Proceedings of the 3rd GCC International Conference on Industrial Engineering and Operations Management
Tabuk, Saudi Arabia, February 2-4, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/GC03.20260032
Published: February 2, 2026

Classification of Spare Parts Criticality: A Multi-Criteria Decision-Making framework with an Application in an Oil and Gas Company

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Abstract

Spare parts are inventoried items stored in warehouses for immediate response to demand requirements of repair jobs and maintenance activities. Most oil & gas companies maintain large numbers of spare parts to ensure stock availability and avoid shortages. Due to the substantial contribution of spare parts to the total inventory cost, it is important to balance stock availability and the inventory holding costs of spare parts. In line with these objectives, the specification of the spare parts to keep in stock is one of the most crucial steps which requires the spare parts to be classified based on the corresponding criticality. The aim of this thesis is to identify the most relevant criteria for the classification of spare parts criticality prior to assessing their impact on inventory management using a large oil & gas company in Oman as a case study. The investigations are based on a methodological framework that integrates two multi-criteria decision-making (MCDM) techniques, namely, Evaluation based on Distance from Average Solution (EDAS) and Ordered Weighted Averaging (OWA) operator. The findings of this study reveal that less than 2.5% of the spare parts require special attention regardless of the optimism level of the decision maker, which enables reducing substantially the inventory costs besides assisting the inventory team in deciding what to maintain in stock and whether to add or remove items from stock.

Keywords
Criticality, Criteria, Spare Parts DEAS, OWA, MCDM.

1. Introduction
With the Gas startup, Oil & gas companies are looking to maintain specific levels of Spare Parts (SPs) are required to be kept on hand for regular operations and maintenance activities' requirements in gas central processing facility (CPF) and gas well export system (GWES). Currently, the most important aspect that these companies focus on is to ensure keeping enough stock to satisfy demand on time and avoid stock-outs. The companies manage stock availability by implementing a stocking strategy that brings more stock into inventory to respond to customer demand and maintain a certain minimum stock level.

The companies hold different categories of spare parts like mechanical spares, electrical spares, chemical spares, instrument spares, etc. But there are other categorizations for the SPs depending on the phase for which the spares are required and the technical use of each spare, such as Capital Spares, Insurance Spares, Commissioning Spares, Operating Spares, Consumable Spares, Special Tools and project & surplus spares. The different categories of spare parts vary in terms of criticality to the business. Defining spare criticality is a challenging task due notably to the absence of specific standards or measures for criticality.

Spares criticality might be assigned based on long lead time, maintenance types, safety requirements or other considerations. However, it is not clear as well what aspects determine the criticality of safety & operation. The large number of spare parts that are procured to satisfy different maintenance activities make the criticality classification a difficult task to handle. This is the case because the operation & maintenance teams always focus on getting the spare ready for the operation and maintenance jobs and ignore any other related issues. The issue of criticality has a big impact on inventory value. In this study, a list of spare parts will be evaluated and analyzed through a multi criticality classification to decide what to stock and what to remove from inventory.

The subsequent sections of this paper are structured as follows: Stating the problem statements which include the research objectives and questions, literature review followed by a discussion about spare parts general background, and spares parts criticality criteria. Section 3 presents research Framework development and discussion results are presented in sections 4 & 5 respectively. Finally, section 6 states the conclusions.

A. Project Problem Statement

The crucial impact of SPs criticality on increasing the inventory value created a need to solve the issue of multi criticality classification of SPs in Oil & Gas company. The issue of unclear assignment and undefined criticality classification has contributed to increasing inventory value and creating overstocking of the SPs, that is, procurement of more than the required SPs levels.

B. Scope of Research

The scope of the project is to study the spare part inventory of a large company in the field of oil & Gas. The company owns an inventory of around 13,488 spares worth $35M. The main use of the SPs is to support the maintenance activities in the central process facility for gas processing operations. The spare parts have no clear criticality guidance, which creates some issues with stock availability and overstocking. This study focuses on defining criticality to each of the SPs to achieve the study objectives defined below.

1.1 Research Objectives & Questions

This research aims to design a multi-criterial classification of SPs in an Oil & Gas company to maintain stock availability of required SPs. It also aims to support inventory levels optimization objective by helping the inventory management team to decide what spares to stock and what to remove. The following research questions are developed to achieve the objectives of this research:

1. What are the relevant criteria for spare parts criticality in the company?
2. What is the practical implication on assigning SPs criticality for oil & gas companie.

2. Literature Review

The literature review chapter presents the fundamental basis for the theoretical part of this study. It highlights the importance of SPs management to the fields they operate in particularly in the petroleum industry as the main field of this study. This chapter defines the main categories of SPs and where they are used and operated. It also provides a review of the studies that have been conducted in the field of SPs and the relevant classification to prioritize the SPs based on their criticality.

2.1 Spare parts in petroleum industry

SPs are inventoried items stored in warehouses for immediate response to any demand requirements. The spares are used in repair jobs or to perform maintenance activities to equipment. SPs evaluation requires the identification of spares storage location or warehouse, total number of stock and delivery time. The major category of SPs used in operations and maintenance services are the operational spares. Operations spares can be found in three major groups depending on the operations services: 1. SPs that are used in planned preventive maintenance (PM), 2. Corrective SPs used in corrective maintenance jobs to response to failure in equipment and 3. Turnaround SPs required for planned maintenance activities during shutdown of overall plant.

2.2 Spare Parts Categories

As started by Antosz and Ratnayake (2019), there are other SPs categories that are considered in the evaluation and control of SPs as below:

- Capital Spares: classified as very high value spares that is a complete set of equipment or units, like pumps, compressors, large motors, large valves, etc. They are critical and failure to replace the spare could stop full operation and shutdown the plant. The decision on the number of spares to keep in inventory should be reviewed seriously due to criticality, long lead time and high value item.
- Insurance Spares: critical spares used to replace failure of identical spares in main equipment. They mostly carry the same characteristics as the capital spare, but they are less expensive.
- Commissioning Spares: spares used in the construction or project phase prior to the operation phase, such as valves, seals, and other electrical an instrumental spare. They are normally recommended by the original equipment manufacturer (OEM). The same types of spares can be used in the next stage of operations as a handover from project to assets.
- Operating Spares: spares used in normal day-to-day preventive and corrective maintenance activities. These spares are used to maintain the life of the equipment during the operations phase. These include valves, bearings, mechanical seals, etc.
- Consumable Spares: required on a regular basis as common items for different equipment. They are low value items and available in large quantities. Examples of these items include o-rings, gaskets, filters, screws.
- Special Tools: linked to equipment meant to complete necessary maintenance activities and then return to stock for storage. These tools are not consumed upon usage, like repair kits, hammers and others.
- Project Surplus items: After completion of specific projects, excess spars are identified as surplus where the consumption lower than the expectation or the order quantity is more than the required. Project surplus shall be handed over to the operations, especially the commissioning spares upon approval for future demand requirements

Antosz and Ratnayake (2019) stated that the evaluation and control of the spares are becoming a hard task due to the nature of the operational assets in terms of the high-risk and the capital expenditure to acquire, maintain, preserve the SPs. SPs have some shared features such as long lead time, obsolescence risk of the spares and the parent equipment and uncertainty of demand. SPs are very crucial for continuous and productive operations and any stockout or delay in the replacement of failed parts can immediately cause plant shutdown and, hence, operation stop, which affects production delivery. Many companies in the oil & gas industry maintain large numbers of spares to ensure stock availability and avoid shortage. However, it is very crucial to balance stock availability and the cost incurred as a result of holding SPs inventories. The decisions on the types of SPs to keep, the appropriate stock levels, and the order quantities are very crucial to inventory management (Muniz et al., 2021). The evaluation and control of SPs require the contribution of different elements, like material management, project management, operations assets as well as the vendor and/or original equipment manufacturer (Antosz & Ratnayake, 2019).

SPs classification is an important requirement in this challenging situation. The most traditional quantitative and qualitative ways for SPs classification are the ABC and VED methods, respectively. The ABC classification is based on the dollar annual consumption value and their contribution to the company's bottom line. The VED classification is a qualitative approach that divides the stock into three classes. Vital importance (V) refers to the case where the availability of spares is very vital to the equipment to run the operations. Essential importance (E) defines the case where the non-availability of the SP may cause a middle impact on the continuity of the operations. Desirable importance (D) is the class of SPs for which the unavailability leaves low effect on the losses.

