Apply 3C Theory in Collaborative Planning, Forecasting, and Replenishment Expert System Formulation

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Abstract

In recent years, both the VICS CPFR committee and ECR Europe have published several reports presenting pilot implementations of the CPFR process model and providing recommendations and roadmaps for companies interested in implementing it. These sources indicate that by implementing CPFR both retailers and suppliers can expect to benefit from increased forecast accuracy, reduced stock-outs, increased sales, and reduced inventories. Based on the commonality, capacity and consumption (3C Theory) of a specific material, a GARCH based collaborative planning, forecasting, and replenishment (CPFR) expert system associated with 3C Theory is proposed in this paper. Meanwhile, through setting an optimal safety multiplier in exception policy, an exception demand also can be efficiently and effectively controlled to maximize the net present value.

Keyword: Collaborative Planning, Forecasting, Replenishment (CPFR), GARCH Model, Expert System, 3C Theory

1. Introduction

Lack of demand visibility has been identified as an important challenge for supply chain management [1,2,3]. Commonly, the only demand information companies have access to are the orders placed by their customers [4]. As both practice and research have shown, order data often give a delayed and distorted picture of end customer demand and what actually happens in the market. The distortion tends to increase when moving upstream in the supply chain, i.e. when moving further away from the end customer. This phenomenon is known as the bullwhip effect [5,6] and it makes demand look variable and unpredictable even when end customer demand is level [7]. Therefore, controlling production and inventories based on this flawed demand information leads to inefficiencies, such as low capacity utilization, poor availability, and high stock levels [6,8].

Demand signal processing is essentially the same mechanism that [7] called inventory policy. According to Forrester, the way companies adjust inventories and in-process orders is likely to be more important to demand amplification in supply chains than any other single characteristic. He suggests that more gradual inventory corrections should be sought in order to increase the stability of the manufacturing–distribution system. Forrester also calls attention to the fact that many sales forecasting methods tend to accelerate inventory reactions to changes in sales levels. Lee et al. [5] further develop this argument by explaining how forecasts that are updated based on observed demand often lead to demand amplification. They conclude that the demand observed at the retailer is transmitted to the supplier in an exaggerated form, and it is impossible for the supplier to distinguish which part of the order reflects an actual change in market demand and which part is caused by the retailer’s inventory adjustment.

The 3C approach developed by Lucent in its Spanish Tres Cantos plant [9] links sales planning seamlessly to component suppliers using a collaboration process based on ranking maximum usage rates of individual components [10]. 3C Theory is the basic theory for realizing global supply chain management and designed to plan and realize global resource project. In the past, we even do not know the disruption between activity processes of order model, purchase, production and manufacturing because we were lack of demand prediction model that could be applied to short product life cycle. For example, the traditional relationship between order model and material requirement planning (MRP) is “planning is planning, order is order, no direct relationship between”, that is, there exists some problems in the stock management of Re-Order Point (ROP) [11].
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Naturally, it is difficult to guarantee the accuracy of the policy-decision on material supply on such basis. Besides, when we use traditional MRP to work out a master production schedule (MPS), what we think will be how much is the production of a product in a certain period not total production of a certain group of products. There is big difference between the production and actual demands of individual product. On the contrary, the difference between predicted total production and actual production of a group of products will be certainly much smaller. That is, traditional MRP could only plan for the requirement of material of individual finished products and lack of capability of material demand planning for a group of products under duplicated production. In the deployment process of bill of material (BOM), although MRP combines common raw materials in calculation that is only for the consideration of batch purchase, the actual purchase strategy is still based on the production demand of MPS that often neglects the purchase benefit brought by the combination of common raw materials [12].

