Hyperconnected Showcasing-Based Retail and Distribution of High-Value Products

Jisoo Park[1,4], Benoit Montreuil[1,2,3,4], Iman Dayarian[1,5],

1. Physical Internet Center
2. Supply Chain and Logistics Institute
3. Coca-Cola Chair in Material Handling and Distribution
4. School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, U.S.A.
5. Culverhouse College of Business, University of Alabama, Tuscaloosa, U.S.A.

Corresponding author: jisoopark@gatech.edu

Abstract: *Although e-commerce has transformed the way products are manufactured, transported, and sold, the pure e-commerce context is not appropriate for high value goods. In these industries, products are not strictly purchased online and the role of offline retail stores remains important as it is crucial for the customers to experience the product prior to the purchase. In fact, in some industries, having the possibility of testing the products could be a deciding factor. In the omnichannel supply chain era, showcasing is then emerging as one of the forthcoming key retailing factors. A showcasing value optimization model for hyperconnected showcasing centers, which maximizes showcasing value with respect to binary variables that represent which models are showcased is developed. The goal is to ultimately best represent the portfolio of products with features that customers expect to experience. Numerical results from our case study suggest that the showcasing value can be optimized to create a more efficient and effective showcase, with 20.4% increase on average across all 17 dealers. We also reiterate that for the model to be sustainable, Physical Internet and highly efficient, interconnected networks, are required.*

Keywords: *Showcasing; Retailing; Merchandising; Hyperconnected Distribution; Physical Internet; Product availability; Optimization; Mixed Integer Programming*

1 Introduction

Online retail has been accelerating ever since the rise of the e-commerce sector, with many customers willing to buy products without having physically seen, touched, and experienced them. However, for some industries, customers prefer to gain sufficient in-person experience with products before making their purchase decision, and thus the purely online setting is not appropriate. An example of such markets are high-value substitutable product markets like cars and recreational vehicles where products often have high values, carry in various models, and getting a first-hand experience of the product prior to purchase is one of the deciding factors for the customers. Vehicle dealerships are well aware of the importance of letting the customers touch, feel and experience the products to increase the chance of a successful sale but are often faced with spatial, financial, and supply chain related limitations that cause incomplete product availability frequently occur in retail centers. Factors such as demand uncertainty and forecast errors, seasonality, high holding costs, broad product mix, limited production capacity, long order-to-delivery times, and storage space limitations contribute to incomplete product availability in high-value product markets making it practically difficult to provide in-person experience to customers for all products and often lead to stock-out-based lost sales.

On the other hand, unlike markets that deal with the daily demand of customers like grocery stores, customers in high-value product markets are usually inclined to wait up to some acceptable time to receive their desired product. This along with high marginal profit and frequent occurrences of incomplete product availability persuades the retail centers to use inventory transshipment from other retailer centers or from the firm's distribution facility to satisfy demands for out-of-stock products. However, the customers who have not experienced some influential features that are found only in out-of-stock products, may not be able to realize their desired product among the firm's product portfolio or be willing to wait and accept a transshipment. This results in feature-out-of-experience-based lost sales which are different from stock-out-based lost sales. In the former case, the retailer can persuade most of the undecided customers that are willing to wait to realize their desired product by providing them the chance of experiencing different features of the products in-person. This requires the retail canters to consider feature availability or showcasing in their stores in addition to product availability.

It is important to make the distinction between stocked items in inventory and showcased items; having a product in inventory does not necessarily mean that the product is showcased. In fact, an optimized showcase may differ from an optimized inventory. Simply put, the inventory insures high availability of product. A product-availability-ratio (PAR) oriented inventory model measures and maximizes product model availabilities for a dealer's portfolio at any given time. The PAR takes the substitution phenomenon into account: whenever a model is not available due to a stockout situation, customers may take a similar available model for equal or lesser value. Given financial and space constraints, smart inventory management optimizes product availability, so as to essentially maximize the probability that a client wanting a given model will be satisfied with the inventory available to the dealer. This takes into consideration inter-model substitution fitness, the customers' preferred delivery time window distribution, and the stock exchange potential from other dealers and the manufacturer.

