The Impact of CPFR on Supply Chain Performance: A Simulation Study

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Abstract

This paper explores the benefits of an emerging initiative in the consumer products industry called Collaborative, Planning, Forecasting, and Replenishment (CPFR) where manufacturers, distributors, and retailers work together to plan, forecast, and replenish products. To evaluate CPFR benefits, we compare it with the traditional reorder point (ROP) method, where members in the supply chain independently plan and operate the supply chain. A comprehensive simulation model is built based on data adapted from the operations of a Fortune-500 company. The simulation compares CPFR with ROP on four performance metrics: fill rates, supply chain cycle time, supply chain inventory, and shareholder value. The results indicate that when compared to ROP, CPFR increases fill rates and shareholder wealth while decreasing supply chain inventory and cycle time, confirming that collaborative planning produces substantial benefits to all trading partners.
1. Introduction

Over the last decade collaborative relationships between trading partners in the supply chain has been recognized as a recipe for operational and financial efficiency. The nature and scope of the collaboration between firms, as the ensuing discussion will show, has taken on different forms, each having its own distinct advantages and shortcomings. This paper studies an emerging initiative in the consumer products industry called Collaborative Planning, Forecasting, and Replenishment (CPFR) where manufacturers, distributors, and retailers work together to plan, forecast, and replenish consumer products.

Our emphasis in this research is to study the benefits of CPFR by comparing it with the traditional reorder point (ROP) method in a complex supply chain. Specifically, our supply chain consists of four echelons with many entities in each echelon: the supplier, the plant, the distribution centers, and retail outlets. Within this framework a simulation model evaluates if collaborative planning, be it for forecasts, production plans, or replenishment between pre-determined entities of the supply chain, produces value to the firm, the customer, and ultimately to the shareholder.

Although there have been several research studies on the costs and benefits of information sharing initiatives, their primary shortcoming arises from the fact that most, if not all, of them study it from a myopic perspective. Specifically, since modeling the entire gamut of entities in the supply chain -- i.e., from the suppliers to the end customers—is intractable, researchers often resort to stylistic models to study the costs and benefits of information sharing. The typical supply chain model consists of arborescent structures, limited to two-echelons, a system of order transmission between these echelons (such as the reorder point system), and a simple, often inventory-related cost structure that encompasses the two echelons. The results and insights are often studied within these stylized environments (for a good overview on the modeling approaches see Tayur, Ganeshan, and Magazine, 1998, pages 337-465). Although such models are very practical, and are effective in providing insight into inventory-related
supply chain performance, their results, barring a few exceptions, cannot be easily extrapolated to realistic supply chains.

While there are several recitations in the trade press on CPFR implementation, the research literature offers little, if any, guidelines to determine the benefits of the CPFR process. To study the benefits of CPFR in realistic situations warrants a view of the supply chain as a total system encompassing all its components (firms, functions, technologies, and activities). Doing so is extremely difficult due to the number and complexity of the decisions to be made, as well as the inter- and intra-organizational issues that must be addressed. Herein lies the dilemma for today’s researchers. Should one model the complexity of the realistic supply chain? Doing so will, in all certainty, make the problem at hand intractable. On the other hand, one can simplify the models to get some key insights, but run the risk of diluting the richness of the model to such an extent that it cannot be extrapolated to “realistic” scenarios. Simulation provides the right middle ground for analyzing such complex models. Although simulating the supply chain we are about to describe in this paper is an arduous task, it nevertheless provides us with a tool to analyze the impact of relevant parameters on supply chain performance, and of course, fits squarely with the intent of this special issue of the journal.

Our contribution to the research literature is three-fold. First, we base our analysis and our results from data collected from a Fortune-500 company. To the best of our knowledge, this is the first research paper that systematically explores the benefits of CPFR in realistic situations with realistic data. Second, we use the three key dimensions of supply chain performance oft-cited in the literature but seldom used together – customer service, time, and shareholder wealth. Finally, as the methodology section will illustrate, our simulation includes most of the relevant costs and constraints, and captures the essential elements of product, information, and cash flows in a typical fast-moving consumer-goods supply chain.

The remainder of this paper is organized as follows. In section 2, we introduce the CPFR process and compare it with the more traditional reorder point system. Section 3 describes the relevant literature on information sharing initiatives in a supply chain. In Section 4 we will present the research hypothesis and the performance measures we will be using. Section 5 describes our data. Section 6 describes the supply chain simulation
and the experiment to test our hypothesis; and in Section 7 is our subsequent analysis. Finally, in Section 8 are our discussion and conclusions.

