)	(5,7,9)	(7,9,9)	(1,3,5)	(7,9,9)	(1,3,5)
Lance Tip Assembly (SP5)	(7,9,9)	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(1,3,5)
Packing Ring (SP6)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)

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After constructing decision matrix (Table 3), normalized decision matrix is calculated. The normalized decision matrix R=[r ij] is obtained by using Eq. 12.

The normalized value rij is calculated as $r_{ij} = \frac{f_{ij}}{\sum_{j=1}^{n} f_{ij}^2}$, where ;

j=1,2,…..n; i=1,2,…..m.. (12)

The weighted normalized fuzzy decision matrix can be obtained multiplying the normalized decision matrix by the weights of the criteria matrix (Table 4) which is found by using fuzzy AHP.

The weighted normalized value vij is calculated as v_ij = w_j r_ij ,j=1,2,…..n; i=1,2,…..m, (13)

Table 4 shows weighted normalized decision matrix.

Table 4 Weighted Normalized Decision Matrix

	C1	C2	C3	C4	C5	C6
SP1	(.048,.063,.088)	(.085,.102,.111)	(.094,.103,.132)	(.020,.042,.054)	(.159,.173,.223)	(.097,.174,.207)
SP2	(.016,.038,.063)	(.143,.143,.143)	(.056,.073,.103)	(.059,.070,.076)	(.159,.173,.223)	(.289,.289,.289)
SP3	(.048,.063,.088)	(.143,.143,.143)	(.056,.073,.103)	(.098,.098,.098)	(.159,.173,.223)	(.289,.289,.289)
SP4	(.114,.114,.114)	(.143,.143,.143)	(.132,.132,.132)	(.020,.042,.054)	(.223,.223,.223)	(.097,.174,.207)
SP5	(.114,.114,.114)	(.143,.143,.143)	(.094,.103,.132)	(.020,.042,.054)	(.159,.173,.223)	(.097,.174,.207)
SP6	(.048,.063,.088)	(.085,.102,.111)	(.056,.073,.103)	(.098,.098,.098)	(.159,.173,.223)	(.289,.289,.289)

The positive ideal solution (V*) and negative ideal solution (V^-) are determined by using the weighted normalized values. Equations 14–15 are used to determine the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS).

PIS and NIS, respectively:

$$V^+ = [v_1^+, \ldots, v_n^+] = \{(\max_i v_{ij} \mid j \in J), (\min_i v_{ij} \mid j \in J')\}, \quad (14)$$
$$V^- = [v_1^-, \ldots, v_n^-] = \{(\min_i v_{ij} \mid j \in J), (\max_i v_{ij} \mid j \in J')\}. \quad (15)$$

Where J is associated with the benefit criteria, and J^' is associated with the cost criteria.

The positive TFNs are in the range [0, 1]. Hence the Fuzzy Positive Ideal reference point (FPIS, V^+) is (1, 1, 1) and Fuzzy Negative Ideal reference point (FNIS, V^-) is (0, 0, 0).

The separation measure D_i^+of each alternative from the PIS is given as:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, i = 1,2 \ldots, m. \quad (16)$$

Similarly, the separation measure Di- of each alternative from the NIS is as follows:

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, i = 1,2 \ldots, m. \quad (17)$$

In the last step, the relative closeness to the ideal solution is calculated using Eq. 18.

The relative closeness of the alternative Ai with respect to PIS V^+ can be expressed as:

$$\bar{C}_i = \frac{D_i^-}{D_i^- + D_i^+}, i = 1,2 \ldots, m. \quad (18)$$

where the index value of (Ci) lies between 0 and 1. The larger the index value, the better the performance of the alternatives.

Table 5 summarizes the results. The higher the closeness means the better the rank, so the relative closeness to the ideal solution of the alternatives can be substituted as follows: CC3>CC2>CC6>CC4>CC5>CC1. SP3, Brake shoes is defined as the most critical spare for the equipment, steel making oxygen lance assembly. The obtained result is discussed in the company just as to investigate the meaningfulness of the selected alternative.

Table5 The Results

SPARES	D_i^+	D_i^-	D_i^-	Rank
Platform Moving Gear Box(SP1)	5.3784	0.3022	0.0532	6
Brake Assembly (SP2)	5.2231	0.3904	0.0695	2
Break Shoes (SP3)	5.1657	0.4002	0.0719	1
Oxygen Lance Assembly (SP4)	5.2375	0.3603	0.0644	4
Lance Tip Assembly (SP5)	5.2878	0.3317	0.0590	5
Packing Ring (SP6)	5.209	0.3869	0.0691	3

3. Conclusions

Identifying critical spare parts of equipment for maintenance operations is one of the critical decision-making activities to obtain lower downtime of equipment and inventory cost. To achieve this goal, the DMs should apply the best method and apply accurate criteria to analyze and rank the spares based on criticality. This paper proposes a novel a two phased methodology to manage an inventory based on fuzzy AHP and fuzzy TOPSIS for selecting the most critical spares from the point of view of their necessity in maintenance operation. In this paper, also the ranking scores are the outcomes of the methodology, and by using ranking scores DM can obtain not only a ranking of the alternatives but also the degree of superiority among the alternatives. For dealing uncertainty and improving lack of precision in evaluating criteria and/or spare parts alternatives, fuzzy methods are used. The present approach applies triangular numbers into traditional AHP and TOPSIS methods. In TOPSIS method the score option can provide better perception to the DM by taking into account both the differences and similarities of the alternatives according to the best and the worse alternative. By applying fuzzy numbers, DMs enables to get better results in the overall importance of criteria and real alternatives. As a result of the study, we find that the proposed method is practical for ranking spares of given equipment based on criticality with respect to multiple conflicting criteria. As a future scope, the proposed methodology may be developed to aid the decision makers to take decisions in presence of incomplete data.

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