Whereas in inventory management, having multiple units of a given product on hand may help to satisfy heavy demand, in showcasing, this would be done only to enable multiple clients to touch and try the same product at the same time in the dealership. In fact, the main goal of showcasing optimization is to demo as many features in each category, given spatial and budget constraints; the showcasing value does not increase from displaying the same feature multiple times in the same showcase. Showcasing optimization takes feature similarities into consideration. However, showcasing and PAR models differ in terms of the criteria considered and the substitution or similarity values. More specifically, the showcasing model focuses on the product features and their feature similarities while PAR looks at products and their substitutability. Thus, it is important for the dealers to optimize both the showcase and the PAR, the former for meeting consumers' expectations prior to the purchase, and the latter for immediate sales since some customers might be reluctant to wait for shipments.

Motivated from a case of recreational vehicles, this paper investigates the assortment planning problem from the showcasing perspectives in a network of dealerships that owned independently or managed centrally by a firm and distribute recreational products. Dealerships do not sell the showcased units except for end-of-season clearance or for renewing the product freshness. When a client purchases a product, he gets a unit of the purchased product shipped from a fulfillment center to the client's location within the desired time window. The firm deploys its stock of products in the hyperconnected network of fulfillment centers, dynamically adjusting the overall quantity of stock in the network and the location of each product unit, aiming for each product to be deliverable efficiently within the various time windows expected to be requested by clients. We use the context of a recreational vehicle manufacturer and its thousand-dealer network across North America as a testbed.

2 Literature Review

The Physical Internet vision, which enables the logistics network to be hyperconnected and thus allows for the full implementation of the showcasing only model, has been proposed as a possible solution to the much called for supply chain revolution to meet the increase in customer's expectations in a sustainable way in modern world (Montreuil, 2011; Montreuil, 2012). The Physical Internet aims to create a sustainable, global, and interconnected logistics network that is analogous to the way information is transferred, handled, and stored in the digital internet (Montreuil, 2011; Montreuil, et al., 2012). The difference between the digital world and the physical world is well-acknowledged by the authors, but the focus is on standardization and interconnectivity that can be implemented in the physical world. Although the Physical Internet is a relatively new concept, it has been gaining significant attention globally from both academia and the industry, with topics ranging from city logistics to business models (Pan, et al., 2017; Crainic & Montreuil, 2016; Montreuil, et al., 2012). Its application in enabling efficient fast-response hyperconnected omnichannel supply chains is key to the widespread deployment of the showcasing model (Montreuil, 2017).

Visual merchandising can be defined as “the art and science of presenting products in the most visually appealing way” for retail stores to “[communicate] with the customers” (Ebster & Garaus, 2015). The authors have studied ways to promote sales through visual merchandising and appropriate design of store space. They accentuate the physical store environment as it can not only provide the customers with important information about the products and entertain them in the process, but also sell products to them, leading to sales. The authors provide a detailed guideline of how to design and present the store to derive such influences, such as customer paths, shelving, etc. but much of these details are not relevant to our discussion of a showroom. However, their argument that a purchase is contingent on a product being visible, tangible, and accessible is one of the key drivers of our study – in store product displays, or the showcase, will have a significant impact on sales.

Ebster and Garaus devote a chapter on using senses as a means to communicate with the customers, noting that high-pleasure and high-arousal store experience will encourage a more satisfactory shopping experience for the customers. Similarly, the four significant dimensions of store atmosphere had been defined as early as the 1970s as visual (sight), aural (sound), olfactory (smell), and tactile (touch) (Kotler, 1973-1974). This idea of sensory channels and their effect on consumer purchase decision and product choice were later reiterated by other scholars such as. McGoldrick (McGoldrick, 2002).

Another chapter in Ebster et al.’s work is in experiential store design, which is encouraging a memorable shopping experience. This concept also dates earlier as Schmitt has shown the need to shift in marketing approach to focus on providing consumers with enjoyable experiences, outlining five different kinds of strategic experiential modules including sensory associations, affective experiences, and physical experiences (Schmitt, 2015). In fact, with this rise of the era of experience economy companies should view the source of revenue as the consumption of experiences rather than products and functions (Pine II & Gilmore, 1998). It can thus be inferred that a showroom that provides customers with the experiences they expect once they purchase the product will best serve their needs, and the importance of providing them with the sensory, affective, and physical experiences for the products they desire is highlighted.