2. The CPFR Process

The key ideas behind CPFR can perhaps best be explained by comparing it to the traditional reorder point (ROP) system. In the ROP procedure, retail level planners collect product information and marketing programs at the store level. Combining that with the point-of-sale (POS) data, item-level forecasts and event calendars that record promotion dates, special marketing programs, etc., are generated. Based on inventory and/or service level targets, the forecasts and the corresponding errors are used to generate reorder points. When inventory of a specified item reaches the reorder point, the retailer places an order to the manufacturer. If the product is available, it is shipped to the retailer; if not, the retailer will look for alternative solutions to replenish the item. The manufacturer, on the other hand, collects product knowledge and marketing programs of major retailers from public sources. Based on retailer orders and historical shipment information, the manufacturer generates a forecast by item, and in most cases, by retailer. These forecasts also drive the production of the items. As the literature review will illustrate, such independent planning between the members of the supply chain results in longer cycle times, poor customer service and inefficient use of working capital. CPFR was designed to counter some of the shortcomings of the ROP approach.

The key idea behind the CPFR initiative is that the trading partners, in our case the retailer and the manufacturer, work off a common forecast. Both the retailer and the manufacturer collect market intelligence on product information, store programs, etc., and share it in real-time over the Internet. In most cases, the retailer owns the sales forecast; if the manufacturer agrees with the forecast, automatic replenishments are made to the retailer via predetermined business contracts so that a specified level of inventory or customer service is maintained. If the manufacturer and retailer cannot agree on the forecasts or if there are exceptions, such as an unusual demand season or a store opening, the forecasts are reconciled manually. Prior to implementing CPFR, the retailer and the manufacturer will agree on several key questions such as how to measure service levels.
and stock-outs, how to set inventory and service targets, etc. As the relationship progresses, the retailer and manufacturer will jointly redesign key business processes such the setting increased sales objectives, or improving transaction mechanisms to reduce costs.

3. Literature Review

The research literature on the efficient management of supply chains has grown exponentially over the last decade. If one culls out the various research streams in supply chain management, they align themselves in one of five broad categories: (i) competitive strategy, (ii) costs and benefits of information sharing, (iii) managing product variety, (iv) supply contracts, and (v) the economics and logistics of network location and optimization (for a comprehensive review of the literature, see Ganeshan et. al., 1998). Since the CPFR initiative is closely related to the information sharing literature, we will restrict our review to the costs and benefits of information sharing, specifically as industry programs, in a supply chain.

Forrester (1961) was the first to initiative the concept of information sharing in a supply chain. He showed that information, as orders, propagates with increased volatility upstream through the supply chain. Recently Lee et. al. (1997a, b) have christened this phenomenon the "Bullwhip" effect. The bullwhip effect has the negative impact of increased inventory levels or large stock-outs for SKUs whose demands are volatile at the customer level (for more discussion on the bullwhip effect see Caplin, 1985; Sterman, 1989). The consensus among researchers is that sharing planning information between supply chain members reduces the bullwhip effect (for a discussion see Chen et. al., 1998). The premise, of course, is that centralizing demand information will make all plans in the supply chain react to the same data, mitigating the bullwhip effect and improving working capital efficiency. Gavirneni et. al. (1999) use multi-echelon inventory theory to show that information sharing between one supplier and one retailer reduces costs substantially. Lee et. al. (1999) show that information sharing reduces supplier demand variance and hence reduces the bullwhip effect.

In an effort to curb the bullwhip effect, and to improve working capital efficiency, several firms have initiated programs that work towards sharing forecast and other
planning information (Lee, Padmanaban, and Whang, 1997a). One example of such an
information-sharing initiative is Vendor Managed Inventory (VMI; see Waller et. al.,
1999). Under this initiative, the supplier or vendor is empowered to monitor and
eventually replenish the customer's inventory according to pre-determined contractual
agreements. Specific company examples include Barilla SpA (see HBS Case: 9-694-046)
where inventory levels substantially reduced while maintaining high item-fill rates. In an
empirical study, Clark and Hammond (1997) show that there are significant benefits to
using VMI. Cachon and Fisher (1997) show how the use of VMI in Campbell Soup has
provided better performance gains.

Efficient Customer Response (ECR) is another initiative to reduce volatility and
uncertainty, primarily in the consumer products and the grocery industries (see for
example HBS Case 9-196-061). A key idea in ECR, in addition to reengineering the order
management process, involves sharing point-of-sale data between various links in the
supply chain, enabling better replenishment, assortment planning, product introductions,
and promotions. Sharp and Hill (1998) estimate that ECR could potentially save more
than 6% of sales in logistics costs and around 41% reduction in inventories for the
grocery industry.

