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Article

A Product Assortment Planning Model for Fast-Fashion Products in Multi-Brand Retail Outlets for Effective Supply Chain Management

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Abstract

Purpose

Effective Product Assortment Planning is critical for fast-fashion products like clothing and accessories with short lifecycles, a large number of Stock Keeping Units and seasonality of the assortments. Traditional product-based demand forecasting approaches using past data and repeatability of purchase are not very effective for them. Emerging PAP optimization models focus on customizing retail assortment at store levels and developing attribute-based approaches. However, these models are highly complex, thus restricting their utility in the field. This paper presents a model to help plan the supply chain under these conditions.

Design/methodology/approach

The authors of this paper developed a model with a modified approach to make it computationally less complex and cost-effective for implementation. The authors developed a Mixed Integer Programming model and solved a Linear Programming relaxation of the model to obtain an effective solution.

Findings

Authors validated the model utilizing field data and inputs that could capture merchandiser experience, nsumer preferences, retailer constraints and environmental factors for a national brand of leather cessories sold through multi-brand retail outlets and found that the model showed an improvement tential of over 25 % in the objective.

iginality

is is an original research conducted by the author, including all fieldwork, pilot implementation and alysis. Since the model was prepared from field data and also implemented to see its effectiveness, it presents a practical and usable model by the Industry straightaway. However, future researchers may plement it in multi-vendor, multi-outlet situations and update the model in accordance with fresh outputs.

search limitations/implications

e model requires further testing and refinement to establish its usefulness, as the current testing was on a small set of data of a representative category. However, considering the similarities in the consumer perception and preferences, retailer constraints and environmental factors, the authors believe this approach of combining data mining with a linear integer model has the potential to deliver superior performance on most categories of fast fashion products.

Practical implications

Through this model, the authors attempted to close a significant gap in research concerning replenishment models for fast-fashion products applicable in emerging countries. Since critical parameters like changing customer preferences, and variation in demand due to seasonality, discounting systems etc., have been factored in a while developing the present model, it can be easily extrapolated to multiple suppliers and multiple numbers of retailers.

Keywords: *Product Assortment Planning, Multi Brand Outlets, SKUs, k-means clustering, MIP, LP relaxation*

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1. Introduction

Product Assortment Planning (PAP) models have traditionally used demand forecasting approaches using past data and leveraging repeatability of purchase. These models are not very effective for fast-fashion products due to the short lifecycles, a large number of Stock Keeping Units (SKUs) and seasonality of the assortments.

For the fast fashion products category, Multi Brand Outlets (MBOs) typically have to plan stocks for hundreds of stores across thousands of Stock Keeping Units. Consumer sales of fast-fashion products like clothing and accessories are dependent on the variety, depth and service levels of the SKUs at the point of sale. These products also have the peculiarity of short lifecycles and long production lead times. Hence, profitability for MBOs is heavily dependent on the efficient and effective planning of these stocks.

In the Indian context, fast-fashion products typically follow a 2-season assortment plan – Spring-Summer (April – September) and Autumn-Winter (October-March). The SKU offerings in each season are usually very different. Accounting for consumer preferences and perceptions, working with retail store constraints and environmental factors makes PAP decisions very complex. Hence, PAP becomes substantially dependent on the category merchandiser experience, substitution effects and discounting levels close to the end of the season.

In this paper, the authors studied the existing replenishment models and, utilizing the readily available and reliable data, developed a PAP model that captures merchandiser experience, consumer preferences, retailer constraints and environmental factors. The model utilizes assortment and store-level aggregation. The model has been tested and implemented in a select chain of outlets, and the experience of implementing the model for a brand of accessories sold through these outlets has been presented.

In this model, the authors used k-means clustering* on sales, supplies and discounting data of the stock keeping units (SKU's) of each category of product to create adequately differentiated SKU clusters (representative SKU's). The standardized values of the supplies capture merchandiser experience, sales units capture consumer preferences and discounting reflects any mismatch in these variables. Store clustering using standardized values on the average retail selling price, sales and supplies of the SKUs of the category helped capture store parameters like store profile, size and footfalls-conversion to create representative stores.

We utilized the sell-through rate and average retail price of a representative SKU from historical data in a representative store as our inputs to an Integer Programming (IP) model. Clustering facilitated the reduction of the problem size and convenience of replenishment with similar SKUs to similar stores. The IP model ensured optimum allocation of available stocks for each product cluster – store cluster to maximize sales. The model was tested with data from one category of a fast-fashion product of a national brand. The results were compared with the output of the heuristic methods currently used by the brand. A linear programming relaxation solution of the IP model showed promising results on the data of the accessories planning for a season. The relaxation was in the integer requirement of the stocks for each SKU. The linear programming relaxation of an integer program is easily solved using any standard linear programming technique to obtain a good solution.

2. Literature Review

2.1 Fast Fashion Products

Fashion and related industries are a collective classification that refers to the garment, footwear, accessory, cosmetics, and fragrance sectors. Often, for simplicity and inclusivity, this amalgam of sectors is described as the apparel industry. It encompasses all facets of dressing, from underwear to outerwear, to shoes, bags, hats, belts, gloves (leather and other materials) and other accessories, jewellery and makeup, fragrance, and bath products, to sports gear and adventure wear, to work and military gear (Nikolay Anguelov, 2020).

Historically, industry insiders referred to "fashion" and "garments" or "accessories" separately. Items described as "fashion" denoted higher price and

* It is a data mining method that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centroid), serving as a prototype of the cluster

target markets, while everything else denoted lower price and mass markets. Improvements in technological efficiency in manufacturing have lowered the pricing of raw materials, whereby higher quality today is available at ever-decreasing prices. This fact has spurred the advent and growth of "fast fashion". (Sheridan et al., 2006)

2.2 Demand Forescating Approaches

Product assortment planning approaches vary across product categories and retailers. Demand forecasting approaches like multinomial logit, exogenous demand, and locational choice have been shown to be effective in assortment planning [Kök, G., M. L. Fisher. 2007]. Suppliers often use relatively simple processes to forecast orders for various SKUs. Time series forecasting methods, such as exponential smoothing, are more commonly used to statistically predict future customer demand, using data on historical orders (Williams and Waller 2010).

