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Inventory classification system in space mission component replenishment using multi-attribute fuzzy ABC classification

Purpose – This project attempts to present a space component inventory classification system for space inventory replenishment and management. We propose to adopt a classification system that can incorporate all the different variables in a multi-criteria configuration. Fuzzy logic is applied as an effective way for formulating classification problems in space inventory replenishment.
Design/methodology/approach – A fuzzy based approach with ABC classification is proposed to incorporate all the different variables in a multi-criteria configuration. Fuzzy logic is applied as an effective way for formulating classification problems in space inventory replenishment of the Soil Preparation System (SOPSYS) which is used in grinding and sifting Phobos rocks to sub-millimeter size in the Phobos-Grunt space mission. An information system was developed using the existing platform and was used to support the key aspects in performing inventory classification, and purchasing optimization.
Findings – The proposed classification system was found to be able to classify the inventory and optimize the purchasing decision efficiency. Based on the information provided from the system, implementation plans for the SOPSYS project and related space projects can be proposed.
Research limitations/implications – The paper addresses one of the main difficulties in handling qualitative or quantitative classification criteria. The model can be implemented using mathematical calculation tools and integrated into the existing inventory management system. The proposed model has important implications in optimizing the purchasing decisions to shorten the research and development of other space instruments in space missions.
Originality/value – Inventory management in the manufacture of space instruments is one of the major problems due to the complexity of the manufacturing process and the large variety of items. The classification system can optimize purchasing decision making in the inventory management process. It is also designed to be flexible and can be implemented for the manufacture of other space mission instruments.
Keywords – Aerospace; replenishment; information system; inventory management; fuzzy ABC classification; Soil Preparation System
Paper type – Research paper

1 Introduction

Inventory acts as a buffer to the product flow in the supply chain. It can be managed manually in a small firm, however, it can be a problem if companies need to manage thousands of different items or materials in their inventory. In many studies on inventory management over the years, numerous methods and applications have been proposed for optimizing the inventory management process. However, only a few studies are related to space inventory management. There is also the issue of security since the data and information on space components and inventory are usually sensitive which results in its non-disclosure.

Effective inventory management in an information system is of crucial importance for those industries where high accuracy of product manufacture scheduling is required, such as aircraft and space-related manufacturing. Because of the complexity of the manufacturing process in the space industry, great attention is directed to different classes of inventory in which different decision processes and policies are required.

Despite there being much research in decision support for inventory management, most of the research is focused on the manufacturing industries and industrial applications. Puurunen et al. (2014) explored a real-life situation in the implementation of an optimization model by evaluating the use of incomplete data in stochastic simulation-based inventory optimization for industrial maintenance. Nakandala et al. (2014) explored cost optimization methods to tackle the uncertain demand environment for cost minimization, different industrial scenarios being used as a case study. Until now, there have not been many studies in information systems that have been conducted in aviation companies. Despite Corallo et al. (2010) conducting interviews in an aerospace company to identify objective methods for the competence management process, the study was mainly based on a qualitative approach. The quantitative approach to support inventory management in information systems to support replenishment decisions was not discussed. Recently, Qin et al. (2020) proposed building a novel model to assist in aircraft MRO procurement and overhaul management problems to support the aerospace industries. Nevertheless, research in inventory information systems for practical space missions is difficult to find.

For a real-life aerospace situation, the development of space instruments needs to consider various criteria qualitatively and quantitatively. For instance, in a space mission instrument, we need to consider the cost of the components, components lead time, duration, substitutability, manufacturing method, availability of the supplier, materials to be used in order to withstand the extraordinary environment requirements such as minimal gravity, vibration, cosmic dust, huge daily temperature changes, etc., as well as the linguistics variables. The number of factors and considerations in a space mission is much higher than in usual industrial applications. These different factors and criteria should be taken into consideration in order to make the system more comprehensive, as tolerance towards error is critical. Therefore, this research presents the following major research difficulties that need to be considered in space instruments information system:

1. How to cope with various qualitatively and quantitatively criteria in the development of space instruments
2. How to ensure the reliability of the information system to support the inventory replenishment decision.