The beginnings of CPFR can be traced to 1995/96 when Wal-Mart and Warner-
Lambert (now part of Pfizer), together with SAP and Benchmarking Capital started an
experiment to jointly forecast and plan the replenishment of Listerene, a popular brand of
mouthwash. The experiment was limited to one Warner-Lambert plant and three Wal-
Mart distribution centers (DCs). As a result of CPFR, Warner-Lambert’s service levels
increased from 87% to 98%, while the lead times to deliver the product decreased from
21 to 11 days. The partnership also increased Listerene sales by $8.5 million over the test
period (Hill, 1999). The success prompted the Voluntary Interindustry Commerce
Standards (VICS) association, in cooperation with over thirty companies from the drug,
grocery, general merchandise, and apparel industries, to set up guidelines for
synchronizing business processes, forecasts, and replenishments, now formalized as
CPFR. The central theme of the CPFR guidelines was to align processes and standardize
technologies to share forecast and other planning information securely, simultaneously,
globally, and in real-time (see for example White, 1999). As of this writing, several pilots
of the CPFR business model are underway (Schachtman, 2000) that allow retailers and manufacturers "share information regarding key planning parameters (i.e. promotions, store openings etc.) impacting forecasts and communicate/resolve variances within item level forecasts" (for details please see www.cpfr.org). Initial results from these studies indicate that CPFR has a substantial impact on service levels and costs (see for example, Hill, 1999; Williams, 1999; Butler, 1999; Parks, 2000; Abend, 2000; and several examples in www.ascet.com).

4. Performance Measures and Hypothesis

Supply chain performance measurement has evolved over the last ten years into a “dashboard” of metrics that broadly fit three categories: customer service; time and response; and financial measures. Our intent in choosing performance metrics was to cover each one these categories.

Customer service elements typically include fill rates, on-time delivery, “perfect” orders, and related measures. We chose fill rates, i.e., the proportion of demand that is satisfied by the retail channel. Fill rates are a good indicator, at least in a retail environment such as the one in our case, of the efficacy of the supply chain to move the product to the retail level to satisfy customer demand. The firm in question has six distribution centers (DCs) supplying sixty-three retail markets. An overall fill rate for the entire supply chain is computed as the volume-weighted average of the fill-rates at each of the DCs (for a similar measure, see Deuermeyer and Schawrz, 1981).

As a related measure, we also use the total inventory in the supply chain as a performance metric. CPFR brings with it the promise of higher fill rates while lowering inventory (Hill, 1999). In our case, the metric just measures the total value of inventory (either as raw material, WIP, or finished goods) in the supply chain.

Time and response metrics measure the response of the supply chain to customer orders. The metrics typically capture the time spent by the product (or its components) at different entities in the supply chain at different points of time; or the time to process and ship orders from any entity in the supply chain. We use a composite metric – the supply chain cycle time – to measure the time dimension of performance. It is defined as the
total time spent by a product, in its various forms, in the supply chain. It includes time as raw material at the supplier warehouse; transit of the raw materials to the plant; as raw material, WIP, and finished goods in the plant; transit of the finished product to the DC and subsequent time spent as inventory in the DC; and finally in transit before it reaches the retailer establishment. Since there is more than one entity in each echelon of the supply chain, time is just the volume-weighted average of the all the relevant times in a particular echelon.

Since we do not model markets forces and stock prices, we use the EVA, a measure developed by Stern Stewart & Co. as a measure of shareholder wealth (see www.eva.com). It is computed as the net operating profit less the cost of capital. The profit is the revenue generated less all the costs that are involved in operating the supply chain. Capital is all the investment outlays incurred -- including all infrastructure and technologies used in the supply chain. EVA of a company therefore measures the wealth created through its operations (Ehrbar, 1998). Several large companies in several industries (for example, Coca-Cola, Morgan Stanley & Company, Eli Lily, United States Postal Service) use the EVA approach. The EVA metric is well suited to measure CPFR effectiveness since it encompasses both the potential revenue increases (via better fill rates) and the lower cost of capital due to more efficient operations.

**Hypothesis**

As the literature review has indicated, the benefits of information sharing initiatives like CPFR are proven only in stylistic models and not in a realistic and complex supply chain as the one we are about to describe. Based on literature on simplistic supply chains, in addition to the results from various pilot studies on CPFR, we would expect, even in the complex system, for CPFR to provide a higher-level fill-rate than the traditional reorder procedures. Additionally, when forecast errors are higher, we would expect information sharing mechanisms to perform even better. This leads us to the following two related hypothesis:
H1a: CPFR produces a higher fill-rate than the ROP method
H1b: The impact of CPFR on fill rates is higher when forecast errors are high

Since sharing of information produces better forecasts, the use of an information-sharing initiative reduces inventory in the supply chain. Furthermore, as in the case of fill rates, one would expect the reduction in inventory to be higher when forecast errors are higher (Hill, 1999; Abend, 2000) These hypothesis can be summed up as:

H2a: CPFR results in lower supply chain inventories than the ROP method
H2b: The impact of CPFR on inventory reduction is higher when forecast errors are high

When using CPFR, the first two sets of hypothesis suggest accurate forecasts and low inventory. One can envisage the supply chain operating in a “lean” mode. Lower inventories imply faster turnover and faster product velocity in the supply chain. Therefore, we can expect the supply chain cycle time or "response time" of the supply chain to be lower with the CPFR system when compared to the ROP system. For example, in an eighteen-month CPFR experiment by Procter and Gamble, cycle times for selected shampoo, beauty, and paper products decreased by 12% to 20% (Schachtman, 2000). This leads us to the third hypothesis:

