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A Clustering Classification of Spare Parts for Improving Inventory Policies

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A Clustering Classification of Spare Parts for Improving Inventory Policies

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Abstract. Inventory policies in a company may consist of storage, control, and replenishment policy. Since the result of common ABC inventory classification can only affect the replenishment policy, we are proposing a clustering based classification technique as a basis for developing inventory policy especially for storage and control policy. Hierarchical clustering procedure is used after clustering variables are defined. Since hierarchical clustering procedure requires metric variables only, therefore a step to convert non-metric variables to metric variables is performed. The clusters resulted from the clustering techniques are analyzed in order to define each cluster characteristics. Then, the inventory policies are determined for each group according to its characteristics. A real data, which consists of 612 items from a local manufacturer's spare part warehouse, are used in the research of this paper to show the applicability of the proposed methodology.

Keywords: Clustering Technique, Inventory Policy System, Spare Part

1. Introduction

Inventory is known as the important things that affect the performance of production in the company. It has a role to anticipate the uncertainty such as demand uncertainty, defective product, and machine break down. The inventory based on type and position of the item can be divided into several varieties. There are raw material inventory, purchased parts/component inventory, supplies inventory, work in process inventory, finish good inventory. Several types of inventory policy are ordering of inventory, storage of inventory, and issuing of inventory [1]. Inventory policy related to storage of inventory has a function to keep and positioned the inventory in the right way and proper place.

The inventory policy problem arises as the scale of the company is getting bigger. In addition, the complexity of the inventory problem arises when the number of item in each type of inventory is getting larger. One way to simplify the way to manage the each item, classification is needed. Classification helps the company to groups the items that have the same characteristic. Therefore,

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classification criteria have to be determined. The result from the classification then can be used to develop inventory policies for each group of items.

One of the famous and oldest methods for classifying the items called ABC analysis. Some of previous research on inventory classification using ABC classification had been done many researchers such as Frey and Gordon [2] who did the research in ABC classification, strategy and business unit performance. Fuerst [3] did the research in small business using ABC analysis for inventory control. Chu et al. [4] did the research in controlling inventory by combining ABC analysis and fuzzy classification followed by Torabi et al. [5] who did the research in ABC inventory classification in the presence of both quantitative and qualitative criteria. However ABC analysis is not the optimal methodology of classification in inventory because the classification is only based on one singles criteria which might not appropriate for big scale of company.

Therefore, many researchers conducted also a research on inventory classification based on multi criteria. Bacchaetti et al. [6] did inventory classification with spare parts and held in Italian household appliance manufacturing company using four criteria. There are life-cycle phase of the related final product, volume, critically, and competition. Kabir & Sumi [7] held the research at Energypac Engineering Limited (EEL), a large power engineering company in Bangladesh using multi criteria inventory classifications through integrating Fuzzy Delphi Method (FDM) with Fuzzy Analytical Hierarchy Process (FAHP). The criteria used in this research are unit price, annual demand, critically, last used date, and durability. Hadi-Vencheh and Mohamadghasemi [8] used Fuzzy Analytical Hierarchy Process (FAHP) to determine the weights of criteria, linguistic terms such as Very High, High, Medium, Low and Very Low to assess each item under each criterion. The Data Envelopment Analysis (DEA) method was used to determine the values of the linguistic terms, and the Simple Additive Weighting (SAW) method to aggregate item scores under different criteria into an overall score for each item. Criteria that used are annual dollar usage, limitation of warehouse space, average lot cost, and lead time. Cakir & Canbolat [9] used a web based decision support system for multi criteria inventory classification using fuzzy AHP methodology using six criteria such as price or cost, annual demand, blockade effect in case of stock out, availability of substitute material, lead time, and common usage of the items. Another research in inventory classification and maintenance at offshore vessel industry had been done by considering lead time from supplier and the cost of downtime failure [10]. Yu [11] did the research about multi criteria ABC analysis using artificial intelligence based classification technique considering several criteria such as cost of the new item, cost to repairing the item, the availability of the item, and the downtime cost. These researchers have compared artificial-intelligence (AI)-based classification techniques with traditional multiple discriminate analysis (MDA). Multi criteria inventory classification using artificial neural network has been done [12]. Some of criteria that used are annual cost usage, lead time and criticality factor. The predicted results are compared to those obtained by the multiple criteria classification using the analytical hierarchy process. Research on multi-criteria ABC inventory classification using an efficient artificial immune algorithm (AIA) has been conducted [13]. The criteria which used are annual dollar usage, lead time, number of request for the item in a year, criticality, commonality, obsolescence, and substitutability into the problem of ABC inventory classification. A genetic algorithm with multi criteria inventory classification has been implemented [14]. Some criteria that used are annual dollar usage, number of requests for the item in a year, lead time, and replace. The results were compared with the classical inventory classification technique using the Analytical Hierarchy Process. Weighted linear optimization in ABC inventory classification with multi criteria using four criteria which are average unit cost, annual dollar usage, critical factor, and lead time has been implemented [15].