Studies have long acknowledged the impact of assortment planning on retailers’ sales and profit, as outlined in Kok’s extensive review of published work on assortment planning (Kök, et al., 2009). Kok et al. define the objective of assortment planning as to “specify an assortment that maximizes sales ... subject to various constraint” and show that a majority of existing studies are on the analytical formulation of the model and on demand estimates that are required for the formulations. The similarities in the concept then becomes obvious, as the goal of the showcasing optimization model is to select the set of products to be displayed as to maximize variety and meet customer demands, and thus maximizing the retailer’s revenues.

Thus, the consequences of an ineffective showcase also mirror those of an ineffective retail assortment — if the selected set does not meet customers’ expectation and fail to provide value, then the sales is jeopardized. An effective showcase displays not only the products customers expect to see, reflecting their demands, but also a variety, as is the case in assortment planning problems (Hoch, et al., 1999). Thus, the showcasing optimization model needs to maximize product variety to increase the chance of displaying the products customers desire for a greater number of customers, as well as to enhance customer’s perception of variety which has a positive influence on store choice and customer purchase (Hoch, et al., 1999; Arnold, et al., 1978). The notion of customers' perception of variety is further explored by Hoch, as they outline the perception of variety is driven by a measure of dissimilarity between different products based on the number of different attributes (Hoch, et al., 1999). Nevertheless, at the heart of assortment planning is not only selecting the product set, but also determining the appropriate inventory levels for the products in that set. In the showcasing optimization model, inventory management is not a factor, especially in the context of hyperconnected logistics that eliminates the need for retail store inventory.

3 Showcasing Portfolio Optimization

3.1 Measuring Showcasing Value

We define the showcasing value as the measure of how much a showroom displays features that customers desire to experience before purchasing an item. The parameters and variables required to calculate the showcasing value are as follows:

- P is the set of all products that can possibly be showcased in a showroom by, and p is a product within that set.
- Each product is characterized by its features from different feature categories. Let C be the set of all feature categories, and c be a category within that set.
- Similarly, be the set of features within feature category F, $c \in C$ and f a feature within that set.
- Binary parameter δ_{fp} equals 1 if feature $f \in F_c$ of category $c \in C$ is a part of product p, or takes a value between 0 and 1 if a similar feature to f is a part of product p. That is, parameter δ_{fp} indicates how representative product p is to showcase feature f. Obviously, if feature f is part of product p then δ_{fp} equals 1, otherwise, it takes of a value between 0 and 1, depending on the level of similarity of f to the corresponding feature in p.
- w_c is the showcasing weight of a feature category that represents how some feature categories hold a greater importance for the customers to experience in a showroom than other feature categories, between 0 and 1. For feature categories that are more important
  all categories is 1, or $\sum_c w_c = 1$.
- d_{fc} is the expected demand share for a feature within a category, between 0 and 1. The demand share value estimates how likely a customer would like to purchase a product with that feature, and thus how much the customers would like to see the feature showcased. For each feature, the showcasing value contributed by that specific feature is multiplied by the corresponding demand share for the feature. Thus, the showcasing value does not simply measure how well a variety of features are showcased – it rather measures how well the showcase portfolio represents what the customers expect to see, as most customers visit the showroom with features in mind for purchase. The resulting showcase then is more likely to give an overall showcasing experience satisfactory for all customers. The sum of $d_{fc,}$ across all features within a category is 1 for every category, or $\sum_c d_{fc} = 1 \; \forall c \in C$.
- Y_{fc} is the showcase value for feature f in category c, which describes how well the feature is showcased in the given portfolio. If the exact feature is showcased by a product in the portfolio and thus the customer has a full exposure of the feature, then $Y_{fc} = 1$. If the exact feature is not showcased but the customer can still gain partial value by being exposed to a similar feature that is showcased, Y_{fc} is between 0 and 1. If the feature is not showcased and none of the similar features are showcased such that the customer cannot gain partial experience of the feature even through similar features, then $Y_{fc} = 0$. For some categories, customers will always want to see the exact feature. In such cases Y_{fc} is a decision variable which is 0 if the feature is not showcased and 1 if it is. When a feature similar to the desired feature can give some value to the customer when showcased, Y_{fc} will be between 0 and 1, the value being higher if the similarity is higher.

