A Method For Determining The Delivery Frequency From A Distribution Center To A Retail Grocery Store

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INTRODUCTION

With uncertainty in fuel costs and an increasing shortage of truck drivers, the cost of transportation is a growing concern for many industries. The rising cost of transportation is of particular concern to the retail grocery industry, which moves large volumes of low-margin goods. Most retail grocery stores are severely constrained in the number of deliveries they require each week due to factors such as limited shelf space, little or no excess product storage (backroom storage, which refers to an area that is not on the sales floor), substantial demand uncertainty, and the large number of Stock Keeping Units (SKU's) sold at each store. These constraints place tight limits on how much freedom supermarket chains have to adjust delivery schedules based on economic factors.

There has been some research conducted in this area, and several methods for determining delivery schedules have been developed, but existing methods fail to incorporate the constraints of both limited physical space at the store and the necessity for deliveries to follow a fixed schedule. Balintfy (1964) and others have done work in determining a replenishment schedule by looking at it in terms of a Joint Replenishment Problem (JRP). The JRP refers to a situation where several different products can be ordered together for one fixed cost for the entire order (usually referred to as a major setup cost) and an additional charge per product (minor setup cost). Under Balintfy's

method, each product is assigned a *can-order*, and a *must-order* level. When one product drops below its *must-order* level, all products below their *can-order* level are ordered. Enough of each product is ordered to raise its level to an *order-up-to* level. For grocery retailers, this is not a logical replenishment method because grocery stores generally prefer to receive only full cases of product, and in cases with very limited shelf-space, the can-order and must-order numbers will be very close to the same. This method also does not lend itself to a fixed delivery schedule.

Cachon (2001) considers a method for determining delivery frequencies which dispatches a truck once the total order size reaches a given threshold. However, this means that the delivery schedule will not be fixed, which makes it very difficult for grocery stores to schedule their stocking labor. Neither Cachon's nor Balintfy's method account for the fact that there is also a cost (in the form of store labor) associated with having to place in the backroom all product that will not fit on the shelves. For high-volume stores with limited shelf space, the amount of product stored in the backroom can be substantial, particularly if the store is required to order only full cases, as is the case for most stores. As the number of deliveries per week decreases, the amount of product that needs to be stored in the backroom increases, and the costs associated with handling this product can become a major trade-off with transportation costs when determining the store's delivery schedule.

For this study, we worked with a New England retail grocery chain (from this point forward referred to as Grocery Chain X) to develop a method for determining the delivery frequency for each individual store based on a defined set of characteristics, including shelf-space, transportation costs, inventory costs, and product handling costs.

Since the stores receive deliveries from multiple warehouses, both those owned and operated by Grocery Chain X and those of its vendors, the project scope was narrowed to one product category delivered from one specific location. The chosen location was a Grocery Chain X-owned distribution center (which we will refer to as DC Y), which supplied approximately 120 stores with dry grocery products.

This paper outlines the method we used for analyzing the delivery frequency to a store by developing a simulation model for the replenishment process of Grocery Chain X. The model can be used to provide insight into when deliveries should be made to each store, as well as other aspects of the replenishment process, such as shelf space allocation, and re-order rules. Using this model, we were able to show that significant cost savings were available to Grocery Chain X by changing the delivery schedules for their stores. We were also able to show that shelf space allocation and the re-order rules can have a significant impact on operational costs for the store.

EXISTING OPERATIONS

Each store that receives product from DC Y places an order with the DC by 4pm the day before the delivery is schedule to arrive. The order is placed by an automated Supervised Re-Order system (SRO) which relies on a forecasting software package to collect Point-Of-Sale (POS) data and to provide it with sales forecasts and Balance-On-Hand (BOH) information. Each store carries approximately 10,000 SKU's of dry grocery products (this number varies from store to store), and each SKU needs to be forecasted and ordered on an individual basis. The order quantity of each product is calculated as follows:

1) The SRO system calculates the quantity of each product expected to be left in the store at the time the next delivery is scheduled to arrive. The next delivery refers to the delivery after the delivery which is currently being sized. This amount (F) is calculated according to Formula 1:

Formula 1: $F_i = BOH_i - E[Sales_i]$, where:

$F_i =$ amount of product i expected to be in the store at the time of the next delivery.

$BOH_i =$ current balance on hand of product i

$E[Sales_i] =$ expected sales of product i before the next delivery, provided by the forecasting system

2) If the amount of product forecasted to be at the store at the time of the next delivery is less than the ROP for that product, enough cases of the product are ordered to fill the shelf to capacity.

In addition to the re-order process described above, on either Wednesday or Thursday of each week, an additional order is added to the base order to deliver promotional items to the store. This order is generated separately and only needs to be accounted for in our model when determining the total amount of product on the truck on the day this order is delivered. The delivery schedule has no bearing on the amount of product included in this order.

Once the order is placed at DC Y, it will be picked and loaded onto a truck the following day. Deliveries to the retail stores originating from DC Y are dispatched throughout the day and are delivered via the Grocery Chain X private fleet. Depending

on the size of the order for an individual store, it may be combined with the orders for up to three other stores. Grocery Chain X's transportation routing system determines how these orders will be combined and how the trucks will be routed the day prior to the deliveries.