The research in this paper is motivated by the real situation happened in one of the chemical manufactured we observed, they use two criteria for spare part classification. There are value of the item and frequency of internal use of the spare part. These 2 criteria generate 9 classifications for their spare part. The ninth classifications are high value with high frequency (FT-NT), high value with medium frequency (FS-NT), and high value with low frequency (FR-NT). The second is based on medium value called medium value with high frequency (FT-NS), the medium value with medium frequency (FS-NS), the medium value with low frequency (FR-NS). The third is based on low value called low value with high frequency (FT-NR), low value with medium frequency (FS-NR), and low value with low frequency (FR-NR). Using current method for classification the company are facing several problem such as: spare part made from metal are stored in the same place as the non metal item such as rubber, polyethylene, and cotton. As the nature of metal and non metal are different, therefore when those items are placed in the same place with same condition for both item, sometimes the condition is not fit for the other, and it cause certain condition such as corrosion. In addition, the current classification does not consider the size of the items and plant site that use the items. As the result, the warehouse staff found some difficulties in handling and managing the items. The research in this paper is purposed to re-classify the spare part in such a way that the problem mentioned above can be reduced or even be eliminated.

The contribution of the work of this paper is the several criteria taken from the qualitative research using in depth interview that are used to classify spare part in this case have not been addressed by previous researchers. The clustering technique is performed to classify the items based on many criteria is clustering technique. According to Halkidi et al. [16] "*clustering aims at identifying groups of similar objects and, therefore helps to discover distribution of patterns and interesting correlations in large data sets*". The advantage of using the clustering technique is how to group data in to a group with similar or close data characteristic considering multiple criteria.

The remaining part of this paper is organized as follows: 1) Identifying Criteria; 2) Clustering Technique; 3) Cluster Profiling; 4) Inventory Policy Recommendation.

2. Identifying Criteria

The purpose of this step is to determine the variable for classifying the spare part. Initially, the output from the Avantis software used by the company are identified. Based on the output and the in depth interview by considering the data ouput from Avantis software, the inventory manager then decided to use 11 criteria to as a basis for classify the spare part they have in the company. Those criteria are: 1) price of item (Rp); 2) average use of item per year (unit); 3) amount of supplier where the company can get the item (unit); 4) lot size purchasing (unit); 5) lead time (year); 6) type of material used for making the spare part (such as metal, rubber, silicon and so on); 7) dimension of items - volume (mm3); 8) dimension of items – diameter (mm); 9) current inventory policy related to minimum level (s); 10) current inventory policy related to maximum level (S) of inventory for each item; 11) the user that use each item.

The next step is observing if the type of data input for each variable metric or non metric. Based on the type data input it is known that the type of data input for variable 1, 2, 3, 4, 5, 7, 8, 9 and 10 are metric while the type of data input for variable 6 and 11 are non metric. In order to perform the clustering technique we used for the research in this paper, the unit measurement to represent variable 6 and 11 are modified in order to get the metric data for data input variable. In depth interview to the inventory manager was conducted and the result is to represent the type of the material used for making the spare part we use melting point (^{0}Celcius). The melting point is shown in Table 1. In addition, to represent the user of the spare part (such as plant 1, 2, 3 and 4) we use the area for each plant as unit measurement (ha). The value of 6.5 ha is Plant 4, the value of 6 ha is Plant 1, the value of 4.5 ha is Plant 2, the value of 4 ha is Plant 3, the value of 30 ha is plant 5. It is noted that if certain items has already assigned to certain plan then it can be only used for that plant. However, there exists items that can be used in all plant site, and this is categorized as plant 6, and the value is 9.33 ha.