While forecasting with temporally aggregated demand, suppliers have generated forecasts of a given retailer's orders using that retailer's past orders. (Jin Yao et al., 2015). Nikolopoulos observed that demand planners still prefer to forecast using temporally aggregated data though abundant analytical evidence can be found in statistics and economics literature on information loss (Nikolopoulos et al. 2011). Even in an autoregressive time series, the existence of information loss has been noticed. (Amemiya and Wu (1972). Therefore, the effects of temporal aggregation can be generalized to include time-series models such as Auto-Regressive Moving Average models with exogenous variables (ARMAX) (Brewer 1973).

2.3 Shelf Space Implications on sales in MBR outlets

Harish Abbott and Udatta Palekar, in their research on Retail Replenishment models with display-space elastic demand**,** covered a single-store multi-product inventory issue in which shelf space was seen to be a major determinant of product sales. The amount of product on display was seen to be impacting the sales. Hence, unless replenishment occurs, the effective shelf space assigned to the product diminishes with time. They incorporated space and cross-space elasticities in their replenishment model for retail stores and confirmed that retailers strongly believed sales get influenced by the amount of product on display. Therefore, until the product is restocked, there should be a negative impact on the sales rate as the product's sales bring down the amount of product on display. This replenishment model determines optimum intervals between replenishments so as to maximize resultant profits (Harish Abbott, Udatta S. Palekar 2007). Even in this Model, the impact of shelf space on demand for fast-fashion products was not specifically studied.

2.4 Vendor Managed Inventory Replenishment Models

Nishant and Ashish proposed a Multiple-retailer replenishment model under vendor-managed inventory to account for the retailer heterogeneity. In this supply chain practice, the supplier is responsible for managing inventory at the retailer's end, which means that it is the supplier who decides, on behalf of the retailer, when to order and how much to order. They developed a nonlinear mixed-integer programming model to arrive at the optimal replenishment frequency and quantity for all retailers to ensure that the total system cost is minimized. (Nishant Kumar Verma and Ashish K. Chatterjee 2016).

Vendor Managed Inventory models have evolved into several variants. One of them, called VMI on consignment, leaves ownership of the item with the supplier until its sale happens (Wang Y, Jiang, & Shen, 2004). Another variant, called VMI with no consignment, was also discussed by some authors, where money gets transferred to the supplier immediately on their delivery to retailers (Lee & Chu, 2005). Notwithstanding which one of these variants is adopted, Vendor Managed Inventory models have generally proven beneficial in terms of reduced inventory cost, improved customer service level, greater transparency and a lower bullwhip effect* (Yao, Evers, & Dresner, 2007). Retailers also stand to benefit from these models in the form of reduced administrative costs as they are no longer responsible for placing the order from their side

* *The bullwhip effect is a concept for explaining fluctuations in inventory or inefficient asset allocation as a result of variation in demand x as you move further up the supply chain. As such, upstream manufacturers often experience a decrease in forecast accuracy as the buffer increases between the customer and the manufacturer.*

(Aichlmayr M, 2000). There are several research studies evaluating the time benefit the supplier has from Vendor Managed Inventory models (Kaipia, Holmstrom, & Tanskanen, 2002) and its variants like shipment coordination mechanism (Cheung & Lee, 2002), sharing of inventory cost (Nagarajan & Rajagoplan, 2008), consolidation of shipment by the supplier (Cetinkaya, Tekin & Lee, 2008), retail shelf allocation (Hariga & Al-ahmari, 2013), multiple-retailer systems under stochastic demand (Mateen, Chateerjee, & Mitra, 2015), etc.

There has been numerous research literature available on this Vendor Managed Inventory System. Single supplier-multiple retailer settings have been studied by Vishwanthan and Piplani(2001), and they proposed a replenishment process under which retailers are replenished at fixed intervals decided by the supplier. Ordering and procurement costs of raw materials were considered by Woo, Hsu and Wu (2001) in their investment and replenishment model. Further literature talked about a model in which the supplier's production cycle was assumed to be constant (Zhang, Liang, Yu, and Yu 2007). Retailers can have different replenishment cycles and order more than once in a production cycle of the supplier. (Zavanella and Zanoni, 2009).

2.5 Models with equal and unequal Replenishment Intervals

The replenishment model proposed by Darwish and Odah, under a single supplier-multiple retailer situation with an upper limit contractual constraint, had shown that retailers have equal replenishment intervals. Verma et al. (2014) generalized this model by relaxing the assumption of equal replenishment intervals and allowing retailers to have unequal replenishment intervals. While equal replenishment intervals might work with fashion products as well, replenishment quantities vary due to customer preferences that change frequently. This needs to be factored-in while developing the model.

2.6 Automated store ordering systems

Automated store ordering systems in retail chains have been discussed in several research works. (Ethrenthal, Honhon, and Woensel 2014). In Automatic Store ordering systems, based on stock-keeping unit-specific inventory control policies and demand policies and demand forecasts, decisions on replenishment orders are taken automatically. The retail outlet has to share information on historical data on consumer sales, inventory levels and ordering policies with the supplier, and the supplier can use traditional material requirements planning models (see, e.g., Orlickly 1975) to forecast the outlet's replacement orders. Ville Sillanpaa and Juuso Liesio, in their research, discussed the issues concerning the value of modelling low and intermittent consumer demand with distributions of estimating replenishment orders in retail business (Ville Sillanpaa and Juuso Liesio 2018). Jonsson and Mattson describe forecasts produced with material requirements planning models as planned orders. Based on information about the inventory levels, the order policies, the delivery schedules, and demand forecasts are commuted by stimulating the SKU's future replenishment orders and the point estimate forecasts of consumer demand. However, Jonnson and Mattson had shown their reservations about generalizing these results to products with low and intermittent demand (Jonnson and Mattson 2013). Several other authors have also maintained that in many applications, point estimate forecasts are not suitable for modelling low and intermittent demand (e.g., Synder, Ord, and Beaumont 2012; Chapados 2014). While point estimate forecasts can be applied to fast-fashion products, issues like seasonality, end-of-season discounts, fading fashion discounts etc., have not been taken into consideration in these forecast models.

