Modelling Inventory Grouping Decisions Using Grouping Genetic Algorithms

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Abstract

Decision makers are often faced with the problem of grouping inventory into categories for cost-effective and efficient management and control of inventory. The classical ABC inventory analysis has been applied widely in industry. However, the approach is associated with practical limitations: the desired service level and budget allocation constraints are not considered simultaneously, there is no guarantee for optimal solutions, and qualitative decision criteria are not modelled explicitly. It is desirable to develop models that can capture quantitative and qualitative criteria, from a multi-criteria optimization view point. In light of these limitations, the purpose of this research is to model the inventory grouping problem using grouping genetic algorithms approach. We first assess the grouping structure of the inventory classification problem, and then model the grouping problem from the grouping genetic algorithm perspective. Further research prospects and applications are evaluated and presented.

Keywords
Inventory grouping, inventory decisions, ABC analysis, grouping genetic algorithm

1. Introduction
In almost all sectors of the industry, such as manufacturing, automotive, healthcare and retail, sufficient inventory of items need to be maintained. Oftentimes, the number of items or stock-keeping units (SKUs) becomes too big to manage effectively. In such cases, the most practical approach is to classify, manage and control the items in groups, rather than individually (Ernst and Cohen, 1990; Millstein et al., 2014). Ultimately, the process of managing and control of groups of inventory will be more cost-effective since this will reduce the overhead of managing individual groups.

A few inventory grouping approaches have been presented in the literature (Erns and Cohen, 1990; Korevaar et al., 2007; Teunter et al., 2010). One of the most widely applied inventory grouping method is the ABC grouping approach (Guvenir and Erel, 1998; Millstein et al., 2014). The approach classifies inventory according to their transaction volumes or value, so that the top 20% are classified as A-items, followed by the next 30% of items in the B class, and the rest in the C-class (Pareto, 1971; Juran, 1954). Other clustering percentages have also been applied in the literature (Juran, 1954). The classical ABC approach, however, does not give a clear guideline on the optimization of the service level, and optimal decisions are usually not achievable (Millstein et al., 2014). Ernst and Cohen (1990) suggested a two-stage procedure with a blend of optimization and statistical clustering techniques. Korevaar et al. (2007) presented a non-linear optimization model for optimizing the inventory budget. Recently,

Teunter et al. (2010) proposed an optimization model to optimize inventory classification and control decisions simultaneously. Recently, Millstein et al. (2014) developed a multi-criteria optimization model for the ABC inventory classification problem, based on mixed integer programming model. Consideration of inventory budget constraints after the ABC grouping may result in infeasible solutions. It is important to note that, in the real-world practice, decision makers often desire to consider multiple criteria in order to make more practical and informed decisions. In this view, managers desire to simultaneously optimize the number of groups, the assignment of items to groups, the desired service level, and the allocation of inventory budget.

In light of the above discussions, the purpose of this research is to model the inventory grouping problem using grouping genetic algorithms approach. In this respect, the following are the specific objectives for the study:

1. To assess the grouping structure of the inventory classification problem;
2. To analyze the inventory classification problem from a multi-criteria perspective; and,
3. To develop a multi-criteria grouping genetic algorithm for solving the inventory grouping problem from a multi-criteria perspective.

The rest of the paper is structured as follows. The next section presents an overview of the ABC inventory classification, deriving from past studies. Section 3 provides a description of the inventory grouping problem, while highlighting its grouping structure. In Section 4, a grouping genetic algorithm is proposed for optimizing the inventory classification problem. Section 5 provides conclusions and further research prospects.

2. ABC Inventory Analysis

Decision makers in industry often use the ABC classification method to control inventory. The method consists of three steps. First, classify inventory items into categories in accordance with their sales volumes. Second, determine the appropriate inventory policies for each group, such as service level for each group. For instance, a common rule-of-thumb policy is to give the highest service level to A-class items, and the lowest to C-class (Armstrong, 1985), while the B-class falls in between. Third, practicing decision makers involved with inventory, sales and finance should then ensure that the inventory control policy falls within the limits of the inventory and management budget.

The problem of optimizing inventory grouping decisions has been intensively studied in the literature on operations management. Two streams of research are found in the literature (Millstein et al., 2014). , that is,

1. Those that consider only inventory grouping decisions; and,
2. Those that consider both inventory grouping and control.

Table 1 presents a classified list of past research on modelling inventory grouping decisions. The literature is categorized into two basic categories: those that focused on optimization of inventory grouping, and the rest which focused on inventory grouping and control. Further analysis is presented based on model features, that is, the objective function, performance criteria (multi-criteria or single criterion), model type (linear or nonlinear), and optimization of number of inventory groups, and consideration of the inventory budget constraint and the overhead management cost associated with the inventory groups.

