

Revising inventory management policies for spare parts: a case study

Rintala Annastiina, Huiskonen Janne

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Abstract

This case study focuses on providing management decision support in a situation where a large global equipment manufacturer is revising its inventory policies for spare parts. A classification model for facilitating the revision of inventory management policies is developed and tested with the transaction data of one product line. Due to the objectives of the case company and the limited amount of data, the study applies some classification criteria that are different from former spare part classification studies. With the presented model it is possible to point out potential pilot items for inventory management development actions, such as moving towards make-to-order, increasing visibility in the supply chain, or moving towards more dynamic inventory control. As this is a single case study, the wider generalizability of the model is limited. However, the study expands the understanding on different spare part classification models and their uses.

Keywords: Spare parts; Inventory management; Supply chain

1 Introduction

It is common today for a significant part of equipment manufacturers' business to consist of maintenance and spare part services. In such a situation, inventory management of spare parts is an essential issue. Balancing associated costs calls for selecting appropriate stock control policies.

In the literature there are several case examples of improving spare part inventory management. The literature presents models for classifying spare parts, and these models are applied in selecting suitable inventory management policies and demand forecasting approaches for different classes of parts. In an ideal situation, other companies can apply these models in their own development work.

The situations for improving inventory management in different companies vary with respect to the objectives of improvement and the available data, however. Many of the former classification models focus on selecting inventory control parameters and forecasting techniques, while in some companies there is a need to deal with several, more fundamental inventory management issues simultaneously, e.g. selecting items to be stocked or not to be stocked, increasing visibility in the supply chain, or pointing out development targets in general. The data varies by its availability, reliability, quantity and variability. In some situations only a few observations about demand events are available, and it is not possible to base all inventory-related decisions on quantitative data only.

This paper presents a case where the whole inventory management system is under construction, and all development targets are not clear yet. There is limited data available about the demand, which is generally highly variable and sparse. The aim is to find out the possibilities of item classification in supporting the development activities in such a situation. In the case company, stocks of spare parts are kept even though the traditional inventory control methods do not suit it well. Currently, the items are classified very simply according to the number of demand events. This leads to the situation that the categories contain very different types of items, and in practice it is necessary to adjust inventory control practices item by item. The current method does not make any difference between different demand profiles. One point to consider is identifying dependent demand, so that the advance information potentially obtained from customers can be utilized more efficiently in inventory planning. If the items could be classified in closer detail by demand characteristics, it would facilitate the development work.

The research questions of the study are:

How to classify spare parts in the case of highly variable demand and limited data?

How to use that classification in pointing out potential development targets in inventory management?

The goal is to present a simple approach that is easy to adopt. The practical needs of the case company provided the starting point for the study, where a classification model for spare parts was built tested with real transaction data of the case company.

The paper is organized as follows. Section 2 contains a literature review of classification models for spare part inventory management. Section 3 presents the case company, and section 4 describes the process of building the classification model, and demonstrates its use with the case material. Section 5 discusses the differences with similar studies, and section 6 contains concluding remarks.

2 Research background

In this section, we present an overview of the special characteristics of spare part inventory management, and present a review of classification models that have been presented to support spare part inventory management decisions.

2.2 Special characteristics of spare part inventory management

Due to their special characteristics, spare parts form a special domain within inventory management. Typically, demand volumes are lower and more volatile than for consumer products. When demand occurs infrequently, it is referred to as intermittent demand (e.g. Boylan et al., 2008). Some spare parts are critical to the continuity of users' operations, which poses high service level requirements. For an extensive overview of literature on spare parts inventory management, see e.g. Kennedy et al. (2002). One special issue is the connection to the maintenance function, which dictates the demand for spares. However, this is typically studied from the spare part user's point of view. E.g. *Age-based replacement* and *Repairable spare parts* are examples of special areas which former spare part inventory management studies have focused on (Kennedy et al., 2002).

However, research on linking maintenance information or other customer-specific information to inventory management decisions seems sparse. Some research has been done on stocking spare parts for equipment with scheduled usage (Bridgman and Mount-Campbell, 1993), and on linking inspection schedule information to demand forecasting (Wang and Syntetos, 2011). Martin et al. (2010) point out that in the literature, the inventory management of spare parts is rarely analyzed from the point of view of the supply chain as a whole, but rather from the point of view of a single actor. However, due to technological progress, it becomes more feasible to take the supply chain perspective into account. Kennedy et al. (2002) note that the biggest change occurring in maintenance has been the introduction of the Internet, which allows increased communication between the supplier and the user, and more research is needed on its benefits.

2.3 Case studies about spare part inventory management

There are several case studies available about inventory management of spare parts. In general, case studies aim at modeling the demand of spare parts that is typically intermittent and lumpy, and automating the selection of inventory control parameters. Nagarur and Baid (1994) present a case where the inventory control parameters are selected on the basis of ABCD-classification, and compare different forecasting approaches (product-reliability model, regression model or time

series forecasting) with past data. Kalchschmidt et al. (2003) deal with a situation where a central warehouse serves both end-customers and intermediate warehouses, and propose approaches for separating these two demand modes for demand forecasting. Nenes et al. (2010) apply gamma distribution with a probability mass of zero for estimating future demand. Syntetos et al. (2010) suggest a more automated approach to stock control that comprises the order-point policy and the use of Syntetos-Boylan approximation as the forecasting technique. Also other inventory-related decisions have been studied. E.g. Persson and Saccani (2009) evaluate different choices about the location of spare parts inventory through a simulation model.

In this paper, we focus on classification studies that aim at improving spare part inventory management. Using classification as a development tool is interesting because classification also serves as a diagnostic tool. An appropriate classification can be used to get a quick overview of the company's situation, prior to more precise development efforts. When understanding accumulates from several case studies, it is possible to build a more general model for diagnosing spare part inventory management policies.

2.4 Classification models for spare part inventory decisions

The focus of this case study is to assist in selecting the inventory policies for spare parts. The former literature provides some decision frameworks for similar tasks. In a recent review, Bacchetti and Saccani (2012) found 27 works dealing with the classification of spare parts or other low-demand items. 10 of these papers address also inventory management issues, and 6 of them develop a decision-making framework considering inventory management. Outside the review, the work of Paakki et al. (2011) and Bacchetti et al. (2013) can be included to this selection of papers. Table 1 summarizes spare part classification studies that contain an inventory-related decision-making framework. It is presented which classification criteria are used and how the classification is to be used in inventory management.