H3: CPFR results in a lower supply chain cycle time when compared to the ROP method

Finally, information-sharing initiatives are sustainable only if they add intrinsic value to the company and consequently the shareholder. To the best of our knowledge, the only study on the impact of collaborative planning on EVA was done by Andersen Consulting in conjunction with Stanford and Northwestern Universities (reported in Austin, 1998). The study involved the personal computer supply chain and shows that collaborative planning procedures increase value in the $135-$330 million range. Additionally it also leads to inventory reductions ranging from 10-50%. In the consumer
products industry, much like the PC supply chain, the use of a CPFR-like initiative reduces working capital by reducing inventories, and increases margins by increasing fill rates, one would expect such initiatives to ultimately add shareholder value. Hence our fourth hypothesis:

\[ H4: \text{CPFR results in higher EVA when compared to the ROP method.} \]

5. The Data

The data used to fuel the simulation model is adapted from the supply chain operations of a Fortune-500 consumer products company. To maintain confidentiality, we have masked the data. However the relative magnitude of the data are preserved.

We chose one product from a product family of household cleaners that are typically sold through grocery, mass-merchandize, or drug stores (we normalize all our calculation in pounds – so our analysis encompasses several SKUs of the same product). We assume that the price of the product is fixed. That is, there are no promotions available for this product. In our example, there are sixty-three markets in the continental USA where this product is sold (see Figure 1). Our data include the mean yearly demand at each of the markets. Each market may have more than one store; our analysis aggregates demands from multiple stores. We divide the year into thirteen accounting periods, and each of these periods has twenty operating days. The demand is seasonal, peaking during the Spring-cleaning season, and the seasonality factors for each of these thirteen periods are also available to us.

These retail markets are replenished by distribution centers (DCs) via Less-Than-Truckload (LTL) shipments on a regular basis. Depending on the market location, and the supplying DC, the order cycle times (i.e., time since the retail order to the point of fulfillment by the DC) times to these retail outlets range from one to five days. We also collected information on the freight rates from any given DC to the markets it supplies.
Figure 1: The Supply Chain Structure

This company had DCs in Los Angeles, California; Denver, Colorado; Dallas, Texas; Chicago, Illinois; Atlanta, Georgia; and Kansas City, Missouri. The cost structure to operate the DC is piecewise linear, changing with the volume of product that is shipped through the DCs. The DCs can be replenished through one of four modes of transport: Less-Than-Truckload (LTL), Truck Load (TL), Trailer or Container on Flat Car (TOFC/COFC), and Rail box Car shipments, each having a shipping capacity of 20,000; 40,000; 50,000; and 90,000 pounds respectively. The freight rates and respective lead-time characteristics from the supplying Denver manufacturing facility are also available to us.

The product in question is made in one manufacturing facility, located in Denver, CO. For the purposes of this study, we assume that the Denver manufacturing facility has enough capacity to satisfy the downstream demand. The initial investment to build and get the plant running was $13 million. The fixed, operating and investment costs for different levels of throughput through the plant are available to us. Once the product is produced, it is stored in an “out-bound” plant warehouse (different from the DC)
adjoining the facility. The operating economics of the plant-warehouse are, as before, piecewise linear and depend on the throughput.

The product requires three raw materials, Cans/Bottles, Corrugated, and Chemicals, that make up 10, 30, and 60 percent by weight of the product. Each of these raw materials is sourced from three major suppliers, located along the Gulf Coast and the Mississippi rivers. Each of these suppliers charges a different price, based largely on the quantity that is ordered and the delivery performance that is promised. The shipments from each of these suppliers to the Denver plant can be made through four available modes of transport -- LTL, TL, COFC/TOFC, and Rail Boxcar. In our simulation, the choice of the freight simply sets the appropriate values of the lot size, freight costs, and lead-time characteristics, all of which were available to us.

We organized the data and some of the interim outputs of the simulation into four databases. Figure 2 summarizes the information in these databases. The yearly sales for the product; the proportion of total sales and seasonality indices in retail markets; the order and shipment information at the plant level are stored in the “Sales” database. The

