Forecasting and Risk Analysis in Supply Chain Management

GARCH Proof of Concept

Shoumen Datta [1], Clive W. J. Granger [2], Don P. Graham [3], Nikhil Sagar [4], Pat Doody [5], Reuben Slone [6] and Olli-Pekka Hilmola [7]

[1] Research Scientist, Engineering Systems Division, Department of Civil and Environmental Engineering, Research Director and Co-Founder, MIT Forum for Supply Chain Innovation, School of Engineering, Massachusetts Institute of Technology, Room 1-179, 77 Massachusetts Avenue, Cambridge MA 02139

[2] Research Professor, Department of Economics, University of California at San Diego, La Jolla CA 92093

[3] Founder and CEO, INNOVEX LLC

[4] Vice President, Retail Inventory Management, OfficeMax Inc, 263 Shuman Boulevard, Naperville, IL 60563

[5] Senior Lecturer, Department of Mathematics and Computing and Executive Director, Center for Innovation in Distributed Systems, Institute of Technology Tralee, County Kerry, Ireland

[6] Executive Vice President, OfficeMax Inc, 263 Shuman Boulevard, Naperville, IL 60563

[7] Professor of Logistics, Lappeenranta University of Technology, Kouvola Research Unit, Prikaatintie 9, FIN-45100 Kouvola, Finland

Abstract

Forecasting is an underestimated field of research in supply chain management. Recently advanced methods are coming into use. Initial results presented in this chapter are encouraging, but may require changes in policies for collaboration and transparency. In this chapter we explore advanced forecasting tools for decision support in supply chain scenarios and provide preliminary simulation results from their impact on demand amplification. Preliminary results presented in this chapter, suggests that advanced methods may be useful to predict oscillated demand but their performance may be constrained by current structural and operating policies as well as limited availability of data. Improvements to reduce demand amplification, for example, may decrease the risk of out of stock but increase operating cost or risk of excess inventory.

Keywords

Forecasting, SCM, demand amplification, risk management, intelligent decision systems, auto-id, GARCH

1. Introduction

Uncertainty fuels the need for risk management although risk, if adequately measured, may be less than uncertainty, if measurable. Forecasting may be viewed as a bridge between uncertainty and risk if a forecast peels away some degrees of uncertainty but on the other hand, for example, may increase the risk of inventory. Therefore, forecasting continues to present significant challenges. Boyle *et al* (2008) presented findings from electronics industry, where original equipment manufacturers (OEM) could not predict demand beyond a 4 week horizon. Moon *et al* (2000) presented demand forecasting from Lucent (Alcatel-Lucent), demonstrating improvement in forecasting accuracy (60% to 80-85%). Related observations (Datta 2008a) resulted in inventory markdowns.

Availability of increasing volumes of data (Reyes *et al* 2007, Reyes and Frazier 2008) demands tools that can extract value from data. Recent research has shown that advanced forecasting tools enable improvements in supply chain performance (Zhao *et al* 2001, Zhao *et al* 2002, Bayraktar *et al* 2008, Wright and Yuan 2008), if certain pre-requisites are optimized (ordering policies, inventory collaboration). Autoregressive models have been effective in macroeconomic inventory forecasts (Albertson and Aylen 2003). Zhao *et al* (2002) and Bayraktar *et al* (2008) emphasize that the role of forecasting in supply chain is to indicate the right direction for the actors rather than being exactly right, at every moment. Choosing the correct forecasting method is often a complex issue (Chatfield and Yar 1988).

The purpose of this work is to explore how advanced forecasting methods could be applied in global supply chain management and their requirements. We present real world results and use simulation of a 4-stage supply chain model, beer-game (Vensim simulation). We have also used SPSS statistical analysis software to construct autoregressive forecasting models. The problems may be described as: (1) how to construct autoregressive forecasting models for a supply chain environment and (2) what changes may be needed in supply chain design to apply these advanced forecasting models? In the next section, we introduce a few challenges and section 3 discusses demand amplification in supply chain management. In section 4 we discuss features of autoregressive models and generalized autoregressive conditional heteroskedasticity (GARCH). Data and analysis from a supply chain inventory model using GARCH is presented and although the results are preliminary, they are encouraging. Concluding thoughts and further research issues are proposed in section 5.