Table 1. Inventory grouping decision models in the literature

Category and References	Objective Function	Performance Criteria	Model	Number of Groups	Budget Constraint	Management Cost
Optimize inventory grouping						
Ernst and Cohen (1990)	Number of groups	Multi-criteria	Linear	√		
Guvenir and Erel (1998)	Distance of expert ranking	Multi-criteria	Nonlinear			
Partovi and Anandarajan (2002)	Distance of expert ranking	Multi-criteria	Nonlinear			
Ramanathan (2006)	Performance score	Multi-criteria	Linear			
Bhattacharya et al. (2007)	Distance from the ideal	Multi-criteria	Linear			
Ng (2007)	Performance score	Multi-criteria	Linear			
Hadi-Vencheh (2010)	Performance score	Multi-criteria	Nonlinear			
Chen (2011)	Performance score	Multi-criteria	Linear			
Chen et al. (2008)	Distance	Multi-criteria	Linear	√		
Tsai and Yeh (2008)	Performance score	Multi-criteria	Nonlinear	√		
Optimize inventory grouping and control						
Crouch and Oglesby (1978)	Cost	Single-criterion	Nonlinear			
Chakravarty (1981)	Cost	Single-criterion	Linear	√		
Aggarwal (1983)	Cost	Single-criterion	Linear	√		
Korevaar et al. (2007)	Inventory cost	Single-criterion	Nonlinear			
Teunter et al. (2010)	Cost	Single-criterion	Nonlinear			
Milistein et al. (2014)	Profit	Single/Multiple	Linear	√	√	√

Though the classical ABC analysis method has been widely applied, this approach cannot yield optimal decisions in regards to service level of each group, and the inventory management budget (Teunter et al., 2010). Moreover, infeasible solutions may arise. Approaches that can optimize the problem from a multi-criteria perspective will be more favorable.

3. Problem Description

In this section, we analyze the multi-criteria perspective of the inventory grouping problem. The inventory grouping problem considers N items, each item i ($i = 1, \ldots, N$), with an average monthly demand of d_i with standard deviation σ_i (Millstein, et al., 2014). Assume that demand for each item is normally distribution, $N(d_i, \sigma_i)$, and the lead time of item i is l_i time units. Each item has a profit π_i. The inventory holding cost per item is c_i. Assume that the inventory budget limit is B. The task of the decision maker is to optimize inventory management so that overhead costs are reduced, which involves classifying N items into M groups and setting up an inventory policy for each group.

Assume that inventory performance can be measured by multiple criteria, $k = 1, 2, \ldots, K$, which can be quantitative or qualitative. Some of the quantitative criteria are demand volume, lead time, and unit cost (Millstein et al., 2006). Examples of qualitative criteria are replaceability and criticality (Guvenir and Erel, 1998; Ramanathan, 2006; Millstein et al., 2004). Let s_{ik} denote the performance score of item i according to criterion k associated with weighting w_k, such that $\sum w_k = 1$. Therefore, the weighted performance score f_i for each item can be defined as follows:

$$f_i = \sum_k w_k s_{ik} \tag{1}$$

where, s_{ik} is the performance score of item i according to criterion k, w_k, is the weighting associated with criterion k so that $\sum w_k = 1$.

It follows that the overall performance can be evaluated using a multi-objective optimization model based on the following expression (Millstein et al., 2014);

$$F_i = \sum_i \sum_j f_i d_i \alpha x_{ij} \tag{2}$$

where, $x_{ij} = 1$ if item i is assigned to group j, and 0 otherwise; d_i is the mean demand of item i; α is the service level associated with group j.

Specific constraints can be included to avoid infeasible solutions, e.g., to ensure that each item is assigned to at most one group, and also to ensure that the budget B is not exceeded. The next section presents a multi-objective grouping genetic algorithm for solving the inventory grouping problem.

4. Grouping Genetic Algorithm for Inventory Grouping

Grouping genetic algorithm (GGA) refers to a genetic algorithm that incorporates a group encoding scheme and the associated group crossover, mutation and inversion operators for solving grouping problems (Falkenauer, 1993). The algorithm was inspired by the need to enhance efficiency of classical genetic algorithms when applied to grouping problems. Classical genetic algorithms generally face problems of high redundancy in chromosomes and disruption of context-dependent information in the genes (Mutingi and Mbohwa, 2016). Basically, the algorithm can be described based on its group encoding scheme and its group genetic operators, namely, group crossover, group mutation, and inversion operators.

4.1 Group Encoding

The main idea behind the group encoding scheme is to code permutations of the objects (or items) and use a decoding procedure which takes into account the actual assignment of items into groups, for each chromosome. We extend this idea for the case of inventory grouping. For instance, consider a chromosome that is made up of three groups A, B and C, which in turn, contain inventory items {1,8}, {2,3,6}, and {4,5,7}, respectively. The group encoding scheme can be expressed in the form [A B C]. It can be seen from this example that each of the three groups represents a gene, and the sequence of items in each group is irrelevant. This group encoding scheme avoids

limitations that are often associated with redundancy found in the classical genetic algorithm scheme. Figure 1 illustrates the group representation scheme for the example above, which yields chromosome [A B C]

Items :	1,8	2,3,6	4,5,7
Groups:	A	B	C

Figure 1. Group encoding scheme for chromosome [A B C]

Having defined the group encoding scheme, the GGA procedure is iterated through a loop consisting of group crossover, mutation, and inversion operators.