Though the ABC classification is the most employed method to rank the items based on dollar consumption, it is less useful for items defined with many criteria (Molenaers et al., 2021).

The SPs criteria are evaluated based on their consequences on the operations, health, safety and environment (Muniz et al., 2021). Historical data of SPs consumption and stock levels support the ABC analysis. Along with traditional classifications methods, lead time, unit cost and criticality are criteria that are also commonly used to classify SPs. Classifying SPs by criticality is the most important way of classification as stated by Molenaers et al. (2012). Criticality is determined by other related criteria that render the decision problem dealing with the SPs to keep in stock a multi-criteria decision-making problem. The classification helps to support the inventory control policy and the management strategy of SPs. It supports deciding on the appropriate stock parameters.

2.3 Criticality Criteria of Spare parts

Criticality is a crucial component of the spare parts management. It is the first factor in determining what resources and efforts are needed to reduce the risk or the effect of any losses. Criticality is determined by the possibility of failure and its effects. Consequences typically include incidents relating to the economy, safety, and environment. Businesses must establish their own measures to determine how crucial a process or piece of equipment. For a study conducted in mining company, the relevant criteria of criticality are categories into 3 categories: maintenance, production and supply. Safety, environment, production failure and equipment availability are the factors of production criteria. While maintenance relevant criteria are spare part reliability and machine priority. Supply criterion that influences spare part criticality are lead time, unit price and number of potential supplier (Muniz et al., 2021). Classifying the whole inventory of spare parts into the appropriate categories is a key task for many assets industries in order to manage the broad and extremely varied categories. Spare parts vary significantly in terms of shortage consequences, item value and demand patterns. Classification helps managers to concentrate on the items that are most "essential" and make the appropriate decisions. Critical items from inventory or logistic perspective are different compared to the important items from operation or maintenance standpoint (Molenaers et al., 2021).

In the research conducted for mining industry, the study addressed the problem that most of the previous studies ignore the initial provisioning of the inventory. There are few studies address the need for spare parts inventory classification in the initial receiving of stock. The study mentioned how the cost as one of the elements that affect the spare part inventory management. Muniz et al. (2021) states that the cost of item represents the criticality and operational importance of spars to the equipment in which they are installed. The study implements MCDM and VED as a first method to group the spares. In the study the spares criteria are categories into three groups: Production, Maintenance and supply. The groups determine the spares classification. Production criterion includes the elements that could impact on the safety of production and environment and the criteria that impact on the quality and performance of the equipment. How reliable are the spares and Machine criticality are the main criteria that are grouped under maintenance. Supply is the third criteria including the lead time, unit price and the number of potential suppliers (Muniz et al., 2021).

Number of potential suppliers as one of the criteria on defining spare parts criticality is also addressed in the case study of criticality classification of spare parts which was developed by Molenaers et al. (2011). In the study of Husum and Leirvaag (2022), availability of potential supplier is also considered as one of the criticality classifications. Other criteria defined in this study are related to equipment criticality, probability of Item failure, replenishment lead time and availability of technical specification for the equipment and ordered spares. If the equipment is categorized to be a critical item, then the spares will take the critical privilege as well (Husum & Leirvaag, 2022). The study is applied in a service provider company operates in an offshore oil & gas filed. VED analysis and AHP methods developed by the researcher to achieve the study objectives.

The case study of criticality classification of spare parts is conducted in a petrochemical plant and addresses two groups of criteria- process criticality and control criticality. The factors related to number of potential suppliers, replenishment time, technical specifications and type of maintenance required for the equipment are all combined under the control criticality while equipment criticality and probability of item failure are part of process criticality. The study implements AHP as a part of multi attribute technique and decision diagram (Molenaers et al. 2011). The AHP method firstly introduces by Satty Such Study as the one researched by Dekker et al. (1998) presents a good overview on equipment criticality as a stocky policy for spare parts demand in a petrochemical plant. The focus of this research is to study the equipment as a factor originate the identification for critical demand and non-critical. Critical demand for spare parts means that the part belongs to critical equipment. Criticality of equipment refers to as the importance of equipment to enable a continues production and smooth operation without breakdown or shutdown. The study helps to handle the situation when the same identical equipment is installed in different functional locations with diffident approximate importance to the production. Therefore, any stockout for some of the spares will have major impact on the operation of one equipment compared with the other installed in different locations (Dekker, et al. 1998).

In the research study by Teixeira, et al. (2017), spare part classification criteria are divided into two categories- function and production impact. The criteria of production impact consider all the factors that cause stop and delay in production or impact the quality or that could reduce productivity. Teixeira, et al. (2017) discusses that both the traditional methods ABC and FSN consider only one criterion where the ABC relies on consumption and the FSN classifies the spares based on the how frequent the movement of items is whether fast, slow or non-moving items. To include a wide set of criteria, the study uses MCDM classification method. After defining spare parts criticality criteria, VED (Vital, Essential and desirable) is used as a first step to assign the level of importance to each spare part.

In the research study of ABC inventory classification with multiple criteria using, weighed linear optimization method is proposed. The method considers the multi criteria inventory classification (MCIC). Traditional ABC analysis is used in this study to classify spares based on the annual dollar usage. Class items are generally less in number but have high annual usage value. It requires close attention and mentoring compared to class C items (Ramanathan, 2006). Items with C classes normally constitute the biggest part of inventory but relatively contribute less to the total inventory value. Ramanathan, (2006) states that the implementation of ABC analysis can success only if the inventory items are homogeneous and they differ in the annul usage value as it depends in one criterion. Research by Antosz and Ratnayake (2019) insist on same issue with ABC analysis where it supports the classification of one factor. In practice and real-world problems, ABC analysis will not provide a spare parts classification because having a verity of items will ultimately serve a wide range of different customer demand. Hence, inventory with variety of items will increase as well (Ramanathan, 2006).

Study such as a review of multi-criteria classification of spare parts from literature analysis to industrial evidence which is conducted by Roda et al. (2014), provides a comparison between the theoretical analysis and the practical implementation in an industrial company. There are many criteria and classification methods have been identified through the analysis for literature and from understanding for the practical implementation in the industry. Roda et al. (2014), said that the comparison results have revealed of defining the main five criteria that shows more potential to be as a classification for spare parts. The main criteria are lead time, item price, turnover rate, stock out cost and Specificity. An intensive review for classification methods have also been developed as part of the study objectives. There are some of the classification methods that are used in the copper mining sector such as Rules of thumb, Qualitative method (VED), Bi-/multi-criteria method (AHP) and ABC analysis using a single criterion. The review allows to identify the features and gaps for each of the classification methods. One of the gaps is related to the subjectivity of data when using expert opinions or judgments and this is mainly concerning the AHP method.

The same gap for AHP is also addressed in the research conducted Braglia et al. (2004).. They present the implementation of AHP in spare part classification. In the study, the researchers describe that AHP highly depends on subjectivity and expert's theoretical judgements, however it went through a modification by incorporating the VED analysis (Antosz & Ratnayake, 2019). The study presents some advantages for AHP method such as qualitative and quantitative approaches are both enabled. Such study as Spare parts' criticality assessment and prioritization for enhancing manufacturing systems' availability and reliability provides some overview on the benefits provided by the methods. There could be a drawback with this method as stated by Antosz and Ratnayake (2019) as this was only employed in one company and it will need to be verified further to be used in other fields.

In the methodology developed by Antosz and Ratnayake (2019), several factors are relied on for spare parts classification. The criteria are categories into groups: Maintenance, logistics and level of criticality. Logistics criteria or supply as addressed by Bacchetti and Saccani (2012), Nurcahy et al. (2017) and Muniz et al. (2021) includes factors such as item's unit cost, lead time, warehouse or storage factors and issues related to supplier limitations. Maintenance criteria in the other side are impacted by type of the machine or equipment, the frequency of the equipment's failure or replacement of spares and level of skills that maintenance employees have.

In addition to the supply issues mentioned by Nurcahy et al. (2017), Operational issues and technical factors are also other criteria that considered for spare parts classification. Technical factor refers to the specification of spares required technically to fit the specific requirements of an equipment. These inputs are normally provided by the original equipment manufacturers (OEM) who issued the certificate of conformity (CoC) and confirmed the procured spare has the specification or meet the required specification. Technical data sheet, drawing and any other certificate for chemical spares are also part of technical criteria. When a spare has a long lead time to be replenished and the number of suppliers is very limited to perform the procurement, then the spare is logically classified as a critical spare part. The same classification is also applicable when the amount of technical information is really not adequate (Husum & Leirvaag, 2022). In the study of Nurcahy et al., (2017), a multi criteria decision making (MCDM applied in airline industry is suggested. The classification method combines the AHP method and VED. The airline industry seems to own a complicated type of asset because of huge number of spare parts required in different maintenance activities. This study is considered as a basis for further studies in the aircraft industry regardless of the study's limitation related to the subjectivity of the experts' judgments (Nurcahy et al., 2017).