This research is critically important as the timeline of space exploration is very tight, and the lead time due to the shortage and replenishment of the inventory items may directly affect the manufacturing schedule. On the other hand, most of the space inventory items cannot be replaced by other types of material and have very low substitutability. The workflow of each inventory replenishment process will contribute to the overall timeline and the possibility of missing the scheduled space mission. This research presents the core contributions not only in extending the classification system to incorporate different qualitative and quantitative variables with multi-criteria to be applied in other aerospace industries, but the model can also be implemented using mathematical calculation tools and integrated into the existing widely adopted inventory management system to ensure higher reliability of the information system. The research is important to support operations, management, and decision-making in an information system.

This paper proposes a space inventory classification system in space inventory replenishment based on Fuzzy ABC classification. An interview was conducted with the inventory manager, who is experienced in space component replenishment, to obtain the fuzzy rule needed for the system. ABC classification with fuzzy variables has been used to classify the inventory items. Fuzzy logic has been applied for formulating the classification problems in space inventory replenishment. Items in the Soil Preparation System (SOPSYS), which is used in grinding and sifting Phobos rocks to sub-millimeter size in the Phobos-Grunt space mission are used in the case study. Further elaboration on the SOPSYS and the optimization theories for workflow management can be found in Yung et al. (2020). The proposed classification approach can also be used in other applications for operations management in an information system.

2. Literature Review

This section presents a review of multi-attribute inventory classification, fuzzy inventory management, and workflow optimization in an information system. The purpose of the study is to review the past research on the concept of multi-attribute classification, the fuzzy logic application in inventory classification, and other inventory management methodologies that are relevant to the study.

2.1 Multi-attribute classification

For most existing inventory systems, the number of stock keeping units (SKUs) is usually too large so that is not feasible to manage every item with equal amounts of resources (Ernst and Cohen, 1990). As a result, items have been classified into different groups and different inventory policies are set for each group of items (Chakravarty, 1981). The grouping method provides an effective means to specify, monitor, and control different inventory items.

Traditionally, ABC classification, representing very important, moderately important, and least important aspects, from A to C, is employed to aggregate the items with the philosophy of concentrating on a "significant few" and spending less on the "trivial many" (Xiao et al, 2011). The top 20% of items with the highest annual usage value are classified as A, followed by B with 30% of items and the bottom 50% as C (Flores and Whybark, 1986). Although the original ABC classification method is aggregated by the annual usage value, authors agree that other inventory criteria such as lead time, ordering cost, commonality, durability, and criticality should be taken into consideration during the classification (Flores and Whybark, 1987; Fuvenir & Erel 1998; Ramanathan, 2006). Iqbal and Malzahn (2016) exposed another main weakness of the transition ABC classification is that the model would become infeasible once there are some items with identical scores. Due to the limitation of the ABC classification approach, several authors have stated that the traditional ABC classification method may not be able to provide a reliable classification of inventory items (Huiskonen, 2001; Partovi and Anandarajan, 2002). Thus, the multi-attribute classification method was proposed to take more criteria into account.

Regarding the methodology of classification, researchers have proposed some heuristic classification models. A classification model using genetic algorithms to determine the weights of the criteria was proposed by Guvenir and Erel (1998). The limitation of the genetic algorithm is the restriction in having a single considering factor. To overcome this issue, Partovi and Anandarajan (2002) proposed the artificial neural network (ANN) approach which learns the optimal weights of different attributes. Moreover, TOPSIS was proposed by Bhattacharya et al (2007) to further optimize the machine learning method by solving the conflicting criteria with incommensurable measures. A decision trees classification model was proposed to classify the whole set of items automatically (Lolli et al, 2017). Particle swarm optimization has been employed to create multi-attribute inventory classification which performs comparatively better and possesses flexibility the numbers of items and objectives (Tsai and Yeh, 2008). The meta-heuristic approaches have an outstanding performance in handling a huge number of items. However, it may not guarantee a good result in all environments (Chuetal, 2005) and a training dataset is required to build up the learning model, which may not be available in certain circumstances (Lolli et al, 2013).

