American Journal of Industrial and Business Management, **2013, 3, 389-394**
http://dx.doi.org/10.4236/ajibm.2013.34046 Published Online August 2013 (http://www.scirp.org/journal/ajibm)

Impact of Forecast Errors in CPFR Collaboration Strategy

Raj Kamalapur

University of Wisconsin Oshkosh, Wisconsin, USA.
Email: kamalapd@uwosh.edu

Received May 24th, 2013; revised June 24th, 2013; accepted July 16th, 2013

ABSTRACT

The primary objective of this research is to investigate the impact of random forecast error and bias forecast error in Collaborative Planning, Forecasting and Replenishment (CPFR) strategy on the cost of inventory management for both the manufacturer and retailer. Discrete-event simulation is used to develop a CPFR collaboration model where forecast, sales and inventory level information is shared between a retailer and a manufacturer. Based on the results of this study, we conclude that the higher random forecast error and negative bias forecast error increases the cost of inventory management for both the manufacturer and the retailer. When demand variability is high, a bias forecast error has a bigger impact on inventory management cost compared to a random forecast error for both the manufacturer and retailer. Also, a positive bias forecast error is more beneficial than a negative bias forecast error to gain maximum benefits of CPFR strategy.

Keywords: CPFR Collaboration Strategy; Inventory Management; Simulation Modeling

1. Introduction

Inventory is a significant and often one of the largest assets for most companies. To provide good customer service, many supply chain members maintain a high level of safety stock inventory which increases the total cost in the supply chain. For example, in 1996, approximately $700 billion of the $2.3 trillion retail supply chain was in safety stock inventory [1]. Also, in recent Annual State of Logistics Report, over $1 trillion was annually spent on logistics, with approximately 33 percent being attributed to the cost of holding inventory [2]. So in recent years, academic researchers and practitioners have emphasized that information sharing between supply chain members can significantly reduce inventory levels and improve service levels in the supply chain. In order to encourage retailers to share information with manufac- turers, collaboration strategies like Vendor Managed In- ventory (VMI) and Collaborative Planning, Forecasting and Replenishment (CPFR) have been developed and implemented in many industries with mixed results [3,4].

Since a supply chain is a complex network, many researchers consider the dyadic structure (two-levels) to study the benefits of information sharing. Many research studies have shown the benefits of demand information sharing in the supply chain [5-7]. Most of these studies assume that the retailer knows the exact customer demand in the supply chain. However in a variable demand environment, the retailer may not know the exact customer demand and have to develop their demand forecast. Retailers generally use different forecasting methods and this can impact the forecast accuracy of the customer demand. So the benefit of information sharing greatly depends on the forecast accuracy of the customer demand in a variable demand environment. There are some studies that consider the impact of forecast errors on the value of information sharing. One research study [8] uses simulation modeling to investigate the impact of forecasting errors on the value of information sharing in a supply chain with four retailers and a manufacturer. They show that forecast errors have an impact on the value of information sharing. Their study only considered forecast information sharing between the supply chain partners. However in a CPFR strategy, along with forecast data, generally sales data and inventory level information is shared between the supply chain partners. There are no studies that consider the impact of forecast errors on the cost of inventory management in CPFR collaboration strategy for both the manufacturer and retailer in a variable demand environment. This study uses discrete-event simulation to develop a CPFR collaboration model where forecast, sales and inventory level information is shared between a retailer and a manufacturer. Using this simulation model, we investigate the impact of random forecast error and bias forecast error on the cost of inventory management for both the manufacturer and retailer in a variable demand environment.

2. Collaboration Model

The CPFR collaboration model used for this research study is a two echelon production-inventory system with a make-to-stock manufacturer (plant and warehouse) and a retailer. Discrete event simulation (Arena software from Rockwell Automation) is used to develop this model. The retailer does not know the actual customer demand and need to develop their demand forecast. Both random forecast error and bias forecast error are introduced into this forecast to investigate their impact on the inventory management cost for both the manufacturer and retailer. Periodic review order-up-to inventory policy (R, S) is used by both the manufacturer and the retailer, where the review period considered is one week. All decisions for the manufacturer and the retailer are made beginning of each period. The order up-to-level "S" for both the manufacturer and the retailer is calculated so as to minimize the inventory holding cost and backorder penalty cost. The customer demand, the order quantity and the production quantity are non-negative.