Additionally, the research study performed by Nariswari et al. (2019) shows a model for spare parts inventory classification implemented in a large company for aircraft's maintenance and repair operations in Indonesia. There are two groups for the aircraft spare's part: consumable spare parts and rotable spares which have higher inventory value than the consumable spares. A set of attributes been taken into account for the classification of the aircraft's spare parts. Similar to the classification criteria considered by Nurcahy et al. (2017), operational criticality, technical characteristics and supply characteristics are the main types of criteria composed into the AHP model. Nariswari et al. (2019) mentions the same supply criteria factors which are addressed in study as Muniz et al. (2021), however, additional factors like specificity, capability repair and aircraft route. Operational criteria as addressed by Nariswari et al. (2019) consider the criticality of spare parts from OEM side to the aircraft priority. The technical characteristics consist of planned demand, reliability issues, the impact of regional climate, planned demand and frequency of scrape spares. There are other sub-criteria that support the VED analysis (Vital, essential, desirable) that need to be evaluated in a sequential manner from the essentiality of original equipment manufacturer (OEM), the importance of SPs to the importance of the aircraft passengers and crew. Due to the fact and the regulation of the aviation industry that empathizes on passenger's safety, operational criticality are the technical factors are the most important criteria. Braglia se al. (2004) focus to develop the a Multi Attributes Spare Tree Analysis (MASTA) that considers criticality of spare parts as the main criteria for inventory classification.

In addition to the study's objective of determining the relevant criteria for spare parts classification, the study proves the effectiveness of AHP as a multi criteria classification system compared to other classification methods such as Weighted linear optimization, Two-dimensional method, Fuzzy linear assignment, AHP K-Veto, Fuzzy AHP and Fuzzy AHP DEA. Nariswari et al. (2019) highlighted the advantages of AHP model in term of its ability to combine both qualitative and quantitative factors, assign different weights to the criteria, easy to implement, provide a transparent way to support the decision-making process. The researchers did not ignore the subjectivity of AHP but they show how that being controlled. Such as Studies Stoll et al. (2015), Braglia et al. (2004) and Molenaers et al. (2011) presents AHP as a method for spare parts classification. Molenaers et al. (2011 a study conducted in a petrochemical plant.

In the research developed by Cakmak & Guney (2023), the aviation industry is the study field for spare parts inventory classification. Aviation companies aim to raise customer satisfaction through ensuring the continuity of the operation. The study proposes the use of Neutrosophic Fuzzy EDAS method. The method is supported by the decision-making process as it is part of multi criteria decision making (MCDM) technique. It is considered as new method where the EDAS is extended to its new version called Neutrosophic Fuzzy EDAS. The method is used for classification in general and for inventory classification in this study in particular. One of the advantages of Neutrosophic Fuzzy EDAS method is that it deals with uncertainty or inconsistency of the information provided about the spare part classification.

Based on the literature, all the identified criteria have been divided into three groups: factors related to the SP itself, demand of SPs and characteristics of supply chain (Cakmak & Guney, 2023). The supply chain group consists of the following factors:

- Lead Time refers to the period of time between placing and receiving the order
- Stock replenishment: This is a policy to monitor the stock level of an inventory and establish the reorder point. The inventory is track using two types of review policies. The periodic review performs stock taking in a regular interval, weekly, monthly and yearly basis while the continues review tracks inventory in a continues basis and automatically replenish inventory when it goes below reorder point.
- The Service level policy: Refers to the level of inventory to be kept during the replenishment cycle so that it will not run out of stock.

The second group of criteria for inventory classification is the factors that are related to feature of spare parts that include:

- Item status: It is the factor that indicates the available stock exists in the warehouse and the physical condition
- Criticality: it describes the importance of the part to the production or maintenance activities. The part importance is identified through measuring the impact of not having the item available in stock on the continuity of the production or the ability to perform the maintenance job.
- Repairability Efficiency: This factor measures how it is possible to maintain or repair a part for re-use when it gets failed.
  Unit Price: the price of spare procured. The item becomes more important when the price is high.
- Commonality: this refers to the items that are sharing similar attributes and can replace others or can be substituted to each other. None or fewer substitutability identifies the item importance.
- Durability: It is the item life cycle that determines how long the item can provide the function or service without any breakage or without the need for repair.
- Part Weight: the higher the weight of the part, the higher the risk of transporting and storing the materials which will make the process of operation and maintenance more complex.

The third characteristic of spare parts criteria is the part demand that refers to the demand for a product anticipated for a year. The demand for a product required for maintenance activities is normally predicted based on the number of failures during the operations. In general, the demand varies from one product to another. The spare parts demand patterns include constant demand, trend market and seasonal demand.

In research study developed by Baykasoglu et al. (2016), Fuzzy linear assignment method (LAM) is proposed for spare parts inventory classification. The case study conducted in textile company in Turky as one of the leading companies in the world in the field of clothing textile. Similar to Neutrosophic Fuzzy EDAS, Fuzzy linear assignment supports the application of multi criteria decision masking (MCDM) under variables factors and instable environment. This method is not famous as other types of multi attributes decision making, however it easy to implement. It combines various concepts for multi-attributed decision making (MCDM) problem that gives it better advantages and capability to be as a useful tool for study. It provides more practical solutions for ranking as one of the steps in the application of fuzzy. The method considers both qualitative and quantitative types of spare parts inventory classification criteria. The Quantitative criteria consist of annual cost and replenishment time while qualitative factors include durability, availability of spares and the importance of the spare to the process or maintenance. To facilitate the spares parts classification through Fuzzy linear assignment, the study classifies the inventory spare parts using traditional ABC analysis to its three known categories (A): Important, (B): moderated and (C): less important (Baykasoglu et al. 2016).

There are diffident methods for spare parts categorization as stated in the methods evaluation conducted by Nareshchandra et al. (2019). The study is conducted in a steel plant to propose techniques for inventory categorization that support inventory management system. Based on the intensive literature review, the study depicts number of techniques available for inventory classification as follows:

- Single Criteria Inventory Classification

This technique is used based on the factor that of most importance to the organization or the criterion that they want to focus on. There are several available techniques under single categorization with different basis for classification such as ABC, FSN, VED, HML, XYZ, SDE, GOLF and SOS.

a) ABC: is one of traditional techniques used to classify inventory based on the value of annual consumption and this type can be applicable to any type for inventory for different businesses.
b) FSN: this technique controls inventory based on consumption or inventory movement throughout the year and can be divided into three types (F) fast moving, (S) slow moving and (N) non-moving inventory. This tool helps to identify the obsolete spares and identify surpluses that can bring a return to the company by exploring options to sell them back to manufacturers, redeployment in different projects or sell them as scrap.

c) VED: The technique classifies spares based on their importance to business and can be classified into (V) Vital, (E) Essential and (D) Desired. It helps to determine the stock level to maintain in the inventory to avoid stockout.
d) HML: To set a control on the procurement value, this tool classifies spares using the unit price of item ranging from high, medium and low.
e) XYZ: This technique helps to review the value and the inventory level within a specific period.
f) SDE: As part of supply chain challenges associated with finding potential suppliers to do procurement or the challenges faced due to issues with lead time, this tool help to classify spares to three types (S) scarce, (D) difficult and (E) easy to procure.
g) GOLF: In addition to SDE that helps on deciding the procurement strategies, GOLF is a tool contributes to find proper channel of supply and can divide classification into Government, Ordinary, Local and foreign supplies.
h) SOS: This technique helps with the classification of the items that comply with seasonality and classifies spare parts as (S) seasonal and (OS) off seasonal.

- Bi- Criteria Inventory Classification

In the second group of classification techniques, Nareshchandra, et al.(2019) mentioned that two criteria can be considered for the inventory classification when single criteria classification cannot provide more reliable results. It depends on the factors that are of the most focus for the business and might be required for effective inventory policy. A matrix introduced by Flores and Whybark (1986) to be used in the case of classification analysis of two criteria, for example item's unit price and consumption pattern where HML and FSN techniques to be used, respectively. Other businesses might focus more on criticality and inventory value of items that required tools such as VED and XYZ. According to the intensive review conducted by Nareshchandra et al. (2019), the medical filed has been identified as the most considered ABC and VED bi- criteria inventory classification technique.