During the overnight shift on the day the delivery arrives, stockers first load the product onto "U-boats" (carts shaped like the letter "U" which are used for taking the product onto the sales floor.) The stockers then take the U-boats onto the sales floor and fill the shelves to capacity (or until they run out of product) and put any remaining product in the backroom. Any product which must be stored in the backroom is then moved to the sales floor throughout the following days as shelf space becomes available. Because the product which must be moved to the backroom has to be handled at least one additional time, stores try to minimize the amount of product that must be stored there.

Current Delivery Schedules

Currently, Grocery Chain X determines the number of deliveries per week from DC Y to the stores based on the total average weekly sales volume for each store, without looking at the overall costs associated with the replenishment process. There is, however, some room for the stores to negotiate on the number of deliveries per week and on which days the deliveries will occur. Stores generally prefer to receive deliveries as frequently as possible (up to daily) to add greater flexibility to their operations and to limit the amount of product stored in the backroom.

METHODOLOGY

Before we could build a model for determining the delivery schedule for a store, we first needed to understand not only how the replenishment process worked, but also (1) which costs are impacted by the delivery schedule, (2) any constraints that would limit possible delivery schedules, and (3) we needed to make certain assumptions to make the model manageable.

Costs Impacted by Delivery Schedule

Transportation Cost: Each time a delivery is made to the store, a cost is incurred equal to the cost per mile for operating a truck multiplied by the distance from DC Y to the store and back.

Order-Picking Cost: Each delivery to the store incurs the cost of DC Y labor having to pick the order and load it onto the truck. This cost changes very little as the amount of product increases due to the manner in which it is picked, so we took this cost to be a fixed cost per order.

Product Handling Cost: Each time a case of product is delivered to the store and will not totally fit on the shelf, this product requires additional handling. Grocery Chain X performed a time study to determine how much store labor time is required to double-handle one case of product. The amount of required time multiplied by the average hourly wage (including benefits) of a store employee yielded the cost per case for double-handling.

Inventory Carrying Cost Changes: Since changing the delivery schedule to a store means the product may spend additional time at the store and less at the DC (or vice versa), differences is carrying costs between the two locations must be included in the model. Also, depending on the replenishment policies of the DC, it is possible that additional product will be stored in the system. In our case, the carrying costs at the different levels were identical, and we determined that the total amount of inventory in the system would see little or no change, so our inventory carrying costs changes were zero. However, we build the model to include these costs in case the policies that dictate these costs are changed in the future.

Stockout Costs: A stockout occurs when the demand for a certain product is greater than the amount of that product in the store. This cost can be extremely hard to quantify because it is influenced largely by customer behavior. For our model, we chose to assign a nominal fixed cost to a stockout event, regardless of which product it was, because

Grocery Chain X was more concerned with the number of stockouts than with the cost associated with them. The model could easily be modified to set the cost of a stockout to be product specific.

Constraints

1. Promotional orders need to be delivered on either Wednesday or Thursday, so removing both days from the delivery schedule is not an option.

2. Each store has a physical limit on how much product can be stored in its backroom.

3. The physical capacity of a truck is 1750 cubic feet. If the size of a delivery exceeds this number, an additional truck is required.

4. Deliveries must be made on the same days of the week every week.

5. All product which the store orders must be delivered on the next scheduled delivery day.

Assumptions

1. Every time a store orders a certain product, that product will arrive on the next delivery. The DC always has every product in stock, and all orders are picked without errors.

2. The delivery schedule of one store has no effect on the transportation routing of the system as a whole, and removing a delivery from one store results in the savings of the transportation costs for one truck traveling from DC Y to the store and back. This

is not actually the case because if one delivery was removed from the system, the transportation routing system would reroute the entire system, and the resulting savings could range from zero up to the costs we assumed for the model. This will be discussed further in the *Results* section.

3. A stock-out occurs when the actual demand is greater than the amount in the store (on the shelves and in the backroom.) This assumption does not necessarily perfectly model what happens in the store because if there is product in the store, it does not necessarily mean that it is on the shelf and available to customers. However, the delivery schedule does not change this phenomenon.

4. Shelves are physically capable of holding a greater number of units of each SKU than the shelf space allocation states. If a stocker is left with only an item or two in the case, many SKU's have the needed flexibility to accommodate the extra product without having to place it in the backroom. For the simulation, we assumed that an additional 25% of each product could be stored on the shelves. Therefore, we used a shelf space adjustment factor of 1.25. We also performed a sensitivity analysis on this variable. The affect that the shelf space adjustment factor had on the percentage of SKU's stored in the backroom is shown in Figure 1. This adjustment factor had no significant impact on the number of stockouts.

