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Retail Supply Chain Coordination and Collaborative Optimization

Wang WenJie
Glorious Sun School of Business & Management, Donghua University Shanghai, 200051, China, wenjiew@dhu.edu.cn

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WenJie Wang
Glorious Sun School of Business & Management, Donghua University
Shanghai, 200051, China
wenjiew@dhu.edu.cn

Abstract— The retail industry plays an important role in the economic development of the world. The Collaborative Planning, Forecasting and Replenishment (CPFR) solution can coordinate the business process between the retailers and manufacturers in the retail supply chain and got its applications in many world-renowned retailers around the world. In this paper, CPFR coordination process and its applications will be briefly reviewed at the beginning. And then, an optimization model which can improve performance of retail supply chain coordination is proposed for CPFR coordination process. Finally, the effectiveness of model is verified through the formulation and analysis.

Keywords--- retail industry, supply chain collaboration, collaborative optimization modeling, formulation

1. INTRODUCTION

The retail industry plays an important role in the world economy development. The supply chain coordination, which abstracted more and more attention from industries and academics in recent years, is the major part of the retailing management. The CPFR is the solution of the retail supply chain coordination that can collaboratively plan, forecast and replenish among partners throughout entire supply chain. The first CPFR project was piloted by Wal-Mart with its suppliers in 1995 [1]. The results of two-year pilot project showed that CPFR could simultaneously reduce inventory levels and increase sales for both retailers and suppliers. Since its original application was initiated, CPFR has had many successful applications in North America, Europe and China.

The CPFR concerns the collaboration where two or more parties in the supply chain jointly plan a number of promotional activities and work out synchronized forecasts, on the basis of which the production and replenishment processes are determined. The coordination process of CPFR requires a proper method to synthesis information and knowledge from retailers and manufactures in the supply chain in order to work out synchronized forecasts. A mathematics model to optimize the retail supply chain coordination, which is based on the combination forecasting model, is proposed in this paper. The combination-forecasting method can combines forecasting models from different parties to smooth coordination in the supply chain and reduce forecasting discrepancies.

At the beginning of this paper, the CPFR and coordination process are discussed briefly. And then, an optimization model based on combination forecasting method is proposed for CPFR coordination improvement. Finally, the formulation results showed the effective of this combination forecasting optimization model in CPFR coordination process.

2. THE RETAIL SUPPLY CHAIN SOLUTION CPFR AND ITS APPLICATIONS

The CPFR, which was proposed by VICS (Voluntary Inter-industry Commerce Standards Association) Working Group in 1995, focuses on coordination process between retailers and suppliers in the retail supply chain. Under CPFR, supply chain partners form a consensus forecast, either by working collaboratively or by first developing their own individual forecasts, which are then used to create a consensus forecast. The coordination and information sharing allows retailers and suppliers to optimize their supply chain activities. Dirk Seifert, a professor at Harvard Business School and the University of Massachusetts, defined CPFR as "an initiative among all participants in the supply chain, intended to improve the relationships among them through jointly managed planning processes and shared information."[1]

CPFR benefits are considered as strong incentives for enterprises to implement the concept. In general, the benefits of CPFR are: faster response to consumer demand, increased forecast accuracy, sustainable improvements in the collaboration relationship, increased sales, inventory reduction, reduction of supply chain costs, increased promotion effectiveness, more predictable order cycles, more frequent deliveries, improved accuracy and availability of information, fewer stock-outs, improved reliability of deliveries, faster inventory turns, real-time information sharing, and reduced inventory holdings[2]. For more details, Transora, a software supplier for buyers and sellers of packaged goods, reported the average benefits of CPFR implementation as: visibility and forecast accuracy improved between 10% and 40%, lowered inventory costs between 10% and 25%, increased sales between 1% and 3%, improved service levels between 0.5% and 2.0%, and improved shelf in-stock levels between 1% and 4%. Ron Ireland, a managing director for the supply chain consulting firm Surgency and a former Wal-Mart executive, helped the Wal-Mart giant in its initial CPFR pilot with Warner-Lambert to improve in-stock levels on Listerine to 98 percent from 87 percent. And, lead times were reduced from 21 days to 11, on-hand inventory was cut by two weeks, orders were more consistent, production cycles were smoothed, Listerine sales increased by $8.5 million, and there was improved joint communication on merchandise and promotional planning. Ireland also claimed that sales for the Sara Lee items in the Wal-Mart CPFR pilot increased 32 percent, while inventories fell 14 percent, and in-stock performance improved by 2 percent [2].

