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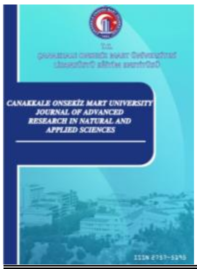

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A Methodology for Clustering Items with Seasonal and Non-seasonal Demand Patterns for Inventory Management

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Research Article

Abstract − Item clustering has become one of the most important topics in terms of effective inventory management in supply chains. Classification of items in terms of their features, sales or consumption volume and variation is a prerequisite to determine differentiated inventory policies as well as parameters, most common of which is service levels. Volume classification is easily obtained by well-known Pareto approach while coefficient of variance is usually used for variation dimension. Hence, it is not always applicable to classify items under different product families with different demand patterns in terms of variation. In this paper, we propose two algorithms, one based on statistical analysis and the other an unsupervised machine learning algorithm using K-means clustering, both of which differentiate seasonal and non-seasonal products where an item's variation is evaluated with respect to seasonality of the product group it belongs to. We then calculate the efficiency of two proposed approaches by standard deviation within each cluster and absolute difference of percentage of volume and item numbers. We also compare the outputs of two algorithms with the methodology which is based on coefficient of variance and is currently in use at the company which is a leading major domestic appliance manufacturer. The results show that the statistical method we propose generates superior outputs than the other two for both seasonal and non-seasonal demand patterns.

Keywords − *Inventory control, item classification, K-means clustering, supply chain management, seasonality*

1. Introduction

Effective inventory management is one of the major area of studies in supply chain management. Optimisation of service levels with respect to inventory carrying and operating costs enables companies to determine their supply chain strategies in terms of customer and product-specific policies. It is almost a necessity to differentiate service levels since obtaining a high service for all product and customer combinations becomes infeasible in terms of cost and working capital management.

A well-known approach to differentiate products for service level differentiation is grouping items based on their volume and one can easily deduce that the well-known ABC classification of items has a great area of use for its validity and simplicity. ABC classification takes Vilfredo Pareto's rule as a basis where the majority of the consequences are determined by a small portion of the items or causes which affect them. Hence, classification of items in order to generate effective inventory policies does not only depend on volume but other features as well. These features may depend on the dynamics of the related industry and production and distribution requirements of the items and thus, some of the various studies and applications will be mentioned afterwards. However, one of the most important features for item classification is taken as the variability of the items' consumption, since variability is also a major feature in terms of inventory management, such as determining the safety stock levels.

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We have conducted this study in one of the leading major domestic appliance manufacturers in the world, which started its industrial life in 1950s and has been producing a wide range of products under various brands at its factories and exports to more than 130 countries since then. The company's supply chain faces challenges in effective planning, especially in terms of inventory management due to high complexity of channel requirements, products, and different demand patterns. The company has the well-known periodically reviewed order-up-to inventory control policy in use, and in order to establish a robust supply chain planning infrastructure, their major area of focus is differentiating the service levels among the high number of product portfolio.