Table 1: Spare part classification works with inventory management implications

Paper	Classification method	Implications to inventory management
Gelders & Van Looy (1978)	ABC analysis - demand value	Selecting inventory models
Huiskonen (2001)	Multi-criteria: (part criticality, demand variability, part specificity)	Guidelines for logistic system design (Network structure; materials positioning; control responsibilities; control principles)
Cavalieri et al. (2008)	Multi-criteria: (part cost, part criticality, demand variability, part specificity, supply characteristics)	Focusing attention; selecting the forecasting approach (reliability based or time series); selecting the stock sizing approach
Porras & Dekker (2008)	Multi-criteria: (part cost, part criticality, demand volume)	Selecting approaches for determining ROP system variables
Boylan et al. (2008)	Multi-criteria: (aspects of demand volume and variability)	Selecting the forecasting method (moving average vs. Exponential smoothing); selecting inventory control rules
Syntetos et al. (2009)	ABC analysis - demand value	Selecting inventory control rules (manually vs. automatically created ROPs)
Paakki et al. (2011)	Multi-criteria (part cost, demand volume, demand variability, supply characteristics)	Focusing development efforts (e.g. to reduce lead times, to understand customer behavior, to revise inventory policies)
Bacchetti et al. (2013)	Multi-criteria: (sales cycle phase, response lead time to customers, number of orders, part criticality, part value)	Selecting forecasting and stock-control methods and targets

The works in table 1 represent the branch of pragmatic studies. According to Bacchetti and Saccani (2012), evidence of empirical application of spare part classification methods in general is relatively rare. However, except for the work of Huiskonen (2001), all the works in table 1 report classification methods that have been actually implemented in companies. Some of the frameworks focus more on selecting inventory control parameter or quantitative forecasting methods (Boylan et al., 2008; Gelders and Van Looy, 1978; Porras and Dekker, 2008; Syntetos et al., 2009; Cavalieri et al., 2008), whereas some focus more on providing qualitative guidelines for development work in general (Paakki et al., 2011; Huiskonen, 2001).

In addition, there are some classification studies that do not directly address inventory management issues, but focus on demand forecasting, which may serve as an input in inventory control. For a profound review of contributions on demand categorization for spare part management, see e.g. Bucher and Meissner (2011).

2.5 The uses of spare part classification models

The classification models presented in table 1 work as a basis for development actions. The use of item classification can be divided into three types:

1. Focusing the attention in general

At its simplest, classification can be used for focusing the attention on a specific group or groups of items. In Syntetos et al. (2009), the manual work of selecting ROP-system parameters focuses on the parts with the greatest sales volume. The importance of focusing the attention is emphasized also in the works of Cavalieri et al. (2008) and Paakki et al. (2011).

2. Forming heterogeneous groups for comparing stock control methods with the simulation approach

In four studies, a simulation approach has been used to compare the suitability of different inventory control methods (Cavalieri et al. 2008, Porras and Dekker 2008, Boylan et al. 2008, Bacchetti et al. 2013). An inventory control method is composed by a criterion that specifies the conditions under which a new order should be issued, and a reference point for the quantity to be ordered. However, simulation requires that there is enough data available to allow reliable conclusions. Cavalieri et al. (2008) do not discuss the issue of data availability. Bacchetti et al. (2013) consider 3 observations about the demand as a minimum requirement for applying a simulation approach. Also items with 18 months from the last order have been classified as dismissed and excluded from the simulation approach. Porras and Dekker (2008) address the issue of very low demand and mention that the items for simulation were selected from a larger group, but do not explicitly describe the selection criteria. In the work of Boylan et al. (2008) data sets from different companies were used, but the simulation approach was not applied for all of them due to the lack of inventory-related data or great variation in demand variability and order intervals over time.

3. Supporting judgment-intensive managerial decisions

Two studies deal with providing improvement suggestions without using the simulation approach. Bacchetti et al. (2013) offer some suggestions for the item groups that are not considered suitable for applying the simulation approach. For low-demand spare parts the suggested approach is using a causal forecasting method which is based on the demand rate of a similar component, employed on similar product models with a longer demand history. For dismissed items, make-to-order (MTO) or a periodic control with order-up-to level on the assumption of Poisson distributed demand is applied. In Paakki et al. (2011), the simulation approach is not applied at all, but qualitative suggestions about further development work are made for different item categories. One of the suggestions is revising the inventory policies, for which the simulation approach is a potential approach. Other suggestions are e.g. understanding customer behavior and reducing lead times, which are more time-consuming efforts, and managerial judgment plays a greater role in their implementation. Therefore, it is more difficult to quantify the potential benefits of these efforts. The benefit of this approach is that some practical suggestions to the case company can be given, even if the data is too “difficult” to be analyzed with simulation. In addition, the suggestions are not limited only on changing inventory control parameters.

Applying different classification models have been reported to provide some benefits for the companies studied, e.g. cost savings, improvement in service levels, or facilitation of further development work. However, because the studies are mostly single case studies, wider generalizability of the results remains unclear. In addition, discussion about the practical applicability of classification methods, (topics like data availability, implementation algorithms,

classification update, solution sensitivity to thresholds, or the role of judgment) is often absent in classification studies (Bacchetti and Saccani 2012). Van Kampen et al. (2012) present a literature review on SKU classification methods for production and operations management, and present a conceptual framework for building a SKU classification model that synthesizes previous work, as groundwork for theory building with respect to SKU classification. The authors point out that much is still to be studied e.g. to understand the reasons for selecting specific classification characteristics or techniques and setting class boundaries.

Our target is to expand the understanding of different classification models and their uses. We present a case example where it is difficult to classify the demand with the existing classification models. In our study we explain the process of selecting the classification criteria.

3 Introduction to the case

The case company is a large global equipment manufacturer that seeks to expand its spare part and maintenance business. The equipment is mostly customer-specific installations to basic industry. The total sales value is around 100 M€ of which the share of service business is 30% and growing. The spare parts in question are non-repairable parts by default.

The company has several stocking points globally. In principle the inventory system is a two-echelon one, consisting of stocks kept in connection to the production units and stocks kept closer to market areas. Currently, inventory control at the various echelons of the chain is completely decentralized. Part of the perceived demand uncertainty is due to the supply chain structure. The central warehouse serves both end-customers and intermediate warehouses, making the demand composite of dependent and independent demand. This kind of supply chain structure is not unusual in the spare part business. A rather similar supply network structure is presented e.g. in the case study of Kalchschmidt et al. (2010).

As the information sharing between the units is currently limited, the analysis in this study focuses on one level, the stocks that are in connection with the production units. The company is currently working on the task of unifying the spare part inventory policies of different units. The process includes reassessing which parts should be kept in stock. If parts are kept in stock, a replenishment policy needs to be decided upon, including the approach for estimating future demand.