<table>
<thead>
<tr>
<th>Master Database</th>
<th>Sales Database</th>
<th>Performance Database</th>
</tr>
</thead>
<tbody>
<tr>
<td>Products</td>
<td>Total yearly sales</td>
<td>Customer Service</td>
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<tr>
<td>Price, Weight, Cube, Bill of Materials</td>
<td>Retail market size (proportion of total sales)</td>
<td>Fill rates for every DC</td>
</tr>
<tr>
<td>Supply Chain Infrastructure</td>
<td>Seasonality by period</td>
<td>Time through the supply chain</td>
</tr>
<tr>
<td>Names &amp; locations of retail markets, DCs, warehouses, manufacturing facilities, suppliers.</td>
<td>Forecast errors</td>
<td>Total Sales</td>
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<td>Network Design Data (who ships to whom)</td>
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<tr>
<td>The investment, fixed, &amp; variable costs of operating the infrastructure for varying throughput levels.</td>
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<td>Transportation Data</td>
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<td>Transport modes available, their capacity, and lead time (mean and standard deviation) for every link in the supply chain</td>
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<td>Freight costs for every feasible link in the supply chain</td>
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<tr>
<td>Other Cost Data</td>
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<td>Inventory holding costs</td>
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<td>Administrative costs (fixed variable, overhead)</td>
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<td>Inventory</td>
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<td>Finished Goods (at DCs, warehouse)</td>
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<td>MPS (at plant)</td>
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<td>Raw Materials (plant in-bound)</td>
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<td>Tracking Sales vs. Forecasts</td>
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<td>Current Plans</td>
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<td>Distribution requirements at DCs</td>
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<td>Shipments plans at plant</td>
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<td>Warehouse &amp; Suppliers</td>
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<td>Production plan at the plant</td>
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<td>Financial Measures</td>
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<td>Profits</td>
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<td>EVA</td>
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![Figure 2: The Data](image)
Sales database is used as the starting point to simulate forecasts.

The “Master Database” contains all the information that does not change during the simulation. This includes the product details such as price, weight, cube, bill of materials, and the cost structure of raw materials from each of the suppliers; details of the supply chain infrastructure – number, location, and the operating costs of each of the supply chain entities; and transportation details such as the capacity (lot size), cost (function of distance, weight, and cube), and lead-time characteristics of each of the four available modes of transportation. Other cost information necessary to compute profits such as the inventory carrying percentage (carrying costs are a percentage of the value of the product) and other administrative costs is also included in this file. Finally, fixed simulation settings such as number of working days/period, number of periods a year, and forecast horizon are also included in this file.

In addition to these input databases, we also maintain, during the course of the simulation, two others: the “Status” and the “Performance” databases that change with each simulation run. The Status database tracks open orders, inventories, and maintains a record through a rolling horizon, of the distribution, production, and sourcing plans for the planning horizon.

The Performance database maintains detailed statistics on customer service, inventory, and cost information at each entity in the supply chain. In addition it also maintains for each simulation run, the overall measures – customer service as fill rate and cycle time, costs, and shareholder wealth as EVA. Figure 3 shows how these databases work in conjunction with the simulation we are about to describe.
Illustrating our data requirements in such detail, we believe, is valuable in two respects: one, it provides the reader with a list of data requirements that will be needed to simulate a realistic supply chain. Of course such data requirements will not be homogenous from company to company, but we believe that most retail distribution channels for fast moving consumer goods are likely to have similar data needs. Second, the reader can perhaps appreciate the difficulty in obtaining the data to simulate a supply chain. Even the addition of a transport mode to the analysis will exponentially increase the data needs.

6. The Simulation Experiment

To accurately capture all the costs and constraints and to appropriately model the CPFR business model, the simulation routines are created using Visual Basic, a
programming platform for the Windows operating system. Table 1 shows an algorithmic view of the underlying logic of the simulation.

The simulation first reads all the data required for a run. Using the data together with user inputs, the simulation's primary objective is to create and execute a rolling horizon plan for distribution, production, and sourcing plan for the supply chain. The planning horizon is thirteen periods, each period consisting of twenty days. The retail markets that each DC supplies are known, as used to compute the total (yearly) sales at every DC. Combining that with seasonality data for each of the thirteen periods, the DC sales for each period are computed. The sales data remain constant between simulation runs. Since we know the forecast error, we can simulate an unbiased forecast for each of the periods at the distribution centers using the following procedure (see also Sridharan and Berry, 1990):

\[
\text{Forecast in period } t = \text{Sales in period } t + \text{forecast error},
\]

where the forecast error is assumed to be a normal variable with mean zero and a variance, \( \sigma^2 \) that is estimated from company data as (see Stenger, 1994) \( a \, S_i^b \), where \( S_i \) is the average sales in period \( i \), and \( a \) and \( b \) are positive constants. Using the procedure described in Sullivan (1976), we generate random strings of forecast errors so the sum of the forecasts always equal the sum of the sales over the life of the simulation, i.e., forecasts are unbiased from run to run.

Using the forecasted demand, forecast error, on-hand inventory, scheduled receipts, transport mode characteristics (lead-time performance & lot-size) and a predetermined fill-rate target, the simulation computes safety stock needs and reorder points at every DC based on the procedure described in Silver et. al. (1998). This in turn establishes a requirements plan for the next thirteen periods for every DC. Under the CPFR initiative, this requirements plan is available to the manufacturing warehouse, so they can plan their shipments. This is achieved via a common planning database that the firms share over the Internet. The plant-warehouse shipping schedule for its planning horizon is achieved by first aggregating the DC needs in a given period and offsetting it
by required transportation lead-time. We assume for the purposes of cost computations that the CPFR procedure costs 0.5% of the sales more the ROP procedure.