FIGURE 1:

EFFECT OF SHELF SPACE ADJUSTMENT FACTOR ON PERCENTAGE OF SKU's
IN THE BACKROOM
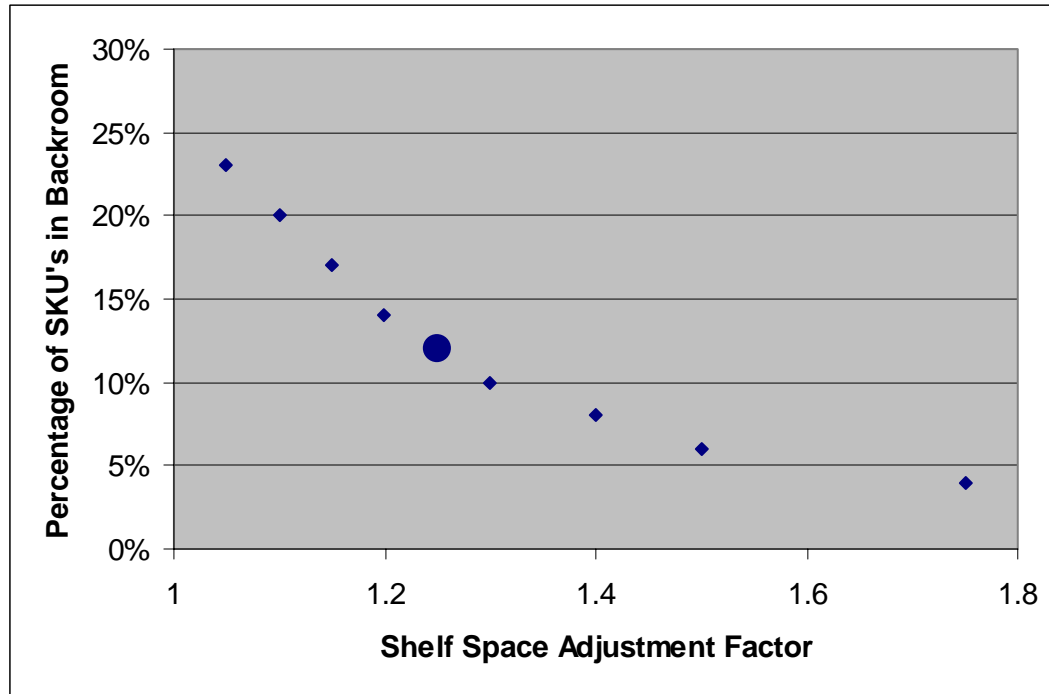
The Model

To create a simulation model that could accurately replicate the re-order and

replenishment systems of the grocery chain, we had to fully understand what decisions

were being made by the automated systems and how and when these decisions were

being made. The two systems we would have to emulate in the model were the

forecasting system and the Supervised Reorder System (SRO). The Transportation

Management System (TMS) actually routes the trucks, but vehicle routing was outside

the scope of this project.

Once we understood the automated systems used in the replenishment process, we replicated them in a model using MS Excel. Next, we needed to add the ability to "randomly" generate sales for each SKU individually. We compiled a year's worth of sales data for one store and used it to decide how we were going to model product sales. We found significant sales variations in most products based on the day of the week, but limited variations from week to week, so we decided to calculate a mean sales value for each product for each day of the week. Sales statistics for each day of the week are shown in Table 1.

TABLE 1:

SALES STATISTICS FOR EACH DAY OF THE WEEK

Day of Week	Mean Total Sales	Standard Deviation	Coefficient of Variation
Sunday	17262	2638	0.15
Monday	13746	1700	0.12
Tuesday	11735	1317	0.11
Wednesday	10716	1208	0.11
Thursday	10359	1098	0.11
Friday	11325	1090	0.10
Saturday	15480	2080	0.13

We determined that a Poisson distribution closely represented what an individual product was actually experiencing in the store. A POISINV function is available in a statistical add-in for Excel called SIMTOOLS. With this function (using the mean sales values for each day of the week), we were able to generate demands which closely

matched the actual demands seen in the sales data for the past year. For those SKU's which experienced very limited demand, particularly the products that saw a maximum of one product sold each day, the Poisson distribution could produce individual demands higher than demands actually seen in the past. This is due to the fact that there is theoretically no limit to the tail on a Poisson distribution, which means that there is no limit to the sales that the simulation could theoretically produce. However, the mean would still be accurate, and the infrequent higher demand would produce a worse-than-actual case because higher demands increase the chance of a stockout. Also, the fact that these are very slow-moving products means that their overall affect on the system will be minimal. For these reasons, we felt that the Poisson distribution would be appropriate for all SKU's, including the very slow-moving products. The Binomial Distribution would be an alternative for the products which saw a maximum of one unit sold per day.

Once we were able to simulate customer demand, we needed to validate the model by comparing the results produced by the model to the actual results seen over the past year. We had data for the total daily sales and daily delivery sizes for a high-volume store receiving deliveries every day, and the results of one simulation run are compared to the actual data in Table 2.