Classification based on Mathematical Optimization techniques have been proposed, which employed different linear and nonlinear models to calculate the global optimal score for each inventory item. Ramanathan (2006) proposed a simple optimization model (R-model) with Data Envelopment Analysis (DEA) to compute a single score for each inventory item. The disadvantage of the model is the inability to deal with categorical and discontinuous news. To alleviate this, Ng (2007) proposed a classification method (NG-model) that aggregated inventory items without employing a linear model. Nevertheless, the output of the NG-model is not dependent on the item weight which can lead to a situation in which the items whose score is extremely high in unimportant criteria will be classified as A-class items (Peng, and Fan, 2006). In light of this, Hadi-Vencheh (2010) suggested a nonlinear optimization model (H-V model) to improve the NG-model. It is worth mentioning that both the NG-model and the HV-model require subjective input from the manager to prioritize the criteria set (Torabi et al, 2012). The main weakness of Mathematical optimization techniques is that a huge number of model calculations are needed when the number of inventory items is large, which is difficult for the inventory manager to handle (Douissa et al, 2016).

Apart from the mathematical optimization and Meta-heuristics model, scholars have suggested another classification model, namely the Multiple Criteria Decision Analysis method (MCDA), which possesses the ability to incorporate both quantitative and qualitative criteria at the same time. Flores et al (1992) proposed the Analytical Hierarchy Process (AHP) based classification model that syntheses different weighted attributes to a priority score for each of the inventory items. The evaluation of the criteria would be performed by a pair-wise matrix (Saaty, 1980). The ranking of inventory criteria is then defined by the eigenvalue method (Ishizaka and Labib, 2011). The main advantage of the MCDA classification is that it possesses a strong ability to incorporate a large number of criteria and it is easy for the inventory manager to use on massive accounting and management system. However, the weakness of the classification is that it is largely based on the subjective judgment of the manager, which may not generate a trust worthy result.

The aforementioned studies have presented different methods for multi-attribute inventory classification. Although different methods have specific advantages for inventory classification, it is important to note that different industries or even companies may have their criteria in selecting the classification method and criteria weighting (Taylor et al, 1981). The decision maker of the company should put their problem parameters for consideration in the selection of the classification criteria.

In this paper, a case study using the components in a space mission is used to investigate the effectiveness of the method. This paper presents the three major differences compared with the previous research. Firstly, the proposed classification model can handle qualitative criteria using a linguistics interview or questionnaire result of the inventory manager and quantitative measurements (e.g. Qualitative: Criticality of stock out, Substitutability; Quantitative: Inventory shortage, Lead time, Annual dollar usage). The model can work under any form of combination, which is important for making managerial judgments. Secondly, the classification method can be easily implemented using mathematical calculation tools (i.e. MATLAB) which do not require complex mathematical calculation. Thirdly, the classification model is included in the integrated inventory management system, and the inventory manager can make the ordering decision based on the classification result in the system without building another system for inventory decision making.

2.2 Fuzzy logic with its application on Inventory classification

Over time, the inventory system for inventory managers has become more complicated due to the increasing uncertainty in conducting business (Giannoccaro et al, 2003). To cope with the uncertainty and complexity elements in the variables of the probabilistic system, soft computing techniques, including genetic algorithms, neural networks, and fuzzy logic, are usually used as an alternative to incorporate imprecision in human judgment into the calculation.

Fuzzy logic aims to resolve problems logically and analyze imprecise data to generate a satisfactory result with low cost (Ko et al, 2010). The concept of fuzzy logic introduced a logic that is similar to the logical behaviour of human intrinsic characteristics towards ambiguity in decision making processes (Cakir and Canbolat, 2008). The theory of using fuzzy logic in generalizing human reasoning is applicable in many aspects of research.

A fuzzy linguistic variable is defined as an expression in natural or artificial language for describing a number of values (Zadeh, 1975). It can define a non-numerical expression by a fuzzy model with the fuzzy number representing the degree of the expression and can be approximated by using intervals. For example, the importance of each item can be defined by the range of important, moderately important, moderately unimportant, and unimportant aspects. It is suggested that the inventory manager would be more comfortable dealing with linguistic terms instead of exact crisp judgments (Ozan et al, 2008). Vencheh (2010) has suggested the DEA-AHP to model reduce the computational requirements, and the Mikhailov model (Mikhailov, 2003), to determine the weights of criteria. Some studies suggested fuzzy data mining techniques to deal with the inventory classification problem (Hu & Tzeng, 2003; Hu et al, 2003). It is important for the process of determining the membership functions and minimum fuzzy support for deciding the fuzzy association rules.