Table 1: Simulation Logic

- **Read Input Database**
- **Read Planning Parameters (the experiment)**
- **Start Product Planning**:
  - For the next 15 periods (or the planning horizon)
    - For each DC
      - Calculate aggregate sales data
      - Simulate Forecasted Demand
      - Calculate projected inventory, safety stock targets, and DC product needs
    - At the manufacturing out-bound warehouse
      - If using CPFR
        - Use DC planning information to calculate aggregate shipping requirements
        - Calculate projected inventory, safety stock targets, and production requirements
        - Plan shipments to DCs
      - else
        - Simulate a forecast for the DC product needs
        - Calculate aggregate shipping requirements
        - Calculate projected inventory, safety stock targets, and production requirements
        - Plan shipments to DCs
    - EndIf
  - At the Denver manufacturing facility
    - Create a Production plan
    - Calculate projected inventory, safety stock targets, and shipping requirements of raw materials
  - At the three suppliers
    - Plan shipments to the manufacturing facility
- **End Product Planning**
- **Begin Simulating**:
  - For this period
    - For each of the next twenty days
      - At each DC, out-bound warehouse, & production facility
        - Realize demand
        - Execute plans: update planned shipments, production
        - Collect relevant statistics
  - At end of this period
  - If end of simulation
    - Calculate overall performance levels
    - End
  - else
    - goto **Begin Product Planning**

Under the ROP procedure, the DC requirements plan is not available to the manufacturing warehouse, and thus the manufacturing warehouse will have to forecast the DC requirements. We use exactly the same procedure to forecast at the plant warehouse as we do in the DC forecasts, i.e., perturb the real orders with a pre-determined error component.

The production plan over the planning horizon is then computed as the quantity that satisfies the warehouse shipping schedule and the safety stock requirements. Once the production quantities by period are known, a standard MRP procedure is used determine raw material needs and shipping schedules from each of the three suppliers.
Once the distribution, production, and supply plans are laid out for the coming year, we simulate material flow every day according to these plans, collecting supply chain performance data every day of the simulation. Demand is realized at the retail level, shipments to DCs are made from the plant warehouse; the product is made at the Denver plant; and raw material shipments to the plant, all carried out according to plan. The simulation updates the plans (for the next 13 periods) at the end of month, i.e., the DC forecasts are updated, ROP or CPFR is performed, distribution, production, and raw material plans are regenerated and so on.

The simulation model, in addition to using the same random seed for every simulation run, is warmed-up for a period of sixty days or three periods. Statistics are collected over three years or thirty-nine periods to average random effects. Any product demand not satisfied is backordered except at the DCs, where it is accounted for as lost sales (and consequently fill-rates are collected). The actual service level at each of the DCs; the average inventory levels; transit statistics; and the financial performance at each entity in the supply chain are the key outputs of the simulation. In addition, we also compute the following overall supply chain measures.

**Overall Customer Service level:**
Weighted average (by volume of product sold) of service levels at each DC. If $\rho_i$ is the service level at DC$_i$ and $V_i$ is the volume of product flow at DC$_i$, then overall level of service, then overall service level is $\Sigma \rho_i V_i$.

**Economic Value Added (EVA):** $\text{EVA} = \text{Profit} - \text{Cost of capital}$
Profit = sales revenues less operating expenses; and the cost of capital = cost of working capital (including inventory at various levels) + cost of investment.

**Time through the supply chain:** Weighted average by volume of either raw material, WIP, or finished goods of:
Time spent in transit from supplier to the plant + Holding time in the plant (as raw material) + manufacturing time + holding time in the out-bound warehouse + transit time to the DCs + time spent in the DCs + transit time to the customer.

For example, there are six plant warehouse-DC links (one for every DC). The composite transit time to the DCs is the weighted average of transit times from the plant warehouse to the DCs weighted by the volume that was shipped on each of these links. This measure measures the time dimension in the supply chain or the responsiveness in the supply chain.

**The experiment**

Our intent is to test the impact of CPFR on supply chain performance under a number of different operating conditions. To do so, we constructed a full factorial design to evaluate our hypothesis via the ANOVA procedure. We have chosen to vary the following parameters, as we believe that these are the most typical decisions planners in fast-moving supply chain will encounter. The levels of these parameters reflect the typical operating ranges of this supply chain.

1. Planning Options: CPFR or ROP
2. Forecast Errors: "High" or "Low." High corresponds to an "a" parameter of 5; and Low to an "a" parameter of 3, with the parameter "b" estimated at 0.8. This represents the typical range of values observed for the forecast errors
3. Service levels at the DCs: 90%, 95%, 99%. These are target fill-rates at the DCs. Effectively these are responsible for the appropriate levels of safety stock at the DC location.
4. Transport Modes: LTL, TL, TOFC/COFC, Rail Boxcar
5. Levels of Safety Stock at the plant warehouse: 0.5, 1.0, 1.5 weeks of supply.
6. Average Levels of Demand: 45, 70, and 105 million pounds a year.
There are a total of 432 combinations. Each combination is run at least 15 times, more if there were any outlying runs for a total of 6522 runs.