Sequence of Events

During each period, the retailer shares forecast, sales and inventory level information with the manufacturer as shown in **Figure 1**. The manufacturer does not forecast and uses this information to determine their production quantity during each period. All decisions for the manufacturer and retailer are made at the beginning of each period. The sequence of events is as follows. Beginning of each period, the retailer receives shipments (if any) from manufacturer, and the customer demand (plus any backorder) is fulfilled from the available inventory. Similarly, the manufacturer's warehouse receives shipments from the plant, and the retailer order (plus any backorder) is fulfilled from the available inventory. Any unfulfilled demand for both the retailer and manufacturer is backordered with a backorder penalty cost. Next, both the retailer and manufacturer use the forecast and their inventory level information to calculate their target order up-to inventory level to determine the order quantity (by retailer) and production quantity (by manufacturer). The manufacturer follows an echelon-based inventory policy in their production planning and inventory replenishment decisions. Under echelon-based inventory policy, the manufacturer considers their own inventory level plus inventory level of retailer and any backorder quantity to determine their production quantity [9]. The manufacturer has unlimited production capacity and uses a lot-for-lot production policy with a lead time of one period. The delivery lead time from the manufacturer to the retailer is assumed as one period.

Retailer cost and manufacturer cost are used as the performance measures and they are calculated based on the inventory level and backorder quantity at the end of each period. The inventory holding cost is assumed \$1.5 per period for the retailer and \$1.0 per period for the manufacturer. Similarly, backorder penalty cost for retailer is assumed 1.5 times the backorder penalty cost for the manufacturer. The customer demand, forecast demand, order-up-to inventory level, the order quantity and production quantity is updated during each period of the simulation run. To facilitate valid comparison and determine the impact of the control variables on the performance measures, the inventory policy and production policy remain the same for all factor combinations.

The output data (*i.e.* performance measures) from the simulation model is used to determine the impact of forecast errors in the CPFR collaboration strategy. To reduce the impact of random variations of input data (*i.e.* customer demand), the same random number sequence is utilized to generate the same customer demand for all factor combinations. A sample size of 30 (number of replications) is selected for the simulation run. The simulation model is run for a total of 1144 periods, with the first 104 periods considered as warm-up to initialize the system and the remaining 1040 periods is used for the analysis. The statistical software "Minitab 16" is used for the analysis.

3. Experimental Design

The purpose of an experimental design is to develop a methodology to track changes in performance measures by varying factors under study during the experimental

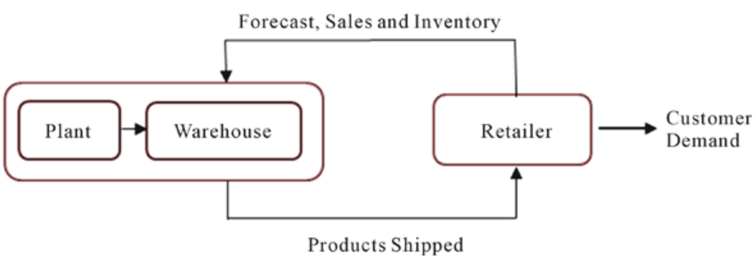


Figure 1. Information sharing in CPFR collaboration strategy.

runs. According to Law and Kelton [10], "One of the principal goals of experimental design is to estimate how changes in input factors affect the results or responses of the experiment". Generally, a variety of experimental designs can be used in the simulation experiments when the objective is to explore the reactions of a system (response variables) to changes in factors (control variables) affecting the system. Some of the relevant experimental designs include the full factorial, fractional factorial and response surface designs. A factorial experiment is one in which the effects of all factors and factor combinations in the design are investigated simultaneously. Each combination of factor levels are used the same number of times. This study employs a full factorial design to gain insight on the impact of the control variables on the performance measures.