On the other hand, inventory shortage is considered as one of the important measures impacting overall procurement lead time. This impact may affect the net present value of a company, thus the dynamic integration and optimization of inventory classification are important to maximize the company profit over the traditional ABC approach (Yang, et al., 2017). Nakandala et al. (2013) presented a fuzzy-based decision support model to monitor the performance of on-time delivery. The model considers variations in demand forecasting including inventory shortage, distribution lead time, etc. These measurements are important in consideration of the fuzzy logic for inventory classification to minimizing business loss.

2.3 Workflow optimization in an information system

An information system is important in handling the flow, as well as the information that supports an industry in operation business decisions. It is an interpretation of data and systematic derivation of the data (Arif, 2012). It is usually defined technically as a set of interrelated elements, which are collected, processed and stored systematically. The information can be distributed and retrieved to support decision making and optimize the process workflow in an industry (Berisha-Shaqiri, 2014).

Workflow optimization in an information system is particularly important as an information system usually consists of a vast amount of data. This information can be used for the task redesign process and optimizing the production workflow. Studies in workflow optimization have been conducted for many years, and can be applied in many different industries, manufacturing plant, and manufacturing process, as well as the aerospace company. Huang (2019) conducted an empirical investigation on the joint effects on reverse factoring adoption from the suppliers' perspective in regard to manufacturing companies. Du et al. (2018) made use of CPN modeling and simulation methods over a period of time in order to study the time and throughput of data-aware workflows. It can be used to reflect the actual workload and gross profit of an enterprise. Nevertheless, most of the existing workflow optimization is applied in logistics, manufacturing, or industrial applications, study related to the aerospace industry is still deficient. Abollado & Shehab (2018) proposed workflow optimization be applied in the aerospace manufacturing industry, however only a framework was proposed in their study. To our best knowledge, this is our first attempt to adopt the information systems to support replenishment decisions in a space mission.

3 Methodology and Data

To perform the Fuzzy Multi-Attribute ABC Classification for space mission component replenishment, the existing information system, SAP, was used as the platform for data management. The mathematical calculation tool, MATLAB was used to perform the fuzzy model calculation and integrate into the existing inventory management system to ensure the reliability, availability, and usability of the information system. In the system, knowledge of the materials and rules were used as the input to support the calculation. In this paper, we make use of the bill of materials (BOM) of the space instrument, SOPSYS, as a case study. On the other hand, the knowledge acquired from the inventory manager is used to build knowledge of the materials and the pre-assigned IF-THEN rules in the classification system. The workflow of the fuzzy classification model is illustrated in Figure 1. At the beginning of constructing the classification system, the knowledge aspects including the Fuzzy variables and weighting are determined based on the knowledge acquisition process. This knowledge can be affected by the information acquired in the classification system. By determining the relationship between the fuzzy variables and the space inventory, the weights of the fuzzy variables can also be assigned. Then, the fuzzy decision matrix can be constructed. Finally, the classification rules are set up and used in the classification model.

3.1 Fuzzy Multi-Attribute ABC Classification

Since the criteria of assessing and classifying space mission components include both qualitative and quantitative criteria, the Multiple Criteria Decision Analysis method (MCDA) is considered as the best ABC classification method for this study. Fuzzy logic is employed for conducting multi-attribute inventory classification. The fuzzy variables were determined by the interview result with the inventory manager of the space project and then inputted to the fuzzy model classification using MATLAB as the software.

Step 1: Knowledge Acquisition
In advance of determining the criteria and weighting of the classification system, a structured interview was conducted with the inventory manager of the SOPSYS mission. A set of questions was prepared for determining the following inputs of the system:

1) Fuzzy variable of the classification system;
2) Weighting of the fuzzy variable in the system;
3) IF-THEN rules of the classification system

Step 2: Determining Fuzzy Criteria
After interviewing the space inventory manager, it was found that several significant factors can effectively classify the importance of the space inventory items. In the proposed classification method, different criteria are selected as the candidates to be the input variable of the fuzzy system, which include lead time, number of available suppliers, product lifetime, and substitutability.