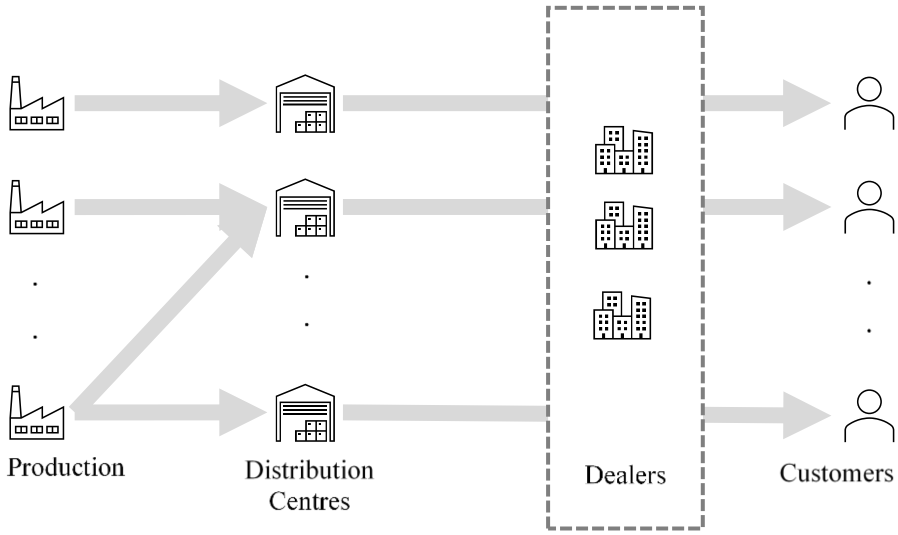


Figure 1. Distribution network of the company's supply chain

As determining the differentiated service levels in such a complex supply chain structure becomes a prerequisite for inventory planning, our study focuses on clustering the products for the abovementioned service level differentiation within a single market, the distribution network of which is shown in Figure 1. Within the order-up-to policy for inventory control, the company uses a classical ABC-XYZ classification of items where ABC classes are determined by volume and XYZ classes by demand variation, and we take the same two dimensions of clustering methodology focusing on variation sub-clusters.

Currently, the company uses the coefficient of variance (CoV) parameter for the XYZ clustering in which the CoV value for SKU i is calculated by (1.1);

$$CoV_i = \frac{\sigma_i}{\mu_i} \tag{1.1}$$

where;
σ_i: standard deviation of sales of SKU i
μ_i: average of sales of SKU i
and

$$i \in \begin{cases} X & ; if\ CoV_i \leq a \\ Y & ; if\ a < CoV_i < b \\ Z & ; if\ b \leq CoV_i \end{cases}$$

Hence, this classification has two major lacking points. First, the outcome of this methodology is highly dependent on the chosen a and b parameters. The company uses 0.7 and 1.1 values respectively for threshold values but there is no scientific methodology nor an optimisation algorithm for determining the mentioned parameters. Selecting the best-fit parameters will require deep industrial knowledge but will also be open to challenges related to dynamic environmental changes in the industry and will demonstrate a weak argument for deployment. The second lacking point lies in the nature of the demand pattern of different products. The clustering methodology is on SKU level by nature, but the company uses same threshold values as well as classifying the products with the same criteria of standard deviation where the product portfolio includes highly seasonal products together with non-seasonable ones. One can easily guess that the standard deviation of seasonal and non-seasonal products will show difference on the basics, and it would neither be theoretically nor practically correct to evaluate these two groups in the same manner.

2. Literature Review

Researchers and practitioners have conducted numerous studies for item classification in inventory control. (Raja et al., 2016) used hierarchical clustering in which they have converted non-metric variables to metric for improving inventory performance in inventory management of spare parts. (Pujiarto et al., 2021) developed a method based on Partitioning Around Medoids algorithm for locating optimal picking points based on cluster classifications. (Razavi Hajiagha et al., 2021) proposes a hybrid fuzzy-stochastic multi-criteria method using possibilistic chance-constrained programming. They have considered demand information as stochastic due to its time-varying nature and cost information as fuzzy due to its cognitive ambiguity and classified items into three groups naming their level of importance. (López-Soto et al., 2017) designed a multi-start constructive algorithm to train a discrete artificial neural network in order to classify new units based on their attributes. Another multi-criteria framework for inventory classification is developed by (Lolli et al., 2017) and applied to intermittent demand. They emphasize the importance of inventory classification with respect to its effect on ordering and replenishment policies. (Rezaei & Dowlatshahi, 2010) also proposed a rule-based multi-criteria approach to inventory classification in which they have taken into account the inherent ambiguities that exist in the reasoning process of the classification system. They have also compared their results with analytic hierarchy process (AHP) method. (Cakir & Canbolat, 2008) proposed multi-criteria decision support system using fuzzy analytic hierarchy process. (Bacchetti et al., 2013) developed a hierarchical multi-criteria classification method and applied it in a spare parts inventory management case study. (Ladhari et al., 2016) developed a hybrid model to overcome the conflicts of various multiple criteria inventory classification model and evaluated the efficiency of consensus outputs.