- Multi Criteria Inventory Classification

For multi criteria inventory classification, the business should consider multiple factors rather than focusing on a single or two criteria. The study proposes various methods to be utilized for multi criteria inventory classification such as:

a) Weighted linear optimization
b) DEA (Data Envelopment Analysis) method
c) AHP (Analytic Hierarchy Process) approach
d) FAHP (Fuzzy Analytic Hierarchy Process) approach
e) ANN (Artificial Neural Network) approach
f) TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method
g) SAW (Simple Additive Weighting) method
h) Peer-estimation approach

The multi criteria classification techniques utilize different combinations of criteria for inventory classification such as Annual demand, Unit price, Annual usage value, Unit weight of the component & Shape of the component, Limitation of warehouse space and Average lot cost & Lead time. Annual demand and unit price are always considered in most of the techniques. Weighted linear optimization, Non-linear programming model, Simulated Annealing and Peer-estimation approach techniques share the same combination of criteria like Average unit cost, Annual dollar usage criticality and lead time. In addition to the contribution of Nareshchandra et al. (2019) to provide useful methods for inventory classification, the study provides a review on previous studies conducted between 2002 and 2018. It is obvious from the figure that the year of 2013, 2016 & 2017 depict the greatest number of publications related to inventory classification. Roda et al. (2012) summarize and discuss some existing scientific papers on multi-criteria classification of spare parts.

Nareshchandra et al. (2019) stated in his literature review that all techniques of multi criteria classification have drawbacks like subjectivity, consume a lot of time, limitation during the practical implementation and the complexity associated with data calculation. Researchers have performed benchmark between different techniques of multi-criteria classification that some techniques like FAHP present better reliable results than AHP.

Some disadvantages for the AHP as a multi-criteria classification technique are also mentioned by Teixeira et al. (2018). Three classification criteria are considered which are criticality, lead time and price. In this study, AHP and multi criteria classification based on rules have been analyzed and compared. The data is collected from An Automotive company as a study filed, and the same data has been used in both AHP and the rule-based multi-Criteria classification. The study is conducted for a small set of data for which it impacts the results of AHP analysis. The AHP technique with large amount of data and considers good number of criteria will reduce the subjectivity that accompanies the AHP results. In general, AHP requires a lot of calculation and that makes the process of implementation more complicated. The study of Teixeira et al. (2018) concludes that multi-Criteria classification based on rules is easier to be implemented than AHP.

Artificial Neural Network (ANN)is part of the techniques of multi-Criteria decision making (MCDM). Artificial Nural Network (ANN) follows the same behavior as of human brain. It imitates human thinking in which it acts as an unskilled human learning a set of knowledge at the first stage. As a second stage, ANN works independently to convert inputs to outputs using the acquired knowledge in first stage. Nural Networks are suitable for more complex situations (Sustrova, 2016). As presented in previous literature review, Artificial Nural Network (ANN) is implemented in several fields steal industry, wholesale trade and pharmaceutical company.

Artificial Nural Networks (ANNs) are one of the quantitative methods addressed by Bacchetti and Saccani (2012) for spare parts classification. ANNs was presented as part of the intensive review on literature for the classification of spare parts. The study addressed other quantitative methods for inventory classification like weighted liner optimization, weighted Euclidean distances with quadratic optimization, matrix model and fuzzy logic. Moreover, the study classify inventory based on such criteria as Spare parts cost, Part Criticality, Supply Characteristic Uncertainty, Demand Volume (value), Demand Variability, Part Reliability, Part life cycle and Part specificity (Bacchetti & Saccani, 2012).

In the study of Partovi and Anandarajan (2002) Artificial Neural Networks in a pharmaceutical company are used. Researchers consider certain criteria for classification which are price of spare, cost of ordering, lead time and demand. The methodology of ANNs developed two learning methods as genetic algorithms (GA) and back propagation (BP). There are no big differences between these two methods.

A recent study on Multi-Criteria Inventory Classification applied have been conducted for intermittent demand used a machine learning method (Francesco et al,. 2018). Machine learning supports the implement under large set of data. The study applies supervised machine learning approach and depends on two classifies

- Support vector machine (SVM)
- Deep neural network (DNN)

The researcher considers the most classification criteria that have an impact on inventory control systems and the selection of inventory policy.

Hua et al. (2017) developed a methodology for SPs classification in an industrial manufacturing field. Dominance-based rough set approach (DRSA) is the method proposed by the researcher where they developed three phases for multi-criterial classification. Below Table 1 describes the criteria used in previous studies for criticality classification:

Table 1. Criticality Criteria selected in previous studies

Classification Technique	Criticality Criteria	Reference
AHP	Annual demand Unit price Criticality Lead time Inventory Status	Nareshchandra et al. (2019), Teixeira, et al. (2018), Molenaers et al. (2011), Roda et al. (2012), Bacchetti & Saccani (2012), Teixeira, et al. (2017), Husum & Leirvaag (2022), Nurcahy et al. (2017), Antosz & Ratnayake (2019). Muniz et al. (2021). Braglia et al. (2004), Stoll et al. (2015)
Neutrosophic Fuzzy EDAS method	1.Current Item Status 2.Criticality 3. Unit Price 4.Repairability Efficiency 5.Commonality-Substitutability/Replaceability 6. Durability/ Obsolescence 7.Part weight (SKU Weight)	Cakmak & Guney (2023)
Fuzzy linear assignment method	1.Durability, 2. Availability 3. Replenishment 4.Criticality 5. Annual Cost	Baykasoglu et al. (2016)
ANN 1.Back propagation algorithm-based learning 2. Genetic algorithm-based learning	1.Price of spare, 2. Cost of ordering, 3. Lead time and 4. Demand.	Partovi & Anandarajan (2002), Sustrova (2016), Bacchetti & Saccani (2012)
Machine learning	1. characteristics of the items, 2. inventory control system	Nariswari et al. (2018)
dominance-based rough set approach	1. Criticality, 2.Price 3.Demand, 4. lead time, 5. obsolescence,	Hua et al. (2017)
EDAS	1.Average unit cost, 2. Annual dollar usage 3.Lead time	Ghorabaee et al. (2015)
ABC classification, MCDM Machine learning techniques	1.Lead time, 2. Annual utilization value, 3. Average cost of a unit of an item	Khanorkar & Kane (2022)

3. Research Methodology

This section of the research presents the research methodology framework which is built to provide answers for the research question. It highlights the data collections and illustrates procedures for step-by-step research methodology. This section also provides an explanation for data analysis and definition for the criteria used for spares classification.

3.1 Data Collection

The data is acquired from a large company in oil & gas industry in Oman to be as a real- case study. It consists of a list of spare parts that are required as part of company's productions and maintenance activities. Besides, it includes information about historical data for inventory transactions that show the spares movements over the years. Other information related to lead time and unit price are also important for the research. The data will be integrated with the study's objectives through:

- **Inventory Status:** Data related to SPs inventory movement which presents the material consumption over a specific period of time. It helps to identify inventory status like very fast-moving material, fast-moving material, slow-moving materials and very slow-moving materials. These types of data fit under the category of supply element that affect the criticality of spares.
- **Spare Unit Price**: Unit Cost is the purchase price to acquire a material. Unit cost will help identify the high value items and low value items. These types of data also help determine how critical the material is to the business due to the high spend incurred to acquire the materials.
- **Planned Delivery Time**: Delivery lead time is the period of time when a new order is placed until the spare from the supplier is delivered. It is part of supply element that affects the criticality classification of spares.
- **Spare Criticality:** Describes the importance of material as recommended by the Operations & Maintenance team that any shortage can impact production performance. The material can also be critical from safety perspective. (The higher the importance of the item, the more critical it becomes)
- **Annual Dollar Usage**: Presents the material annual consumption value over a specific period. It is calculated by multiplying the annual unit consumption by material unit cost. These types of data fit under the category of supply element that affects the criticality of spares. The higher the annual dollar usage, the more critical the materials become.

3.2 Method

The investigations are based on a methodological framework that integrates two multi-criteria decision-making (MCDM) techniques, namely, Evaluation based on Distance from Average Solution (EDAS) and Ordered Weighted Averaging (OWA) operator.