TABLE 2:

SIMULATED RESULTS COMPARED TO ACTUAL

Day	Simulated Delivery (cubic feet)	Actual Delivery (cubic feet)	Percent Difference	Simulated Sales (units)	Actual Sales (units)	Percent Difference
Sunday	1311	1117	17%	16,400	17,245	-5%
Monday	1034	905	14%	13,667	13,747	-1%
Tuesday	890	870	2%	11,415	11,825	-3%
Wednesday	2080	1650	26%	10,600	10,883	-3%
Thursday	720	685	5%	9600	9961	-4%
Friday	806	917	-12%	11,020	11,216	-2%
Saturday	1100	1108	-1%	14,820	15,292	-3%
Total	7940	7252	9%	90,67	87,522	-3%

The size of the delivery on Wednesday saw the greatest deviation from the actual results, but this was due, at least partially, to the fact that Wednesday's delivery had the promotional order added to it. The size of the promotional order varies slightly from week to week, but we did not have actual data for past year which told us what portion of Wednesday's delivery was promotional product. So for the simulation, we chose to use a fixed size for this portion of the delivery and to use a large enough number to err on the high side to produce a worst-case scenario, meaning we would be more likely to fill a truck and require an additional one.

Once we were satisfied that the model was producing results in line with the data we had for Grocery Chain X's replenishment system, we simulated this process for three

stores in the chain. We discovered through various test simulations that for Grocery Chain X's replenishment process, the major trade-off in costs was between the transportation costs (including the order-picking cost associated with each delivery) and the product handling costs. When a delivery was removed from the schedule, the delivery on the day prior to the day skipped received a much larger-than-normal delivery, so the extra product needed to be moved to the backroom, resulting in higher product handling costs.

The number of stockouts did not seem to be significantly impacted by the delivery schedule. This can be explained by the fact that there are two competing factors that are affecting the number of stockouts. (Recall that we defined a stockout as a situation where the demanded number of a specific product is greater than the amount of that product in the store, both on the shelf and in the backroom.) The first factor is that by removing a delivery from the schedule, the product that would normally be delivered on the day which is now skipped, is now delivered with the previous delivery. This means that now the product is actually in the store before it normally would have been there. The competing factor which balances the effects of delivering the product earlier is that by skipping a delivery day, the forecasting system is forced to forecast one day further into the future, which decreases the accuracy of the forecast. If the delivery day was not skipped, the order for that day would be placed one day later, which means that an extra day's sales would be known, rather than having to be forecasted.

Once we determined the major trade-off in the replenishment process, we were able to develop some general guidelines for determining logical delivery schedules to run through the simulation.

**General Procedure for Choosing Possible Delivery Schedules**

One method for finding the delivery schedule with the lowest costs for a store is by mass enumeration. The total number of possible delivery schedules for a store (not including the promotional delivery) is only two to the seventh power, or 128 possible schedules, so this is a plausible method. However, since running this model 128 times would be somewhat time-consuming, we were able to establish a general procedure for eliminating certain groups of delivery schedules which did not make sense. This procedure is specific to stores that follow the replenishment process used by Grocery Chain X, and is outlined below.

1. Run the simulation with deliveries on every day of the week, without including the promotional delivery. This will provide the approximate amount of product required each day of the week.

2. Determine the total amount of product required each week by adding the delivery sizes for each day found in Step 1.

3. Determine the minimum number of truckloads of product required each week. This is accomplished by taking the total amount of product required each week (found in Step 2) plus the promotional product, and dividing this sum by the capacity of one truck. In the case of Grocery Chain X, this number was 1750 ft^3. The number of deliveries must be rounded up to the nearest integer. This will provide the lower limit to the number of truckloads required each week; and all possible delivery schedules which provide fewer deliveries than this lower limit can be eliminated. This

minimum number of truckloads may or may not actually be possible, depending on how the product requirements are distributed throughout the week.

4. Look at the results of the simulation from Step 1 and try to find daily deliveries that can be combined, onto one truck. Remember that the promotional product must be combined onto a truck on either Wednesday or Thursday. Figure 2 shows the delivery sizes from a medium-volume store, and one possible way of combining them into three deliveries, the minimum number required found in Step 3. There may be several ways of doing this. As stated earlier, it is possible that there will be no way to combine the deliveries into the minimum number found in Step 3. If this is the case, combine deliveries into the minimum number possible.

FIGURE 2:

COMBINING DELIVERIES
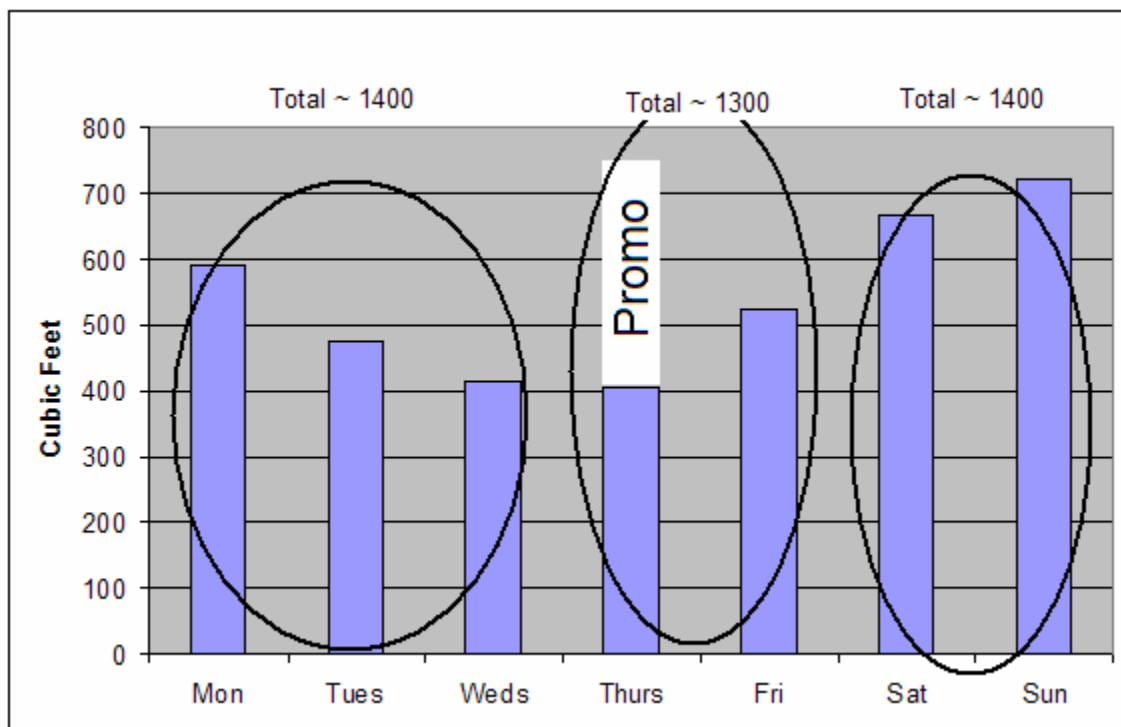
5. If either Wednesday's or Thursday's delivery plus the promotional product, or if one day's delivery alone is greater than the capacity of one truck, try to combine another day's delivery with this one if it can be done without requiring a third truck. Combine the remaining deliveries for the week in the same manner as in Step 4.

6. Run the simulation for all of the delivery schedules found in Steps 4 and 5 to determine the lowest cost option.

7. It is possible that making the minimum number of deliveries per week (from Steps 4 and 5) is not the lowest cost option, depending on how much product will need to be stored in the backroom. For this reason, repeat Step 4, but this time, add one more delivery per week.

8. Run the simulation for all delivery schedules found in Step 7 and compare the results to those from Step 6. Find the lowest cost option.

RESULTS FOR GROCERY CHAIN X

Individual Store Results

We used the method outlined in the previous section to determine which schedule would yield the best results for three stores. We were able to draw several conclusions from the simulation, some specific to Grocery Chain X's operations, some more widely applicable. For Grocery Chain X, we found that the method they are currently using to determine the number of deliveries per week results in more deliveries than are necessary, and that transportation savings (and overall cost savings) are available by reducing this number. In particular, one store which has one of the highest ratios of sales

volumes to available shelf space of any store in the chain, can remove two deliveries per week and can cut 10% of overall replenishment costs. We also discovered that the day or days of the week that do not receive deliveries can have a sizeable impact on overall costs. Therefore, determining only the number of deliveries per week each store should receive is not enough, but the days of delivery must also be specified to realize the lowest overall cost. The day or days of the week that are the best choice for one store to skip, are not necessarily the best for another store, so the simulation must be run for each store individually.

**System Impact of Changing One Store's Delivery Schedule**

After running the simulation for each store individually, we needed to determine how changing the delivery schedule of one store would impact the system as a whole. Because one truck may contain deliveries for multiple stores, one store's delivery schedule is not completely independent of those of other stores. To determine how the system would react to a change in the delivery schedule of one store, we preformed several test runs on Grocery Chain X's Transportation Routing System (TRS). We accomplished this by running the TRS for a typical daily delivery route and then comparing the results to those when we removed a delivery from a store or a group of stores.

By removing only one store's delivery from the system, the mileage reduction is only about ten percent of the expected reduction (distance from DC Y to the store and back.) However, as the number of stores removed from the delivery schedule on a single day approaches ten stores, this number increases to over 40%. The actual results from

this test can be seen in Figure 3. Because the TRS routes the deliveries based on which stores need to receive deliveries and the size of the deliveries, the routing will be different each day. This is just one sample routing and actual daily results may differ substantially, depending on how the removed deliveries were combined with other loads. If a scheduled delivery was a dedicated truck going from the DC to the store, and that load was removed, the entire mileage would be dropped from the routing. Generally, this is not the case for Grocery Chain X, however, so removing one delivery results in the TRS system rerouting several of the deliveries. Overall, from the TRS test runs we performed, we found that there is a better chance of Grocery Chain X seeing greater savings in total miles traveled when a greater number of deliveries can be removed on the same day, compared to the case where the removed deliveries are scattered throughout the week. Depending on the number of stores and deliveries in the system, this fact could have an impact on driver utilization. However, in Grocery Chain X's system, there are over 200 stores, so distributing the days which are removed from the delivery schedule throughout the week should not be difficult.