The current inventory policy in the case company is such that items with 3 or more orders per year are classified as “items with repeating demand”. For those items, a re-order point (ROP) system is applied. Economic order quantities (EOQ) s are calculated on the basis of two-year average demand volume, and provided as a guideline for the decision makers. The parameters are updated every 6 or 3 months, depending on the sales value of the item. From some items, judgmental forecasts are collected from sales units every 3 months, but they are not formally connected to the decision process. This general policy is not implemented in its full scope yet, but is being piloted with named product lines. Traditionally, the inventories have been managed locally, and the policies have not been documented. In general, the whole inventory system is under construction. The decisions to consider include what items should be kept in stock, and how dependent demand could be identified better so that stocks are not kept for pre-known demand.

The group of items, for which the inventory plans are currently made, is quite heterogeneous. The decision maker needs to decide judgmentally if the suggested ROPs and EOQs are applicable in each case, and if other sources of information should be taken into account when making replenishment orders. Therefore, in the case company there is interest in examining the possibility

of creating a more detailed decision framework, in order to facilitate the planners' work. To put it briefly, this study seeks to develop and test a classification model for spare parts with a limited data set.

4 Research process

The research process consisted of different phases, as presented in Figure 1. There was some iteration between the phases. Below, the phases of the research process are described in more detail.

Figure 1: Phases of the research process

4.1 The objectives of classification

The focus of this study was decided upon in discussions with the case company staff. The main objective was to develop a more detailed classification for demand patterns, which would take into account the special characteristics of the case company, define its potential implications for inventory management, and compare it with the current inventory policies.

The potential consequences of the analysis were suggestions on:

1. Which items should be considered to be made to order (MTO)
2. When it would be most necessary to collect customer forecasts or advance orders
3. For which items the inventory control parameters should be revised and how

The aim was to revise the current inventory policies, and to point out potential development targets. Even though inventory control parameter revision is one possible outcome of this analysis, it is not the main focus, unlike in many former studies (See table 1). If compared with former studies, our objectives are closest to the work of Paakki et al. (2011), where the emphasis is on focusing development efforts in general.

4.2 Collecting and cleaning data

The quantitative data was gathered from the company's ERP system. This data included transaction data: data about incoming orders and deliveries. The data from one product line was selected for piloting the data analysis. This was because data from the longest time period was available in this unit, and the quality of the data was relatively good. This was the same product line for which a common inventory policy had been developed, so it was natural to analyze a data set where it was possible to compare suggestions against current inventory policies. Also, the unit was located so that it was possible to gather interview data from the unit as well. It was possible to get sales data of 48 months, and more detailed delivery data of 12 months.

In practice, the documented demand history of an item is influenced by several in-company factors that need to be understood before classifying demand patterns in detail. It was noticed that there were big differences in the total yearly (and monthly) sales values. There were also clear temporal coincides in the demand of individual items. These observations were explained by company members responsible for the sales operations of the product line. In this case, the following internal causes were found: 1) structural changes in the sales department as well as in production, 2) product substitution and standardization, and 3) internal purchases.

A major part of the 13 000 items were left out of further analysis for the reason that they were either categorized as obsolete or there were not enough demand events to allow calculating e.g. demand-

interval variation. “Obsolete” items are items that have been replaced with another item, or in some cases out-of-date product names. For the sake of simplicity, only items that were currently selected to be stocked were selected for further analysis. The number of items was 1 679, but some of those items were sold in both units, so the number of item-unit combinations was 1 783. The current structure of the sales department and the product line had prevailed for the last 24 months, so that data was selected for doing detailed analysis of the demand patterns at this point. All the anomalies in total demand could not be explained, and the possibility of errors in the data could not be totally eliminated. Therefore, the possibility of errors must be taken into account when interpreting the results of the analysis.

Figure 2 provides a general view of the 1783 item-unit combinations that were currently selected for stock-keeping. It shows how many observations about the demand were available per item. For 21 % percent of the stocked items, there were less than 3 orders, and for 50% 5 or less orders during the last 24 months. The less orders there were available, the less there was place for statistical analysis. For a substantial part of items there were only few orders. This weakened the possibility to draw reliable conclusions from the demand data only. Also the quality of the data was questionable. Therefore, the results of the classification should be used as a suggestive guideline to be qualitatively verified rather than an automatic way of determining inventory policies.

Figure 2: A view of selected data

4.3 Defining a classification model

Van Kampen et al. (2012) present that selecting an SKU classification method consists of three interrelated decisions: 1) selecting the classification characteristics, 2) selecting the classification technique type, and 3) determining the number of classes and the boundaries between them. In this section we explain how these steps were performed in this case and how the context and the aims of the company influenced these decisions.

The most popular classification criteria in former spare part classification studies are part cost and part criticality, followed by demand volume or value and supply characteristics, such as replenishment lead time or supplier availability. Also demand variability has been used in several works (Bacchetti and Sacconi 2012). Below we explain why some of the most common classification criteria were excluded and why some uncommon criteria were included.

This study focuses on the classification of the demand profile. In the case company, items with 3 or more orders per year were originally classified as “items with repeating demand”. The problem with this classification was that the group of “items with repeating demand” was known to be very heterogeneous. The aim was to find out whether it was possible to sort out different types of demand in this group. The ABC- classification was already in use in the case company, which steers the amount of attention that is paid to the items (e.g. how often inventory control parameters are to be updated). This classification can be used parallel with the suggested classification scheme, so it was not considered necessary to include part cost as a classification criterion in the model. The popular classification criteria in former studies, part criticality and supply characteristics, were left out of this model since it was not possible to obtain detailed information about these issues, and the main focus of interest in the case company was on the demand profiles. However, part criticality and supply characteristics are not negligible matters even though they are not included in this model.

Some models for spare part demand classification have been presented in the literature. We have used the model of Syntetos et al. (2005) to provide a general view of the data set studied (Figure 3). A forecast review period of one month is assumed. Only two of the 1 783 item-unit combinations have the coefficient of variation (CV^2) less than 0.49, and 337 items have the average inter-demand interval (p) less than 1.32. Being so, a majority of the demand can be described as erratic or lumpy, the group of lumpy demand items being quite heterogeneous.

Figure 3: Demand patterns described by using the classification model of Syntetos et al. (2005)

4.3.1 Definition of classification criteria

In this section we describe the classification criteria used in this study. Even though former literature contains models for demand classification, e.g. the model of Syntetos et al. (2005), this type of methods have been developed for selecting statistical demand forecasting techniques, which is not the objective in our case. Instead, we have focused on detecting the special characteristics of demand in the case company, and finding out if the perception of special characteristics of demand can be facilitated with data analysis.