2. Supply Chain Management and Demand Amplification

Despite rapid advances in SCM and logistics, inefficiencies still persist and are reflected in related costs (Datta *et al* 2004). In developing nations the actual amounts are lower, but proportional share is higher (Barros and Hilmola 2007). One of the logistically unfriendly country groups are oil producers (Arvis *et al* 2007).

The high cost for operations offer prosperity for the service providers. In 2006, AP Moller-Maersk raked in US$46.8 billion in revenues (Hilmola and Szekely 2008). Deutsche Post reported revenues of €63.5 billion in 2007 (Annual Report 2007). Profitability and growth of these services are increasing, fueled by globalization. Global transportation growth exceeds global GDP growth (United Nations 2005 & 2007), since trade grows twice as fast as GDP. For decades companies emphasized lower inventories and streamlined supply chains but it has resulted in a situation (Chen *et al* 2005, Kros *et al* 2006) where material handling in distribution centers has increased (transportation growth combined with lower lot sizes). Management science and practice continues to explore ways to decrease transaction costs (Coase 1937, Coase 1960, Coase 1972, Coase 1992) through real-time information arbitrage. Cooper & Tracey (2005) reported that in the 1990's Wal-Mart had an information exchange capacity of 24 terabytes. While massive investments in information technology (IT) may be prudent, the sheer volume of data begs to ask the question whether we have the tools to separate data from noise and if we have systems that can transform data into decisionable information.

In supply chain management, the issue of demand amplification or Bullwhip effect has been in the forefront for some time (Forrester 1958, Lee *et al* 1997) but it took decades before its importance was recognized. The development of supply chain management (Oliver & Webber 1982, Houlihan 1985) catalysed by globalization, highlighted the strategic importance of logistics and pivotal role of information technology. Small demand changes in the consumer phase resulted in situations, where factories and other value chain partners faced sudden peaks and down turns in demand, inventory holdings and a corresponding impact on production and delivery (delivery structure phenomenon due to Bullwhip effect is referred to as "reverse amplification" by Holweg & Bicheno (2000) and Hines *et al* (2000) referred to it as "splash back"). Human intervention to tame the Bullwhip effect, compared to simple heuristics, leads to higher demand amplification (Sterman 1989).

It follows that demand amplification may have serious consequences due to increased uncertainty and increases the significance of risk management. During a down turn, Towill (2005) showed that amplification causes possible shortages on product volume (products are not ordered, even if demand is undiminished) and variety as well as on idle capacity in operations and involves potential layoff costs. In the case of positive demand, Towill (2005) identifies that stock deterioration and sales cannibalization produces lost income.

Consumers purchase products lured by discounts and that diminishes sales in the following time periods or seasons (Warburton & Stratton 2002). During upswings, operations cost a premium for manufacturing and distribution (orders increase rapidly), but also decreases productivity development and increases waste levels. Recent emphasis on outsourcing and large-scale utilization of low cost sourcing has worsened demand amplification (Lowson 2001, Warburton and Stratton 2002, Stratton and Warburton 2003, Hilletofth and Hilmola 2008). Risks associated with production and transportation delays are considerably higher. To mitigate such risks, some corporations are using responsiveness as a strategic differentiator and have built their supply chains to react on market changes through more localized supply networks, for example, Benetton (Dapiran 1992), Zara (Fraiman and Singh 2002), Griffin (Warburton and Stratton 2002, Stratton and Warburton 2003), Obermeyer (Fisher *et al* 1994) and NEXT (Towill 2005). The carbon footprint of sourcing strategies will become increasingly relevant in view of future legislation. Logistics may ultimately benefit from a disruptive innovation (Datta 2008b) in energy sourcing and management using wireless sensors networks.

In recent decades, even macroeconomists are including inventory as a key indicator of economic decline of national economies (Ramey 1989, Albertson an Aylen 2003). Ramey (1989) argued that manufacturing input inventories, raw materials and work in process (WIP), fluctuated most in recession, while end-item or finished goods inventories fluctuate less (Table 1). However, the labour market volatility is also an issue in changing economic environments (Ramey 1989). Although, inventory positions seem to fluctuate, Albertson and Aylen (2003) argue that autoregressive forecasting models are able to forecast next period situation with a 50% accuracy. While autoregressive techniques have been widely used in finance (and economics) in the past few decades, they may not have been applied or explored as decision support tools by supply chain planners or analysts in the area of supply chain management (Datta *et al* 2007) or in other verticals (healthcare, energy).