Step 3: Construction of the Fuzzy Decision Matrix
In order to conduct the fuzzy classification, a membership function is required for presenting the behavior of the fuzzy variable. It is proposed that the membership functions can be obtained by breaking down the restriction of the fuzzy variable (Tamaki et al, 1998). However, this method requires a complex procedure to identify the membership function. Also, different types of fuzzy membership functions have been proposed by scholars such as the triangular membership function, trapezoidal membership function, Gaussian membership function, and Z Spline membership function which can be employed in the fuzzy classification. (Medasani et al., 1998; Zhou & Khotanzad, 2007). According to the result of the interview with the space inventory manager, it was found that the fuzzy variable related to space inventory demonstrated a linear relation in the case study. Therefore, the triangular fuzzy membership function is employed (Figure 2). After the process of knowledge acquisition, different weights are assigned to the inventory criteria according to the importance of the criteria (see Table I).

Insert Table I here

According to Chang (1992), the pair-wise comparison approach is based on Triangular Fuzzy Numbers (TFNs),

Let $X = \{x1, x2,...,xn\}$ be an object set

$U = \{u1,u2 ,....,um\}$ is a goal
$M = M_{gi}^{1}, M_{gi}^{2}, \ldots, M_{gi}^{m} 1$, i=1,2,3,...,n are extent analysis values (a, b, c) with the most and largest possible values.

In the fuzzy classification, the TFNs are firstly determined based on the pair-wise comparison using a fuzzy analytic hierarchy process scale. Then, the extent analysis method is conducted to obtain the priority weights based on the synthetic extent value of the comparison. By making use of the different criteria relevant to the overall objectives in the fuzzy linguistic variables and TFNs, the criteria of the fuzzy evaluation matrix can be created.

We define the value of the fuzzy synthetic extent concerning the i^{th} object as:

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

The degree of possibility of M_1 and M_2 is defined as:

$$V(M_1 \geq M_2) = \sup_{x \geq y} \lfloor \min(\mu_{M_1}(x), \mu_{M_2}(y) \rfloor.$$

When a pair of (x, y) exists, and $x \geq y$ and $\mu_{M1}(x) = \mu_{M2}(x), V(M_1 \geq M_2) = 1$.

M_1 and M_2 are convex fuzzy numbers, is given by:

$$V(M_1 \geq M_2) = 1 \quad \text{iff} \quad m_1 \geq m_2$$

$$V(M_1 \geq M_2) = \text{hgt}\ (M_1 \cap M_2) = \mu_{M_1}(d),$$

where d is the y-coordinate of the highest intersection point between μ_{M1} and μ_{M2} (see Figure 3).

When $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$, the y-coordinate of the highest intersection point is given by

$$V(M_2 \geq M_1) = \text{hgt}\ (M_1 \cap M_2)) = \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}.$$

M1 and M2 are compared by determining both values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$.

The possibility for a convex fuzzy number > k for $M_i(i = 1,2,\dots k)$ can be defined by

$$\begin{aligned} V(M \geq M_1, M_2, \dots, M_k) &= V[(M \geq M_1) \\ &\text{and } (M \geq M_2 \text{ and} \dots \text{and } (M \geq M_k)] \\ &= \min V(M \geq M_i), i = 1, 2, 3, \dots, k. \end{aligned}$$

Assume that:

$$d'(A_i) = \min V(S_i \geq S_k).$$

For k=1, 2, ..., n; where k is not equal to i, then the weight vector is given by:

$$W' = (d'(A_1), d'(A'_2), \dots, d'(A_n))^T$$

where $A_i(i = 1,2,\dots n)$ consists of n elements.

By performing normalization, the normalized weight vectors is given by:

$$W = (d(A_1), d(A_2), \dots, d(A_n))^T$$

where W is a non-fuzzy number.

Step 4: Rule Firing and Defuzzification

After determining the fuzzy variables and membership functions, different rules were structured according to the knowledge acquired during the structured interview with the inventory manager. All the data were inputted into the fuzzy inference system. MATLAB was employed for the computation of the fuzzy system for calculating the defuzzification.

Step 5: Application of Multi-Attribute ABC Classification

According to the output scores of the calculation in the software for each of the inventory items, the inventory groups are described as class A, class B, and class C based on the methodology of ABC classification mentioned in the literature. Different groups represent different meanings of the classification system. For class A, it means this item is of significantly high importance whereas a class C item has relatively low importance. This classification result is taken into consideration for the classification system below.