This analysis focuses only on items that currently have an inventory policy. In principle, the company has inventory plans only for items that have at least 3 orders per year. In practice, also items with lower demand are kept in stock. We have excluded these items from further analysis for two reasons: there was no access to information on the special reasons why the stocks are kept, and the very sparse demand (or no demand) did not allow any statistical analysis.

Figure 6 presents a conceptual model for categorizing the items. The definition of the classification criteria is explained below.

1. When the demand patterns were observed visually, it was noticed that for some items the orders seemed to arrive in “bundles”, i.e. the orders arrived during a short time period or there were very long intervals (over one year) between the orders (Figure 4). The typical assumption of stationary demand did not seem to hold in all cases. Therefore the average interval is not necessarily a sufficient metric in distinguishing the different patterns in this case. Non-stationary demand is in theory unsuitable for continuous inventory planning. Therefore items that have a “bundled” demand history, which means that all the orders have arrived within a very short time period, or there have been extremely long intervals between orders, are distinguished. For these items, it is relevant to evaluate if the demand has actually ended or similar patterns are to be expected in the future. After that, it can be evaluated if it is economical to keep such items in stock in the first place or if they should be made to order.

Figure 4: Examples of "bundled" demand

For category 1 (bundled demand) there were no ready-made classification criteria available, as the typical assumption is that the demand is stationary. The demand interval may seem regular, but all the observations are from a short time period. For pointing out these cases, the time between first and last order serves as the criterion. In the case company, there was interest to view also the cases in which there was more than one bundle of orders in the demand history. Pointing out these cases was not straightforward, but to facilitate the observation also the items with one very long interval were included in this category, as also that does not fit the assumption of stationary demand.

2. The customer base is two-fold. Items are sold both to internal and external customers. In addition, some of the internal customers hold stock. In such a case, stock replenishments are somehow planned in advance and therefore predictable to some extent. The basic idea is to identify items that are already kept in stock at a lower level of the supply chain. If that is the case, the aim is to create a central inventory plan that takes all stocks into account, to prevent a bullwhip effect. It is feasible to start such a search from the items that are only sold to internal, warehousing customers. Therefore the customer base is one classification criterion. This criterion is unambiguous: the customers are either internal or external and they either have or no not have a warehouse to serve their own customer demand. This information was easily available in the company data.
3. Next, items with a mixed customer base were examined further. Items that had a low base demand, but exceptional demand “peaks” were distinguished (Figure 5). The case company staff assumed that very large order quantities are stock-replenishment orders (and in some cases errors), where the customer is not in acute need of the items. For such items, the idea was to plan the inventory by default for the low base demand only, and to determine longer lead times for exceptionally large quantities.

Figure 5: Examples of low base demand with peaks

The issue of identifying demand “peaks” from “stable demand” has been discussed in former literature. Kalchschmidt et al. (2003) present a method for filtering “peaks” from the more stable demand. The idea is to build a threshold that separates what should be considered “stable” from what should be considered “irregular”. Every demand observation lower than the threshold is considered “stable”, otherwise it is considered irregular. The threshold is built by first eliminating the most variable phenomena using the median and standard deviation of the total demand series. The new series obtained is much less variable, and its median and standard deviation are closer to the real stable pattern, and can be used as a basis for estimating the threshold. The authors have used this filtering method for separating two demand patterns to be forecasted separately.

The situation in our case was slightly different. Instead of separating two observed demand patterns from each other for forecasting purposes, we simply aimed at identifying the situations where the demand seemed to consist of two patterns: low base demand and demand peaks. What we really wanted to do was to rate the items on the basis on how well their demand followed the pattern described. The challenge was that the number of orders was typically very low, so in very few cases it was possible to separate a demand component that could be referred to as “regular”. Being so, we had to use two-dimensional criteria. The number of orders determines how reliable conclusions can be made on the basis of past demand data, and the abnormality of the order distribution is measured using other metrics. We chose the metric that identifies the situations where a small share of orders represents a large share of the total demand volume. There are two variables in this metric, and in order to get a value for this metric, the other variable needs to be fixed (e.g. 30% of the largest orders). It needs to be noted that the order distribution abnormality can be measured also using other metrics, e.g.

$$X = \frac{Mean - Median}{Median}$$

The greater the x , the more it implies that there is one or a few large orders among smaller orders.

4. There are relatively large changes in the demand volumes on the yearly level. This may be explained e.g. by the growth of the installed base. If the demand growth is explained by the number of equipment maintained, it may be considered permanent by nature, depending on the terms of the maintenance contracts. The existing inventory control plan for the items was quite static, because two-year average was used as the future demand estimate. The aim is to distinguish items for which a more dynamic inventory control could be suggested. A possible very simple step towards more dynamic control would be decreasing the time period from which the demand is evaluated.

We used a very simple metric for measuring the trends in demand: growth of the yearly demand volume. This simple metric was selected because the demand intervals varied greatly among the items. In case of more continuous demand, a more sophisticated metric could be used.

Figure 6: Categorization of items

4.3.2 Selecting the cutoff rules

The next step is to set the cutoff values between the categories. The question is how the cutoff values should be selected. In former spare part classification models, the use of unspecified, ad-hoc or judgmental cutoff values is common for part cost, demand value/volume, supply characteristics and criticality. Demand variability is the only criteria for which also some analytically obtained cutoff values have been applied (Bacchetti et al. 2013).

Setting analytically obtained cutoff values for demand variability is based on the premise that it is possible to identify conditions for superior forecasting performance, and then to categorize the demand on the basis of these results. This approach is applied e.g. in the work of Cavalieri et al. (2008), Boylan et al. (2008) and Syntetos et al. (2010). The performance of different forecasting methods can be estimated quantitatively with the simulation approach, and therefore somewhat exact cutoff values can be set, although there is variation depending on the data set and performance metrics used, as noted e.g. by Boylan et al. (2008). However, applying the same cutoff rules will not necessarily guarantee superiority in stock-control context (Boylan et al., 2008).

In our case, the potential new policies that are considered are moving towards MTO, increasing visibility in the supply chain, and applying more dynamic inventory control. These suggestions are general, and the exact way of implementation is planned only if potential pilots for implementation are found. The cost-effects of this type of decisions cannot be modelled exactly a priori, so the prerequisites for setting exact cutoff values are weak. The whole point of classification is to help find the most potential pilots for the development actions. Instead of a strictly limited group of items, we aim at framing a group of items among which the potential pilots, that is the extreme cases, exist.