Table 1. Inventory changes in recession in USA during 1960-1982 (Ramey 1989)

Recessions	Retail	Wholesale	Manufact. Finished Inventories	Manufact. Input Inventories
1960:1-1960:4	-6.3	-1.7	-3.1	-6.3
1969:3-1970:4	-8.2	1.2	-0.4	-5.2
1973:4-1975:1	-16.0	-5.8	2.4	-13.2
1980:1-1980:2	3.6	1.9	-0.3	-4.1
1981:3-1982:4	-7.6	-2.3	-7.8	-11.1

All numbers billions of US dollars (1972), annual rates of change.

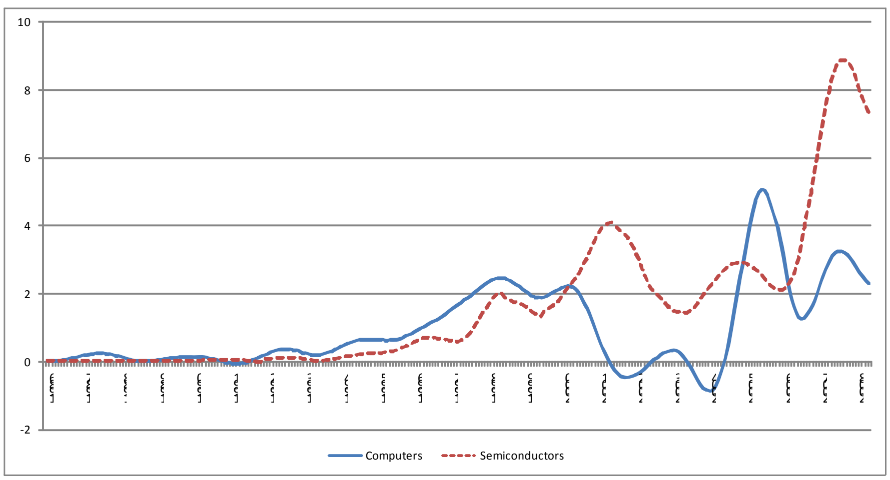

Figure 1. Capacity addition change in US computer and semiconductor 1986-2008 (Federal Reserve 2008)

Logic of demand amplification is evident in economic cycles (Forrester 1976, Sterman 1985). Order backlog, existing inventory holdings, amount of production, amount of employment and capacity additions were used in simulation trials to forecast different levels of economic cycles. In long-term changes, both Forrester (1976) and Sterman (1985) have emphasized the importance of capacity additions. A similar methodology has been used in maritime economics to estimate price level changes (Dikos *et al* 2006) and investment cycle lengths in capital intensive industries (Berends & Romme 2001). Hilmola (2007) has shown that capacity additions in US in semiconductors and computers industries may explain the behavior of stock market indices.

3. Beer Game and Role of Advanced Forecasting Methods

Forrester (1958) introduced a classical 4-stage beer-game simulation and revealed that demand information amplifies within the supply chain as we move further upstream. Figure 2 shows, customer demand is flat at 8 units per time period (it increased from 4 to 8 during time period of 100), but over-under reaction appears when supply chain is moved further with respect to time. Production orders spike to over 40 units per period, while waiting collapses to 0 units only 15 time units later. This occurs mostly due to time-delayed supply process in each stage, which is following make-to-stock (MTS) inventory principles (each phase has “target” for end-item inventory levels, which they try to reach with order algorithms).