Table 1. Data of Melting Point

Name of Material	Melting Point (Celsius)
Rubber / Poly norm	400
Stainless Steel	1510
Brass	1000
Tungsten	3422
Ceramic	1760
Carbon fiber	1871.1
Ethylene	169.2
PTFE / Teflon / polyurethane	327
Silicone	1414
Neoprene	260
Aluminum	660.3
Kalrez	275
EPDM	150
HDPE / Polyethylene	130
Graphite	4200
White Asbestos	1500
Copper	1085
Iron	1127
Cotton	150
NBR / Perbunan	108
Poly-made Cage	190
Synthetic rubber / Viton	160
Brazing Rod Welding	1482

3. Clustering Technique

The clustering technique conducted in the research in this paper several steps as follows: 1) detecting the outlier, 2) normalization of data using Z score; 3) test the assumption of clustering technique, 4) clustering process, 5) profiling and validation process, and 6) interpretation of clustering process. 612 spare parts will be clustered using 11 criteria as it was mentioned in Section 2.

3.1. Detecting the Outlier

This step is conducted by observing the extreme value for all 612 items to be clustered for each variable. It is conducted in order to simplify the clustering process, as usually the objects that has extreme value will form their own clusters. Detecting outlier was performed using Box-Plot, that is a graphical representation of data using 5 parameters namely: 1) minimum value; 2) maximum value; 3) median; 4) 1st quartile; 5) 3rd quartile. The example of the result from this step for Variable "Price" is presented in Figure 1.

3.2. Normalization of Data using Z score

After observing the value data for all items to all of variable it is known that its value has different of scale. Based therefore the data need to be standardized. Standardizing the data was done by using *Z* score. The entire of *Z* score for 612 items was calculated with SPSS software and the result is presented in Table 2.

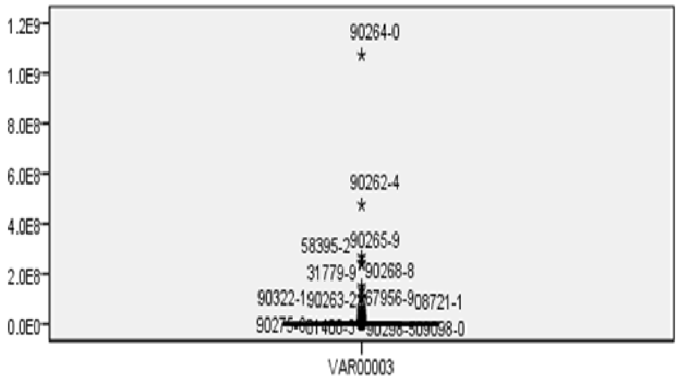

Figure 1. Box-Plot for Detecting Outlier for Variable "Price"

3.3. Test the assumption for clustering technique

The assumption of clustering technique is multicollinearity testing to check if there are interdependencies among variables. The test was performed using SPSS software and the decision was made by looking at the collinearity statistic. If value of tolerance more than 0.10 and value of VIF less than 10.00 than there is no multicollinearity happened. The result from this step is presented in Table 3. From the result presented in Table 3 it can be known that there is no interdependencies among variables.

3.4. Clustering Process

In the research conducted in this paper, the hierarchical clustering algorithm with ward's method is used. To measure the similarity among objects the Eucledian Distance is used [17]. The clustering process was then performed by SPSS software. The stopping rule approach that used is coefficient in agglomeration (see Table 4) and look to the every cluster that formed. The amount of cluster is appropriate if every cluster already had a characteristic. The characteristic is find by see the homogeneity of value in variable for each cluster. This is the formula for decided amount of cluster based on a coefficient in agglomeration schedule.

Amount of clusters = Amount of cases – Number of Stage

= 535 – 515

= 20

Based on the calculation above, the author get the appropriate amount of cluster is 20 clusters.

3.5. Profiling and Interpretation

After the cluster is formed, the profile of each cluster is identified by interpreting its main characteristics. The result of this step is presented in Table 5.