(Ernst & Cohen, 1990) developed a statistical clustering method using operations related groups (ORGs). The groups they used took into consideration all the related product characteristics that have impact on operations management. They also included an application of the mentioned methodology in spare parts distribution in automotive industry with substantial advantages of outputs. (Ramanathan, 2006) built a weighted linear optimisation model scheme with illustrated application. (Russo, 2019) conducted widespread research and proposed alternative method for ABC-XYZ classification of items in multi-echelon structures, identifying the most important features for classification. (Chu et al., 2008) combined ABC analysis and fuzzy classification to handle variables with both nominal and non-nominal attitudes and implemented their approach on the data of Keelung Port with satisfactory outcomes. (Park et al., 2014) suggested a cross-evaluation-based linear optimisation for multiple criteria inventory clustering which incorporates the cross-efficiency for ranking of inventory items. They also conducted a comparative experiment with the previous related investigations by simulation. (Rossetti & Achlerkar, 2011) evaluated multi-item group policies and grouped multi-item individual policies and compared them to ABC analysis via a set of experiments. (Yang et al., 2017) investigated the dynamic integration and optimisation of inventory classification to maximise the net present value of profit over the planning horizon using mixed-integer linear programming. (Tavassoli et al., 2014) used data envelopment analysis (DEA) to classify inventory items into three groups with weight restrictions in order to allow managerial preferences. Another model simultaneously optimises the number of inventory groups, corresponding service levels and assignment of SKUs within the group (Millstein et al., 2014). (Narkhede & Rajhans, 2022) discusses an integrated approach where they use rank order clustering (ROC) technique to redesign inventory management strategies for small and medium-sized enterprises.

While the use of multi-criteria decision making, linear optimisation, fuzzy systems and analytic hierarchy process is widespread, methodologies for item clustering is not limited to them, especially with the increasing application of machine learning techniques. Many studies take into account k-means algorithm, which is an incremental approach and dynamically adds one cluster centre through a deterministic global search procedure consisting of executions with the number of data points (Likas et al., 2003). (Balugani et al., 2018) used k-means and Ward's method algorithms to cluster items into homogenous groups with uniform inventory control policies. (T. Kanungo et al., 2002) proposed an efficient k-means algorithm together with its analysis and implementation. (Mohamad & Usman, 2013) analysed the performances of three standardization methods on conventional k-means algorithm on dataset of infectious diseases. They conclude that the z-score standardization method is more effective and efficient than min-max and decimal scaling methods. (Bellini et al., 2022) proposed a recommendation system based on a multi-clustering approach of items and users in fashion retail, where their proposed solution relies on mining techniques. (Liu et al., 2022) uses dynamic clustering scheduling for optimisation of big data parallel scheduling tasks. Their approach can also be adapted to item scheduling for inventory management where multiple criteria are used. Another strong technique which can be adapted to inventory management is linear programming (LP)-rounding to be used in machine learning and used for facility location clusters (Negahbani, 2022).

3. Methodology

Within the light of listed studies with various methods, we have generated a statistical and a k-means based methodologies to overcome the lacking features of current clustering technique which is based on simple sorting of CoV values for each SKU. To do so, we start by determining each SKUs variability relative to the variation of the product group it belongs to, and therefore we first define the coefficient of variance of product group p by (3.1);

$$CoV_p = \frac{\sigma_p}{\mu_p} \tag{3.1}$$

where;
σ_p: standard deviation of sales of product group p
μ_p: average of sales of product group p