4.2 Group Crossover

The crossover operator is the main procedure whose function is to facilitate guided information exchange between selected chromosomes. In so doing, its end goal is to generate new chromosomes while avoiding adverse disruptions of the crucial group structure of the selected chromosomes. We further explain the crossover operator based on an example of two parent chromosomes P1 = [A B C], and P2 = [D E F G]:

1. Randomly select two cross-points in any two randomly selected chromosomes, and select a crossing section from first parent, P1.
2. Inject the crossing section from first parent P1 into the second parent P2, which yields a new offspring likely to contain repeated item (or doubles).
3. Empty the groups with doubles.
4. Eliminate those groups that contain doubles and empty groups.
5. Re-insert missing items using problem-specific heuristic.
6. Interchange the roles of P and P2 and repeat steps 2 to 4
7. Repeat the process until the required number of offspring is obtained.

From the above illustration, we note that the crossover operation must be repeated until the desired population of new offspring is generated. To illustrate further, consider two randomly selected parent chromosomes, (i) chromosome [A B C], consisting of groups of items {1,8}, {2,3,6}, {4,5,7}, and (ii) chromosome [D E F G] comprising groups of items {2,4}, {1,7}, {3,8}, {5,6}. The crossover operation for the two chromosomes is presented in the figure (Fig. 2). By the group crossover operation, we obtain two final offspring, namely, O1 = [D A G] and O2 = [E F H I], as shown in Figure 2.
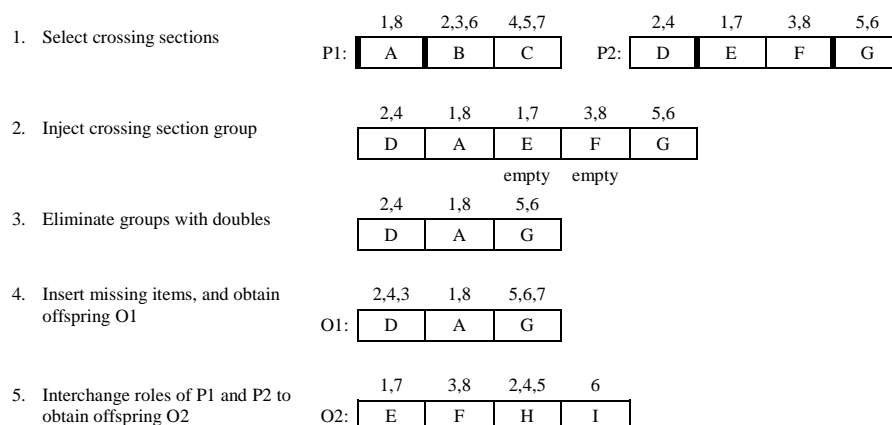

Fig. 2. An illustration of the group crossover operation

4.3 Group Mutation

As with the crossover operator, the group mutation should work with groups, and not individual items (Falkenauer, 1994; Mutingi and Mbohwa, 2016). There are three possible procedures for executing group mutation: (i) by creating new groups, (ii) by eliminating some selected groups, and (iii) by shuffling a few selected items among the groups. In practice, computational implementation depends on the problem domain that is to be solved. Domain specific constructive heuristics may also be utilized.

4.4 Inversion

The purpose of this operator is to facilitate transmission of good schemata from parents to offspring in order to ensure increased rate of sampling of better performing schemata (Mutingi and Mbohwa, 2016). The mutation operator works by overturning the order of groups between two points in a randomly selected chromosome. To illustrate, assume that we are given chromosome [A B C D] and two points are selected as shown below. Then the chromosome,

[A |B C D|]

could be inverted to:

[A D C B],

Assuming that it is known that it is more desirable to have A and D closer together, then this increases the probability of transmitting both groups (genes) A and D together into the next generation when the next crossover is performed.

5. Concluding Remarks and Further Research

The GGA approach has is the only evolutionary algorithm that has been refined to especially model grouping problems by taking advantage of the grouping structure of the problems. The algorithm can be adapted to a wide range of grouping problems (Mutingi and Mbohwa, 2016). In this paper, it was observed that the ABC inventory classification problem is a grouping problem whose grouping structure can be modelled using grouping algorithm approaches. As a result, we proposed and presented a GGA methodology for addressing the inventory classification problem with a wide range of possible groups, and from a multi-criteria perspective. In summary, the proposed approach has the following advantages:

1. GGA approach uses an efficient group encoding scheme which avoids time-consuming redundancies in the chromosomes, which helps to improve the efficiency of the algorithm;
2. GGA avoids adverse disruption of essential information encoded in the groups of each chromosome, thereby improving the effectiveness of the algorithm;
3. GGA can easily model and optimize the number of groups by searching over a wide range of possible group sizes, which gives the decision maker a wider search than is possible with previous approaches; and,
4. GGA can model inventory classification problems based on multiple criteria, including, number of groups; assignment of items, service level for each group; and budget allocation to groups of items.

Further research is envisaged to involve numerical experimentation based on benchmarks as well as case studies to be gathered from literature. Comparative analysis will be beneficial in proving the efficiency of the proposed GGA approach to inventory classification problem.

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Biography

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