FIGURE 3:

RATIO OF ACTUAL-TO-EXPECTED MILES REMOVED FROM ROUTE
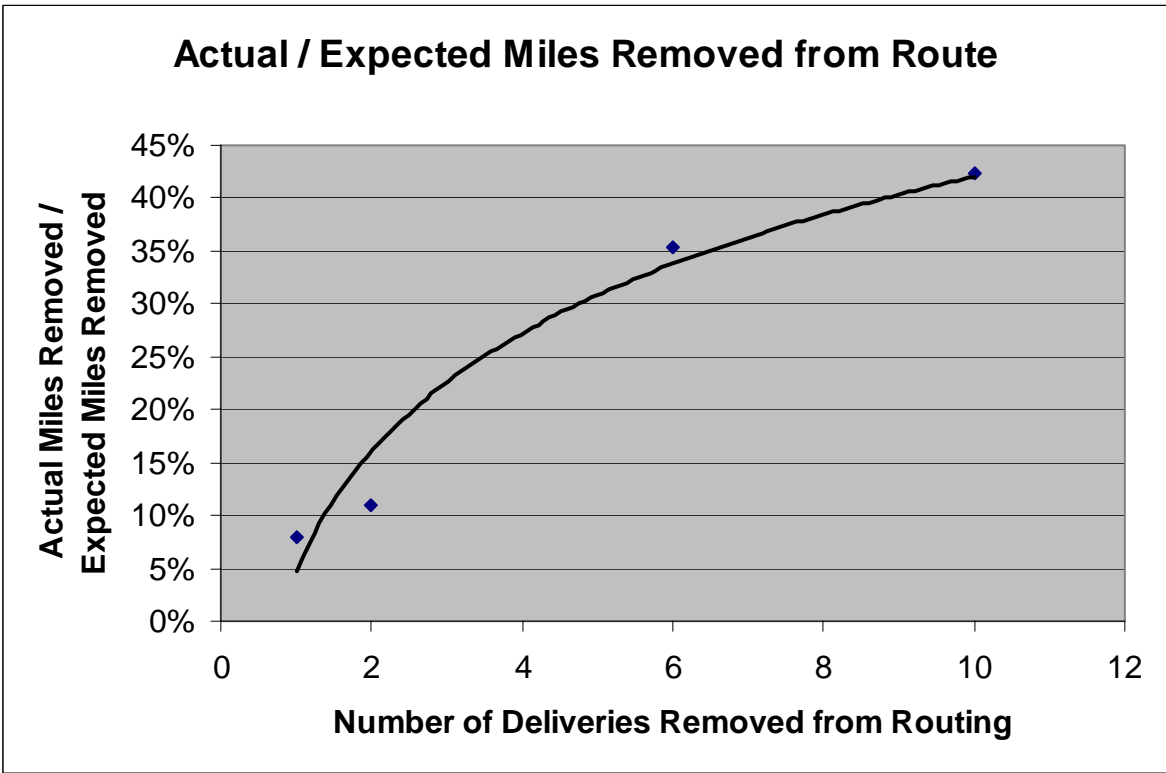
EFFECTS OF RE-ORDER POINTS AND SHELF SPACE ALLOCATION

After running the simulation to determine how the delivery schedule impacted the

replenishment costs, we looked at how changing the Re-order Point (ROP) and shelf

space allocation for each product would change the overall results.

Re-Order Points

We changed the existing ROP for each product using several different methods,

all of which were simple formulas applied to all products, and all of which produced

similar results. For example, when we set the ROP for each product in The High-Volume

Store according to Formula 2, we found that the relative order of the best days to skip

remained essentially the same but, the number of products stored in the backroom was

reduced by over 45% for each delivery schedule, which lead to replenishment cost

reductions of over 20% for Grocery Chain X.

Formula 2: $ROP_i = Max[2, Max(\sigma_{D\text{-}i})]$, where:

ROP_i = the re-order point for Product i

$\sigma_{D\text{-}i}$ = Daily standard deviation of demand for Product i

By adjusting the Re-Order Points in this manner, 11% of the SKU's saw increases

in their Re-Order Points, but the majority (80%) of the SKU's saw decreases in their Re-

Order Points, for many of the slower moving products, significant decreases. 9% of the

Re-Order Points remained unchanged. The distribution of the ratios of New Re-Order

Points to Current Re-Order Points is shown in Figure 4. The SKU's which saw

significant increases in their Re-Order points were the very fast-moving products which

currently have ROP's which are set lower than they otherwise would be because of

limited shelf space.