Since the emergence of CPFR in the mid-nineties, the implementation of this strategy has expanded rapidly around the world. The VICS and Global Commerce Initiative (GCI), together with some of the largest companies in the North American consumer goods industry, have laid the cornerstone for the success of CPFR. After its successful CPFR pilot with Warner-Lambert, Wal-Mart extended CPFR collaboration with Sara Lee in 1998. Many other large global retailers and suppliers started to join in with their own CPFR applications. Procter & Gamble has begun projects across their entire supply chain in order to bring CPFR to realization: between CBD (Customer Business Development) planning and retail companies, between CBD teams and demand planning internally, and between factories and their suppliers. In 2001, Sears and Michelin implemented a CPFR initiative, but this was not out of a desire to follow the latest business trend. Instead, it was to solve a very real problem in their passenger tire supply chain. Inventory at Sears distribution centers and Michelin warehouses was high, and yet Sears was still experiencing shortfalls on some items at its retail stores. "Through CPFR, the two companies have been able to cut our combined inventory levels by 25 percent while streaming their key business processes." said Hank Steermann, former senior project manager for supply chain at Sears who was responsible for the Sears-Michelin CPFR project. In Canada, Canadian Tire has one of the largest retail CPFR programs in place today. With fifteen suppliers active in the program, Canadian Tire originally focused its efforts on the promotional activity in its business---collaborating with suppliers on promotional forecasts and agreeing to replenishment plans to meet the consensus demand forecast. The process has evolved over time to include all components of the demand forecast.

Important European retailers like Carrefour in France, Metro in Germany, and Tesco in the United Kingdom understood early on the significance of CPFR and have been consistently working towards its exploitation, for potential improvements in efficiency. Manufacturers, such as Proctor & Gamble in the Netherlands, Germany, Denmark and Greece, Johnson & Johnson in Great Britain, Kimberly-Clark in France, Germany, and Great Britain have been involved in CPFR collaboration with well-known retailers in Europe.

CPFR use has also expanded in Asia, South America and Africa. Retailers and manufacturers in China, Japan, Brazil, Colombia, and South Africa are successfully using CPFR in their business processes, adapting it to their own market conditions, and creating best practices.

3. CPFR COORDINATION PROCESS

The CFPR is a business coordination process that seeks to reduce the variance between supply and demand. The CPFR coordination process is normally divided into three phases, which is the planning phase, forecasting phase, and replenishment phase [3]. The planning phase creates the collaborative front-end agreement and joint business plan. The forecasting phase negotiates exception items and produces sales and order forecasts. The last replenishment phase implements firm orders translated from the order forecast. The key of coordination utilizing CPFR becomes the jointed demand forecast between retailers and manufacturers, which is then used to synchronize replenishment and production plans throughout the entire supply chain.

The collaborative forecasting process that is major phase of the CPFR coordination gives a guarantee for precise demand by implementing the jointed forecasting process inside the corporation and among the supplying chain of partners. The accuracy of collaborative forecasting, which are very important for the CPFR forecasting process, can be determined by establishment of discrepancies standards and discrepancies handling methods. The forecasting discrepancies may be causes by inaccuracy of the data for forecasting or differences of the forecasting models used by different partners. The inaccuracy of the data for forecasting may be produced from inaccurate and un-timely sale data and the un-timely communication for changes caused by demands, such as alteration of advertisement plan, products promotion plan and alteration. CPFR collaborative forecasting process among partners can improve the accuracy of data for forecasting. In this paper, we will focus on the discussion of the ways to reduce discrepancies caused by forecasting models differences. A coordination optimization model based on combination forecasting method is proposed to reduce this kind of discrepancy in order to improve the demand forecasting accuracy and CPFR coordination process.

In the CPFR collaborative forecasting process, partners in the supply chain will use different forecasting model and forecasting cycles because of their different forecasting knowledge backgrounds and resources. For example, in order to forecast items demand the retailer may use the simple moving average (MA) method and the manufacturer may use Forecast including trend (FIT) method at the same time. The forecasting cycles of the retailer may be several weeks or even one quarter due to numerous varieties of sale item. However, the manufacturers may forecast much accurate because their forecasting cycle might be one week due to fewer products varieties and more complex forecasting models using. The discrepancy of forecasting results between retailers and manufacturers might reach to 3 times of the lower forecasting results[4]. In order to collaboratively forecast among CPFR partners, a jointed forecasting model which can combine forecasting models from different parties should be used. The combination of the complex forecasting model and professional forecasting knowledge owned by manufacturers and timely sales data and market information sourced from retailer will guarantee the forecasting accuracy and effective supply chain collaboration.