2.7 Statistical Time Series Models and Planned Order Replenishment Systems

From the suppliers' point of view, they require forecasts of incoming orders to plan their inventory control and order picking operations with effectiveness (De Koster, Le-Duc, and Roodbergen 2007). This suggests the use of statistical time series models that predict the store's orders based on their past order data obtained from POS. This method does not take into account the store's current inventory level and hence is not very useful from the retailers' point of view (Williams and Waller 2011). Williams et al. (2014) took care of this aspect in their model by using both POS data and supplier's order history together.

Typically, both the supplier and the retailer agree on fixed and regularly repeating points for ordering each product (Kuhn and Sternbeck 2013). Such planned orders prove quite useful when a retailer is analyzing the effect of large variations in customer demand on quantities covered in replenishment orders. Several authors have concentrated their research on planned orders and reported that using them for forecasting benefits the supplier. Zhao, Xie, and Leung (2002) tested planned orders under different assumptions of demand and found that forecasting with planned orders is far better than forecasting methods which incorporate only sales data or historical order data. Byrne and Heavey (2006) showed that using planned orders also reduces supply chain costs for both the supplier and the retailer. Jonnson and Mattsson (2013) also provided insights about the advantages of planned orders, but their research did not include the performance of planned orders under low and intermittent demand conditions.

2.8 Optimization Approaches

The replenishment model used by Montanari et al. (2015) assumes the use of an economic order quantity (EOQ) based policy by retailers. Kiesmuller and Broekmeulen (2010) have developed optimization models where parameters of retailers' replenishment policies are used as decision variables to minimize both retailers' and suppliers' costs.

Unlike other businesses, in retail, how a customer responds to stockouts mostly depends on customer loyalty (Campo, Gijsbrechts, and Nisol 2000). Retail chains tend to use heuristic order models to replenish stores as costs of lost sales are difficult to estimate. Ethrenthal and Honhon discussed about a dynamic lot-sizing problem by including the seasonality of demand in the Model (Ethrenthal, Honhon, and Woensel 2004), and they concluded that replenishing a retail SKU over time is essentially a dynamic lot-sizing problem. Feng, Rao, and Raturi developed approaches for identifying optimal order policies under time-varying demand distributions (Feng, Rao, and Raturi 2011).

2.9 Attribute Approaches & Aggregation Models

In fast-fashion categories like clothing and accessories, extended sales history and complex demand estimation models are of limited use due to rapidly changing tastes (Fisher M and Vaidyanathan R., 2011). Consumer behaviour issues like substitution are very relevant to fast-fashion categories but equally difficult to model. Hence, models are to be specifically developed for these categories considering changes in consumer behaviour and varying demand patterns with changing seasons and products.

Attribute approaches are more useful for this category of products. In this approach, an SKU is viewed as a set of attributes and historical sales data is used to estimate market shares of each attribute-store combination. Earlier researchers have created effective models which include substitution behaviour but did not consider inventory decisions (Fisher M and Vaidyanathan R., 2011). The attributes approach also allows for forecasting of store-SKU demand for SKUs not currently carried in the stores (Rooderkerk et al., 2008)

Researchers have shown product aggregation reduces variance in demand forecasting and better accuracy (Williams & Waller, 2011). Aggregation of inventory holding locations has also been extensively studied by researchers showing variance reduction and lower forecast errors. (Das and Tyagi 1999). Location-based aggregation reduces safety stock and results in variance reduction (Maister 1976).

Many researchers have shown Temporal aggregation (Jin et al., 2015) to reduce variance in demand forecasting, resulting in lower forecast errors. Their conclusion is that the random errors are cancelled in the time series aggregation. They also conclude temporal aggregation impacts forecast accuracy due to loss of information. Loss of information is primarily in the time series properties such as seasonality, autoregressive orders, and short-time cyclical variations.

For the fast–fashion category of products, temporal aggregation would be of limited utility as the preferences change every season. Product and stores (location) aggregation are free from the loss of information identified in temporal aggregation. As we utilize data from half of a season to create the aggregation-based model within the season, we expect some information loss on specific attributes of products or stores as inevitable but not serious.

The improvement in the forecast due to variance reduction far outweighs the loss of information effect for this category of products.

Given below is an Overview of Selected Assortment Optimization Studies with this study added at the end to highlight the similarity and differences (Extension of Rooderke et al., 2013)

Study	Data Type	Modelling of SKU Parameters	Accounting for Similarity Effect	Marketing mix	Assortment endogeneity	Price endogeneity	Store Level optimization	Joint assortment and price optimization
Borin and Farris -1995	Synthetic	SKU-specific	No	Shelf Space	No	No	No	No
McIntyre and Miller -1999	Empiricalb	SKU-specific	No	Price	No	No	No	Yes
Smith and Agrawal -2000	Synthetic	SKU-specific	Yes	None	No	No	No	No
Chong et al. -2001	Empirical	Brand-specific	Yes	Price, Promotion	No	No	Yes	No
Mahajan and van Ryzin -2001	Synthetic	SKU-specific	Yes	None	No	No	No	No
Kok and Fisher -2007	Empirical	SKU-specific	Yes	Price, Promotion	No	No	Yes	No
Misra -2008	Empirical	Attribute -based	Yes	Price	Yes	No	No	No
Miller et al. -2010	Empirical	SKU-specific	Yes	Price	No	No	No	No
Sinha et al. -2012	Empirical	Attribute-based	Yes	Price	No	No	Yes	Yes
Rooderkerk et.al (2013)	Empirical	Attribute-based	Yes	Price, Shelf Space, Promotion	Yes	Yes	Yes	Yes
This study	**Empirical**	**Brand-specific**	**Yes**	**Price, Shelf Space, Promotion**	**Yes**	**Yes**	**No**	**Yes**

3. Problem Description and Assumptions:

To conduct focused research on replenishment models for fast-fashion products under scenarios like heavy seasonality, discounting and changing consumer preferences with special reference to emerging countries like India, where the purchase of fashion products is highly discretionary.

Traditional product assortment planning models presently being used by retailers in these countries are demand forecasting or attribute-based approaches. Attribute-based models have been more effective in the fast-fashion category of products. These models have utilized the market share of attribute-store combinations accounting for some aspects of consumer perceptions and preferences. The effect of merchandiser experience, discounting, variety, depth and service levels of the SKUs at the point of sale are to be adequately addressed in both demand forecasting and attribute-based models.