Authors, such as Lee et al. [6] and Barratt and Oliveira [13] argue that although sharing of downstream sales data is beneficial, it does not provide enough demand visibility. Instead, companies should share and collaboratively develop forecasts. Aviv [14] examines the value of forecasting collaboration in a two-echelon supply chain of a single product that faces independent, identically distributed demand. The members of the supply chain are a single supplier and a single retailer. Aviv compares a situation called collaborative forecasting, where the retailer and the supplier develop and employ a joint forecast, to a situation termed local forecasting, where each party develops and employs its own forecast. Assuming a collaboration method that results in the joint forecast always being at least as good as the best individual forecast he demonstrates that collaborative forecasting is beneficial.

In a more recent paper, Aviv [15] further develops the model by introducing autoregressive demand. Forecasts are developed and updated by the supplier. In the third setting, called collaborative forecasting, inventory is managed centrally and all demand-related information is shared. A joint forecast is developed and updated based on both parties’ demand information. The study shows that the value of information sharing increases when the explainable portion of demand variability increases and that the choice of the best inventory control approach – centralized inventory control or different types of decentralized inventory control - depends on whether the retailer or the supplier has more explanation power.

In recent years, both the VICS CPFR committee and ECR Europe have published several reports presenting pilot implementations of the CPFR process model and providing recommendations and roadmaps for companies interested in implementing it [16,17,18]. These sources indicate that by implementing CPFR both retailers and suppliers can expect to benefit from increased forecast accuracy, reduced stock-outs, increased sales, and reduced inventories. Other suggested benefits include reduced delivery lead-times from suppliers to retailers and higher capacity utilization for suppliers.

Based on the discussion above, in this research, we try to propose a collaborative planning, forecasting and replenishment (CPFR) expert system to smooth the demand disruption in the supply chain management. As a result, this paper is organized as follows: the CPFR expert system associated with 3C Theory is generated in section 2. In section 3, a real case of famous chain stores in Taiwan applied to the CPFR expert system is discussed and numerical analyzed, finally, the conclusion is proposed in section 4.

2. Expert System Generating

Forecasting demand and subsequently setting inventory levels is difficult owing to the influence of promotions, changing demand patterns, and competitive pressures. Co-operative planning between trading partners facilitates better matching of supply and demand. Rather than trying to independently project demand patterns, buyers and sellers share information in advance and work together to develop realistic, informed, and detailed estimates that can be used to guide business operations, see, e.g. [5,6,19]. In addition, there are studies suggesting that even greater benefits would be attained by further tightening inter-company integration through implementation of collaborative forecasting in supply chains [15,6]. Authors, such as Lee et al. [6] and Barratt and Oliveira [13] argue that although sharing of downstream sales data is beneficial, it does not provide enough demand visibility. Instead, companies should share and collaboratively develop forecasts [20,21].
2.1. Collaborative Forecasting Model Generating

Traditionally, a normal approximation has been used to estimate the relationship between safety stock and demand uncertainty, replenishment lead time, and lead time uncertainty. According to Eppen and Martin [22], this approximation is often justified by using an argument based on the central limit theorem, but in reality, they say, “the normality assumption is unwarranted in general and this procedure can produce a probability of stocking out that is egregiously in error.” In addition, the literature suggests that the traditional iid demand assumption may not be appropriate to describe practical settings because demands in different periods are often correlated, see, e.g. [23,24,25]. To remedy this problem, the methodologies that have been used in sales forecasting are typically time series algorithms that can be classified as linear or nonlinear, depending on the nature of the model they are based on. In a more recent paper, Aviv [15] further develops the model by introducing autoregressive demand. A joint forecast is developed and updated based on both parties’ demand information. Linear models, like autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) [26] are the most popular methodologies, but their forecasting ability is limited by their assumption of a linear behavior and thus, it is not always satisfactory [27].

In order to address possible nonlinearities in time series modeling, researchers introduced a number of nonlinear methodologies, including nonlinear ARMA time series models. Their main drawback is that the type of nonlinearity is not known in advance and the modeler needs to select the structure of the model by trial and error. Advanced artificial intelligence technologies, like artificial neural networks (ANN) [28] and fuzzy logic systems, for example a dynamic evolving computation system (DECS) model proposed by Chen and Lin [29], use more sophisticated generic model structures that can incorporate the characteristics of complex data and produce accurate time series models, by eliminating the time consuming trial and error procedure.

