Int. J. Production Economics 148 (2014) 71–80

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Optimizing ABC inventory grouping decisions

Mitchell A. Millstein, Liu Yang, Haitao Li *

Department of Logistics and Operations Management, College of Business Administration, University of Missouri – St. Louis, United States

ARTICLE INFO

Article history:
Received 10 June 2013
Accepted 6 November 2013
Available online 21 November 2013

Keywords:
Inventory grouping
ABC analysis
SKU rationalization
Mathematical programming

ABSTRACT

Inventory managers often group inventory items into classes to manage and control them more efficiently. The well-known ABC inventory classification approach categorizes inventory items into A, B and C classes according to their sales and usage volume. In this paper, we present an optimization model to enhance the quality of inventory grouping. Our model simultaneously optimizes the number of inventory groups, their corresponding service levels and assignment of SKUs to groups, under limited inventory spending budget. Our methodology provides inventory and purchasing managers with a decision-support tool to optimally exploit the tradeoff among service level, inventory cost and net profit. The model and solution are applied for an inventory classification project of a real-life company, and outperform the traditional ABC method. Computational experiments are performed to obtain managerial insights on optimal inventory grouping decisions.

1. Introduction

A manufacturer often keeps inventory of various raw materials and components to meet production needs. A repair shop needs to ensure availability of different parts for replacement and maintenance work. A retailer usually holds certain amount of various merchandize to satisfy market demand. A hospital must keep sufficient medical supplies of all kinds for its clinical and operational needs. In the above inventory systems, the number of stock keeping units (SKUs) may be so large that it is often not practical to control them individually (Ernst and Cohen, 1990).

One way to manage a large number of SKUs is to aggregate them into different groups, and set common inventory control policies for each group (Chakravarty, 1981). Grouping provides management with more effective means for specifying, monitoring and controlling inventory performance. From the operational perspective, grouping may achieve more efficient inventory management by reducing the overhead of managing each inventory group. Inventory policies also align better with item groups than each individual item. For instance, inventory groups with different service levels often reflect a company's order fulfillment strategy and customer relationship policies, e.g., the service level agreement (SLA). Service levels have a direct impact on the company's revenue and profit.

A well-known implementation of the inventory grouping idea is the ABC classification method widely used in industry. It was first developed by GE in the 1950s (cf. Flores and Whybark, 1986; Guvenir and Erel, 1998). In a typical ABC approach, one classifies inventory items according to their transaction volume or value. A small number of items may account for a large share of volume; an intermediate category may have a moderate percentage of volume; and a large number of items may occupy a low proportion of volume. These categories are labeled A, B and C. Taking insights from Pareto (1971), it is often found that a small percentage of the inventory items contribute to the majority of a company's sales and revenue. This has led to the *80–20 rule*. That is, the top 20% of items are given the A classification, the next 30% of items the B classification and the bottom 50% the C classification (Flores and Whybark, 1986). Alternatively, Juran (1954) claims that A-items are the highest 5% of the items in dollar value, C-items are the bottom 75% and B items are the middle 20%.

Practitioners often employ the ABC classification scheme in a three-step approach to control inventory. First, SKUs are grouped into categories according to their sales volume. Second, inventory policies, e.g. the target service levels, are determined for each group. A common wisdom to determine the service level is that one should concentrate on the A category to enhance managerial effectiveness. As a rule-of-thumb, the A-class items get the highest service level settings and C-class the lowest (Armstrong, 1985). Finally, inventory managers, in collaboration with sales management and finance, need to make sure that the inventory control policy is feasible within the available inventory and management budget.

The above ABC inventory grouping and control approach has several disadvantages. (a) According to Teunter et al. (2010), there is no clear guideline in the literature to determine the service level for each group. (b) Since the grouping decision is made

* Correspondence to: 229 ESH, One University Blvd, St. Louis, MO 63121. United States. Tel.: +1 314 516 5890.

E-mail address: lihait@umsl.edu (H. Li).

0925-5273/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.ijpe.2013.11.007

independent from and before the service level decision, their interactions have not been exploited, thus neither of the two decisions can be optimal. (c) Because the available budget was not considered until the last step, there is no guarantee that the grouping and/or service level decisions made in the first two steps are feasible. Thus one often needs to iteratively revise the grouping and/or service level decisions until feasibility is reached. This can be a tedious process for a large number of SKUs, and may lead to sub-optimal solutions. These deficiencies have motivated us to develop a new optimization approach to enhance the existing ABC inventory grouping and control decisions.

Our model and solution will help inventory and operations managers to simultaneously optimize: (i) the number of classification groups for the SKUs; (ii) optimal assignment of each SKU to a group; (iii) target service level for each group; and (iv) optimal allocation of available inventory budget to groups of SKUs. These decisions are made to maximize the total net profit, subject to explicit inventory budget constraints. We have implemented our methodology for an industrial products' distributor using real-life inventory data.