Four control variables as shown in **Table 1** and two performance measures as shown in **Table 2** are considered for this study. Demand variability plays an important role in the supply chain collaboration. This study considers the auto-correlated demand pattern with three levels of demand variability. Auto-correlated demand is generated using the following formula

$$D_t = d + \rho D_{t-1} + \varepsilon_t \quad (1)$$

where, d = initial mean, ρ = correlation factor and ε_t = i.i.d. normally distributed with mean zero and standard deviation σ. The correlation factor is 0.5 and three levels of demand variability are generated by varying σ in the above equation. The average customer demand for the retailer is 100 units per period. The demand forecast is generated according to the following formula.

$$F_t = D_t + \text{BFE} + \text{RFE} \times \text{snormal}() \quad (2)$$

where, F_t and D_t are forecast and demand during period t (t = 1, 2, 3 …), BFE is the bias forecast error, and RFE is the random forecast error, and snormal() is the standard normal random number generator.

Table 1. Control variables for the experimental design.

Control Variables	Details for Variables	Other Details
Demand Variability (DVR)	Low Demand Variability, σ = 05 Med Demand Variability, σ = 15 High Demand Variability, σ = 25	Average Demand is 100 units per period
Random Forecast Error (RFE)	Low Random Error, ε = 05 Med Random Error, ε = 10 High Random Error, ε = 15	Random Forecast Error for Demand Forecast
Bias Forecast Error (BFE)	Negative Bias Error = −10 Neutral Bias Error = 0 Positive Bias Error = +10	Bias Forecast Error for Demand Forecast
Back Order Penalty (BOP)	Low Backorder Penalty, 09 Med Backorder Penalty, 19 High Backorder Penalty, 32	Backorder Penalty is factor of Holding Cost

Table 2. Performance measures for the experimental design.

Performance Measures	Performance Measure Details
Retailer Cost per Period	Inventory Holding Cost for Retailer plus Backorder Cost for the Retailer
Manufacturer Cost per Period	Inventory Holding Cost for Manufacturer plus Backorder Cost for Manufacturer

Periodic order-up-to inventory policy is used to determine the target inventory levels for both the manufacturer and retailer. Generally, inventory holding cost and backorder penalty cost are important parameters in determining order-up-to inventory level. Instead of changing both the inventory holding cost and backorder penalty cost at the same time, the inventory holding cost is held steady and backorder penalty cost is changed as shown in **Table 1**.

4. Results and Discussions

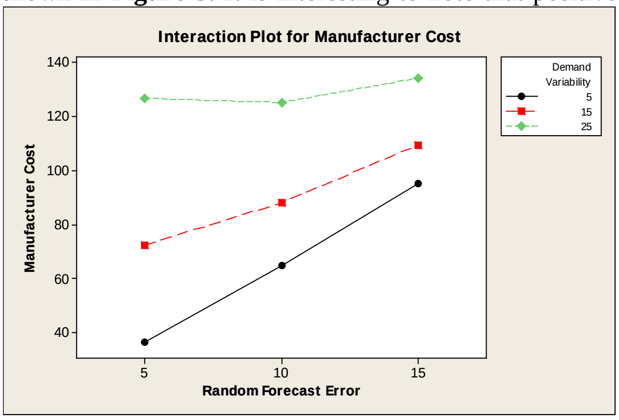
The output data from the simulation model is analyzed to determine the impact of forecast errors in the CPFR collaboration strategy. In a supply chain, the consequences of forecast error can either lead to increased inventory holding cost or increased stockout/backorder penalty cost. Some of the main results of this research study are shown below.