Since the demand uncertainty could be divided into predictable and unpredictable components, the later is the real risk we can not foresee. Of course, with traditional forecasting method just like the ARMA (and/or ARIMA), we can easily fit the historic demand behavior of sales, but we can’t just rely on the historic fitting model to forecast the future. The unpredictable events in and out of market resulting in volatility clustering effects may also impact the sales in certain period which make the curve unsmooth and affect the demand prediction. The prediction for us is not to simply forecast the predictable changes as the traditional models provide us with, such as demand and supply models, but to take volatility into account to forecast the future, whether in long-term or short-term.

Robert Engle used MA(q) technique in 1982 to model the time varying volatility in a series and proposed the so called Autoregressive Conditional Heteroskedasticity model referred to as ARCH (Engle, 1982). The “conditional” nature of non-constant variance (heteroskedasticity) refers to forecasting of variance conditional upon the information set available up to a time period \( t \). Using ARCH technique, the variance of the random error term \( \{ \varepsilon_t \} \) can be explained in terms of current and lagged values of squared \( \varepsilon \) as follow

\[
\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \varepsilon_{t-2}^2 + \cdots + \theta_q \varepsilon_{t-q}^2
\]  \hspace{1cm} (1)

where \( \sigma_t^2 \) is the variance of \( \varepsilon_t \).

An assumption underlying this model is that volatility is changing over time and there is tendency that a large error will be likely followed by a large error and a small error followed by a small error. The variable \( q \) is the period of volatility clustering. This characteristic coincides with the findings of Fama (1965) and Mandelbrot (1966) that the volatilities of financial series cluster.

The MA(q) representation of \( \sigma_t^2 \) was later generalized to an ARMA representation of \( \sigma_t^2 \) by Tim Bollerslev in 1988 and is, naturally, referred to as the Generalized Autoregressive Conditional Heteroskedasticity model or GARCH. Tim Bollerslev [30] extended Robert Engle’s MA(q)
representation of $\sigma_t^2$ (the ARCH) to include an AR(p) process, that is, regressing a variable $\sigma_t^2$ on its own lagged values $\{\sigma_{t-1}, \sigma_{t-2}, \ldots, \sigma_{t-p}\}$ as well. Thus, variance of the random error term in a certain period $\{\epsilon_t\}$ can be modeled to depend not only on squared past errors $\{\epsilon_{t-1}^2, \epsilon_{t-2}^2, \ldots, \epsilon_{t-q}^2\}$ but also on the lagged value of the variance $\{\sigma_{t-1}^2, \sigma_{t-2}^2, \ldots, \sigma_{t-p}^2\}$ as follows

$$y_t = \beta_0 + \sum_{j=1}^{N_y} \varphi_j y_{t-j} + \sum_{k=1}^{N_x} \sum_{i=1}^{N_x} \alpha_{ki} X_{i,j} k_{t-i} + \epsilon_t$$

$$\sigma_t^2 = \theta_0 + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}^2 + \sum_{j=1}^{p} \tau_j \sigma_{t-j}^2$$

where $y_t$ is the demand at instant $t$ and $X_{k_i}$ is the explanatory variable $X_k$ (e.g. price etc.,) at instant $i$ that is used to explain variations in the dependent variable $y_t$. $N_X$ represents the period up to which the lagged values of $X_{k_i}$ will be used in the equation $\alpha, \beta, \theta$ and $\tau$ are coefficients to be estimated based on $X, Y, \epsilon$ and $\sigma^2$.

In developing the GARCH model, Eq. (2) and Eq. (3) take into account the lagged values of the dependent variable, the impact of multiple explanatory variables ($K$ number of X’s that influence demand such as price etc.) and their respective lagged values as well as time dependent heteroskedasticity of the error term.