A practical criterion for setting the cutoff values is that a class contains a manageable number of items, taking into account the action targeted to the class. This criterion is mentioned also in some former studies (e.g. Syntetos et al. (2005), Porras and Dekker (2008)). We have set the cutoff values so that the number of items is less than 100 in each category for which new policies are suggested. This limit was set in cooperation with the case company. In this size selection of items it is relatively easy to select suitable pilot items judgmentally for piloting a new rule or action. We have

preferred round numbers for the cutoff values to emphasize the fact that these values are not rigorous. The result of using round numbers was that in one class (positive trend in demand) the number of items exceeded the limit of 100, but this was not considered harmful. The cutoff values and the number of items in each category are summarized in Table 2.

Table 2: Cutoff rules for categories and the number of items in them.

Category	Criteria	Cutoff rules	Number of items
1	Unstationary demand	One very long (>395 days) interval, or the time between the first and last order is short (less than 90 days)	93
2	Internal warehousing customers only	All orders come from internal customers that have a warehouse	49
3	Low base demand with peaks	Less than 30% of orders represent more than 70% of the total demand volume, and the number of orders is equal to or greater than 10	63
4	Positive demand trend	300% or greater growth in demand between 2010 and 2011	408
5	No trend	Less than 300% growth / -80% decrease in demand between 2010 and 2011.	776
6	Negative demand trend	-80% or greater decrease in demand between 2010 and 2011	21

It needs to be noted that the cutoff rules are case-specific and suggestive. In this case, the cutoff rules were discussed with the company representatives, as managerial understandability of the classification method as a whole is important. The rules are intentionally quite robust. More sophisticated methods would have been available e.g. for trend measurement, but this rough measure was selected for the sake of simplicity, to start with. It was noticed that a positive trend in the volume was stronger and far more often observed than a negative one, and therefore the percentage limit in category 4 is higher than that in category 5. For categories 1 and 3, the parameters were iterated so that a comprehensible number of items were included in the category, and that the demand profiles of those items in general reflected the managers' perception of "slow demand with peaks" or "bundled demand". The proposed actions for each category are presented in Table 3.

Table 3: Proposed inventory management actions for each category

Category	Proposed action
1	If non-stationary demand is confirmed, consider MTO.
2	If the demand is confirmed to be dependent, increase visibility in the supply chain and consider centralized inventory planning.
3	If exceptionally large orders are confirmed to represent dependent demand, move large orders to MTO and set appropriate lead times. Stock control parameters are estimated for the low base demand.
4 and 6	If the trend is judgmentally confirmed, set more dynamic inventory control.
5	Evaluate the performance of the current policy.

As discussed in section 4.1., in the beginning of the process of building a classification model, the objectives of the classification were defined in cooperation with the company representatives. The propositions were ones that the case company was interested in and willing to accept at this point. The aim was not to increase the number or stocked items, but rather to limit it. This classification model will help in sorting out the items that could be chosen fully or partially for MTO (categories 1 and 3). This classification does not directly suggest moving the items to MTO, but rather points out the group of items within which this possibility is studied further. In category 2, the demand consists of orders that come from internal customers that have a warehouse, so all the orders are possibly stock-replenishment orders. However, in the current situation it is not known which items are kept in stock at these customers, and which are ordered according to end-customer orders. In general, the aim is to increase visibility in the supply chain, and it would be advisable to choose the pilot items from this category. Currently, forecasts are collected from sales unit for some items, and these forecasts are dealt with as advance orders. The development of this process could be continued with special attention on category 2. For categories 4 and 6, more dynamic inventory control is suggested. A possible very simple step towards more dynamic control would be decreasing the time period from which the demand is evaluated. Currently, the company is in process of evaluating the performance of the current policy. It is suggested to focus the evaluation on category 5, from which the clearest anomalies have now been removed. However, category 5 is still quite heterogeneous with respect to all the metrics used. Currently, the case company is evaluating the performance of the current policy both by observation and simulation, as the policy has not yet been fully implemented in all units.

4.4 Implementation and managerial implications

The potential benefits of the suggested development actions can be presented at the idea level. We refrain from presenting euro values for the saving potential, as the implementation potential of the suggestions depends on factors that could not be included in this model.

The suggestions for categories 1 and 3 concern moving towards MTO either generally, for certain periods of time, or for certain customers. The potential benefit comes from the decrease of stock levels needed. Increasing the visibility in the supply chain serves the same purpose. The need for overall inventory is decreased if information about the forthcoming orders can be obtained earlier and if stock replenishment decisions can be made centrally.

The potential benefit of setting more dynamic inventory control comes from more exact demand volume estimates. Currently, EOQ is used. The benefit of using an exact demand estimate can be presented theoretically. The total yearly inventory holding costs (relating to demand volume) can be written as:

$$Total\ costs = \frac{D}{Q}S + \frac{Q}{2}ic$$

where D: yearly demand volume, Q: order quantity, S: stock replenishment cost, i: inventory holding cost and c: the euro value of the item. If the EOQ is calculated with erroneous demand volume, the total costs are:

$$Total\ costs = \frac{D}{\sqrt{x}Q}S + \frac{\sqrt{x}Q}{2}ic$$

where x is the erroneous demand volume divided with the correct demand volume. For example, if the real demand volume is 4 times greater than the estimated volume, calculating EOQ with the erroneous demand volume results in double stock replenishment costs and half inventory holding costs (though greater total costs) than if EOQ is calculated with an exact demand estimate. For items for which the level of demand has permanently increased, and is expected to continue to rise, one year average gives a more exact demand estimate than two year average (as currently used). However, this analysis was designed to only point out a subset of items for which moving against more dynamic inventory control could be explored in more detail.

At the time of writing this paper, the company was interested in implementing the classification model. Some observations (e.g. about the bundled demand) were new to the company. Different kinds of demand patterns had been identified earlier (e.g. low base demand with peaks), but the prevalence of such patterns was unclear. This model was used for focusing the development resources, but later on it can be used as decision support in making replenishment decisions. Quite simply, an integral part of the implementation was to transfer the spreadsheet procedures to the use of the person responsible for the development work.

Currently, the special characteristics of the items are taken into account manually when making the replenishment decisions. This classification model does not eliminate the need for manual work, but it helps in saving time, when an information system automatically points out the category into which the items fall. All the calculations used in this work were performed with a spreadsheet application, so the system requirements are not high. However, expanding the use of the framework to some other unit or its ongoing use requires verifying that the cutoff rules are relevant and up-to-date.