The combination forecasting method can jointly utilize different forecasting models from different partners to smooth coordination in the supply chain and reduce forecasting discrepancies. And also, the different interests of retailers and manufactures in the supply chain produce the discrepancies between their forecasting results. For example, retailers might concern more about sales loss caused by goods shortage, while manufacturers may concern more about overstock cost caused by surplus stock and transportation cost caused by goods returning. It is impossible to accept only one party's forecast result, or just abandon one party's forecast model. A jointed forecasting model is needed to combine both parties' considerations. Based on the data from point-of-sale, the initial forecasting results are calculated by combination forecasting model that combines different forecasting models from the retailer and the manufacturer. And then, the final optimized forecasting report is created after discrepancies correction to the forecasting result that cannot be accepted by the CPFR exception standard. The exception standard is jointly created by retailers and manufacturers. This kind of collaborative forecasting process reduces forecasting discrepancy by removing the factor that makes it happen. The combination forecasting applied in CPFR collaborating forecasting process can reduce forecasting discrepancy caused by forecasting model difference between retailer and manufacturer.

4. THE RETAIL SUPPLY CHAIN COORDINATION OPTIMIZATION MODELING

The optimization model for the retail supply chain coordination is created on the combination forecasting method, which was first proposed by Bate-Granger in 1969[5]. It makes use of the variance-covariance relation in the single item forecasting method and the information from the single item forecasting to obtain much more accurate estimating results by combing effective single forecasting methods. The basic hypothesis, which is the requirement for combination of possible single forecasting method, is that forecasting target and its result are stationary sequence, or there is co-integration relationship between forecasting target and single forecasting method. The general form of combination-forecasting for n single item forecasting f_{it}, i=1,2,…, n, is as follows.

$$f_{ct} = w_0 + \sum_{i=1}^{n} w_i f_{it} + w_{n+1} y_{t-1} \tag{1}$$

Here, w_i is the weight, $1 \le i \le n$, and y_{t-1} is the actual demand of $t-1$ period. The weight w_i can be estimated by ordinary least squares (OLS)、recursive least squares (RLS) and Stein-rule estimate (STN).

The ordinary least squares (OLS) estimate for $W = [w_1 \cdots w_k]'$ can be calculated by the following equation (2).

$$\hat{W} = S^{-1} X' y \tag{2}$$

Here, $S = X'X$ and residual is $e = y - XW$

If the recursive model is taken as,

$$\begin{cases} Y = XW + e \\ RW = 1 \end{cases} \tag{3}$$

then, the recursive least squares (RLS) estimate can be calculated by the following equation (4)

$$\hat{W} = A_{11} X' Y + A_{12} \tag{4}$$

Here, $A_{12} = S^{-1}R'(RS^{-1}R')^{-1}$, $A_{11} = S^{-1} - S^{-1}R'(RS^{-1}R')^{-1}RS^{-1}$,and $S = X'X$. The weigh estimates are the unbiased estimates.

The stein-rule estimate (STN) decreases the risk of parameter estimate and improves parameter estimate capability. And also, it optimizes the balance between the variation and estimate difference. The stein-rule estimate (STN) can be calculated by the following equation (5).

$$\hat{W}_{SR} = \left(1 - \frac{a e' e}{W' R' (RS^{-1}R')^{-1} RW}\right)(W - \hat{W}) + \hat{W} \tag{5}$$

Here, W is the OLS estimate or non-sample data weigh vector. The residual is $e = y - XW$, R is calculated by equation (3), and $\hat{W} = W - S^{-1}R'(RS^{-1}R')^{-1}RW$, $0 \le a \le 2(2-m)/(n-k+2)$, $m=rank(R)$, n is the number of fitting data and k is the number of single forecasting methods.

Furthermore, the forecasting error is corrected on the combination-forecasting results to improve forecasting performance and optimize the supply chain coordination. The error correction model is created as the following equation (6).

$$Y=(\bar{y}-\sum_{i=1}^{k}\frac{S_y}{S_i}\bar{f}_{it})+\sum_{i=1}^{k}\frac{S_y}{S_i}f_{it} \tag{6}$$

Here, $S_y=\sqrt{\frac{\sum_{i=1}^{n}(y_i-\bar{y})^2}{n-1}}$, $S_j=\sqrt{\frac{\sum_{i=1}^{n}(f_{it}-\overline{f_{it}})^2}{n-1}}$ 。

5. FORMULATION AND RESULTS

In this paper, the CPFR combination forecasting method is modeled from effective single forecasting methods through sequence analyzing on previous forecasting results. The single forecasting methods are chosen for combination according to the following three principles. The existing forecasting methods used by CPFR parties have first priority to be chosen as single forecasting method due to their effectiveness tested by time. And, single forecasting methods from different sources are needed to be added into combination model. Finally, the proper single forecasting methods are also determined by statistics feature of forecasting target and forecasting cycles.