Therefore, this research is going to use the GARCH model based on the ADL (Autoregressive Distributed Lag) models to involve the volatility consideration to fit the demand behavior, and then forecast the short-term demand in respect to the historic volatility features to develop a GARCH based collaborative forecasting model. Then, use of GARCH model will enable business to explicitly model the volatility associated with sales demand and in turn calculated the values at risk (VaR). Ability to evaluate and qualify risk associated with volatility by GARCH will, in turn, enable businesses to collaboratively manage inventory risks better and, in the end, benefit both trading parties.

2.2. Collaborative Replenishment Policy Generating

Order batching refers to the practice of accumulating a certain amount of demand before placing an order up the supply chain or on the manufacturing process. Batching is often the result of an economic order quantity (EOQ) calculation or similar technique. Burbidge [31] discusses the problems that this causes in detail. Among other things, he shows how the different order cycles generated by EOQ calculations may cause large, seemingly random fluctuations in demand. In order to stabilize the order and material flow, Burbidge recommends moving to single-cycle flow control in production. Lee et al. [5,6] discuss the impact of built-in cycles in companies’ processes. Many manufacturers, for example, place purchase orders with suppliers when they run their material requirements planning (MRP) systems. Since these MRP runs often take place only once a month, the result is significant batching in the supply chain. Finally Lee et al. [5,6] highlight the importance of institutional habits, such as end-of-quarter or end-of-year surges when salespeople are trying to meet their sales targets.

Comparing to the relationship between order model and resource requirement plans of 3C, the 3C model is an operation model that will integrate the relationship between order model and resource requirement plans. The biggest difference between 3C model and traditional model is “3C accepts order only when it could do it whereas the traditional idea is that accepts order before confirming
whether it has capability to carry out”. This difference is the key to win in competition for an enterprise (Huang, 2004). The value of 3C theory in application is to help enterprises to solve the problem of resource management and reestablish global supply chain management system.

3C Theory is to classify and expand the prediction of demands from markets by the model of commonality, capacity and the replenishment of consumption with the changes of markets. Followings are their descriptions:

[A]. The basic idea and value of commonality is to achieve the goal of reducing the cost of development, simplifying resource management, reducing the quantity of stock and providing customers with diversified products through extensive use of the strategy of “common material or resources”. The characteristics of commonality are enhancing the commonality of materials and reducing the number of product varieties and considering the expression of product on Internet at the stage of research and development.

[B]. The basic idea of capacity is to plan the allocation of resources through the application of theory of constrain (TOC) at the same time of accepting the order to enhance the client satisfaction and avoid delivery delay due to running out of stock or insufficient capacity. The characteristics of capacity is that the demand of material and capacity have their ceiling, so when a manufacturer receives order, they have to consider whether material and capacity have capability to fulfill their promise to customers. It is an act according to their ability and a model that compares the material situation in the plan with the product varieties or materials selected by customer before answering to the customer.

[C]. The basic idea of consumption is a mechanism that combines the replenishment model of market demand through instant market information to buy materials when need. Such mechanism aims to achieve the goals including reduction of stock standard, fund reserve and loss due to discount of stock. The characteristics of consumption are that the materials are purchased with the changes of practical demands in the markets and emphasize on the simultaneity with the demands from the markets.

[D]. Based on the definitions, the construction of 3C Theory in stock management system is conducted according to following procedures:

I. Calculate maximum consumption rate of each material based on capacity limit: Estimated sales rate of a product, \( TOP_p \), multiplying by the use amount of material \( m \) by the product \( p \), \( BOM_{pm} \), we could obtain the consumption rate of material \( m \) by the product. Then pick up the maximum value of consumption rates of material \( m \) by individual products to obtain \( RBOM_m \), where \( RBOM_m = \max \{TOP_p \times BOM_{pm} \} \). In fact, the \( RBOM_m \) has considered the maximum sales rate of product \( p \), \( MSR_p \), is the output rate of the product in the supply chains \( MSR_p = \min \{MOR_{pf} \} \), where \( MOR_{pf} \) is the maximum output rate of Product \( p \) at production unit \( f \); consumption \( (TOP_p \text{ multiplies } BOM_{pm}) \), commonality (maximum value of consumption of \( m \) by individual products). It is the core of 3C Theory.