IOP Conf. Series: Materials Science and Engineering **114** (2016) 012075 doi:10.1088/1757-899X/114/1/012075

Table 2. The example of the entire of Z score for 612 items

No	S/N	Z price/item	Z Item Used/year	Z Supplier	Z lot size	Z lead time	Z Melting Point	Z Diameter	Z Volume	Z MIN	Z MAX	Z Plant site
1	16274-4	.10225	-.04043	.10947	-.108	.18279	-.78891	-.17185	-.08543	-.2119	-.0900	-.12742
2	43570-8	-.10311	-.04043	-1.15456	-.093	1.2247	.56696	-.00724	-.08543	-.1757	-.0840	-.17488
3	00965-2	-.14241	-.04043	.10947	-.093	.45350	.56696	-.16637	-.08543	-.1636	-.080	-.12742
4	02062-1	-.14875	-.04043	-1.15456	-.086	.45350	-.78891	-.23001	-.08543	-.1516	-.078	-.12742
5	05085-7	-.15096	-.04043	.10947	-.071	-.24847	.56696	-.27940	-.08543	-.0912	-.0629	-.12742
6	09240-1	-.14956	-.04043	1.37349	-.101	-1.1834	.56696	-.26513	-.08543	-.1878	-.0855	.63190
7	11950-4	-.13262	-.04043	-1.15456	-.111	.45350	.56696	-.18283	-.08543	-.2119	-.0900	-.17488
8	12010-3	-.15081	-.04043	.10947	-.106	.45350	.56696	-.27940	-.08543	-.1878	-.0870	.63190
9	12910-0	-.14487	-.04043	1.37349	-.102	-1.1834	.56696	-.19380	-.08543	-.1878	-.0870	-.11160
10	12941-0	-.14688	-.04043	1.37349	-.108	.45350	.56696	-.20477	-.08543	-.1998	-.0900	-.11160
11	14760-5	-.13022	-.04043	1.37349	-.107	-.99136	-.05601	-.20477	-.08543	-.2119	-.0900	-.12742
12	14839-3	-.08237	-.04043	-1.15456	-.102	.45350	-.78891	-.22672	-.08543	-.1516	-.0734	-.12742
13	14930-6	-.06869	-.04043	-1.15456	-.042	-.32402	-.78891	-.06609	-.08543	-.0912	-.0387	-.12742
14	17259-6	-.14750	-.04042	-1.15456	.002	1.3979	-.78891	-.02919	-.08543	-.0188	-.0447	-.12742
15	18129-3	-.14521	-.04043	1.37349	-.105	.45350	-1.04542	-.23770	-.08543	-.1757	-.0840	-.12742
.												
.												
.												
612	06780-6	-0.02881	0.04046	-0.10956	0.108	-0.77670	-0.60410	-1.01527	0.08550	0.2121	0.0901	0.20082

Table 3. Summary of Multicollinearity Testing Process

Model	Unstandardized Coefficient		Standardized Coefficient	t	Sig.	Collinearity Statistic	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	506834	87705.1		5.779	0		
Z Price	174.7	34.02	0.218	5.136	0	0.923	1.08
Z Used	12530345	2169709	0.32	5.775	0	0.541	1.85
Z Supplier	3.465	7.12	0.2	0.487	0.63	0.981	1.02
Z Lot size	280.31	173.7	0.148	1.614	0.1	0.197	5.06
Z Lead time	2.354	7.856	0.013	0.3	0.77	0.946	1.06
Z Melting point	1.812	7.557	0.01	0.24	0.81	0.957	1.05
Z Diameter	- 14.11	15.014	- 0.039	- 0.94	0.35	0.976	1.02
Z Volume	- 63.32	99.239	- 0.26	- 0.64	0.52	0.993	1.01
Z Min	- 216.012	115.569	- 0.293	-1.87	0.06	0.168	6.74
Z Max	118.735	484.901	0.043	0.245	0.81	0.154	7.54
Z Plant used	- 36.573	33.268	- 0.45	- 1.1	0.27	0.986	1.01

Table 4. Footage of Agglomeration Schedule

Stage	Cluster Combined		Coefficient	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
510	15	28	23.211	475	479	515
511	402	481	24.036	487	0	524
512	2	4	24.917	494	503	527
513	61	62	25.822	501	406	525
514	124	219	26.824	490	493	531
515	15	166	27.829	510	0	523
516	52	190	**30.038**	491	483	530
517	3	5	30.136	485	498	520
518	6	8	31.401	481	506	528
519	24	294	32.866	509	497	521
520	3	232	34.537	517	508	522
521	13	24	36.434	454	519	527

Table 5. Clusters and Their Characteristics

Name of Cluster	Characteristic
Cluster 1	1. Item used per year less than equal 10 item. 2. It has 2 suppliers. 3. Lot size less than equal 10 items. 4. Lead time less than equal 7 months.
Cluster 2	1. Item used per year less than equal 10 items. 2. It has 1 supplier.
Cluster 3	1. It has 2 suppliers. 2. Lead time more than 7 months.