FIGURE 4:

NEW RE-ORDER POINTS COMPARED TO OLD
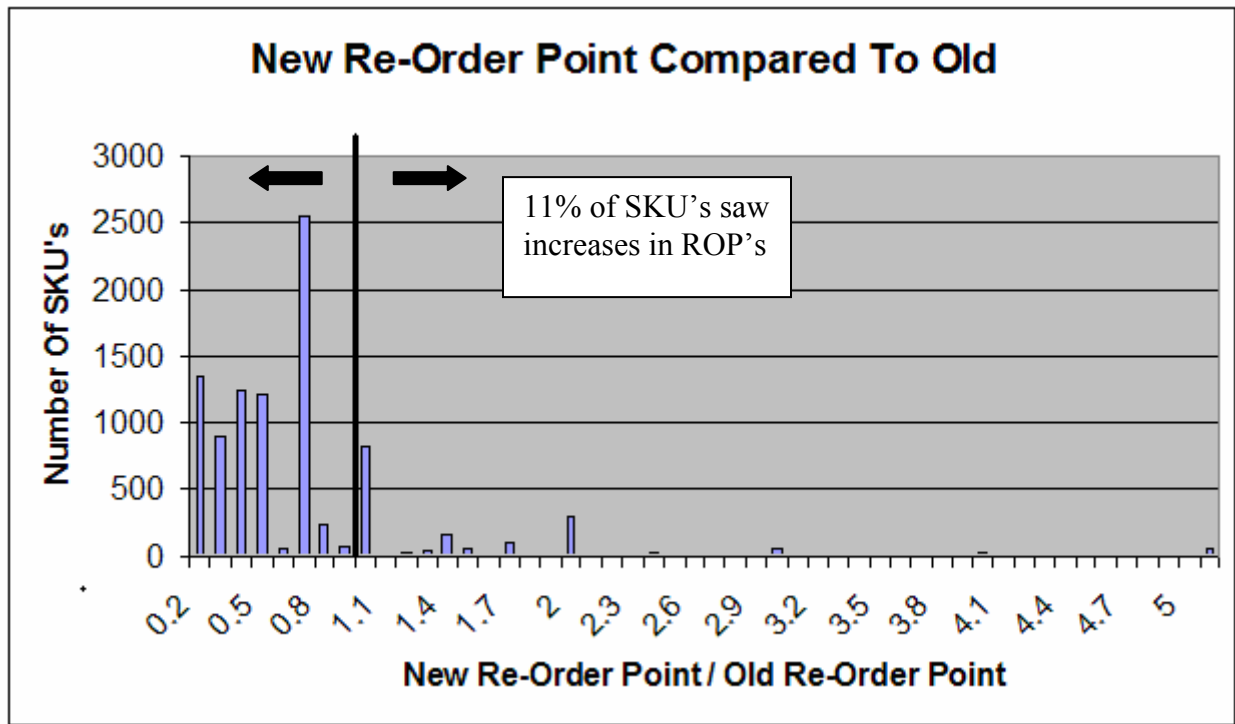
The method we used for determining ROP's is not necessarily the best way to accomplish this and was only an attempt to find the magnitude of the effect of changing this parameter. A more sensible approach to setting the ROP's may be to group products by factors such as daily sales, standard deviation, and/or shelf-space allocation, and then to set the ROP's for each group of products using a separate formula for each group. How the ROP's should optimally be set remains a possibility for future research.

Shelf Space Allocation

After adjusting the Re-Order Points to try to lower the number of cases stored in the backroom, we looked at the effect of shelf space allocation on the replenishment operations. Currently, shelf-space allocation is influenced by sales and marketing factors much more so than by operational or supply chain factors. This is typical of the way most retail stores allocate their shelf-space because it has been shown in numerous studies, Cox (1970), Curhan (1972), Dubelaar et al. (2001), and countless others, that where and how much of each product is displayed on the shelves can have a significant impact on sales. In our model, we took a cursory look at how the backroom stock would be affected if shelf-space was allocated based on trying to reduce the number of cases stored in the backroom, rather than by the factors currently being used.

To try to determine the affect of shelf-space allocation on the number of cases stored in the backroom, we used a high-sales-volume store with limited shelf space as our case study. We first needed to get a rough idea of how much usable shelf-space was actually available in the store. We assumed that shelf heights were adjustable and therefore chose to measure the amount of shelf-space in cubic feet rather than in square feet, since product height differs greatly among SKU's. This may or may not be an appropriate way to look at this for all stores, depending on how flexible shelf height truly is.

To find the total amount of shelf-space available in the store, we took the current shelf space allocation in number of units for each product and converted this number into number of cases. We then took the number of cases and multiplied it by the physical size

of a case. After doing this for each product, we took the sum of the amounts of shelf-space allocated to each product to arrive at a total amount of shelf-space available in the store. After we knew the total amount of shelf-space in the store, we allocated to each product an amount of shelf-space according to Formula 3.

Formula 3: $SS_i = ROP_i + PS_i$, where:

> SS_i = Shelf Space Allocated to Product i in number of units
>
> ROP_i = New Re-Order Point of Product i (found in previous section)
>
> PS_i = Number of units contained in one case of Product i

The idea behind this formula was that when the Balance-On-Hand (BOH) of a product dropped below its Re-Order Point, a case would be ordered, and theoretically the entire case should fit on the shelf, thereby basically eliminating product in the backroom. This process worked for the vast majority of the products and nearly eliminated the necessity of storing product in the backroom. However, there were a few fast-moving products which had daily sales greater than one case plus the Re-Order Point, and these products would need to be restocked throughout the day.