3.2.1 Evaluation based on Distance from Average Solution (EDAS)

The research uses Evaluation based on Distance from Average Solution method (EDAS). EDAS proposes the use of both positive and negative distance from average solution (Ghorabaee et al. 2015). The performance of this method is illustrated with the use of 9842 SKUs from a real-life example of inventory data from Oil & Gas company. The SKUs are assessed based on four criteria. The section of framework development describes the analysis of data. EDAS method, as stated by Ghorabaee et al. (2015), is illustrated in eight steps below:
<u>Step 1</u>: Select the most relevant criterion that has an impact on criticality
<u>Step 2</u>: Decision Making is constructed with alternatives and criteria

$$\text{x} = \left[x_{ij}\right]_{nxm} = \begin{bmatrix} x_{11} & x_{12} & \dots x_{1m} \\ x_{21} & x_{22} & \dots\ x_{2m} \\ & & \vdots \\ x_{n1} & x_{n2} & \dots x_{nm} \end{bmatrix} \quad (1)$$

where x_{ij} denotes the performance value of *i* th alternative on *j* th criterion.
<u>Step 3</u>: Calculate the average solution to all criteria:

$$AV_J = \left[AV_j\right]_{1xm} \quad (2)$$

Where,

$$AV_J = \frac{\sum_{i=1}^{n} x_{ij}}{n} \quad (3)$$

Where AV indicates the average value of each criterion

Step 4: Calculate the positive & negative distance from average criteria

$$PDA=\left[PDA_{ij}\right]_{nxm} \qquad (4)$$

$$NDA=\left[NDA_{ij}\right]_{nxm} \qquad (5)$$

If jth criterion is beneficial,

$$PDA_{ij}= \frac{max\left(0,\left(X_{ij}-\ AV_j\right)\right)}{AV_j} \qquad (6)$$

$$NDA_{ij}= \frac{max\left(0,\left(AV_j-\ X_{ij}\right)\right)}{AV_j} \qquad (7)$$

Where:

PDA_{ij}: indicates the positive distance of ith alternative from average solution in term of jth criterion

NDA_{ij}: indicates the negative distance of ith alternative from average solution in term of jth criterion

Step 5: Determine the weighted sum of PDA and NDA for all alternatives, as shown below

$$SP_i= \sum_{j=1}^{m} w_j\, PDA_{ij}; \qquad (8)$$

$$SN_i= \sum_{j=1}^{m} w_j\, NDA_{ij}, \qquad (9)$$

where w_j denotes the value of the weight of *j*th criterion

Ghorabaee et al. (2015) assume that the wights are equally distributed across all the criteria. In this study and as a new contribution to the literatures, the researcher determines the Ordered Weight Averaging (OWA) using the minimax disparity model (MMD) that is introduced by Wang and Parkan. The weights are calculated by using a mathematical Linear Programming model.

$$\min \delta$$

$$s.t. \sum_{k=1}^{n-1} \left(\frac{n-i}{n-i}\right)\ wi=\alpha \quad \alpha\in[0,1] \qquad (10)$$

$$\sum_{i=1}^{n} wi=1 \qquad (11)$$

$$-\delta \le wi-w_{i+1} \le\delta \quad i=1,\dots,n+1$$

$$wi\ge 0 \quad i=1,\dots,n$$

Where:

n: indicates number of criteria

i: indicates each criterion 1, … ,4

α: indicates the orness value that represents the attitude of decision maker in the optimism level

wi: indicates weight of each criterion

MMD is a Linear Programming (LP) model. The objective of the LP is to reduce the variation or gaps between the weights w_i . The OWA integrates the level of optimism α, also known as orness, which reparents the attitude of decision maker. The values of α vary between 0 and 1. The orness values0≤α≤1 expressed the decisions of optimistic and pessimistic decision makers. The orness values 0≤α<0.5 refer to pessimistic decision makers, while 0.5<α≤1 represents optimistic decision makers.

Step 6: Normalize the values of SP and SN for all alternatives, shown as follows:

$$NSP_i = \frac{SP_i}{max_i\ (SP_i)} \qquad (12)$$

$$NSN_i = 1 - \frac{SN_i}{max_i\ (SN_i)} \qquad (13)$$

Where:
SP_i: weighted sum of PDA for all alternatives
SN_i: weighted sum of NDA for all alternative

Step 7: Calculate the appraisal score (AS) for all alternatives, shown as follows

$$AS_i = \frac{1}{2}\ (NSP_i + NSN_i), \quad (14)$$

Where

$$0 \leq \ AS_i \ \leq 1$$

Where:
NSP_i: Normalize value of SP for ith alternative
NSN_i: Normalize value of SN for ith alternative
Step 8: Rank the alternatives according to ABC classification.

3.2.2 Inventory ABC Classification Using EDAS

The same criteria identified as having impact on items' criticality are considered as criteria for ABC classification. The value of Appraisal score is used to assign ABC class to each weight relevant to each alternative. Ghorabaee et al. (2015) use AS values to assign the ABC classes from the highest of AS to the lowest.
Braglia et al. (2004) mentioned that the traditional ABC classification adapted by many companies categorizes spares into three classes: very important (A-class), important (B-class), and less important (C-class).

4. Framework Development

4.1 System Analysis

The researcher utilizes the work experience to determine the availability of data that can be exported from Enterprise Resource Planning (ERP) system, SAP. The Original Inventory data collected is around 13,488 spares from the period 2017-2021. The data are combined from three different reports: inventory value report, MRP report and material movement report. The main data collected consists of a list of spares and the relevant criteria that impacted the spares critically. After data cleansing, the total number of spare parts used in the research is 9842.

4.2 Criteria Selection

The criticality criteria which are (Unit Price, Criticality, Delivery Time and Inventory Status) selected in the basis of their importance to the company's management; they represent key indicators for the supply chain performance and in particular for material management performance. From a theoretical perspective, the criteria selected have also been identified by other authors in previous studies as criteria that have an impact on spares criticality, as summarized in Table 1. As for data cleansing, the researcher considers the data that have common available criteria. In the sense that the spares that have no information about certain criterion are removed from the sample of data. Given that the company started its first gas production in the late of 2017, many spares have not been used in any maintenance jobs due to new facility and new equipment. This indicates that the spares have no consumption within the same period. Some spares were also procured as part of the original equipment, so there is no specific purchased price identified as a spare unit price. This study accounts for the full cycle of operations and the turnaround during the shutdown operation to perform maintenance for the whole facility.

The researcher thought about using ABC classification with annual usage value and this is the reason behind including annual usage value in the original selection of the criteria. However, due to the fact that the consumption for 80% of inventory items between the period (2017-2021) is equal to zero, the adaption of ABC classification with annual usage value is inappropriate. Khanorkar and Kane (2022) mention that ABC classification using the annual usage value is not sufficient for multi-criteria decision-making problem because there are other criteria that impact the items criticality and influence the classification. Table 2 presents the original data collected for research:

Table 2. Original Data Collected

Aged Inventory	Description	Score
0-2	Very fast-moving items	4
2_3	Fast moving	3
3-4/4-5	Slow moving	2
> 5	Very slow-moving items	1

Table 3. Scores for Aged Inventory groups

Material	Description	Unite Price	Criticality	Delivery. Time	Inventory Status
M0001	Cable,Elec:Ext,8.5m Lg,	191.81	1CR	67	3-4 Years
M0002	Pwr Sply:Ac Redundant,	998.09	1CR	50	2-3 Years
M0003	Pwr Sply:Adapt,Red	164.31	1CR	60	4-5 Years
M0004	Fuse:Semi-C,160a,690v,Gu	116	1OS	67	3-4 Years
M0005	Indicator:V-2158-401-A-745	58	1OS	67	3-4 Years
M0006	Gskt,Spwd:2in Pipe,Class 300	16.25	1OS	126	4-5 Years
M0007	Pkng,Bulk:Rope,Ptfe,	240.39	1CN	67	0-2 Years
M0008	Gskt:Asme B16.20	21.27	1OS	126	4-5 Years
M0009	Proximitr:5mm Probe Dia,	1021.07	1OS	189	0-2 Years
M0010	Cable,Elec:Ext,8m Lg,	291.99	1OS	67	0-2 Years
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
M9842	Mat: Drop Object Prevention,	264.39	1OS	77	0-2 Years

Criticality are described as 1CR,1OS, ICN and 1CH. Maintenance engineers assign 1CR to the strongly critical items,1OS to the moderate critical items and 1CN &1CH to the weakly critical items. In this study, the researcher assigns the score of criticalities in a scale from 1-3 from strongest to weakest. The criticality is assigned based on recommendations from the operations& maintenance and safety teams. As per the company inventory KPI, aged inventory represents the status of inventory from very fast-moving items to very slow-moving items in a scale from 1-4. Below Table 3 shows the scores given to each aged inventory group that describe the inventory status.