It is also necessary to study with the help of field data to capture the effects of merchandiser experience, discounting, variety, depth and service levels of SKUs (variables affecting inventory decisions) and combine it with the store profile and product attributes to enable effective PAP decisions for the peculiarities of fast-fashion products. Authors attempted to research in this area and used product and store level aggregation to leverage the variance reduction effect of aggregation and handle the substitution effects. Through this paper, the authors attempted to develop a model which uses the basic tenets of attribute-based models with additional parameters of merchandiser experience, discounting, variety, depth and service levels of the SKUs at the point of sale.

While conducting this research, for ease of computation, the authors assumed equal replenishment intervals. This can be later extended to unequal replenishment intervals.

This research focused on multiple store locations of a retailer using one representative fast-fashion product.

4. The Proposed Model

Product Assortment Planning in MBOs dealing with multiple categories, thousands of SKUs and hundreds of stores is a complex problem. Rooderkerk et al., have in their paper on Optimizing Retail Assortments, developed an implementable and scalable assortment optimization model that adopts an attribute-based approach to capture preferences, substitution patterns and cross-marketing mix effects. They applied their model to store-level scanner data on liquid laundry detergent and could demonstrate an increase in retailer profits in the range of 37 -44%. Their retail assortment planning problem involved finding a store-level assortment that maximizes retail profit while satisfying a set of constraints. Recognizing this problem is NP-complete.* The authors use a large neighbourhood search heuristic to obtain a good solution.

The merchandisers with retail stores have sophisticated planning tools in the form of ERP systems, up-to-date and reliable sales and stock data. Hence, merchandiser experience, sell-through rates, stock availability and discounting become very useful data for fast-fashion PAP, even for a two-season annual plan.

We use Rooderkerk's Model as the basis of our proposed model. Our focus was to modify the model to make it computationally less complex and cost-effective for implementation. We utilize merchandiser experience of stock planning in a season as a substitute for product attributes and store characteristics. We utilize sales data, selling price and discounting to capture customer preferences, substitution and cross-marketing mix effects. Our retail assortment planning problem involved finding optimal store-level assortment to maximize the sell-through rate for the total stocks of the brand across all the stores while satisfying a set of constraints like availability of SKUs, shelf space, and minimum allocations. We applied our model to store-level scanner data for leather belts of a single brand and could demonstrate an increase in sell-through rate of 35%+ over the existing heuristic-based method in use for replenishment. Our model is a mixed-integer programming model, and we solve a Linear Programming (LP) relaxation of the model to obtain a good solution.

* NP-complete problems are a class of computational problems for which no efficient solution algorithm has been found.

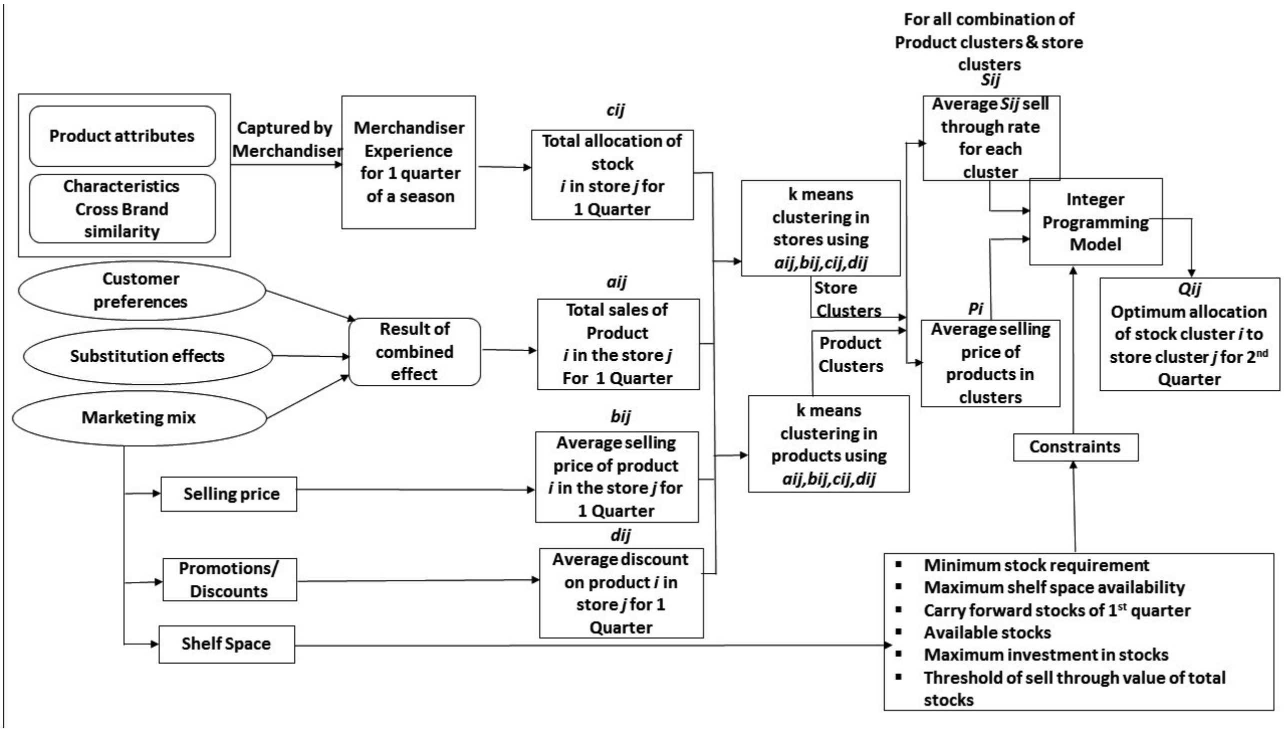

Fig.1 Integer Programming Model for PAP proposed by the Authors

In the model presented in this paper, the data utilized is for one representative retailer with multiple stores across locations with equal replenishment intervals which can be extended to unequal replenishment intervals with some increase in complexity.

5. Clustering of products and stores.

For clustering of products, the authors used the past supply quantities for the SKUs of the season to capture the merchandiser experience (includes good/bad decisions), the actual sales quantities to capture the response of the consumer (includes any substitution effects), the actual selling price and MRP of the product (discount at which the SKU's were finally sold) to capture merchandiser reactions to the mismatch between the stocking decisions and consumer response.