Hence, we would like to obtain the relative variability of a single SKU with respect to variability of the product group it belongs to, and combining (1) and (2), we define the ratio of variability ϕ as in (3.2):

$$\phi_i^p = \frac{CoV_i}{CoV_p} \tag{3.2}$$

Generating the Φ_i values for each SKU, we apply two approaches for clustering -a statistical approach where the classes are formed by the distance of Φ_i to the median of the Φ_i values within that product group, and an unsupervised machine learning algorithm using k-means clustering. For the statistical modelling that is based on median values, we first determine the range of Φ values by the difference of maximum and minimum of the parameter within each product group (3.3a) and obtain the quartiles with respect to the median of Φ data set (3.3b and 3.3c). The XYZ clusters are formed based on comparing the Φ value of the SKU with obtained quartiles:

$$R_{i,p}^{\phi} = Max\phi_i^p - Min\phi_i^p \tag{3.3a}$$

$$Q_{i,p,1}^{\phi} = med(\phi_i^p) - \left(R_{i,p}^{\phi}/4\right) \tag{3.3b}$$

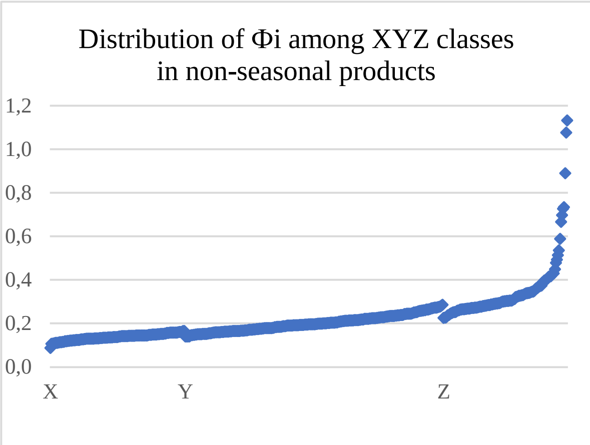
$$Q_{i,p,3}^{\phi} = med({\phi_i}_i^p) + \left(R_{i,p}^{\phi}/4\right) \tag{3.3c}$$

$$i \in \begin{cases} X & ; if\ \phi_i^p \leq Q_{i,p,1}^{\phi} \\ Y & ; if\ Q_{i,p,1}^{\phi} < \phi_i^p < Q_{i,p,3}^{\phi} \\ Z & ; if\ Q_{i,p,3}^{\phi} \leq \phi_i^p \end{cases}$$

In addition to the statistical method we have developed, we have also used a k-means clustering algorithm. K-means methodology requires the number of clusters to be obtained as the initial step and this parameter is usually generated by additional techniques such as elbow method. Since the number of clusters we need is already three, we pre-set this parameter. Then each Φ_i within the product group p is iteratively grouped based on the cluster of nearest data point and the XYZ clusters are iteratively finalized.

4. Results and Discussion

As stated above, our methodology fundamentally aims to differentiate seasonal and non-seasonal products and generates a new parameter of SKU variation with respect to product groups' variation. We therefore analyse the outputs of the two algorithms based on this new parameter of relative coefficient of variation and compare the results with the current sorting method as well as with each other both for seasonal and non-seasonal product groups. We start with visualising the distribution of relative coefficient of variation, where the distribution of obtained Φi points is given in Figure 2.



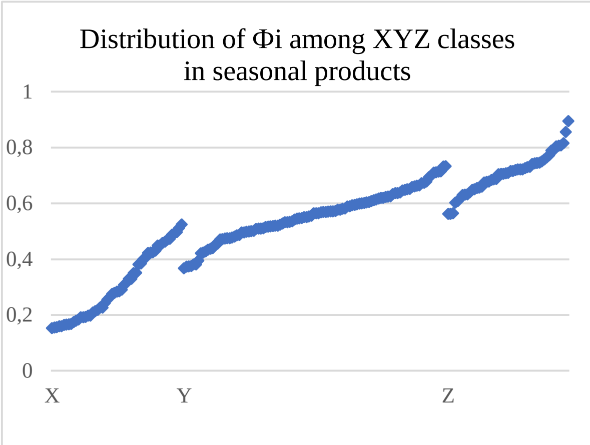


Figure 2. Distribution of Φi data points in non-seasonal and seasonal product groups

In order to determine the efficiency of the three methods, we first analyse the correspondence of each cluster with respect to volume. We obtain this efficiency by calculating the absolute value of the difference of percentage of volume and percentage of number of items within that cluster as in (4.1).