4.3 EDAS Steps

With system analysis and data cleansing, Step 1 & Steps 2 of EDAS are illustrated in Tabe 4,below:
<u>Step1:</u> Select the most relevant criteria that have an impact on criticality.
<u>Step2:</u> Decision making matrix is constructed along with alternatives and Criteria

Table 4. Criticality Criteria

Material	Description	Unite Price	Criticality	Delivery. Time	Inventory Status	
M0001	Cable,Elec:Ext,8.5m Lg,	191.81	3	67	2	
M0002	Pwr Sply:Ac Redundant,	998.09	3	50	3	
M0003	Pwr Sply:Adapt,Red	164.31	3	60	2	
M0004	Fuse:Semi-C,160a,690v,Gu	116	2	67	2	
M0005	Indicator:V-2158-401-A-745	58	2	67	2	
M0006	Gskt,Spwd:2in Pipe,Class 300	16.25	2	126	2	
M0007	Pkng,Bulk:Rope,Ptfe,	240.39	1	67	4	
M0008	Gskt:Asme B16.20	21.27	2	126	2	
M0009	Proximitr:5mm Probe Dia,	1021.07	2	189	4	
M0010	Cable,Elec:Ext,8m Lg,	291.99	2	67	4	
	.					
	.					
	.					
M9842	Mat:Drop Object Prevention,	264.39	2	77	4	

<u>Step 3</u>: Determine the average solution according to all criteria
<u>Step 4:</u> Positive distance from average (PDA) and the negative distance from average (NDA) matrixes are calculated according to the type of criteria (benefit and cost) as illustrated in Table 4. The researcher considers two measures for the appraisal scors which are called Positive Distance from Average (PDA) and Negative distance from Average (NDA). The four criteria are classified as a beneficial type of criteria based on the positive impact of criteria on criticality: the more is better (Benefit):

- Inventory Status: The faster an item moves, the more critical it is.
- Spare Unit Price: The higher the unit price of an item, the more critical it is.
- Planned Delivery Time**:** The longer lead time of an item, the more critical it is.
- Spare Criticality: The higher the importance of an item from safety, production or maintenance perspectives, the more criterial it is.

PDA and NDA calculations are illustrated below in Table 5 and Table 6, respectively:

Table 5. PDA Calculations

Material	Unite Price	Criticality	Delivery Lead Time	Inventory Status
	PDA	PDA	PDA	PDA
M0001	0.0	0.0	0.0	0.00000
M0002	0.0	0.0	0.0	0.02740
M0003	0.0	0.0	0.0	0.0
M0004	0.0	0.0	0.0	0.0
M0005	0.0	0.0	0.0	0.0
M0006	0.0	0.16905	0.16905	0.0
M0007	0.0	0.0	0.00000	0.36986
M0008	0.0	0.16905	0.16905	0.00000
M0009	0.0	0.75357	0.75357	0.36986
M0010	0.0	0.0	0.0	0.36986
.	.	.	.	.
M9842	0.0	0.0	0.0	0.36986

Table 6. NDA Calculations

Table 6. NDA Calculations

Material	Unite Price	Criticality	Delivery Lead Time	Inventory Status
	NDA	NDA	NDA	NDA
M0001	0.9	0.0	0.37836	0.31507
M0002	0.4	0.0	0.53609	0.00000
M0003	0.9	0.0	0.44331	0.31507
M0004	0.9	0.1	0.37836	0.31507
M0005	1.0	0.1	0.37836	0.31507
M0006	0.99030	0.13420	0.0	0.31507
M0007	0.85656	0.56710	0.37836	0.00000
M0008	0.98731	0.13420	0.0	0.31507
M0009	0.39074	0.13420	0.0	0.0
M0010	0.82577	0.13420	0.37836	0.0
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
M9842	0.8	0.1	0.28558	0

Step 5: As illustrated in the methodology section, instead of using the mean (Table 6) as equal weight for all criteria, the weights are calculated using liner programming model. The table below shows 11 pairs of scores are calculated, where each pair corresponds to optimistic level. The LP is written as below. The value of w is calculate using Microsoft excel where n=4,

$$\min \ \delta$$

$$s.t.\ w1 + \frac{2}{3}\ w2 + \frac{1}{3} w3 = \alpha \quad \alpha \in [0,1]$$

$$\begin{aligned} w1+w2+w3+w4 &= 1 \\ w1 - w2 - \delta &\le 0 \\ w2 - w3 - \delta &\le 0 \\ w3 - w4 - \delta &\le 0 \\ w1 - w2 + \delta &\ge 0 \\ w2 - w3 + \delta &\ge 0 \\ w3 - w4 + \delta &\ge 0 \\ w1, w2, w3, w4 &\ge 0 \end{aligned}$$

Table 7 below depicts the Weights calculated using LP that are calculated as part of step 7:

Table 7. Weights calculated using LP

Orness	w1	w2	w3	w4
0.25	0.025	0.175	0.325	0.475
0.30	0.070	0.190	0.310	0.430
0.35	0.115	0.205	0.295	0.385
0.40	0.160	0.220	0.280	0.340
0.45	0.205	0.235	0.265	0.295
0.50	0.250	0.250	0.250	0.250
0.55	0.295	0.265	0.235	0.205
0.60	0.340	0.280	0.220	0.160
0.65	0.385	0.295	0.205	0.115
0.70	0.430	0.310	0.190	0.070
0.75	0.475	0.325	0.175	0.025

The Sum product is calculated to assign highest weight to the highest value of criteria for the approach of pessimistic decision maker. For the pessimistic decision maker, the smallest weight is assigned to the largest value of criteria. The weights are increasing for α between 0.25- 0.45 for the pessimistic decision maker while they are decreasing for α between 0.55- 0.75 for the optimistic decision maker. The below formulas are used to calculate the SP_i and SN_i. Table 8 & Table 9, shows the results of SP and SN, respectively:

Table 8. The Results of SP

Material	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75
M0001	0	0	0	0	0	0	0	0	0	0	0
M0002	0.001	0.002	0.003	0.004	0.006	0.007	0.008	0.009	0.011	0.012	0.013
M0003	0	0	0	0	0	0	0	0	0	0	0
M0004	0	0	0	0	0	0	0	0	0	0	0
M0005	0	0	0	0	0	0	0	0	0	0	0
M0006	0.034	0.044	0.054	0.064	0.074	0.085	0.095	0.105	0.115	0.125	0.135
M0007	0.009	0.026	0.043	0.059	0.076	0.092	0.109	0.126	0.142	0.159	0.176
M0008	0.034	0.044	0.054	0.064	0.074	0.085	0.095	0.105	0.115	0.125	0.135
M0009	0.271	0.311	0.350	0.390	0.430	0.469	0.509	0.549	0.588	0.628	0.668
M0010	0.009	0.026	0.043	0.059	0.076	0.092	0.109	0.126	0.142	0.159	0.176
M0011	0.106	0.138	0.170	0.202	0.234	0.265	0.297	0.329	0.361	0.393	0.425
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
M9842	0.009	0.026	0.043	0.059	0.076	0.092	0.109	0.126	0.142	0.159	0.176

Table 9. The Results of SN

Material	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
M0001	0.191	0.232	0.272	0.313	0.354	0.395	0.436	0.476	0.517	0.558	0.599
M0002	0.084	0.114	0.145	0.175	0.205	0.235	0.265	0.296	0.326	0.356	0.386
M0003	0.203	0.245	0.288	0.330	0.373	0.415	0.458	0.500	0.543	0.585	0.628
M0004	0.256	0.292	0.329	0.366	0.403	0.440	0.476	0.513	0.550	0.587	0.624
M0005	0.256	0.295	0.333	0.372	0.410	0.448	0.487	0.525	0.563	0.602	0.640
M0006	0.124	0.171	0.218	0.265	0.313	0.360	0.407	0.454	0.502	0.549	0.596
M0007	0.244	0.285	0.326	0.368	0.409	0.451	0.492	0.533	0.575	0.616	0.657
M0008	0.123	0.171	0.218	0.265	0.312	0.359	0.406	0.453	0.501	0.548	0.595
M0009	0.033	0.053	0.072	0.092	0.112	0.131	0.151	0.170	0.190	0.210	0.229
M0010	0.130	0.171	0.212	0.253	0.294	0.335	0.375	0.416	0.457	0.498	0.539
M0011	0.115	0.146	0.177	0.209	0.240	0.272	0.303	0.334	0.366	0.397	0.428
	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.
M9842	0.115	0.155	0.195	0.235	0.275	0.316	0.356	0.396	0.436	0.476	0.516