The remainder of this paper is organized as follows. Section 2 reviews the related research literature and highlights contribution of our work. Section 3 formally describes the addressed optimization problem and presents a mixed-integer linear programming (MILP) formulation to model it. In Section 4, we provide a case study of our approach on a real-world inventory grouping application. A comprehensive computational experiment is conducted to further examine the behavior and performance of our model when problem parameters vary. The computational results and managerial insights are presented in Section 5. Finally, Section 6 draws conclusion and discusses future research directions.

2. Related literature

Optimizing inventory classification and grouping decisions have been intensively studied in the research literature of inventory and operations management. The existing research can roughly be classified into two lines of works: one considering only the inventory clustering/classification issues, and the other addressing both inventory grouping and control.

While the classical ABC analysis makes grouping decisions based solely on a volume/cost metric (cf. Pareto, 1971), a vast line of research generalizes it into a multi-criteria clustering framework. For instance, Flores and Whybark (1986, 1987) developed a multi-criteria ABC analysis approach by considering other classification criteria such as obsolescence, lead times, substitutability, reparability, criticality and commonality. They employ a qualitative approach using the concept of joint criteria matrix. Partovi and Burton (1993) proposed a systematic approach to quantify the priority of inventory items through the analytic hierarchy process (AHP, Saaty, 1980). An artificial neural network (ANN) approach was developed by Partovi and Anandarajan (2002) to learn the optimal weights of different criteria. They show that ANN outperforms an alternative statistical approach based on the multiple discriminate analysis (MDA). Bhattacharya et al. (2007) proposed a method, called TOPSIS, to account for various conflicting criteria having incommensurable measures.

Other researchers approach inventory grouping as an optimization problem. Notably, linear programming approach, based on the *data envelopment analysis* (DEA), has been developed by Ramanathan (2006) and Ng (2007), and recently improved by Hadi-Vencheh (2010) and Chen (2011). The advantage of DEA based approach is that it is able to alleviate the impact of subjectivity on the criteria weights. Chen et al. (2008) proposed a case-based distance model to find optimal classification thresholds using quadratic programming. Hadi-Vencheh and Mohamadghasemi (2011) developed a combined AHP-DEA methodology to account for ambiguity of decision-maker's judgments. For large instances, various metaheuristic methods have been developed including genetic algorithm (Guvenir and Erel, 1998) and particle swarm optimization (Tsai and Yeh, 2008) among others.

All the aforementioned works address a pure inventory grouping/clustering problem without explicitly considering inventory policy and performance. Although researchers have found ways to implicitly incorporate inventory control measures in the multi-criteria framework, their grouping solutions do not address the question whether the *three* (A–B–C) group classification scheme is optimal, neither do they consider the interactions between inventory grouping and control decisions.

A second line of research in ABC analysis explicitly addresses and exploits the relationship between inventory classification and control decisions. Early works focus on minimizing total inventory costs, i.e. the inventory holding cost plus ordering cost. They also make strong assumptions to simplify a realistic inventory control system. For instance, Crouch and Oglesby (1978) classified SKUs into a given number of groups, while minimizing the total inventory cost. Their model assumes that the inventory holding cost is the same for all the items, which rarely holds in the practical setting. Chakravarty (1981) considered a more general problem setting and showed that the optimal grouping can be obtained by ordering the items according to the product of demand rate and holding cost rate (or PDHC). The use of PDHC significantly enhances the efficiency of their dynamic programming algorithm. Aggarwal (1983) further proposed closed-form expressions to obtain optimal grouping boundaries under the assumption that the cumulative distribution of inventory value can be characterized by a Pareto function. These works share the following commonalities. Firstly, they all assume that a group has either the same order cycle or the same order quantity. This assumption sets up a generic inventory control policy for a group, which reduces the burden of managing each SKU individually. However, the implication of this assumption is that items within the same group may have different service levels, which leads to a different probability of fulfilling customer demand. Secondly, they all assume unlimited spending on inventory cost, but do not address optimal allocation of inventory budget or the tradeoff between inventory cost and service level.

Ernst and Cohen (1990) proposed a two-stage approach based on a blend of statistical clustering procedures and optimization methods. Their procedure starts with solving a clustering problem to maximize the degree of dissimilarity among inventory classes, which is computed as a statistical measure as a function of inventory item attributes and clustering decision. Once the clusters/classes are determined, the second optimization problem seeks to minimize the number of groups by assigning SKUs to selected groups, subject to generic inventory control policy for each group and various operational performance constraints, e.g. cost, lead time, inventory turnover ratio, etc. Ernst and Cohen's approach provides a more general way for inventory grouping and control, but does not directly optimize inventory performance measures. Its two-stage nature may also lead to sub-optimal grouping decisions.

The work of Korevaar et al. (2007) optimizes the inventory budget using a nonlinear optimization model. Their decision variables include whether or not to stock an SKU, the safety stock level and reorder points of SKUs to achieve an optimal budget that achieves a specified service level target. Their model is solved by a simulated annealing metaheuristic.

Teunter et al. (2010) recently developed an optimization model to simultaneously optimize inventory classification and control decisions. Rather than using the service level as performance measure, they proposed an alternative metric, known as *fill rate*, i.e. the fraction of demands that are satisfied directly from stock on hand, to be the classification criterion. A nonlinear optimization