The showcasing value then can be modeled as follows:

$$Showcasing\ value\ \Gamma\ = \sum_{c\in C} \sum_{f\in F_c} d_f Y_f \quad (1)$$

3.2 Showcasing Optimization

The objective function is then written as the maximization of equation (1) from the previous section with respect to Y_f with the following constraint sets:

$$Y_f \geq \delta_{fp} X_p \quad (2)$$

$$Y_f \leq \sum_{p\in P} \delta_{fp} X_p \quad (3)$$

$$U_f \leq 1 - (Y_f - \delta_{fp} X_p) \quad (4)$$

$$\sum_{p\in P} X_p \leq m \quad (5)$$

$$\sum_{p\in P} c_p X_p \leq m \quad (6)$$

$$U_f \in \{0,1\} \quad (8)$$

$$X_p \in \{0,1\} \quad (9)$$

$$Y_f \geq 0 \quad (10)$$

Constraint set (2), (3) and (4) guarantee that variable Y_f for a given feature in each category will be a positive value between 0 and 1 and thus contribute to the showcasing value if and only if a product with the feature in the category is showcased. Moreover, customers will benefit from the product that best represents the desired feature, and thus Y_f takes the maximum value possible. Binary variable X_p is 1 if product p is showcased and 0 otherwise. This variable then is multiplied by δ_{fp}, the feature representivity for feature f of category c that is a part of product p. Parameter δ_{fp} is 1 if the exact feature f is a part of p, between 0 and 1 if a similar feature is a part of product p, and 0 otherwise. Thus, δ_{fp} X_p represents the value a specific feature within a category adds to the overall showcasing value when a product with that feature is displayed, taking the feature representativeness into account. Another assumption is made here as if multiple products with partial feature representativeness are showcased, then max δ_{fp} X_p will take the maximum value, which means the customer benefits from the feature most similar to the desired feature. When multiple products are showcased and these products represent any feature that is similar to a particular feature f, then customers will gain utility only from experiencing the feature that best represents the desired feature. Constraint (6) ensures that the given dealer cannot showcase more products than the maximum number m. To keep the total expense of the showcase within the budget, constraint (7) is included so that the given dealer cannot spend more than the budget B to showcase the products. Constraints (8), (9) and (10) give the type and domain of the variables of the model.

Then the goal is to maximize showcasing value for a dealer through deciding which products to showcase given physical and budgetary constraints. The assumption is that higher showcasing value means lower chance of a customer not purchasing the product because desired features were not showcased.

4 Experimentation

4.1 Numerical Example with a Dealer

This section illustrates a numerical example of the model with data collected from the industry. Specifically, it is from a company that manufactures and distributes recreational vehicles, focusing on a particular type of such vehicles. The showcase for seventeen dealerships, referred to as dealer 1, dealer 2, etc., in a state in the United States is considered, as it was the site for pilot testing.

Table 1: Showcasing Weight of Feature Categories

Feature Category	Weight (%)
Color	13.6
Engine	9.1
Platform	18.2
Seat Capacity	13.6
Segment Industry	45.5
Sum	100

In table 1 we provide a list of key categories of product features that contribute to the showcasing value, as well as the corresponding showcasing weight w" for each feature category, based on the weight given for each category for demand share calculations.

These feature categories are defined as key categories of product features that customers want to physically touch and feel on a product in the dealership in order to differentiate correctly between products and to gain sufficient confidence that an ordered product will satisfy their needs and meet their expectations.