5 Discussion

In this section, we present a summary of how classification models can be used for improving spare part inventory management practices. This summary is based both on former case studies and our study. Van Kampen et al. (2012) present that selecting an SKU classification method consists of three interrelated decisions: 1) selecting the classification characteristics, 2) selecting the classification technique type, and 3) determining the number of classes and the boundaries between them. We present that before the phases presented by Kampen et al. (ibid.), there should be:

1. Defining the objectives of an improvement project
2. Rough-cut data analysis.

Below, we summarize typical improvement objectives, present how to demonstrate the availability of data and how these issues affect the type of classification model that can be used.

5.1 Defining the objectives of an improvement project

A list of objectives that have appeared in spare part classification studies, including the present one is given below. It presents what kind of decisions can be potentially supported with part classification. Of these objectives, stock control and demand forecasting are well represented in former studies, whereas in our study the emphasis is more on fundamental stock-keeping issues. Our focus was largely due to the fact that the target company's inventory management practices were not on a mature stage: the policies were new and not yet implemented in their full scale, and the stock control in the supply network was decentralized.

Fundamental decisions for stock-keeping:

- Selecting the items to be stocked and not to be stocked
- Identifying dependent demand
- Deciding on the promised delivery times

Stock control:

- Selecting between centralized and local stock control (in a multi-echelon system)
- Selecting stock control parameters
- Selecting the update frequency of stock control parameters

Demand forecasting:

- Selecting statistical demand forecasting techniques for the stocked items
- Selecting the focus for salesforce forecasting

The objectives of an improvement project can be put roughly into two categories: 1) selecting ways of working, and 2) selecting control parameters. "Selecting the ways of working" includes the strategic decisions in inventory management, whereas "selecting control parameters" (for inventory management, demand forecasting or both) is a focused objective and lends itself for the simulation approach in searching for the solution. The main difference between these two is that more managerial judgment is needed when making strategic decisions, whereas control parameter selection can be automated if there is enough data available.

5.2 Rough-cut data analysis

The availability of data dictates how reliable conclusions it is possible to make on the basis of it. In general, the more observations there are about the demand, the better. However, the problem is that the demand for spare parts is typically very sparse, so sometimes there are only a few observations about the demand. We suggest using a graph to demonstrate the type of data (Figure 2). The graph presents the number of observations that are available for the items. In general, the type of case data has not been presented in former case studies. The graph can be used to communicate with the target company of what is the potential role of calculations in the decision making. For example, in the target company there was interest towards statistical forecasting methods, but because the number of demand events was so low, it was noticed that the applicability of statistical forecasting methods was very limited.

The limits in the graph have been drawn from the following reasoning: in minimum, three observations are needed for calculating an average interval between demands; in minimum, five observations are needed to be able to calculate two independent values for average demand intervals. Otherwise, it is not possible to evaluate the reliability of the calculations on the basis of the data. However, data availability is only a preliminary classification criterion, and does not guarantee that the optimization of inventory control parameters is possible.

5.3 Defining a classification model

The objectives and the available data dictate the selection of classification criteria. In this section, we review the classification criteria and the selection practices of the cutoff rules that have been used in spare part classification studies.

5.3.1 Defining classification criteria

The classification criteria can be divided roughly into three categories: for some of the classification criteria, their utility and reliability depend on the number of observations, whereas some are independent of number of observations. In addition, there are criteria that can be determined both statistically and qualitatively. In case of limited data, classification may be supplemented with qualitative techniques.

Criteria that are independent of the number of observations (can be applied for items with less than 3 demand events)

- Demand volume (value)
- Part cost
- Part criticality
- Part specificity
- Response lead time to customers
- Supply characteristics
- Sales cycle phase

Criteria for which the utility and reliability depend on the number of observations (can be applied for items with 3 demands, reliability can be evaluated with 5 demands, and reliability improves with more demands)

- Demand variability, determined on the basis of:
 - demand interval and its variation
 - order size and its variation

Criteria that can be determined both statistically and qualitatively

- Demand source (Internal/external demand)
- Trends in demand
- Demand distribution abnormality:
 - abnormality of order interval distribution
 - abnormality of order size distribution

Some new metrics were applied in this study. This was due to the practical need to make a distinction between items. We presented some metrics for estimating the abnormality of demand interval distribution (“bundled demand”) and abnormality of order size distribution (“low demand with peaks”).

5.3.2 Defining cutoff rules between classes

The selection of cutoff rules in item classification has been identified as a potential area of future studies (Kampen et al., 2012). We present that the selection of cutoff rules between classes depends on the use of the classification model. The possible use of the classification model itself is dictated by both the objectives of the improvement work and the amount of available data. Figure 7 illustrates the role of demand analysis in improving inventory management practices.

The objectives of improvement work can be put roughly into two categories: 1) selecting parameters for inventory control or forecasting, or 2) selecting the ways of working, such as the production mode, supply chain collaboration practices, or making other strategic choices. The difference between the two is that in category 1 the update of control parameters is relatively easy to implement, whereas implementing strategic decisions is more time-consuming and calls for more managerial judgment, as all important factors cannot be modelled. For category 1 the objective of the classification may be finding the most potential items for piloting new ways of working, whereas in category 2 the objective is to automate the selection of control parameters, and thus strict limits between the classes are needed.

If there are less than 3 observations about demand, the data availability is considered extremely low. In the case of extremely low demand availability, the items can be classified only roughly on the basis of demand volume and factors that do not depend on demand frequency (criticality, cost, etc.). The possible role of data analysis is that the attention can be focused on items that are considered the most important by using e.g. traditional ABC analysis. In some former case studies, the simulation approach has been applied for selecting control parameters for items with 3 demands. Even though some suggestions may be given on the control parameters, they are based on the assumption that the demand characteristics will remain the same in the future. This assumption may be either incorrect or correct.

In the case of low data availability (less than 5 observations about demand), it is possible to make some conjectures about demand patterns, but it is not possible to evaluate the reliability of these conjectures. Suggestions for control parameters can be given, but their correctness cannot be verified. Data analysis may give an idea of demand patterns, but it needs to be judgmentally evaluated if the idea is correct and not caused by exceptions and errors in the data.

If there are 5 or more observations about demand, it becomes possible to make basic evaluation of the reliability of such metrics as demand frequency or average order size. With more data it becomes possible to notice regular patterns in demand, if such patterns exist. If the demand is predictable, and the aim is to select control parameters, it becomes possible to try to seek for optimal solutions, which requires setting exact cutoff rules between the classes. However, in the case of extreme demand variability this may not be possible, as noticed e.g. in the study of Boylan et al. (2008).