4 Experimentation and Results

In this project, a case study for the SOPSYS is employed to examine the effectiveness of the proposed inventory classification in the inventory management process of the information system. The inventory item dataset was collected from an actual space mission to provide valid evidence for proving the feasibility and effectiveness of the proposed classification system. The device was used for the Phobos Grunt mission to Mars in November 2011. Figure 4 shows the outlook of the SOPSYS. The SOPSYS is capable of grinding rocks on Phobos down to less than one millimeter in diameter for in-situ analysis and bringing them to Earth for the study of the solar system and the formation of Mars. In order to withstand the extreme environment on Mars, the system was made to be able to withstand minimal gravity, vibration, cosmic dust, and huge daily temperature changes. Under the constraint of the space project, this system was designed to be small and weigh only 400 grams, under precise specifications for each component.

To perform the experimental studies, data was collected based on the inventory items from the BOM. The data was used as the input of the fuzzy classification system and was fuzzified in the fuzzy inference engine according to the fuzzy membership function. The outputs named as the purchase index in this study were calculated according to the pre-defined rules in the fuzzy classification system. Finally, the result was defuzzied to a non-fuzzy variable which is an index within pre-assigned ranges (Purchase Index). The ABC classification was determined according to the purchase index of the different inventory items. The inventory item with the highest purchase score was classified as a Class A item, followed by 20% of the inventory items classified as Class B, and the remaining items are classified as Class C. This classification result serves as a reference for the inventory manager to make the purchase decisions and better manage the project schedule by optimizing the time needed for the purchase process. The results for the quantitative and qualitative analysis, as well as the classification, are illustrated in the following sections.

4.1 Quantitative Analysis Result (System criteria)

The BOM of SOPSYS was used to investigate details of the inventory items. In the illustration of the case study, the BOM information is focused on the assembly method, the number of inventory items, part numbers, and items description. There are 54 items in the BOM list, with 11 assembly items and 43 parts, in which 50% (27 items) of the inventory items come from in-house fabrication, and 31.5% (17 items) were outsourced. There are only 7.4% (4) items made by vendor fabrication and 5.56% (3 items) are made by purchase consigned to the vendor. Based on this information, half of the materials required further processing after receiving from the supplier and the processing time contributed to the total manufacturing time of the inventory items. Thus, this type of inventory item should be purchased in advance so as to prevent any delay in the schedule.

4.2 Qualitative Analysis Result (Fuzzy Variable)

From the result of the quantitative data analysis, it is found that there are many types of inventory items and most of the items are not replaceable. This finding means that most of the inventory items are unique and cannot be substituted by another related inventory. Table II illustrates the classification factors in selecting the input feature for the classification system. Classification of the inventory items is important in order to have better scheduling for the procurement process.

Insert Table II here

4.3 Classification Result

After the data and pre-set rules are inputted to the system, a graph presenting the correlation between the two variables and the purchase index is generated. As shown in Figure 5, the dark blue area represents the area with a low purchase score since the lead time is short, which means that the inventory item requires relatively less time for purchase. The light blue region represents a medium purchase index since the lead time is relatively short in this area and the number of available suppliers is relatively high. The yellow color region represents the area with a high purchase score. The lead time in the area is relatively high which means the item requires a longer time for the purchase process and the number of available suppliers is relatively less than other inventory items. The purchase index and the classification results are shown in Table III.

Insert Table III here

As shown in Table 3, the Encoder receiver, delivery motor with encoder, sieve motor, sieve encoder PCB, and sieve encoder receiver have the highest purchase scores (Around 0.86 - 0.82). It is an expected result since most of them are electrical items that require more time for purchase and manufacture generally. These inventories are classified as Class A inventory items.

The following nine items have relatively high purchase scores (from 0.819 -0.5). They are the driver IC, metal connector, FPGA, controller cover, grounding motor, encoder PCB, grounding head, grounding chamber, and delivery chamber. These inventory items are classified as Class B items

The remaining items have relatively low purchase scores (from 0.486 - 0.135). Most of these inventory items have relatively fewer complex items, which require less time to purchase and manufacture. As a result, they are classified as Class C items.