The authors used k-means clustering to create adequately differentiated clusters from historical data for each quarter. The number of clusters was determined by a process of trial and error to ensure high F statistic values.*

The variables used for product clustering of data over the period were - the quantity of the SKUs supplied, sales achieved and average selling price of the product. The variables used for store clustering over the same period were a quantity of category supplies, sales of category supplies and average selling price in the category.

Data used: For each product 'i' in store 'j'

a_{ij} = Total Sales over 1 quarter

b_{ij} = Average Selling Price

c_{ij} = Total Supply in the quarter

d_{ij} = Average Discount

n = Number of Product

m = Number of stores

* The use of the F statistic in clustering is called a Pseudo – F statistic – it describes the ratio of cluster variance to within-cluster variance. The higher the number, the more dispersed the cluster. The lower the number, the more focused the cluster. Between cluster variance measures how separated clusters are from each other.

Vectors used for clustering:

$$\text{Products(P)}: \mathbf{x}_i = \left(\sum_{j=1}^{m} a_{ij}, (\sum_{j=1}^{m} b_{ij})/m, \sum_{j=1}^{m} c_{ij}, (\sum_{j=1}^{m} d_{ij})/m\right) \quad \text{for each } i = 1,2,\ldots\ldots n$$

$$\text{Stores(S)}: \quad \mathbf{y}_j = \left(\sum_{i=1}^{n} a_{ij}, (\sum_{i=1}^{n} b_{ij})/n, \sum_{i=1}^{n} c_{ij}, (\sum_{i=1}^{n} d_{ij})/n\right) \quad \text{for each } j = 1,2,\ldots\ldots m$$

Clustering Results: For Products refer Table 3

For Stores refer Table 1

k-means clustering of x_i and y_j using the following algorithm

a. Initialize cluster centroids for a set of values for j and l where j is the number of Product Clusters and l number of Store Clusters)

$$\mu_1, \mu_2, \ldots\ldots \mu_j; \textit{ Product Clusters Centroids}$$

$$\gamma_1, \gamma_2, \ldots\ldots \gamma_l; \quad \textit{Stores Clusters Centroids}$$

b. Repeat till convergence

$$P_{index} = \text{avg} \min_{p} \|x_i - \mu_p\|^2$$

$$S_{index} = \text{avg} \min_{q} \|y_j - \gamma_q\|^2$$

For each p, q reset centroid using

$$\mu_p = \frac{\sum l.\,(P_{index} = p)x_i}{\sum l.\,(P_{index} = p)}$$

$$\gamma_q = \frac{\sum l.\,(S_{index} = s)y_j}{\sum l.\,(S_{index} = s)}$$

Stop at final j, l values that maximize the pseudo F score.

Subsequently, the data for the period (quarter) was scored using the clusters obtained above. The sell-through rate for each product cluster – store cluster combination was obtained for this period. *[Table 7].* The integer programming model used these sell-through rates of each product cluster – store cluster combination to enable PAP planning for the 2nd quarter of the season.

5.1 Integer Programming model

This is a standard integer programming model using the average sell-through rates for each product cluster – store cluster combination extracted from historical data. A separate implementation is required for each category - sub-category of products. Constraints are formulated taking into account ground realities or preferences.

Integer Programming Model for optimal stock cluster allocation to store cluster

$$\text{Objective Function: } Z = \max \sum_{i=1}^{n} \sum_{j=1}^{m} S_{ij} \times Q_{ij} \times P_i$$

Where:

Q_{ij} = Quantity of Products in cluster i to be allocated to stores in cluster j

S_{ij} = average sell-through rate of products in cluster i through stores in cluster j

P_i = Average selling price of a product in cluster i

n = Numbers of Product Clusters

m = Numbers of Store Clusters

Constraint sets

$$\text{a) } L_j \le \sum_{i=1}^{N} Q_{ij} \le M_j \qquad \forall j$$

$$\text{b) } O_i \le \sum_{j=1}^{M} Q_{ij} \le W_i \qquad \forall i$$

$$\text{c) } \sum_{i=1}^{N} P_i \sum_{j=1}^{M} S_{ij} \times Q_{ij} \ge R \times I$$

$$\text{d) } \sum_{i=1}^{N} P_i \sum_{j=1}^{M} Q_{ij} \le I$$

Where:

L_i, M_j: are lower and upper limits on allocation in store cluster j due to minimum stock requirement and maximum shelf space available

O_i, W_j: Minimum and Maximum allocation of products in cluster i due to carry forward stock and available (maximum) stock

R: Threshold for sell through value of total stock

I: Maximum investment in stock

6. Validation of the proposed Model with Case Study Data

We tested the model with scanner level data obtained from a retail chain owning 14 multi-band outlets across the country. The authors implemented the model in a firm manufacturing leather accessories and working with the retail chain on a Sale or Return (SOR)model. This firm was an SME owning a national brand of leather accessories with an annual turnover of Rs. 500 Lakhs and worked with many retail chains. The retail chain would share their scanner level data with the firm every month. The firms PAP model was a heuristic model based on (s,S,T) and past experience with T being fixed at 1 month and (s,S) values based on experience and availability of stocks.

We limited our validation data to this single national brand of leather accessories. We utilized data on the brand SKUs, MRPs, discounts, stock and selling prices for leather belts of the brand, capturing merchandiser experience, substitution effects, and discounting effects on planning allocation/replenishment of stocks for three months of a season. We utilized the model solution of product cluster allocations to store clusters to estimate the improvement in sell-through rates that could be achieved if the model solution was used for the PAP process for the remaining three months of the season. This was compared to the current method being utilized by the retailer, which followed a heuristic-based an s,S,T policy with T fixed as a monthly interval and s (min stock values), S values (max stock values) based on merchandiser experience and availability of stocks.

The validation data was of a smaller dimension with 135 SKUs and 14 MBOs. However, we expect the model to be as effective in improving the PAP for MBOs working with many categories, 1000's of SKUs and hundreds of stores due to the similarities in the assumptions and objectives of the planning model.

We utilized data for the season Spring-Summer (SS) for 14 stores of a retail chain spread across the country. The stockist had supplied 135 SKUs in the stores. The data of the first three months of the season (April- June) was used to create the product and store clusters. Information captured by the model from data over half the season (3 months) would be relevant and useful to plan SKU-store allocation only for the 2nd half of the season. While this may result in overfitting of the model to the data set, the approach is useful and generalizable to any category of fast fashion products, considering the seasonal nature of this assortment planning.