7. Results and Analysis

We used SPSS v7.0 to analyze the outputs from these runs. The findings (for example, see Neter, Wasserman, and Kutner, 1990) indicate that that all main effects and two interactions, Planning Options with Forecast Accuracy; and Planning Options with Fill Rates are significant determinants of performance. Table 2 shows the F-statistic and the P-values that were obtained for each of the four performance measures via the ANOVA procedure, confirming our analysis. To test our hypotheses, however, factor-level means are computed to test significant differences.

Table 2: ANOVA results

<table>
<thead>
<tr>
<th></th>
<th>Supply Chain Time</th>
<th>Supply Chain Inventory</th>
<th>Observed Fill rates</th>
<th>EVA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Planning Options</td>
<td>9.46</td>
<td>14.75</td>
<td>120.11</td>
<td>425.29</td>
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<tr>
<td></td>
<td>(0.002)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.002)</td>
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<tr>
<td>Forecast Errors</td>
<td>24.05</td>
<td>64.81</td>
<td>1401.27</td>
<td>667.03</td>
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<tr>
<td></td>
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<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Service levels at the DCs</td>
<td>37.11</td>
<td>51.51</td>
<td>111.94</td>
<td>401.71</td>
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<td></td>
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<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Transport Modes</td>
<td>73.82</td>
<td>79.37</td>
<td>981.62</td>
<td>475.33</td>
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<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.002)</td>
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<tr>
<td>Safety Stock at the plantwarehouse</td>
<td>570.39</td>
<td>601.68</td>
<td>9.95</td>
<td>424.67</td>
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</tr>
<tr>
<td>Average Levels of Demand</td>
<td>986.27</td>
<td>5261.23</td>
<td>227.42</td>
<td>598.73</td>
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<tr>
<td></td>
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<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Planning Options X</td>
<td>11.77</td>
<td>11.91</td>
<td>98.58</td>
<td>428.67</td>
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<tr>
<td>Forecast Errors</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Planning Options X</td>
<td>77.55</td>
<td>140.39</td>
<td>118.88</td>
<td>534.01</td>
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<tr>
<td>Service levels at the DCs</td>
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<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
</tbody>
</table>

F-Statistic is shown in bold and the corresponding P-values are in parenthesis.
Figure 4 shows the pair-wise comparisons between the CPFR and the ROP methods of the mean levels of each of the four performance measures used. To test hypothesis H1a & b, our plots include the interaction of fill rates with forecast error. When using lower forecast errors, the ROP procedure yields a fill rate of 90.2%, while the CPFR procedure yields 90.6%, significant at 99% confidence level. On the other hand, when high forecast errors are used, the ROP procedure yields a fill rate of 84%, while the CPFR procedure yields 86.8%, also significant at 99% confidence level. These two observations provide evidence for H1a. While these observations suggest that CPFR produces higher fill rates, it also suggests that when compared to the traditional reorder systems, the impact of CPFR on fill rate increases as forecast errors increase, further confirming (Hypothesis H1b) the fact that the biggest benefits of CPFR are when forecast errors are high.

**Figure 4: Pairwise Comparisons**

All differences are significant at the 99% level.
errors are high.

The overall supply chain fill rate using the CPFR method is 88.7% while that of the ROP method is 87.2%. Although in absolute terms the 1.5% difference seems small, it has a big impact on the bottom line. On an average, 1.5% of the demand ranges from 675,000 pounds of the product (at the 45 million pounds level of demand) to 1,575,000 when the demand is 105 million pounds. Therefore the use of CPFR becomes very important for high volume items.

When using low forecast errors, Figure 4, shows that the percentage decrease in inventory using the CPFR procedure is about 2.34%. Using higher forecast errors, however, produces a substantially higher -- 5.8% -- drop in inventory levels. In both cases, the difference in mean levels is significant (at 99%) providing evidence for H2 a & b. Herein lies the biggest impact of information-sharing initiatives -- they increase the observed fill-rates while reducing inventories (also see demonstration in the Barilla SpA case). The explanation lies in the fact that for the same fill-rate, the CPFR procedure requires lesser inventories because of lowered forecast errors.

As shown in Figure 4, the supply chain cycle time using the ROP procedure is 75.282 days while the CPFR procedure yields a cycle time of 73.966 days, significantly lower than the ROP procedure-- confirming hypothesis H3. The CPFR procedure warrants lesser inventory at the DCs and the plant warehouse, and consequently a higher turnover ratio thus increasing the velocity of product flow across the supply chain.