Step 6: Normalize the values of SP and SN for all alternatives, the results for NSP and NSN are shown as follows in Table 10 and Table 11:

Table 10. The Results of NSP

Orness	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
Max(SP)	4.25	11.88	19.52	27.16	34.80	42.43	50.07	57.71	65.35	72.98	80.62
Material	**NSP**										
M0001	0	0	0	0	0	0	0	0	0	0	0
M0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
M0003	0	0	0	0	0	0	0	0	0	0	0
M0004	0	0	0	0	0	0	0	0	0	0	0
M0005	0	0	0	0	0	0	0	0	0	0	0
M0006	0.008	0.004	0.003	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
M0007	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
M0008	0.008	0.004	0.003	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
M0009	0.064	0.026	0.018	0.014	0.012	0.011	0.010	0.010	0.009	0.009	0.008
M0010	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
M9842	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002

Table 11. The Results of NSN

Orness	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
Max (SP)	0.50	0.53	0.56	0.59	0.62	0.66	0.69	0.72	0.77	0.82	0.87
Material	**NSN**										
M0001	0.617	0.563	0.515	0.472	0.433	0.398	0.366	0.342	0.332	0.323	0.316
M0002	0.831	0.784	0.742	0.705	0.672	0.642	0.614	0.592	0.579	0.568	0.559
M0003	0.594	0.537	0.488	0.443	0.403	0.367	0.334	0.309	0.299	0.290	0.283
M0004	0.487	0.448	0.414	0.383	0.355	0.330	0.307	0.291	0.290	0.288	0.287
M0005	0.485	0.443	0.406	0.373	0.343	0.317	0.292	0.275	0.273	0.270	0.268
M0006	0.752	0.678	0.612	0.552	0.499	0.451	0.408	0.372	0.352	0.334	0.318
M0007	0.511	0.462	0.419	0.380	0.345	0.313	0.284	0.264	0.258	0.253	0.249
M0008	0.752	0.678	0.612	0.553	0.500	0.452	0.409	0.374	0.354	0.336	0.320
M0009	0.933	0.900	0.871	0.845	0.821	0.800	0.781	0.765	0.755	0.746	0.738
M0010	0.738	0.677	0.622	0.573	0.530	0.490	0.454	0.425	0.410	0.396	0.384
	.	.	.	.	.	.	.	.	.	.	.
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M9842	0.770	0.708	0.653	0.603	0.559	0.519	0.483	0.453	0.437	0.423	0.410

Step 7: Calculate the appraisal score (AS) for all alternatives, AS= 1/ 2 (NSPi + NSNi), for each alternative. Table 12 shows the results of AS calculations:

Table 12. The Results of AS

Orness	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
1	0.309	0.281	0.257	0.236	0.217	0.199	0.183	0.171	0.166	0.162	0.158
2	0.416	0.392	0.371	0.353	0.336	0.321	0.307	0.296	0.290	0.284	0.279
3	0.297	0.269	0.244	0.222	0.202	0.184	0.167	0.155	0.150	0.145	0.141
4	0.243	0.224	0.207	0.191	0.177	0.165	0.153	0.146	0.145	0.144	0.144
5	0.243	0.222	0.203	0.187	0.172	0.158	0.146	0.138	0.136	0.135	0.134
6	0.380	0.341	0.307	0.277	0.251	0.227	0.205	0.187	0.177	0.168	0.160
7	0.257	0.232	0.210	0.191	0.173	0.158	0.143	0.133	0.130	0.128	0.125
8	0.380	0.341	0.307	0.278	0.251	0.227	0.205	0.188	0.178	0.169	0.161
9	0.499	0.463	0.444	0.430	0.417	0.405	0.395	0.387	0.382	0.377	0.373
10	0.370	0.339	0.312	0.288	0.266	0.246	0.228	0.214	0.206	0.199	0.193
9842	0.386	0.355	0.327	0.303	0.281	0.261	0.242	0.228	0.220	0.212	0.206

Step 8: Rank the alternatives according to ABC classification. The ranking pattern followed is illustrated as follows:

- $0.45 < AS$, Corresponds to A Class
- $0.3 < AS \leq 0.45$, Corresponds to B Class
- $0 \leq AS \leq 0.3$, Corresponds to C Class

In EDAS method, the values of AS are ranked using ABC classification. In this research, AS values are also ranked through ABC classification as illustrated in Table 11 and Table 12. EDAS follows three ranking patterns that depend on the value of AS. For alternatives that have AS value greater than 0.45, class A is assigned to the alternative. As shown in table 11 with alternative M0009 for orness value equal to 0.25 & 0.30, the alternative is assigned with A class. When AS value of an alternative falls within the range between 0.3 and 0.45, class B is assigned to the alternative. M0002 is an example of alternative has AS value within the range of $0.3 < AS \leq 0.45$ and assigned with B class. C class is assigned to alternatives that have AS values less than 0.3. Alternative M0001 are indicated with C in all orness values within the optimism level except for orness value equal to 0.25 as shown below (Table 13) in the result of ABC classification.

Table 13. Results of ABC Classification

Orness	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
M0001	B	C	C	C	C	C	C	C	C	C	C
M0002	B	B	B	B	B	B	B	C	C	C	C
M0003	C	C	C	C	C	C	C	C	C	C	C
M0004	C	C	C	C	C	C	C	C	C	C	C
M0005	C	C	C	C	C	C	C	C	C	C	C
M0006	B	B	B	C	C	C	C	C	C	C	C
M0007	C	C	C	C	C	C	C	C	C	C	C
M0008	B	B	B	C	C	C	C	C	C	C	C
M0009	A	A	B	B	B	B	B	B	B	B	B
M0010	B	B	B	C	C	C	C	C	C	C	C
M0011	B	B	B	B	B	C	C	C	C	C	C
M0012	A	A	A	A	A	A	A	A	A	A	A
M0013	A	B	B	B	B	B	B	C	C	C	C
M0014	A	B	B	B	B	B	B	C	C	C	C

M0015	A	B	B	B	B	C	C	C	C	C	C
M0016	A	B	B	B	B	B	C	C	C	C	C
M0017	A	B	B	B	B	C	C	C	C	C	C
M0018	A	B	B	B	B	C	C	C	C	C	C
M0019	B	B	B	B	C	C	C	C	C	C	C
M0020	A	A	A	A	B	B	B	B	B	B	B
M0021	C	C	C	C	C	C	C	C	C	C	C
M0022	A	A	A	A	B	B	B	B	B	B	B
M0023	B	B	B	B	B	B	B	B	B	B	B
M0024	C	C	C	C	C	C	C	C	C	C	C
M0025	C	C	C	C	C	C	C	C	C	C	C
M0026	B	B	B	C	C	C	C	C	C	C	C
M0027	B	B	B	C	C	C	C	C	C	C	C
M0028	B	B	B	C	C	C	C	C	C	C	C
M0029	B	C	C	C	C	C	C	C	C	C	C
M0030	A	A	A	A	A	A	A	A	A	A	A
M9842	B	B	B	B	C	C	C	C	C	C	C

5. Results & Discussion

Through the EDAS process, the results shows that the ABC criticality classification is assigned to the alternatives which represents the operations& maintenance spares. The results of classification identify the proportion differences of ABC classification classified at different optimism level (optimistic& pessimistic) in comparison with classification determined through the average weight 0.5 used in the original EDAS that assume equal importance to all criteria. The proportion differences of the ABC classification are illustrated in Table 13 below. In addition, table13 shows less variation between classification for the optimistic decision maker which supports the objective of minimizing the gap between the weights. The proportion for orness values equal to 0.55 is 6.323. For the pessimistic decision maker, where α between 0.25 &0.45, the difference of the classifications is significant compare to the mean.