4.1. Impact of Random Forecast Error and Demand Variability

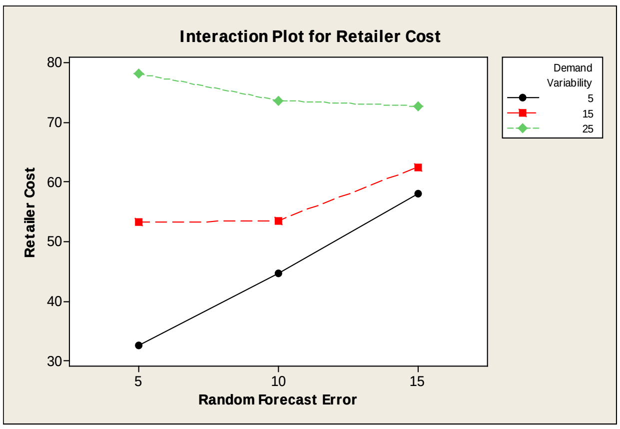
The impact of random forecast error and demand variability on the inventory management cost for both the retailer and manufacturer in CPFR collaboration strategy are shown in **Figure 2**. When demand variability is low, the cost for both the manufacturer and retailer increases as random forecast error increases. It is interesting to note that when demand variability is high, the impact of random forecast error is generally lower. This may be due to the fact that when demand variability is high, generally higher level of inventory is carried which can offset any forecast error. Higher inventory levels can help in reducing backorder penalty costs when demand variability is higher. However, when demand variability is high, the overall cost of inventory management is higher for both the manufacturer and the retailer.

4.2. Impact of Bias Forecast Error and Demand Variability

The impact of bias forecast error and demand variability on the inventory management cost for both the retailer and the manufacturer in CPFR collaboration strategy are shown in **Figure 3**. It is interesting to note that positive bias forecast error is more beneficial for both the manufacturer and retailer in reducing cost compared to negative bias forecast error. Generally, the positive bias forecast error helps both the manufacturer and retailer to carry enough inventories to reduce backorder penalty cost. However when bias forecast error is negative, the cost goes up for both the manufacturer and the retailer due to increased backorder penalty costs. So a positive bias forecast error is preferable to negative bias forecast error. The impact is more significant for both the manufacturer and retailer when demand variability is high and bias forecast error is negative. At lower demand variability, no bias forecast error has lowest cost for the retailer.



(a)

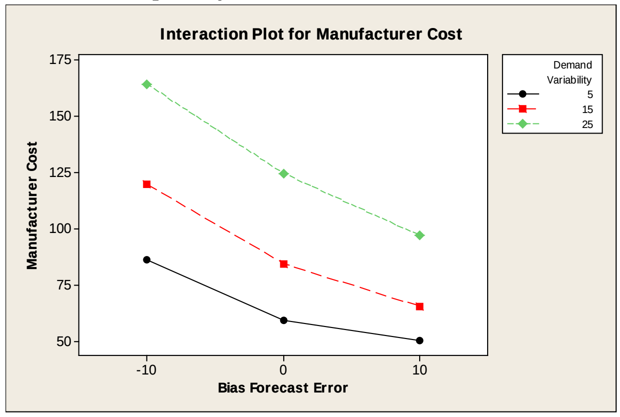


(b)

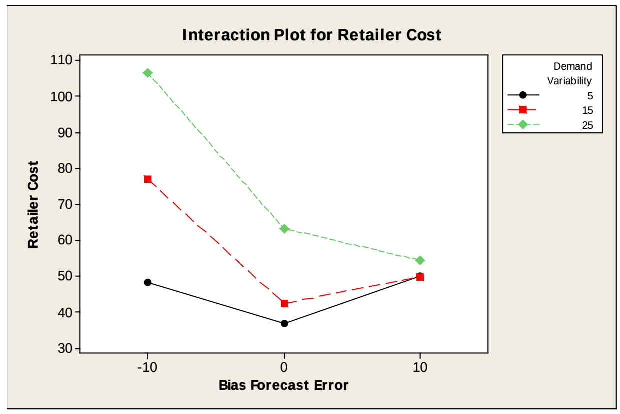
Figure 2. Impact of random forecast error and demand variability.

4.3. Impact of Random Forecast Error and Backorder Penalty Cost

The impact of random forecast error and backorder penalty cost on the inventory management cost for both the retailer and manufacturer in CPFR collaboration strategy are shown in **Figure 4**. It can be seen that as random forecast error increases, the inventory cost increases for all backorder penalty costs for both the manufacturer and the retailer. The cost of inventory management becomes higher for both the manufacturer and the retailer with increase in random forecast error. We can see that when the random forecast error increases, the benefit of information sharing in CPFR strategy decreases under all backorder penalty costs.