To capture the discounting effect, a ratio of the selling price to the MRP could be used. However, in this sales and stocks data over three months of SS, we did not see a substantial difference in the discounting on the selling price of the SKUs and excluded the discounting variable in our validation process.

Our objective was effective PAP decisions, eventually resulting in an increase in the inventory turnover ratio. We translated this into the objective of maximizing the sales across 'groups of similar' SKUs and stores for each category of products using historical data to estimate the sales effectiveness of each SKU group - store group. We used a sell-through rate as the ratio of sales in the quarter and the average monthly stocks. This ratio is directly proportional to the inventory turns ratio, and we avoided converting our results into the inventory turns ratio. Data on constraints of stock availability, shelf space, carryover stocks, minimum and maximum stocking levels and maximum sales potential of a store were taken into account in the model.

7. Results and Discussion

Two adequately differentiated clusters were created from the store data [Table 1]. The store clusters had an F value of 18.7. The sales, stocks and selling price averages for each cluster were used as a representative store of the cluster. The metro stores (larger stores with sizes of 70,000 – 1,00,000 Sq. Ft) had a higher stocking and higher sales but 6% lower average selling prices. The lower average selling prices are possibly a competition – discount-related effect.

Table 1: Clustering of April-June data on Stores

Stores	Cluster	Cluster
	1	2
No. of Stores	6	8
Relative Size	42.9%	57.1%
CLUSTER AVERAGES –**Standardized**		
Sales Quantity	1.09	-0.81
Average Selling Price	-0.18	0.13
Supply Quantity	1.11	-0.83
Calculated Values		
Sales Quantity	791.68	101.62
Average Selling Price	354.13	376.10
Supply Quantity	1052.30	147.65

Results from the K-means cluster analysis

F Value	18.69
SSB/(SSW+SSB)	60.9%

The k means clustering algorithm created the clusters on stores in metro cities and non-metros, as shown in [Table 2].

Table 2 : Dominant attributes of the store clusters

Location Code	Location	Cluster	Location Type	Size
1001	MALAD STORE-1	1	**Metro**	Large
1002	VASHI STORE-2	1	**Metro**	Large
1006	CYBERABAD STORE-6	1	**Metro**	Large
1008	EMBASSY PARAGON-BGLR	1	**Metro**	Large
1009	BIG THANE	1	Non-Metro	Large
1015	BANGALORE 2	1	**Metro**	Large
1003	BHOPAL	2	Non-Metro	Medium
1005	SUNCITY STORE – 5	2	Non-Metro	Medium
1007	AMRITSAR STORE-7	2	Non-Metro	Large
1010	ALPHA ONE AHMEDABAD	2	Non-Metro	Medium
1014	LUDHIANA	2	Non-Metro	Medium
1016	PUNE	2	Non-Metro	Large
1017	THANE VIVA MALL	2	Non-Metro	Medium
1019	BANGALORE 3	2	Metro	Medium

For the Belt SKUs we utilized 7 product clusters created with an F value of 173 [Table 3]. The lower rows in the table show the average April-June Sales, selling prices and Supply quantities for each cluster.

Table 3 : Clustering Results: Products

Belts	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
No. of SKUs	28	18	17	32	17	17	6
Relative Size of Cluster	20.7%	13.3%	12.6%	23.7%	12.6%	12.6%	4.4%
Cluster Averages - Standardized and Calculated values							
April-June Sales	-0.657	**1.334**	**0.526**	-0.691	-0.692	**0.070**	**3.020**
Avg Selling Price	**1.377**	-0.943	-0.762	-0.080	-1.000	**0.869**	-0.640
Supply	-0.622	**1.356**	**0.580**	-0.761	-0.787	**0.295**	**2.648**
Apr-June Sales	5.27	72.56	45.24	4.13	4.09	29.83	129.55
Avg Selling Price	752.65	240.83	280.92	431.33	228.36	640.57	307.66
Supply	10.70	85.69	56.26	5.39	4.42	45.45	134.71
Sell-through rate	0.493	**0.847**	**0.804**	0.766	**0.926**	0.656	**0.962**
Supplies	300	1542	956	173	75	773	808

Results of the Cluster Analysis

F Value	173.74
SSB/(SSW+SSB)	89.1%

These clusters are differentiated in terms of the Belt attributes, retail price, material used, sizes, and buckle designs (flat, reversible, pin, auto-lock), as can be seen in the output below [Table 4].

Table 4 : Extreme Clusters (1,7) Partial Data with Dominant Attributes clearly visible

Item Code	Cluster	Retail Price	Material	Color	Buckle	Rvrsble	FORMAL	Plain / design
NDLMB15577	1	895	**Leather**	B/B	REV	DUAL	FORMAL	PLAIN
NDLMK27545	1	845	**Leather**	B/B	REV	DUAL	FORMAL	PLAIN
NDLMK31577	1	895	**Leather**	B/B	REV	DUAL	FORMAL	PLAIN
NDLMK35577	1	895	**Leather**	B/B	REV	DUAL	FORMAL	PLAIN
NDLMK36577	1	895	**Leather**	B/B	REV	DUAL	FORMAL	PLAIN
NDLMN04706	1	1095	**Leather**	B/B	REV	DUAL	FORMAL	DESIGN
HDLML38255	7	395	**PU**	B/B	PIN	DUAL	FORMAL	DESIGN
HSLBL14223	7	345	**PU**	BLACK	PIN	SINGLE	FORMAL	PLAIN
HSLBL35223	7	345	**PU**	BLACK	PIN	SINGLE	FORMAL	DESIGN
HSLBL38223	7	345	**PU**	BLACK	PIN	SINGLE	FORMAL	DESIGN

A Linear Programming relaxation solution to the Integer Programming optimization model was used to recommend the optimum stock values for each store cluster-product cluster for the July-September quarter of the Spring Summer Season. The total stock actually supplied in July-September, was used as the stocks available (upper limit) constraint for each product cluster. The average price of the stocks in each cluster was an input into the model. [Table 5].