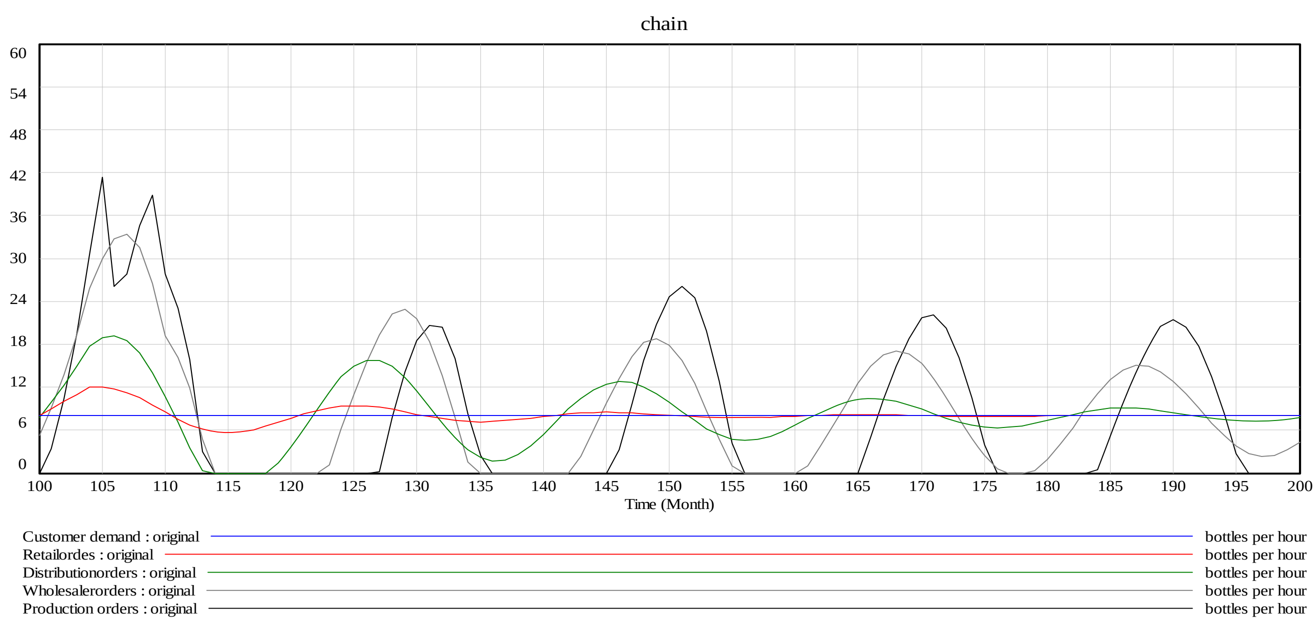

Figure 2. Forrester effect (delay = 4, step-wise demand change from 4 to 8 units during time unit 100).

It may be observed from previous research that conventional forecasting methods do not reduce negative impact from demand amplification. As shown in Figure 3, classical forecasting techniques such as exponential smoothed moving average (EWMA) only heightens demand amplification (highest value reaches above 50 units per time period) due to the assumption that all previous values should be used to predict demand. Although, use of EWMA may be justified under certain circumstances, the non-discriminatory or mandatory use of past data to predict future demand may often generate an undesirable over-reaction.

Figure 4 reveals implementation problems for sharing of demand information. Often different supply chain phases use different competing suppliers to gain cost efficiency and true demand is often confidential. Lam and Postle (2006) describe 60% of respondents in a survey (in China) indicating that their customers are not willing to exchange information. Sharing data about high demand periods could result in inflated purchase price if suppliers decide to form cartels. However, it has been shown in a signaling game theoretic approach that sharing of information increases total supply chain profit (Datta 2004).