(a)

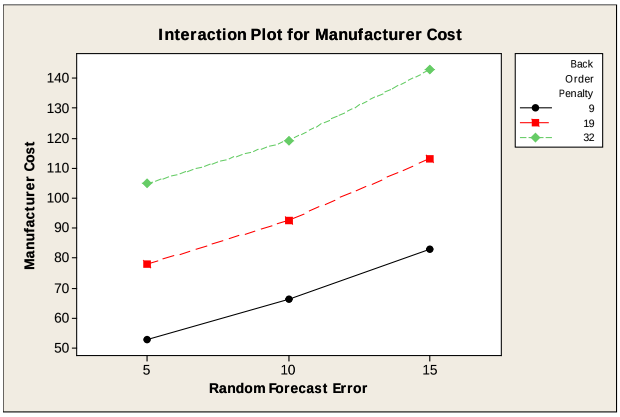


(b)

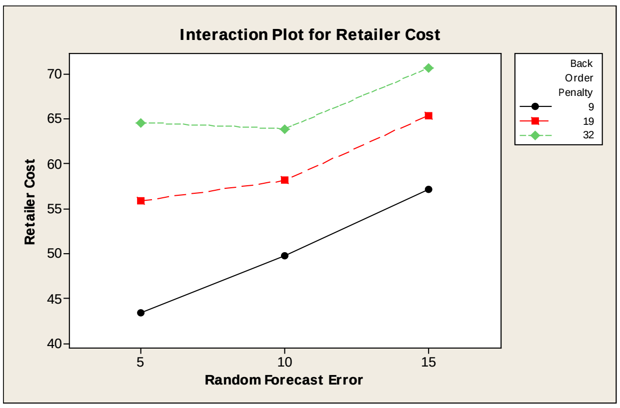
Figure 3. Impact of bias forecast error and demand variability.

4.4. Impact of Bias Forecast Error and Backorder Penalty Cost

The impact of bias forecast error and backorder penalty cost on the inventory management cost for both the retailer and the manufacturer in CPFR collaboration strategy are shown in **Figure 5**. It can be seen that for all backorder penalty costs, negative bias forecast error has a significantly higher cost for both the retailer and the manufacturer. For the manufacturer, positive bias forecast error is beneficial under all backorder penalty costs. When backorder penalty costs are higher, negative bias-forecast error can significantly increase the cost for both the manufacturer and the retailer. However, it is interesting to see that, the lowest cost for the retailer is achieved when the forecast has zero bias error and the lowest cost



(a)



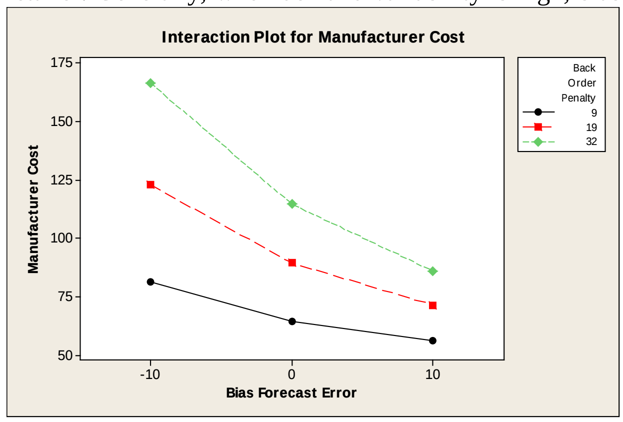
(b)

Figure 4. Impact of random forecast error and backorder penalty cost.