$$\delta_i^{p,q} = \left|\chi_v^{p,q} - \chi_i^{p,q}\right| \tag{4.1}$$

where;
$\chi_v^{p,q}$: Percentage of volume of cluster q within product group p
$\chi_i^{p,q}$: Percentage of number of SKUs in cluster q within product group p
$\delta_i^{p,q}$: Absolute value of difference of percentages

The outputs of this calculation are shown in Figure 3. Both for seasonal and non-seasonal products, statistical method gives the biggest sum of absolute values with 41.7% and 55.2% of values respectively. K-means algorithm has 35.8% for seasonal and 3.6% for non-seasonal products while sorting method has 10.1% and 1.0% values with the same order. Considering these values statistical method gives the best output, however for seasonal products, 21 points of 41.7% arises from cluster X in reverse side, which means 25.5% of number of items in cluster X corresponds to only 4.6% turnover. These numbers enable to question the absolute efficiency of the algorithm, leading to carry out further analysis.

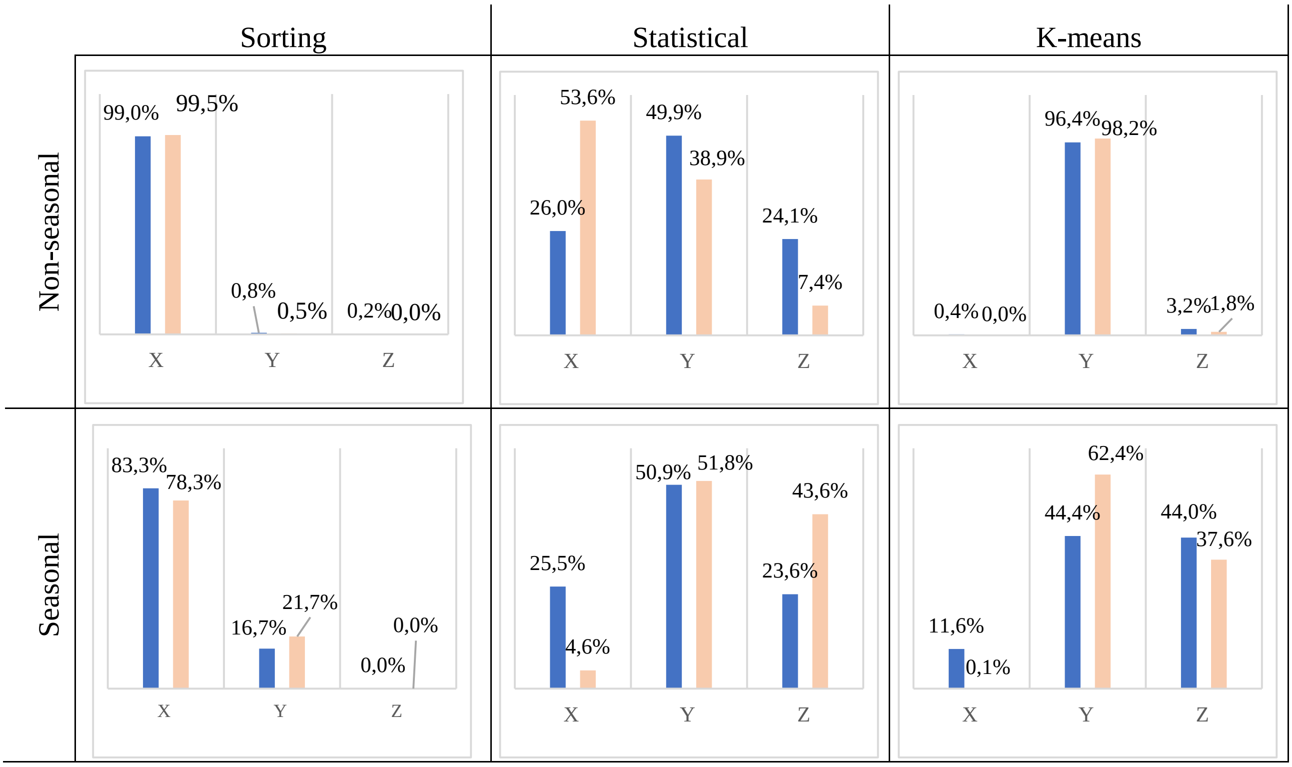


Figure 3. Correspondence of items within clusters to volume (■number of items, ■volume)