Table 5 : Belts Clusters - Input into MIP model

Belt Clusters								
Price & Qty	B1	B2	B3	B4	B5	B6	B7	Total
Avg Selling Price (Rs.)*	729.47	192.80	184.40	351.69	273.94	683.01	264.83	
Stocks Available (Qty)*	291	735	873	1976	39	732	157	4803

* Clusters are created using April-June Sales, Supplies and Selling Price Data
* Avg. Selling Price of the Product Clusters and Stocks Available are extracted from the July-September data

The closing stock data of the end of June for each store cluster – product cluster combination was input as the minimum stocking level for this combination and the data is shown in the table below [Table 6].

Table 6 : Constraints in IP model - stocks carried forward end June for each product –store cluster

Store Clusters	Belt Clusters							
	B1	B2	B3	B4	B5	B6	B7	Total
Stores Cluster 1 (S1)	73.00	40.00	127.00	268.00	2.00	192.00	19.00	721
Stores Cluster 2 (S2)	33.00	16.00	41.00	66.00	3.00	31.00	7.00	197

Sell-through rates for each store-product cluster combination as an input in the model are shown in the table below. [Table 7]

Table 7 : Sell through rates from April - June data - input into the IP model

Store Clusters	Belt Clusters						
	B1	B2	B3	B4	B5	B6	B7
Stores Cluster 1 (S1)	0.69	0.86	0.70	0.87	0.86	0.84	0.86
Stores Cluster 2 (S2)	0.64	0.73	0.76	0.78	0.70	0.72	0.98

The maximum stocking level was set for each store cluster from the July-September data using the actual supplies to each store cluster. A maximum sales potential of each store cluster was added in by arbitrarily increasing the actual sales achieved figures of July-September by 20%. No upper limit was set on the allocation quantity for a product cluster- store cluster.

The existing PAP process used by the brand was as follows - SKUs were planned for two seasons Spring-Summer and Autumn-Winter, and stocks were planned with a two-month lead time for production. Allocation of stocks to each store (or group of stores) was typically once a month.

With so many different features in the SKUs coupled with the need to make 1800+ (135 x 14) allocation decisions every month, the stock allocation process was highly dependent on merchandiser experience implemented through some thumb rules to decide s, S and T values. The thumb rules used were equal quantities allocation to all stores of all SKUs based on stocks availability, a lower (s) and upper limit (S) on stocks in a store, ensuring approximately three months cover on the previous month's sales, topping up a stock of SKUs sold in the previous month, restricting supplies of visibly slow-moving designs and balancing availability at the warehouse.

There was some use of sell-through rate (sales/supply) to understand the movement of the SKUs in stores, but the lack of a completely automated stocks allocation system or model was a drawback in the planning process and was likely to be sub-optimal. Some additional issues were the non-availability of some of the 135

SKUs of the season with the warehouse at the time of allocation and logistics problems of the regulatory and working environment (sales tax forms not reaching the warehouse, natural and manmade disturbances in states, stores having problems of inwarding due to lack of space etc.).

A linear programming relaxation solution for the Integer Programming model was used to recommend the optimum $Q_{i,j}$ values for the July-September quarter of the Spring Summer Season. Analytic Solver was used for the solution of the model. The optimum objective value from the model would be the expected sales value if the recommended stocking plan output of the model were to be implemented.

We utilized this current PAP process of the brand to compare the improvement that our model delivered. Our model and its product and store clusters appear to mitigate the effects of these problems showing a 35% + potential improvement, as can be seen from the improved sell-through of 0.82 [Table 8] over the current PAP process sell-through rate of 0.59. [Table 9]

Table 8 : LP relaxation Solution - recommended stocks allocation plan July-September

Store Clusters	Belt Clusters							
	B1	B2	B3	B4	B5	B6	B7	Total
Stores Cluster 1 (S1)	258	449	127	1910	36	701	19	3500
Stores Cluster 2 (S2)	33	286	746	66	3	31	138	1303

Objective Function = Expected Sales Value (Rs.) **1,450,029**

Stocks Supplied Value (Rs.) **1,762,134**

Sell-through rate expected **0.82**

The output of the existing PAP process and sales was achieved with the sub-optimal stock planning. The sell-through rate of this process was observed to be 0.59.

Table 9 : Heuristic-based stocks allocation - for the period July-September, actual supply and sales achieved

Supply	B1	B2	B3	B4	B5	B6	B7	Total Supply
S1	212	568	739	1601	18	515	87	3740
S2	79	167	134	375	21	217	70	1063

Actual Sales Value (Rs.) **1,031,496**

Stocks Supply Value (Rs.) **1,762,134**

Sell-through rate achieved **0.59**

Sales	B1	B2	B3	B4	B5	B6	B7	Total Sales
S1	184	528	631	914	17	173	72	2519
S2	60	148	102	151	19	77	52	609

8. Strategic and Managerial Implications of Effective Product Assortment Planning using the model

In our interaction with the firm where this model was implemented for testing, we were asked if the model could provide direction on the following processes:

1. Identifying designs for each season's production plan and estimating production quantities of each SKU to meet the season's demand
2. Allocation of available stock SKUs to stores with maximum sell-through potential for those SKUs and substitution with similar SKUs in case the stock out / low stocks SKU at store level was not available.
3. Correcting errors of high inventory due to the poor product–store allocation decisions

We evaluated how these issues were being hitherto handled and concluded the firm was using rudimentary methods, convenience and gut feel driven. There was a strong possibility of their decisions being influenced by a memory bias. We implemented the clustering- MIP model, and it showed an encouraging improvement in their financial performance.

8.1 Identifying designs for each season's production plan :

Design identification was largely based on continuing successful designs of the previous season with the addition of a few new experimental designs based on trends projected in fashion magazines. Production quantities were kept at a minimum production run (100 pcs) for new designs, and for old designs, a 10% increment on the quantity sales of the previous season. Issues of raw material availability matching the SKU attributes resulted in some ad hoc substitution of production quantities.

The PAP models suggested by Rooderkerk et al. (2013) and other authors were complex, and with a large number of SKUs the stores would require the firm to use a heuristic approach to find good solutions in a reasonable computational time.

Using a clustering-MIP approach with attributes of the SKUs built into the model and a subsequent decision tree application produced useful insights on attributes which were built into new designs. Production planning was improved by shifting the planning to product clusters rather than individual SKUs. This also helped the firm handle issues of raw material non-availability by providing substitution alternatives based on data of SKUs within a cluster. Our model with attributes built-in and clustering on attributes similarity was useful in reducing the computational time and permitting the search for an optimal solution.