Name of Cluster	**Characteristic**
Cluster 4	1. It has 2 suppliers. 2. Lead time less than equal 7 months. 3. ***Type of item's material is metal***.
Cluster 5	1. It has 3 suppliers. 2. Lot size less than equal 10 items. 3. Lead time less than equal 7 months. 4. ***Item is used at plant site of PKPL***.
Cluster 6	1. It has 2 suppliers. 2. Lead time less than equal 7 months. 3. ***Item is used at plant site of PKPL***.
Cluster 7	1. It has 3 suppliers. 2. Lead time less than equal 7 months. 3. ***Type of item's material is metal***.
Cluster 8	1. Item used per year less than equal 10 item. 2. It has 3 suppliers. 3. Lead time more than 7 months. ***4. Type of item's material is metal.***
Cluster 9	1. Item used per year less than equal 10 item. 2. It has 1 supplier. 3. Lead time less than equal 7 months. 4. ***Type of item's material is Nonmetal***.
Cluster 10	1. Item used per year less than equal 10 item. 2. It has 3 suppliers. 3. Lead time less than equal 7 months. 4. ***Type of item's material is Nonmetal***.
Cluster 11	1. It has 1 supplier. 2. Lead time less than equal 7 months. 3. ***Type of item's material is metal***.
Cluster 12	1. It has 2 supplier *2.* ***Items with type of material with extreme melting point. (Tungsten and Graphite)***
Cluster 13	1. It has 2 suppliers. 2. Lot size more than 10 items. 3. Lead time less than equal 7 months.
Cluster 14	1. Item used per year less than equal 10 item. 2. It has 1 supplier. 3. Lot size less than equal 10 items. 4. ***Diameter of item is more than 100 mm***.
Cluster 15	1. Item used per year less than equal 10 item. 2. It has 2 suppliers. 3. Lead time more than 7 months.
Cluster 16	1. Item used per year more than 10 items. 2. Lot size more than 10 items. 3. Lead time less than equal 7 months. 4. ***Type of material's item is metal***. 5. Reorder point (min) and max has a big quantity.

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Name of Cluster	Characteristic
Cluster 17	1. Item used per year less than equal 10 item. 2. It has 2 suppliers. 3. Lead time less than equal 7 months. 4. ***Type of material's item is metal***.
Cluster 18	1. Item used per year more than 10 items. 2. Lead time less than equal 7 months.
Cluster 19	1. It has 1 suppliers. 2. Lead time less than equal 7 months. 3. ***Diameter of items more than 100 mm***.
Cluster 20	1. High price more than Rp 99,778,156.00 2. Lead time more than 7 months. 3. ***Type of material's item is high quality of metal. (carbon steel and stainless steel***) 4. ***Diameter of item more than 100 mm***.

4. Managerial Implications

Based on the characteristics of each cluster formed in the previous step, some inventory policy procedures, especially for storage and control policy, can be recommended as the managerial implications of the clustering results. Table 6 summarize the recommendations.

Table 6. Recommendation of Inventory Policy Procedures

Name of Clusters	Inventory Policy Procedures
Cluster 4, 7, 8, 11, 12, 16, and 17	1. Inventory must be stored in enclosed room with normal humidity and not exposed to the water. 2. Every a month warehouse staff checking the humidity and coat the items with oil.
Cluster 20	1. Inventory must be stored in enclosed room with normal humidity and not exposed to the water. 2. All of the items in this cluster must be separated with another cluster with exclusive use room, under lock and key. 3. All of the items in this cluster wrapped with VCI paper.
Cluster 9 and 10	1. Inventory must be stored in enclosed room with room temperature.
Cluster 14 and 19	1. Inventory must be stored in enclosed room with normal humidity and room temperature also not exposed to the water. 2. These cluster must be positioned to facilitate efficient handling, checking and near the entrance door of warehouse.

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