Table 1 The Sales Data of One Goods in One Company

Week	1	2	3	4	5	6	7	8	9	10
Actual Demand	800	1400	1000	1500	1500	1300	1800	1700	1300	1700
Week	11	12	13	14	15	16	17	18	19	20
Actual Demand	1700	1500	2300	2300	2000	1700	1800	2200	1900	2400
Week	21	22	23	24	25	26	27	28	29	30
Demand Forecast	2400	2600	2000	2500	2600	2200	2200	2500	2400	2100

The effectiveness of this CPFR combination forecasting method is verified by a simple case analysis which uses the sales data of one goods in a certain retail company in thirty weeks showed in table 1. The sales data in first 20 weeks are used to create combination forecasting model. The sales data in week 21 to week 30 are forecasted with combination forecasting method. The sales values y_t are first order stationary *I(1)*. The co-integrate relationship between sales values and single forecasting method is analyzed on the following equation (7).

$$Y_t = cons\tan t + \sum_{i=1}^{3}\beta_i f_{it} + \varepsilon_t \tag{7}$$

When D.W.=1.808, $\alpha = 0.05$, variables k=3 , n=18, $d_L = 0.93$, $d_U = 1.69$, $d_u < d_1 < 4 - d_u$. So, ε_t is stationary. And, The sales values and single forecasting method have co-integrate relationship. The combination forecasting model can be used to analyze this group of sales values.

The recursive combination model is used in this case formulation. The recursive combination mathematics equation that is showed in equation (8) is formed when weight w_0=0 and the actual demand y_{t-1} of *t-1* period is not separately considered in equation (1).

$$f_{ct} = \sum_{i=1}^{n} w_i f_{it} \tag{8}$$

Here, the weights w_i (i=1,2,…n) can be estimated by ordinary least squares (OLS)、recursive least squares (RLS) or Stein-rule estimate (STN). The mean absolute difference (MAD) index is used to measure the forecasting difference between recursive combination forecasting results and actual demands. The mean absolute difference (MAD) is taken as the indicator to evaluate the forecasting methods. The MAD is calculated as following equation (9).

$$MAD = \frac{\sum_{i=1}^{n} |Y_t - F_t|}{n} \tag{9}$$

Here, t represents an interval and n is the number of intervals. The Y_t represents the actual need in the interval and the F_t is the forecasting need in the interval.

Table 2 Recursive Combination Forecasting MAD

Time Period	Recursive Combination Forecasting			Single Forecasting
	OLS1	RLS1	STN1	MA
Week 4~20 match	233	238	233	263
Week 21~25 forecast	238	236	192	233
Week 26~30 forecast	282	277	284	240

The mean absolute difference (MAD) between recursive combination forecasting results and actual demands are showed in table 2, in which data in row OLS1, row RLS1, and row STN1 are separately recursive forecasted on estimating weight by ordinary least squares (OLS)、recursive least squares (RLS) and Stein-rule estimate (STN). The MAD of recursive combination forecasting method indicated improved forecasting accuracy comparing with MAD of single moving average (MA) forecasting method as showed in table 2. Especially in match forecasting period from week 4 to week 20, the average MAD values of OLS1 model (233) and RLS1 model (238) and STN1 model (233) are lower than that of single forecasting MA method (263). In the forecasting period from week 21 to week 25, the forecasting performance of recursive forecasting model STN1 (MAD=192) is obviously better than single forecasting model (MAD=233). However, from week 26 to week 30, the recursive combination model doesn't work well and the forecasting accuracy is slightly low.

The formulation results verified the effectiveness of combination forecasting model to improve forecasting accuracy of retail supply chain and optimize the CPFR coordination performance. From above formulation results, it can be found that combination forecasting model has better performance in short time forecasting which is one month in this case. In current competition environment, the development of innovative electronic business operation model and Internet of Thing technology shorten the product life-cycle and management decision cycle of the retailers. So, the combination forecasting model is the proper optimization method for nowadays short-terms retailer decision activities.

6. CONCLUSION

The CPFR provides the solution for retail supply chain coordination. The collaborative forecasting phase is the core part of CPFR coordination process, which is the basis of determination of the production and replenishment phases. A combination forecasting method, which can combine effective forecasting methods from different parties, is modeled for the optimization of the CPFR coordination between retailers and manufacturers in the supply chain in this paper. A simple case formulation and analysis showed that forecasting discrepancies are reduced and collaborative forecasting accuracy is improved. So, combination forecasting method is an effective model for retail supply chain coordination optimization. The further research on retail supply chain coordination and optimization will be extended into more complex goods demand change pattern and formulation in the future.

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