When both the Re-Order Points and the Shelf-Space Allocations were adjusted, the overall replenishment costs we cut by about 50% when compared to the results using the current values, because the amount of product needing to be stored in the backroom was reduced to nearly zero. However, this model assumes that sales will not be altered by the changes in shelf-space allocation, which, as stated earlier, has been shown not to be the case. Also, using this model allocated very large amounts of shelf-space to certain

large, fast-moving products. For example, one-gallon bottled water received almost 15 times the amount of shelf-space currently allotted to that product, probably not a practical solution for a store. There were a few SKU's like the water, that saw increases to their shelf space allocation of greater than 100%, but these products comprised less than three percent of the total number of SKU's. 66% of SKU's saw no change or a decrease in their allocations, while only 34% saw increases. Figure 5 shows the distribution of the ratios of new allocations to current allocations for all products.

FIGURE 5:

NEW SHELF ALLOCATION COMPARED TO OLD
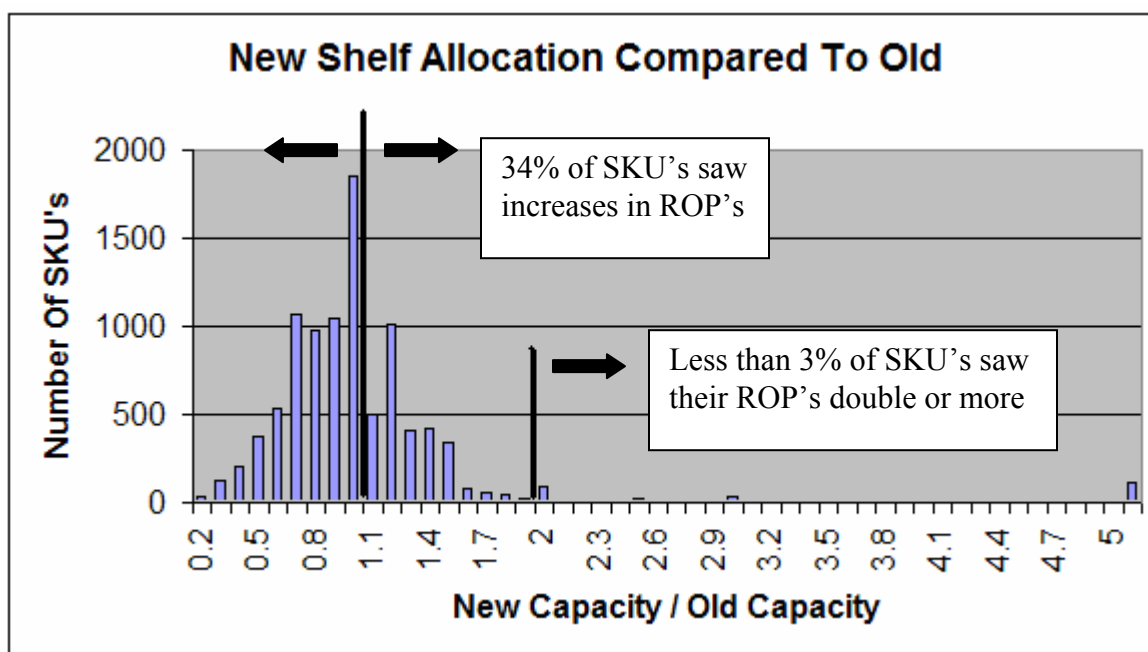
Using this model, the overall shelf-space requirement for The High-Volume Store decreased from 9200 ft^2 to 8700 ft^2, so the remaining 500 ft^2 could be re-allocated by the store on a discretionary basis.

This paper does not advocate re-allocating shelf space based solely on the method we used in the model, which does not take into account the effect this re-allocation would have on sales. It only shows that shelf space allocation can have a significant impact on store operations and, therefore, replenishment costs. Incorporating the findings of this thesis into existing methods for allocating shelf space remains a possibility for future research.

CONCLUSIONS

In this paper, we were able to show that the limitations of current methods used for determining the delivery schedule from a distribution center to a retail store can make the existing methods impractical for many applications. We have produced a method for modeling the replenishment process of a grocery chain which is able to provide insight into how to improve delivery schedules to retail stores when constraints such as a fixed delivery schedule and limited physical store space are present. We were able to show that significant replenishment cost savings are available to Grocery Chain X if the delivery schedules to retail stores are adjusted according to the results of the model. The method used for developing the model can easily be modified to fit the replenishment process of other retail chains, grocery or otherwise, to aid in determining delivery schedules to stores.

The model developed in this paper can also provide insight into areas of the replenishment process other than delivery schedules. For example, Grocery Chain X can greatly reduce the amount of product which must be stored in the backroom and, therefore, the necessity for double-handling product by adjusting the Re-order Points for

their products. By reducing the amount of double-handling of product, replenishment costs are further reduced.

Using the model, we were also able to show that the way in which shelf space is allocated to products can have a major impact on replenishment operations and costs. Several studies have shown that sales can be significantly impacted by shelf space allocation, and stores often allocate shelf space based on principles described in these studies. However, these studies do not account for the fact that shelf space allocation also impacts operations. A model which incorporates both the relationship between shelf space allocation and sales and the relationship between shelf space allocation and operational costs could prove to be very valuable in maximizing the overall performance of retail stores.

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