Finally, to test H4, we compare the mean levels of EVA computed from the ROP and the CPFR procedure. The average EVA with the ROP procedure is 8.54 million dollars, while with the CPFR procedure yields an EVA of 9.06 million dollars. This difference is significant at 99% confidence, providing evidence for H4. The difference can be explained due to the simultaneous reductions in working capital and increase in revenues due to the CPFR procedure. At every entity at each echelon in the supply chain, there is (i) a reduction of inventory, (ii) faster turnover rates lead to lower operating costs (recall that at the DCs and plants, the fixed and variable costs are a function of the volume), and finally (iii) the higher revenues brought about by higher fill rates at the DCs.
We have to point out here that the EVA values are computed assuming that the CPFR procedure costs 0.5% of sales more than the ROP procedure. While this estimate is realistic, our analysis shows that the results will not change even if the cost is increased by 50%, further bolstering our claim that CPFR affects the bottom line. Clearly, any company thinking of instituting an initiative such as CPFR can point to these savings if they need to get shareholder approval.

8. Summary and Conclusions

This paper was analyzes in a systemic manner the benefits of information sharing mechanisms, specifically CPFR, on four dimensions: fill rates, supply chain inventory, supply chain cycle time, and shareholder value. We hypothesized that using CPFR increases margins and decreases working capital consequently increasing fill rates and EVA; and decreasing inventories and supply chain cycle time. An elaborate simulation of the supply chain is constructed and used to compare the impact of CPFR and the traditional ROP inventory planning method under a number of supply chain configurations. The analysis led to the following findings:

1. CPFR increases fill-rates. This increases the volume of product sold to the retail outlets thereby increasing the revenues and profit margins. Additionally, the impact of CPFR is higher when the forecast errors are higher.

2. CPFR decreases supply chain inventories. At the plant-DC level, joint planning reduces any inventories that are used to buffer the added uncertainties that ROP systems warrant. This implies the plant will not have to inflate its production schedules to meet this excess inventory. This in turn impacts procurement of raw materials – plants with realistic schedules demand lower quantities and consequently hold lesser amounts of cycle inventories of raw materials in their warehouses. All this reduces the overall inventory level in the supply chain. Furthermore, the reduction in inventory is more when the forecast errors are high. In certain industries with high uncertainty, like fashion goods, collaborative planning mechanisms can make a significant impact on reducing inventory levels.
3. CPFR reduces supply chain cycle time. The reduction of inventory in the entire pipeline increases the number of turns and hence speeds up the flow of the product from the raw material to the retail outlets. Hence CPFR leads to a compressed and more responsive supply chain.

4. Finally, CPFR increases shareholder wealth. High fill rates and low inventories lead to higher margins and lower working capital, increasing EVA.

Although this research is one of the first to empirically validate the benefits of CPFR, it has a few limitations that can be addressed by future researchers. First, the results are based on data from one product in one company in one industry. One can therefore question the applicability of these results in other firms and other industries. We believe that while information sharing will benefit most, if not all, supply chain operations, issues regarding how much of it and how it is shared need to be addressed to determine the efficacy of initiatives such as CPFR. The results indicate that CPFR in a fast-moving consumer goods supply chain where forecasting, shipping, and production information are jointly developed will significantly impact supply chain performance. Future research can perhaps focus on the feasibility, costs, and benefits of CPFR and/or other information sharing agreements in other industries, especially in high technology and fashion industries, where compressed product life cycles and high uncertainties often lead to operating inefficiencies in the supply chain.

Second, implementation issues have not been considered. We simulate the supply chain under the assumption that CPFR process can be easily implemented. In most cases, working in a CPFR system requires a different mindset that is not always easy to implement quickly and cost efficiently. The premise is that real-time data shared and planned together will benefit both parties. Several firms may not be willing to share sensitive sales or financial data. Furthermore, implementation of collaborative practices requires collaboration-support technology such as e-commerce applications, front-end and back-end application servers to execute the collaboration, and the appropriate databases to feed these collaborative-support technologies, all of which require time, money, and people that are not explicitly modeled in the simulation. Future research can study the impact of CPFR implementation on short- and long-term performance of the supply chain.
Finally, we assume that the CPFR system is used in the right way. In our experience, planners often confuse the collaborative-technology with collaborative planning – but the success of any partnership depends on the ability to use information, not having access to it. Some of the steps firms can take to harness CPFR or similar initiatives to its full extent is to setup joint teams between trading partners to set standards on how to analyze the data and make joint decisions on demand, replenishment, and production plans. While there are several initiatives underway to standardize CPFR initiatives (see www.cpfr.org), future research can address how these standards affect performance.

There is no one formula to effectively implement CPFR initiatives in a firm. Austin (1998) suggests that firms use a three-pronged approach. First, a firm should evaluate the risk and rewards of a collaboration initiative. Much like the simulation described in this paper, a firm can access the cost of implementation and the potential benefits of a collaborative initiative. Second, there is a need to reshape relationships between trading partners. Relationships between companies should move from just electronic transaction – might it be over EDI or the Internet – to a more interactive one with the customer perspective in mind. Issues of trust, goodwill need to be addressed explicitly before the collaborative arrangements are undertaken. Third, as the nature of collaborative agreements change with time and the improvement of technology, firms should make it a priority to reevaluate and execute newer and more effective collaborative agreements.
References