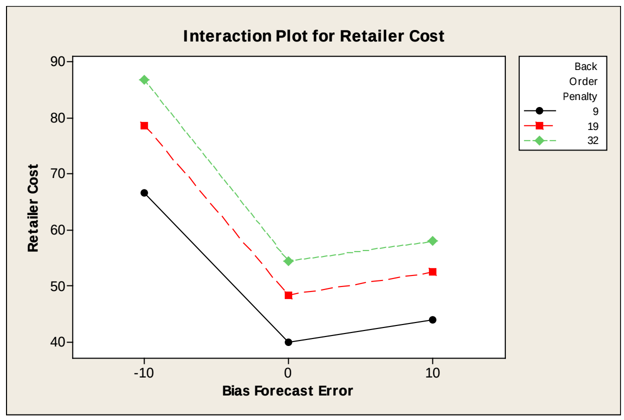
for the manufacturer is achieved when the forecast has positive bias error. So to gain maximum benefits of CPFR strategy, it is important to minimize the negative bias error to help in reducing the cost of inventory management for both the manufacturer and the retailer.

5. Conclusion

This research study investigated the impact of a random forecast error and a bias forecast error on the cost of inventory management in CPFR collaboration strategy for both the manufacturer and the retailer. In the real world, the consequences of a forecast error (*i.e.* positive or negative) are not the same. Positive forecast error (*i.e.* forecast higher than demand) leads to increased inventory holding cost and negative forecast error leads to increased stockout/backorder penalty costs. Based on the results of this study, it is fair to conclude that higher random forecast error and negative bias forecast error significantly increases the cost of inventory management for both the retailer and the manufacturer. Also, positive bias error is generally preferable (than negative bias error) to reduce inventory cost for both the manufacturer and retailer. Generally, when demand variability is high, bias



(a)



(b)

Figure 5. Impact of bias forecast error and backorder penalty cost.

forecast error has a bigger impact on the inventory cost compared to random forecast error for both the manufacturer and the retailer. Also when backorder penalty cost is high, the impact of negative bias forecast error is significantly higher for both the manufacturer and the retailer. So in conclusion, negative bias forecast error and higher random forecast error increases the overall cost of inventory in a CPFR strategy for both the manufacturer and the retailer. So to gain maximum benefits of CPFR collaboration strategy for both the manufacturer and the retailer, it is important to minimize the random forecast error for all demand variability's and to avoid negative bias forecast error in the demand forecast.

REFERENCES

[1] T. Lewis, "Electronic Warehouses," *Datamation*, Vol. 44

No. 1, 1998, pp. 17-18.

[2] R. Wilson, "17th Annual Logistics Report," Council of Supply Chain Management Professionals, Lombard, 2006.

[3] J. Baljko, "VMI Study Shows Cost Disparity among Partners," *Electronic Buyer's News*, 7 April 2003.

[4] J. Cooke, "VMI: Very Mixed Impact," *Logistics Management and Distribution Report*, Vol. 37, No. 12, 1998, pp. 51-53.

[5] G. Cachon and M. Fisher, "Supply Chain Inventory Management and the Value of Shared Information," *Management Science*, Vol. 46, No. 8, 2000, pp. 1032-1048. doi:10.1287/mnsc.46.8.1032.12029

[6] H. Lee, K. So and C. Tang, "The Value of Information Sharing in a Two Level Supply Chain," *Management Science*, Vol. 46, No. 5, 2000, pp. 626-643. doi:10.1287/mnsc.46.5.626.12047

[7] Z. Yu, H. Yan and T. Cheng, "Benefits of Information Sharing with Supply Chain Partnerships," *Industrial Management & Data Systems*, Vol. 101, No. 3, 2001, pp. 114-119. doi:10.1108/02635570110386625

[8] X. D. Zhao, *et al.*, "The Impact of Forecast Errors on Early Order Commitment in the Supply Chain," *Decision Sciences*, Vol. 33, No. 2, 2002, pp. 251-280. doi:10.1111/j.1540-5915.2002.tb01644.x

[9] S. Axsater and K. Rosling, "Installation vs. Echelon Stock Policies for Multilevel Inventory Control," *Management Science*, Vol. 39, No 10, 1993, pp. 1274-1280. doi:10.1287/mnsc.39.10.1274

[10] A. Law and W. Kelton, "Simulation Modeling and Analysis," 3rd Edition, McGraw Hill, New York, 2000.