Figure 7: The role of demand analysis in improving inventory management practices

6 Conclusions

The focus of this study was on classifying spare parts to facilitate inventory management decision-making. This issue was studied from the point of an equipment manufacturer that supplies spare

parts for its customers. The demand is especially sparse, since many of the items are very customer-specific. This paper has presented a classification model developed for the case company.

The selected classification criteria differed from the popular criteria presented in former studies. This was due partly to the fact that e.g. ABC analysis was already in use in the case company, and the classification was intended primarily to refine the existing classification by focusing on the demand profile, which in the existing classification was taken into account only very roughly. On the other hand, some new classification criteria for demand patterns were presented, since the ones presented in former literature were insufficient for distinguishing the patterns that were observed in the case.

The proposed model facilitates the process of pointing out pilot items for potential inventory management development actions, such as moving towards MTO, increasing visibility in the supply chain, or moving towards more dynamic inventory control.

Because this study was a single case study, the model cannot be generalized and transferred to another company as such. The theoretical contribution of this study is that it expands the understanding on what kinds of use the spare part classification models may have, and what kind of classification criteria may be used.

Some case studies with a similar aim exist – improving the current inventory management practices with the help of a classification model. Applying the models have been reported to have provided benefits, so it is relevant to study further the use of models in different kinds of environments. An interesting future research question is what factors are driving, or which should guide the choice of the components of a classification model. Based on this study, at least the company's business environment, the existing classification practice, the characteristics of demand and the quality of data available are factors that have an impact on the model requirements, restrictions, or the chosen classification criteria. Accumulation of information via several case studies in different environments will allow the construction of a more general theory.

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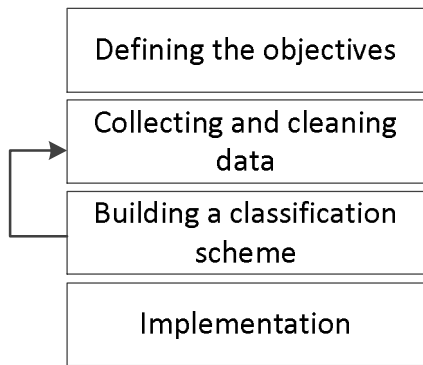


Figure 1: Phases of the research process

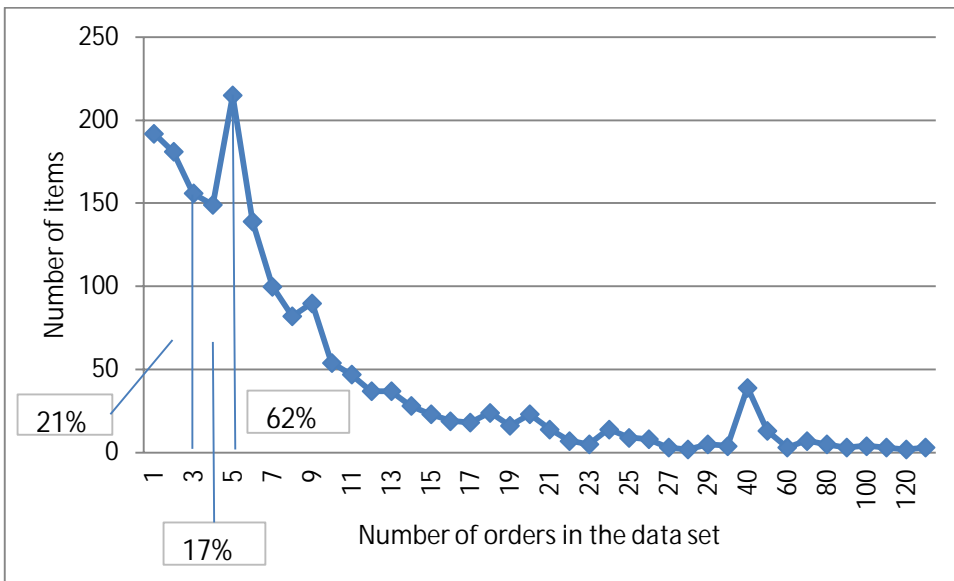


Figure 2: A view of the case data

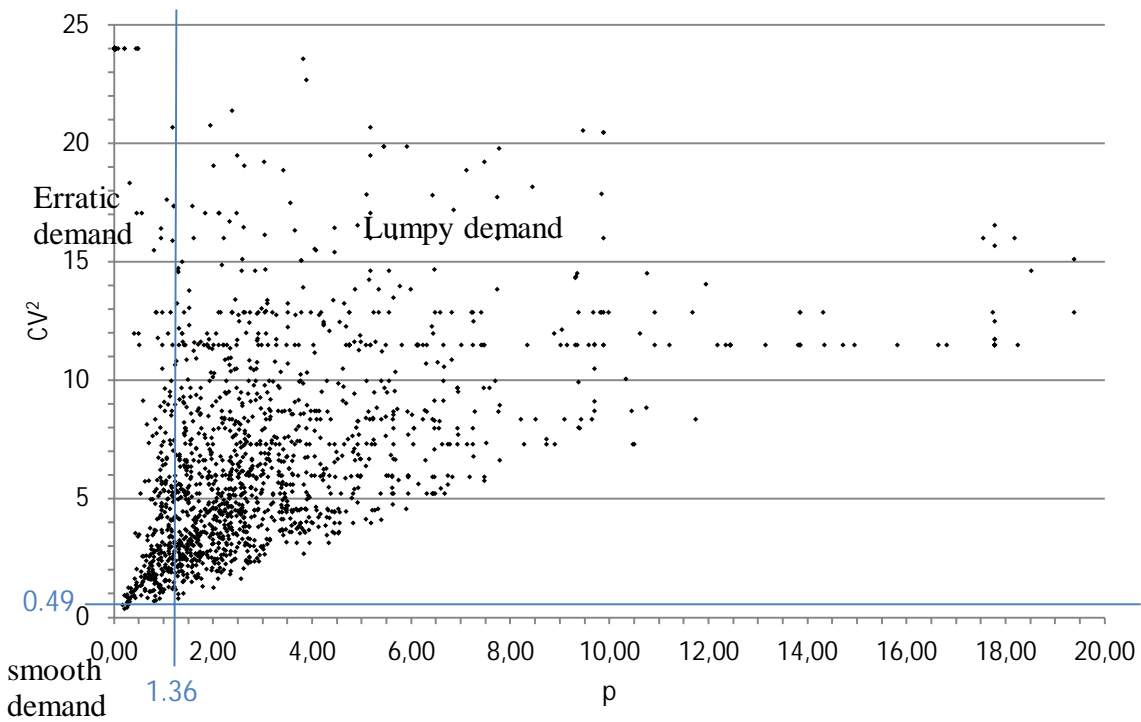


Figure 3: Demand patterns described by using the classification model of Syntetos et al. (2005)