II. The material “commonality index” is used as the performance indicator of stock management. Commonality is not only a conception but also the concrete indicator that could be measured and called “commonality index”. In the best situation, the commonality is 1 whereas at the worst situation, the commonality is 0. At the best situation, the stock amount is the lowest, set as \( Inv_{best} \), the stock amount is highest at the worst situation, set as \( Inv_{worst} \). Assume the cost of material \( m \) is \( C_m \) and there are \( P \) varieties of products, then:

- At the best situation, all products completely use common materials, the stock amount is:

\[
Inv_{best} = \max_p \{TOP_p \times BOM_{p1} \} \times C_m \quad (4)
\]
At the worst situation, all products completely not use common materials. So

\[
\text{Inv}_{\text{worst}} = \sum_{p} \sum_{m} \text{TOP}_p \times \text{BOM}_m \times C_m
\]  

(5)

Under normal situation, the stock amount is:

\[
\text{Inv}_{\text{pract}} = \sum_{m} \text{RBOM}_m \times C_m
\]  

(6)

\[
\text{COMI} = \frac{\text{Inv}_{\text{worst}} - \text{Inv}_{\text{pract}}}{(\text{Inv}_{\text{worst}} - \text{Inv}_{\text{best}})}
\]  

(7)

2.3. CPFR expert system Generating

Based on the nine steps of VICS, the CPFR expert system developed in this research is proposed and depicted in Figure 1 as follows:

I. An optimal collaborative forecasting model based on the GARCH approach is established to minimize the bullwhip effect, meanwhile, a set of forecasting data \( \{(\mu_t, \sigma_t)\}^{t+R}_{t} \) in a given planning time horizon is generated.

II. Based on the forecasting data \( \{(\mu_t, \sigma_t)\}^{t+R}_{t} \), the commonality index (CMI) can be calculated with Eq.(7); therefore, an optimal \((R, s, S)\) inventory policy for material \(m\) is developed to maximize the total net present value (NPV) for each retailer as follows:

(A). \( R \), the review period, \( R = \text{BOM}_m \times \text{EOQ}_m + \text{RBOM}_m \)  

(B). \( S \), Order-Up-to-Level, \( S = \text{OUT}_m = \text{RBOM}_m \times \text{BOM}_m + \text{SS}_m \)  

(C). \( s \), safety stock level, \( s = \overline{D}_m \times LT_m \times \alpha \times \sigma_m \)  

where \( \overline{D}_m \), the average daily demand of material \(m\); \( LT_m \), the lead time of purchasing material \(m\); \( \sigma_m \), the standard deviation of demand of material \(m\); \( \alpha \), the customer service level.

III. Through safety multiplier \( (K) \) setting, an exception policy is proposed to optimally identify exceptions for order forecasting.

IV. An optimal collaborative planning, forecasting and replenishment CPFR expert system \((R, s, S, K)\) for each retailer is developed.

3. Conclusion

In this paper, a collaborative planning, forecasting and replenishment (CPFR) expert system associated with 3C Theory is proposed. Through GARCH forecasting, a set of forecasting data
(μₜ, σₜ)_{i}^{t+R} in a given planning time horizon can provide necessary information to generate an optimal \((R, s, S)\) inventory policy associated with 3C Theory. Meanwhile, by setting the safety multiplier \((K)\), an exception demand in retailer’s sales can be efficiently and effectively controlled optimally. Then, an optimal collaborative planning, forecasting and replenishment (CPFR) expert system \((R, s, S, K)\) can be generated in each planning time horizon.

4. Reference

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