The demand share for each feature *f*, or d_f , was translated from the demand share for a product *p* for year 2018. Based on the historical sales data for a one-year period, the demand for a feature

was estimated by multiplying the product demand matrix (which shows the demand share for each product for each month) and the product-feature matrix (which shows whether the feature is a part of the product or not). Exponential smoothing was then used with the ratios from the sales data to calculate estimated demand share for each feature in year 2018. Table 2 shows an example of the demand share used for calculating the showcasing value.

Table 2: Demand Share for Features in Category Seat Capacity

Feature	Demand Share (%)
2 Seats	36.0
3 Seats	23.9
4 Seats	11.8
6 Seats	28.4
Sum	100

To further illustrate how the current showcasing value is measured, dealer 13 is taken as an example. Assuming the current stock is equivalent to the showcase, Fig. 1 below is a visual representation of the current showcase and the features represented by the products with this showcase.

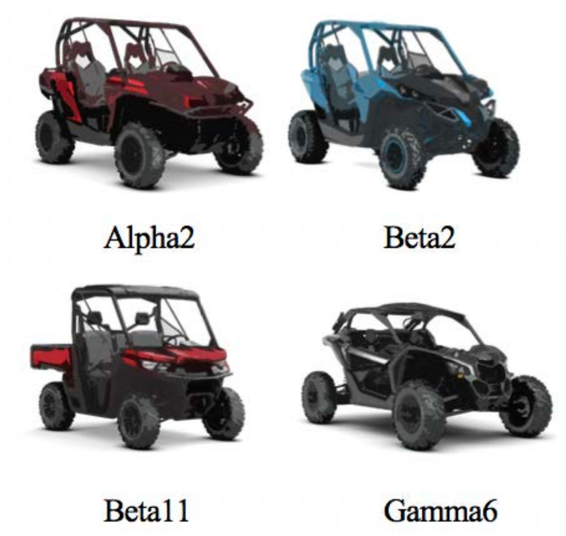


Figure 1: Current showcase for dealer 13, assuming that the inventory is the showcase

Because this showcase is not optimized, the products represent the same or similar features in a number of cases (eg. Alpha2 and Gamma6 both feature the color which corresponds to the color "Red", and three out of four vehicles are 2 passenger seats). With the current showcase, the showcasing value for dealer 13 is 48.8%. The features for all categories considered are shown in the table 3.

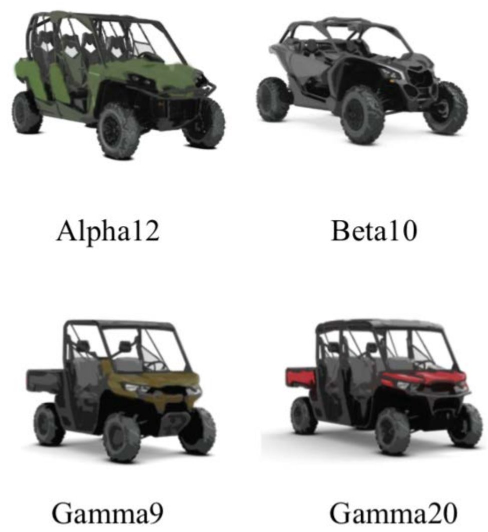
Table 3: Features for the current showcase for dealer 13

Category	Alpha2	Beta2	Beta11	Gamma6
Color	Red	Blue	Black	Red

Engine	1000 Twin Cylinder	1000 Twin Cylinder	Turbo	Pro 100
Platform	A2	A2	A2	A3
Seating	2	2	2	3
Segment Industry	Recreational	Sport-1	Sport-2	Utility

With the model we propose, the showcasing value for the same dealer was maximized, with the optimized showcase shown in Figure 2.

Figure 2: *Optimized showcase for dealer 13, assuming that the inventory is the showcase*



This optimized showcase offers a more variety of features for customers to experience, especially the more demanded features when possible. For example, compared to the current showcase that displays only two features in the category passenger seats (2 and 3), the optimized showcase displays all four features available in the category.