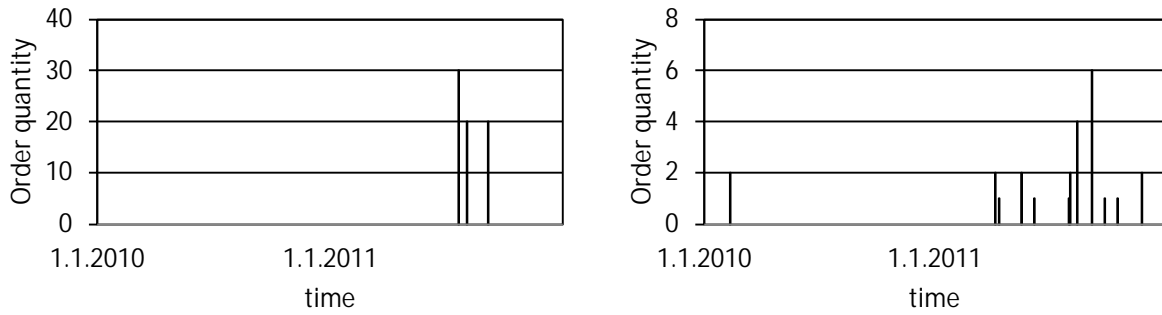


Figure 4: Examples of "bundled" demand

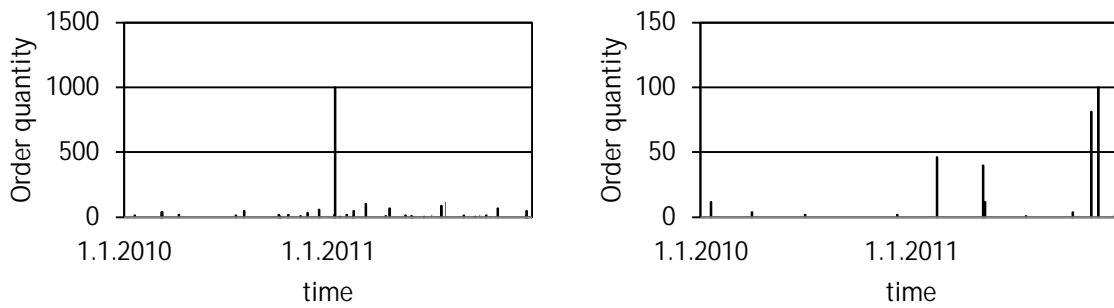


Figure 5: Examples of low base demand with peaks

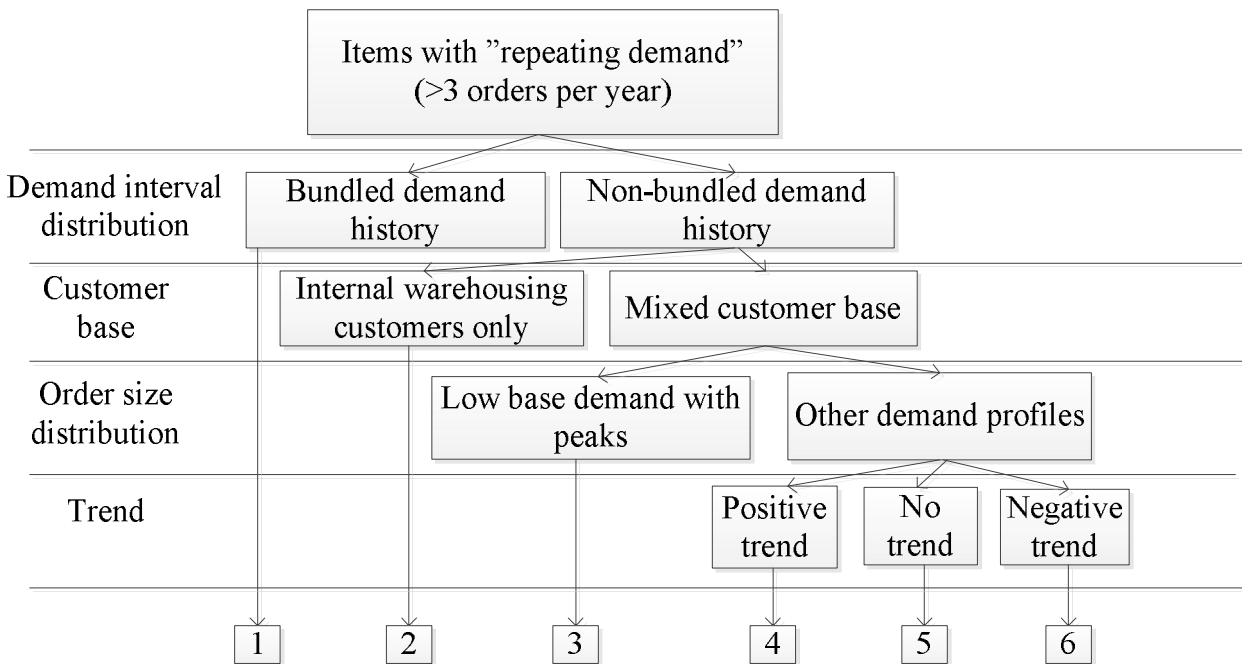


Figure 6: Categorization of items

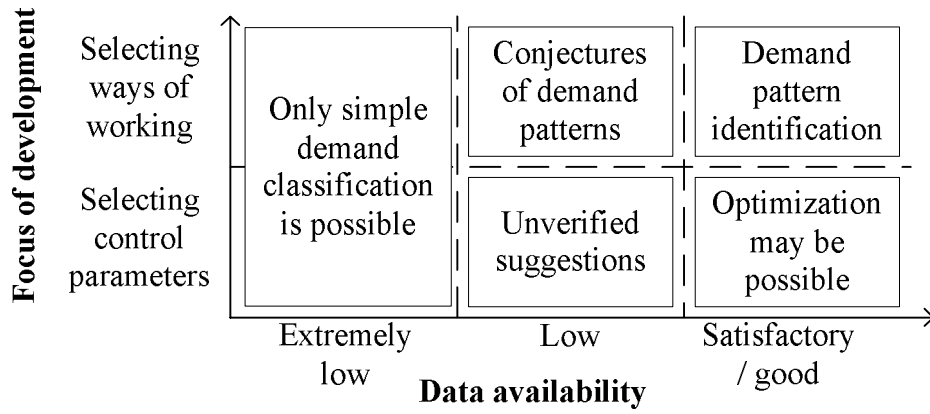


Figure 7: The role of demand analysis in improving inventory management practices