4.4 Results analysis

Based on the information from the SOPSYS, the proposed classification result was computed. The determined classification results and the purchase index were validated by comparing with the interview result from the inventory manager and the actual inventory priority in the space mission. Based on the classification result, the inventory manager can determine the materials to be purchased in advance in order to make a better decision for optimizing the schedule of the space project. This is because most of the space project has a tight timeline and most of the inventory items have a long lead time for the purchasing, and optimizing the purchase process would greatly contribute to the optimization of the scheduling. The experimental results have shown that the classification system generated a satisfactory result by providing a purchase score and ABC classification result. This quantitative indication is useful for optimizing the purchase decision making process.

5 Discussion

5.1 Variety and complexity of the space mission

According to the insights obtained in the structured interview, the requirements, specifications, and manufacturing procedures of space inventory components are unique. Also, even for the same space project, different stages of the project (Conceptual model, electric model, and flight model) have different requirements in the inventory components. Therefore, an information system that can fit most of the space mission components is difficult to build.

In light of this, we propose that the information system should be designed to be more flexible, where the inventory manager can optimize the system by modifying the fuzzy membership function. Also, different inputs can be taken into consideration based on the requirement of the specific space mission. By adopting the information system in the proposed model, the system can perform data recording, inventory classification, and purchasing optimization, which is particularly important for the space inventories that involves a lot of components and high-efficiency requirements.

In addition, it is found that most of the space inventories have a long lead time and a low number of available suppliers because of the high-level requirement of space components. In view of this finding, these two factors are taken as the input in the proposed system and it is suggested that these two factors can be taken as the preliminary input for other space projects.

5.2 ABC classification for space inventory management

In this study, ABC classification is employed to classify the space mission inventory items. ABC classification provides a mechanism to identify items that make a significant contribution to specified factors. The top 20% items with the highest purchase index are given Class A classification, following by Class B with 30 items and the bottom 50% as Class C items (Flores and Whybark, 1986). This mechanism focuses on the significant few rather than the trivial many (Xiao et al., 2011).

Although the ABC classification is widely adopted in manufacturing, it is not the only available classifying method. The ABC classification is particularly important for the classification of a vast amount of space mission inventory items in an information system. Some other classifying methods are discussed below.

5.2.1 FSN classification

This classification method separates the inventory items based on the quantity, rate of consumption, and frequency of issue and use. According to the methodology of the FSN classification, an inventory item is classified as F (Fast-moving inventory) which represent the inventory items that are frequently used or issued, S (Slow-moving inventory) represents inventory items that are used or issued for a certain period, and N (Nonmoving inventory) represents the inventory items that not used or issued over a long period.

The advantage of this classification is that the model can handle the moving inventory material effectively. The fast-moving inventory material is classified in a group so that some special procedures and protocols can be established to enhance the overall efficiency of inventory management.

However, this classification method may not be suitable for classifying space inventory. As found in the data analysis result, most of the inventory items will only be used once in a space mission, which makes the FSN classification not very effective in classifying space inventory material. Moreover, according to the dataset of the case study, the frequency of usage is irrelevant to the lead time or purchasing-related factors of the space inventory. Therefore, the FSN classification is not suitable for classifying the space inventory material.

5.2.2 HML classification

Apart from the ABC and FSN classifications, HML has been proposed as a classifying method that focuses on the unit cost of the inventory item. This method classifies items based on their product price or unit price. According to the unit price of the inventory items, they are classified as H (High cost), the inventory items with a high unit value, M (Medium cost), inventory items with a medium unit value, and L (Low cost), inventory items with a low unit values (Fama and French, 1993).

This classification method is suitable for companies that are very sensitive to inventory costs. Some measures can be taken to insure and protect the high-cost inventory items in order to prevent any loss. This is also suitable for some small companies since they may not be able to bear losses on high-cost inventory items.

Despite the advantage of the HML classification method, it is not suitable for classifying space inventory items. As found in the project, most of the inventory items are unique and cannot be replaced by other inventory material. Therefore, the purchase decision should be made regardless of the unit price of the inventory item, unless it is out of the budget of the project. To conclude, this classification method is not relevant for optimizing the purchasing decisions for space inventory.