The attributes with the highest impact on sales were implemented in most of the new designs. This action was useful in cutting down the average stocks of raw material required to be maintained by 20% (an average of Rs. 1.2 L per month) by progressively reducing stocks of lower impact attributes. Further, the clustering enabled the reduction of finished goods stocks resulting in the number of SKUs in the leather belts category being reduced from 135 to 110 in the season for the implementation of the model.

8.2 Effective allocation of available stocks to stores :

The existing policy of allocations of stocks to stores was largely based on a 'top up' policy. Whatever was sold was topped up to the initial allocation quantity for the store. Initial stocks were based on the categorization of stores into low, medium and high potential. Initial allocation was equal quantities of the SKUs available. Based on past sales data, stocks in the store were maintained at approximately three times the monthly average sales value. There was no consideration of product attributes or product-store matching on the basis of sell-through rates. In case of non-availability of an SKU, a substitute was supplied closest in price to that SKU.

This rudimentary inventory planning was resorted due to the high volume of data and complexity of working with product attributes and characteristics, local customer preferences, substitution effects and marketing mix elements (pricing, promotions and shelf space).

SKU focused models by earlier researchers would have been useful for working only with specific aspects of the marketing mix (Shelf Space - Borin and Farris -1995, Price - McIntyre and Miller -1999), substitution effects (Smith and Agrawal -2000).

Our model simplified the capture of most of the aspects relevant to a scientific allocation of stocks. The clustering facilitated the substitution of SKUs considering multiple attributes rather than just the closest price.

The implementation of our model improved the sell-through rates in the following season for this same category of product by 10% over a season. The average sell-through rates were in the range of 0.7-0.85 in the three months of the earlier season. On implementation of the model, these sell-through rates improve to 0.75 – 0.95 in the following season.

8.3 Correction of errors due to poor product-store allocation decisions :

In the firms existing working, correction of errors due to poor product-store allocation decisions was impossible due to the high logistics costs of return of products and re-dispatch. Other than transport, costs of damage and theft in transit added to the costs of poor product-store allocation decisions. This problem was further aggravated by the profiling of stores on their size and sales potential without considering the local effects. The clustering effect resolved these issues with allocation decisions limited to between clusters of products and stores. Store clusters were no longer dependent on the size of the store but based on marketing mix, substitution effects and local competition/ customer preference effects.

The reduction in the closing stock observed an impact of this at the end of the season by 30%, indicating smaller quantities of slow / non-moving stocks in the stores. Some of this could be a combined effect of (1) and (2) above. The high logistics costs for returns of this stock result in this stock being disposed off at a discount before the new season's stocks come to the stores. The discounts on these stocks were also reduced by an average of 5%, considering the small quantities available.

In the year of implementation of our model, the stock turnover ratio for the firm improved substantially. The firm continues to use the model, acknowledging a substantial improvement in their processes (1-3 above). The model outputs are helping them better understand the attributes valued by local customers, substitution effects and reduce costs of errors in product-store allocations.

9. Conclusion

Additional constraints which may have constrained the actual stock allocation plan were not available to see how much they would affect the performance of the model.

While much remains to be explored in the product assortment planning problem, we have presented an approach that should be useful for the fast-fashion category. Our approach uses data readily and reliably available in ERP systems of retailers to enable assortment planning decisions. The model factors in merchandiser experience, consumer response to the assortment and handling of mismatch between the two for the category. The impact of sizes of stores, shelf space allocated to the category and footfalls-conversions is extracted from historical data.

We used product and store clustering on historical data with an integer programming model to optimize the assortment planning for each group of products and stores. The objective was to maximize expected sales from available stocks. For assisting product planning for the following season, we suggest the use of a decision tree algorithm on extreme clusters to understand the attributes affecting the best and the worst performing clusters.

With the basic constraints, the model was able to deliver an improvement of over 35% for the belts category. This is a huge improvement as the existing heuristic method was rudimentary and apparently not a very effective method. Other than some qualitative use of sell-through rate, the data of an earlier quarter with valuable insights was hardly used in the existing stock planning process.

10. Contribution

Through this model, the authors attempted to close a significant gap in research concerning replenishment models for fast-fashion products applicable in emerging countries. Since critical parameters like changing customer preferences, and variation in demand due to seasonality, discounting systems etc., have been factored in while developing the present model, it can be easily extrapolated to multiple suppliers and multiple numbers of retailers.

11. Limitations and Future Scope

Our model in its current form would possibly be useful for ongoing product assortment planning for fast fashion products within a season. Once there is a change of season, the past data required for the model would need to be from an earlier year for the same season.

The model requires further testing and refinement to establish its usefulness, as the current testing was on a small set of data of a representative category. However, considering the similarities in the consumer perception and preferences, retailer constraints and environmental factors, we believe this approach of combining data mining with a linear integer model has the potential to deliver superior performance on most categories of fast fashion products.

Though the model has been created using field data of Indian retail markets, it can be easily extrapolated to all retail situations in any country where fast fashion goods are involved and parameters like seasonality, end-of-season discounts, and fast-changing customer preferences apply.

Further work could be used to explore the attributes of the clusters through the use of a decision tree algorithm with sell-through rate as a target variable. We would be able to determine the specific attributes that dominate the product and store clusters. A tree classification could be useful to determine attributes dominant in the extreme clusters – those with the highest average sell-through rate and the lowest average sell-through rate.

Our data set being small, we did not proceed with the decision tree algorithm as the dominant attributes were clearly visible in the clusters. For belt clusters, PU belts had a superior sell-through rate over clusters with primarily leather belts. [Table 4]. This is possibly due to the data being from stores of a particular retailer that caters to a value-conscious segment. Store clusters were visible as metro/non-metro characteristics dominating the 2 clusters [Table 2].

These characteristics and studying combinations of relevant characteristics would be useful in the designing and planning of the following season's offerings, including identifying gaps in the product offerings and attributes that are successful /not very successful. While consumer preferences may change from season to season and year on year, the attributes identified in the tables over earlier years (corresponding seasons) can provide useful information to designers and merchandisers. For the category of accessories, the stability of the attribute preferences by consumers is quite high.

Further researchers may also extend this model with unequal replenishment intervals and test its effectiveness in field conditions.

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