The results also present that the variation proportion within the optimism level varies between the optimistic and pessimistic decision maker. There is less variation between the results of the classification for the optimistic decision maker while the variation within the pessimistic is quite high. The percentage of variation when α equal to 0.25 is 66.961% while the variation when α equal to 0.45 is 8.9607. The variation proportion between AV & OWA are demonstrated below in Table 14 and Figure 1.

Table 14 Difference between AV & OWA

Orness	**0.25**	**0.30**	**0.35**	**0.40**	**0.45**	**0.50**	**0.55**	**0.60**	**0.65**	**0.70**	**0.75**
Proportion	66.961	53.419	35.416	20.248	8.961	0.000	6.329	8.900	10.312	11.206	11.785

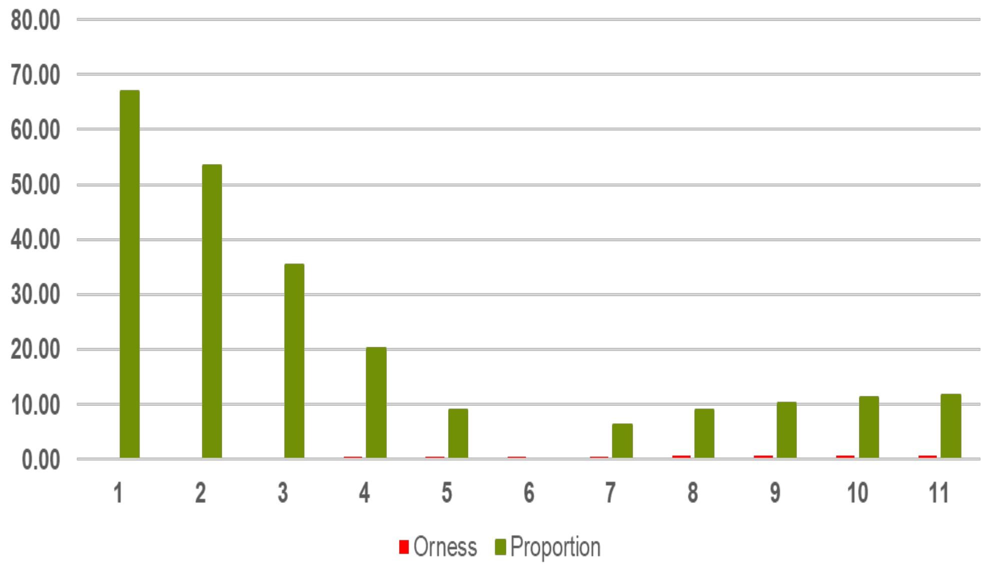

Figure 1. Difference between AV & OWA

The research discusses the results of assigning ABC classification to the value of Appraisal Score (AS) calculated using the EDA through the measures of PDA & NDA. Table 1 presents the sizes of classes: A, B and C at the optimism level. The results shows that the sizes of criticality classification are not affected by the attitude of Decision Makers and this can be noticed clearly at optimistic approach. The following Table 15 presents the sizes of classes for each orness value:

Table 15. Size of Classes

Orness	**0.25**	**0.30**	**0.35**	**0.40**	**0.45**	**0.50**	**0.55**	**0.60**	**0.65**	**0.70**	**0.75**
A	2885	1810	1117	921	803	590	492	461	442	437	433
B	5412	5895	5509	4408	3533	3077	2650	2459	2362	2292	2245
C	1545	2137	3216	4513	5506	6175	6700	6922	7038	7113	7164

The below graph (Figure2) depicts that the sizes of class A within the optimism level is stable as the number of items within the sample is in the range of 400-500 for the optimistic approach. The size of class A when α equal to 0.75 is 433 items and 492 when α equal to 0.55. The sizes of samples are also close for classes B and C, which indicates that the size of classes is not influenced by the attitude of the optimistic Decision Maker. In pessimistic approach, there is large variation in the size of classes, particularly with class C. The size of class C when α equal to 0.45 is 5506 items and 1545 when α equal to 0.25.

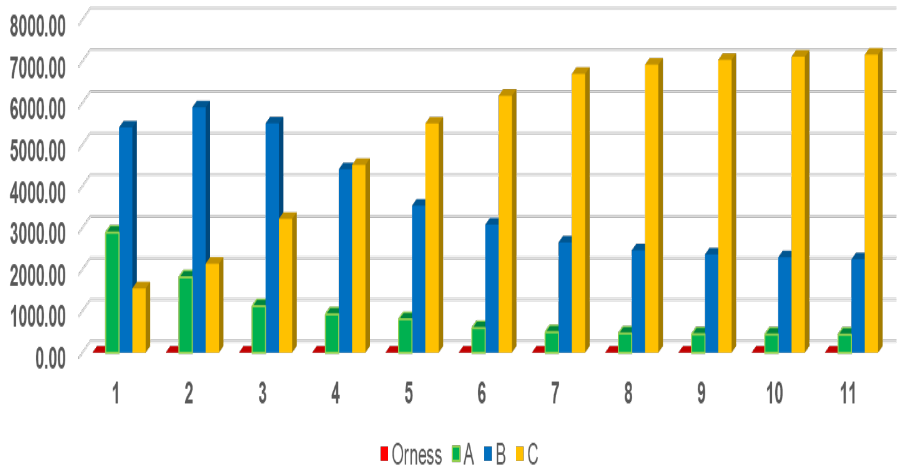

Figure 2. Size of Classes

5.1 Data & Results Validity

The result of arithmetic mean (0.5), which corresponds to the EDAS approach, is compared with other OWA using T-test to check the data validity and the range of differences. however; the T-test rejects the null hypothesis as P-value < 0.5. Therefore, Figure 2 shows comparison between the ranking instead of comparing the scores.

6. Conclusion

This section presents a summary of the study, discusses the practical implementation and future recommendations as detailed below:

The research objective was to establish a tool for spare parts inventory classification. The framework tool was developed with application from oil & gas industry. A total of 9842 out of 13,488 of Spares were utilized in this research. The study proposes a method of Evaluation based on Distance from Average Solution (EDAS). This study introduces the use of the MMD to calculate the weight into the EDAs method. Instead of assuming equal weights to all selected criteria, the proposed methods calculated the Ordered Weight Averaging (OWA) using LP Model. The selection of the four criteria (Unit Price, Criticality, Delivery Time &Inventory Status) is based on the reasons explained above, which are related to the importance of these criteria to the Supply chain management as inventory KPI. To ensure data validity as well, all the data and criteria are exported from ERP system, which is the only system to report and record inventory transactions as a reliable source of data.

A point of discussion would be whether EDAS is the suitable method to be used. From the researcher's viewpoint, the literature review of EDAS presents that the method is easy to be adapted by any company with no investment on special software, especially considering that the case company, during the time of this study, is not relying on any tools in spares classification, except that they are depending on maintenance experience and the history of consumption. On the other hand, and through the review of EDAS, assigning equal weights to all criteria does not really reflect the actual practices so it presents a gap to the method implementation. In addition, the criteria in EDAS are sorted according to PDA & NDA, indicating that there is no subjectivity or, more precisely, regulated subjectivity within the optimism level of decision making.

6.1 Practical Implications & Recommendation

The research finding illustrated identifies 3 classes of criticality: A, B and C, the managerial focus will be on A class as the most critical spares. The optimism level reduces the size of A sample. From a managerial side, instead of the company managing around 9 thousand spares, they will manage a number of spares in the range from 400 to 500 items. On the flip side, since the size of C class is larger, it will definitely have the least priority as its spares are less critical. Therefore, the supply chain management can take a decision to eliminate the C class spares from the inventory or negotiate the option to treat them as consignment so the supplier will take the ownership and responsibility of managing the spares. Additionally, classifying spares into classes will provide the company with a tool to prioritize them based on the score, the higher the score, the higher the priority given to the item. There is a capacity to rank from the highest score to the lowest so the company can identify which items in each class should be given more priority.

From a financial side and given the reduced size of A class, the company can invest on a continuous review system and implement the period review system for C class. The continuous review system is more expensive to implement for inventory control, however; it can be less costly for the proposed size of class A than investing this inventory control for the full inventory size.

6.2 Limitation & Future Work

This could be referred to as an extension of this work instead of calling it a limitation. There will be chance to consider the original spares categories: Mechanical Electrical, Instruments and Chemical, particularly if there are different maintenance teams responsible for each category. In the methods, future research could study how the spare parts inventory classification influences reduction of the internal workload required for Inventory Control.

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