5.2.3 Classification by category

Besides classifying inventory items by a specific factor (Moving rate, Unit cost), some companies opt for simple classification by category. This classification is considered a very general and simple classification method since it does not require any sorting and computation. The classification result and the number of classes are defined by categories defined by the inventory manager. The classification assumes inventory items within the same category have similar characteristics.

The advantage of the classification is that it is very simple to process since no calculation is needed. However, it is not effective for achieving a specific classification goal such as optimizing the purchase procedure nor increasing the efficiency of inventory management. In addition, since inventory items in the same category are not necessarily have similar characteristics, this model cannot guarantee the classification result.

Therefore, this classification method is not suitable for classifying space inventory material since it has great uncertainty. According to the inventory data obtained in the quantitative data analysis, there are many types of inventory for a space mission. This would make the classification less effective since it results in many categories of items.

5.2.4 Advantage of ABC classification

Compared to the above classification methods, the ABC classification is more flexible and feasible for the proposed system since it does not limit the criteria for the classification. Also, since there are many inventory items involved in a space mission and most of the inventory items are unique, the inventory manager may not have enough time to make decisions and track the process for all the inventory items. Therefore, it is more effective to focus on the significant few inventory items which may potentially affect the timeline of the whole project.

However, there is a shortcoming with the ABC classification, as it only focuses on the significant few but not most of the inventory items. This classification is only suitable for a project that is potentially affected by some significant few inventory items. For inventory items that have low variability, this method may not be suitable. For space projects, according to the result of the case study, since most of the inventory items are irreplaceable, and if a delay in the purchase process occurs in any inventory items, it may affect the whole timeline of the project. Therefore, it is important to focus on the inventory item which have a long lead time and a low number of available suppliers. In view of this, the ABC classification is suitable for space mission inventory items.

5.3 Fuzzy logic in space inventory management

In the proposed model, fuzzy logic is chosen as the mathematical model of inventory classification for two reasons. Firstly, similar to other Multi-Criteria Decision Analysis methods, the fuzzy model can incorporate both qualitative criteria and quantitative criteria which makes the model more flexible to modify and optimize. Also, the fuzzy membership function can be modified according to the space inventory data.

Secondly, compared to other Multi-Criteria Decision Analysis methods, the fuzzy model is relatively more objective. For the AHP model, most of the qualitative data is obtained based on the interview or questionnaire result of the inventory manager. This method often results in high subjectivity. In contrast, the fuzzy model can incorporate quantitative data by fuzzifying the data with the designed fuzzy membership function.

6 Conclusions

In this project, a classification system is proposed to shorten the purchasing time in space missions by providing quantitative analysis regarding the availability of inventory items. This information system aims to enhance the decision-making efficiency regarding the purchasing process with the mean of MCDA. The classification process is conducted using MATLAB fuzzy toolbox and integrated into the existing information system. A case study using the data from the SOPSYS bill of material is conducted. The data is input to the classification system and the result is satisfactory. This classification system can implement not only in the SOPSYS dataset but also similar space missions in order to optimize the purchase decision process in the proposed system of this project. In this research, space mission projects are unique and complex. This article is not only beneficial in building an information system that assists inventory management, but the system also supports decisions so that time and effort on manual prioritizing inventory items can be saved.

6.1 Research Implications

This article addresses several major research difficulties in space missions. First of all, the timeline of space exploration is tight, the inventory shortage and lead time for replenishment are critical. On the other hand, most of the space items are usually irreplaceable and have very low substitutability, and most of the space items are usually very costly. Considering the safety and extreme environmental conditions of a complex space mission, the space items are required to satisfy a large number of design specifications and requirements. Therefore, the possibility of postponing in an inventory item, and delay in the decision workflow and inventory replenishment process will contribute to the overall timeline and result in missing the scheduled space mission. As such, the research has important research implications in several aspects:

1. The proposed decision model can handle qualitative or quantitative classification criteria that commonly occur in the replenishment of space items.
2. To ensure the higher reliability of the decision supported information system, the proposed classification can be implemented using mathematical calculation tools and integrated into the existing inventory management system.
3. The proposed algorithm has demonstrated the feasibility and applicability of supporting the replenishment of components with large sets of design

specifications in an actual space mission.
4. The model also demonstrated important implications in optimizing the purchasing decisions so as to shorten the research and development of other space instruments in space missions in order to reduce the lead time for space components replenishment decisions.

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