Our second analysis is based on the standard deviation of Φi values within each cluster. It can easily be concluded that the smaller the standard deviation within each cluster, the more efficient the clustering algorithm would be. However, since the main parameter for clustering is coefficient of variation for sorting method, we have taken standard deviation of CoV values for it. Standard deviation values of CoV_i and Φi within each cluster for both type of product groups is given in Table 1.

Table 1
Analysis of standard deviation of clusters for seasonal and non-seasonal items

	Seasonal			Non-seasonal		
	X	Y	Z	X	Y	Z
Sorting	.3159	.1649	-	.1935	.3879	-
Statistical	.1202	.0877	.0726	.0151	.0359	.1467
K-means	.0321	.0694	.0808	.0186	.0699	.3022

Since sorting method yields to only one data point in cluster Z, we do not have any calculated standard deviation figure for that cluster. Deep-diving into the calculated values, we again observe statistical algorithm outperforming both sorting and k-means algorithms. The exceptional figure is again cluster X of seasonal products where the standard deviation value of k-means algorithm is less than statistical algorithm. These outputs lead us to conclude that the analysis of standard deviation is in line with our first figure namely correspondence of percentages in terms of items and volume. Therefore, the statistical algorithm based on median value and defining quartiles as the threshold values outperforms simple sorting and k-means algorithms, except cluster X of seasonal products.

5. Conclusion

This study is conducted in major domestic appliances industry which has a highly complex supply chain structure in terms of demand and distribution characteristics, and therefore requires a sophisticated inventory management policy. The base of effective inventory management lies on setting differentiated service levels for different types of products, which brings item clustering as a prerequisite. The company where this study is conducted uses a simple sorting method for clustering in which they use coefficient of variation parameter as the indicator for all product range. This paper analyses the clustering methodology of items based on their sales (consumption) variation with the fundamental aim of differentiating seasonal and non-seasonal product groups. In order to execute this idea of differentiation, we have generated a new relative variation indicator in which an item's variation is measured with respect to the product group's variation that the item belongs to. Having generated this indicator, we have developed two algorithms in order to form XYZ clusters. The first algorithm is based on a statistical analysis, where the quartiles are obtained around the median of the relative variation data set and clusters are formed based on these quartile threshold values. The second algorithm uses the classical k-means machine learning techniques where the number of clusters is set to three and data points are assigned to each cluster iteratively.

We have analysed the results of the three algorithms in terms of two main perspectives: correspondence of percentage of items in each cluster to the percentage of volume, and standard deviation of data points within each cluster. The result of the analysis demonstrates that both statistical and k-means algorithms overperform the simple sorting method which is currently used by the company and proves our idea of differentiating seasonal and non-seasonal products would provide better results for effective inventory management. In addition, the statistical method we have developed provides better results rather than k-means algorithm both in seasonal and non-seasonal product groups, except the X cluster of seasonal products. Considering the higher computational effort of k-means algorithm as well, it is more advantageous for the company to apply the statistical method based on quartiles around the median value.

However, deep-dived data analysis might provide additional insights for the performance of the two algorithms, especially for product groups with higher seasonality. Also, our study is limited to one industry only and takes into account only historic sales variation. Especially for highly seasonal products, future demand variation may differ from historic data. Therefore, further studies would be much more enlightening especially in different industries with both seasonal and non-seasonal products, focusing on the features that affect the demand pattern and variation. We have only tried to establish a base for differentiation of products, and various techniques can be added in order to enrich the study.

Conflicts of Interest

The author declares no conflict of interest.

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