Table 4: Features for the optimized showcase for dealer 13

Category	Alpha12	Beta10	Gamma9	Gamma20
Color	Green	Grey	Brown	Red
Engine	1000 Twin Cylinder	Turbo	Pro 80	Pro 100
Platform	Alpha6	D38	B5	B15

Seating	4	2	3	6
Segment Industry	Multi	Sport-1	Utility	Utility Multi

4.2 Numerical Example with All Dealers

When the current showcasing values are measured for all dealers in the state, the average showcasing value is 62.3%. Dealers with either an efficient showcase, or higher budget and maximum number of vehicles to be showcased display relatively higher showcasing values. When the proposed optimization model is applied to all seventeen dealers, the average of the optimized showcasing value increased to 82.7%.

Because the budget was part of the constraint of the optimization model, the new budget for the optimized showcase is never higher than the current budget. In fact, we saw a decrease in the average required budget to achieve the maximum showcasing value across all dealers.

Table 5: Showcasing value and budget for all dealers

Dealer Number	Current Showcasing Value	Optimized Showcasing Value	Current Budget (USD)	Optimized Budget (USD)
1	42.9%	77.6%	80296	78396
2	64.3%	86.2%	131994	122194
3	31.9%	43.3%	37298	35998
4	39.2%	60.2%	51397	51397
5	96.6%	100.0%	635068	622468
6	77.6%	98.1%	327081	324283
7	94.9%	99.5%	466376	472776
8	35.3%	82.2%	128995	103495
9	88.3%	98.5%	349082	348282
10	59.9%	87.4%	127992	127893
11	70.6%	84.6%	110494	108494
12	34.8%	42.7%	33198	32498
13	56.8%	82.2%	123495	103395
14	91.4%	99.1%	399079	395479
15	68.1%	91.7%	164391	164091
16	43.7%	77.6%	86696	78496
17	62.1%	94.8%	273889	216989

Average	62.3%	82.7%	207460	199213

5 Conclusion

In this paper we described the key decisions, objectives, and constraints in dynamically optimizing the showcasing portfolio of each dealer, then we contrasted baseline vs optimized portfolios in terms of showcasing value, dependent on budget decisions. The showcasing value aims to measure how well each feature is represented in a given dealer's portfolio. The showcasing value optimization model for hyperconnected showcasing centers then maximizes the sum of all the feature representivity for a given dealer, weighted by expected demand for that demand and then by the importance of the category to showcasing. The model is formulated as a mixed-integer programming model, with binary variables that represent which models are showcased, and concurrently the features showcased. With the empirical application of the model, it shows that the data-driven model can be solved efficiently for industry cases. The results illustrate that the showcasing value can be optimized significantly given certain conditions are met with an increase of 20.4% in showcasing values on average across all 17 dealers. With efficient decision support systems for optimizing showcase, the showcasing model can allow to take full advantage of the fast replenishment from hyperconnected networks in the Physical Internet world, benefiting retailers, manufacturers and customers. Indeed, optimized showcasing can be implemented in practice only if the supply chain is agile enough with a short lead time to deliver the products to the customers within the time frame they expect, from sources ranging from fulfillment centers, warehouses and factories.

The implication on the downstream supply chain of the manufacturer to support the fast and reliable availability of products demanded at the showcasing dealers across the market territory is then clear. In traditional settings, a higher level of inventory is oftentimes kept in dealers, distribution centers, and fulfillment centers minimize the possibility of lost sales. Dealerships would also keep what they think is the best showcase to meet customers' needs. Once the customers gain confidence in their decision from their visit to the showcase they would make a purchase directly from that retail store. However, with the advancements in the Physical Internet, the independent dealers, OEM distribution centers and fulfillment facilities will be hyperconnected; as these facilities now share all the information and networks, with fast replenishment, products available in one of the facilities would be available in all other facilities in the network within a short time frame. Such flexibility and end-to-end visibility across the supply chain means that products could now be delivered from any point to the customer within an acceptable period of time. In-store inventory is then not a necessity anymore, transforming the role of dealerships from retail stores to showcasing centers. In this context, the importance of having a showcase that meets customers' expectation is now greater than ever. To successfully induce the client to make a purchase, the showcase would need to help the customers understand the options by letting them experience the features, especially the ones they desire. We thus accentuate the role of showcasing as one of the forthcoming key retailing models in the omnichannel supply chain era, together with the opportunities offered by the emerging Physical Internet.

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