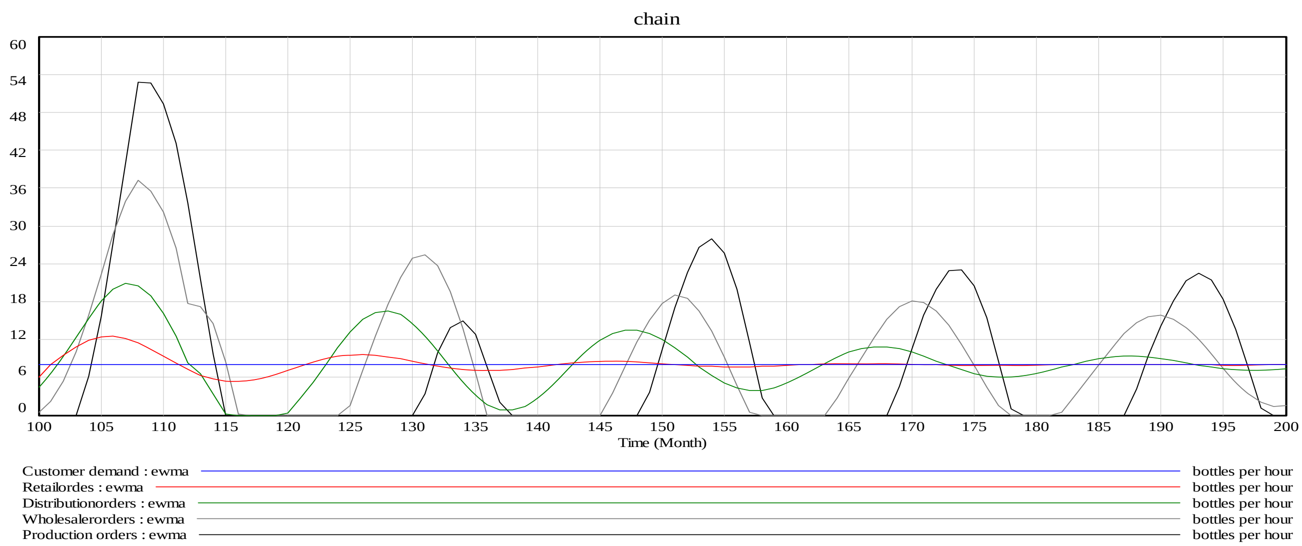

Figure 3. Forrester effect in a supply chain as it tries to use EWMA at local level (0.5 weight) within original setting (delay = 4, step-wise demand change from 4 to 8 units during time unit 100).[1]

[1] Juha Saranen, Lappeenranta University of Technology, Finland.

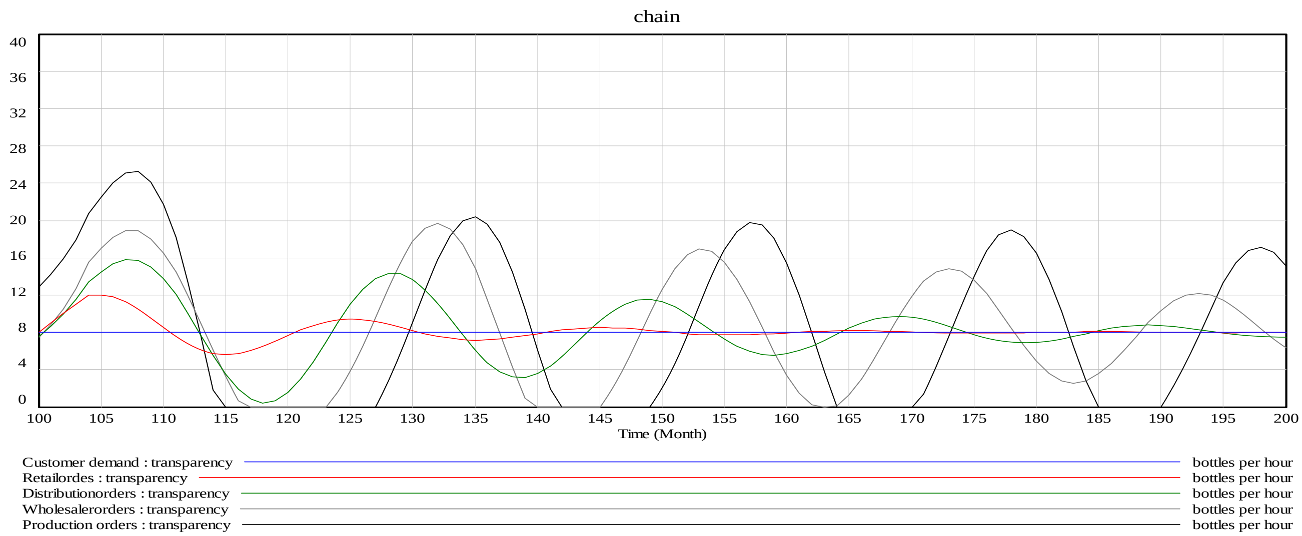

Figure 4. Forrester effect in four stage supply chain, where we have transparency for the next stage (delay = 4, step-wise demand change from 4 to 8 units during time unit 100).

In previous and current work, we suggest that improving forecasting accuracy could be profitable by using advanced forecasting methods, such as autoregressive moving average (ARMA) models. Figure 5 shows that demand forecasting in an amplified environment may be completed by assigning a positive value for last observed demand and a negative co-efficient for older observations (we have used lag of one and two).

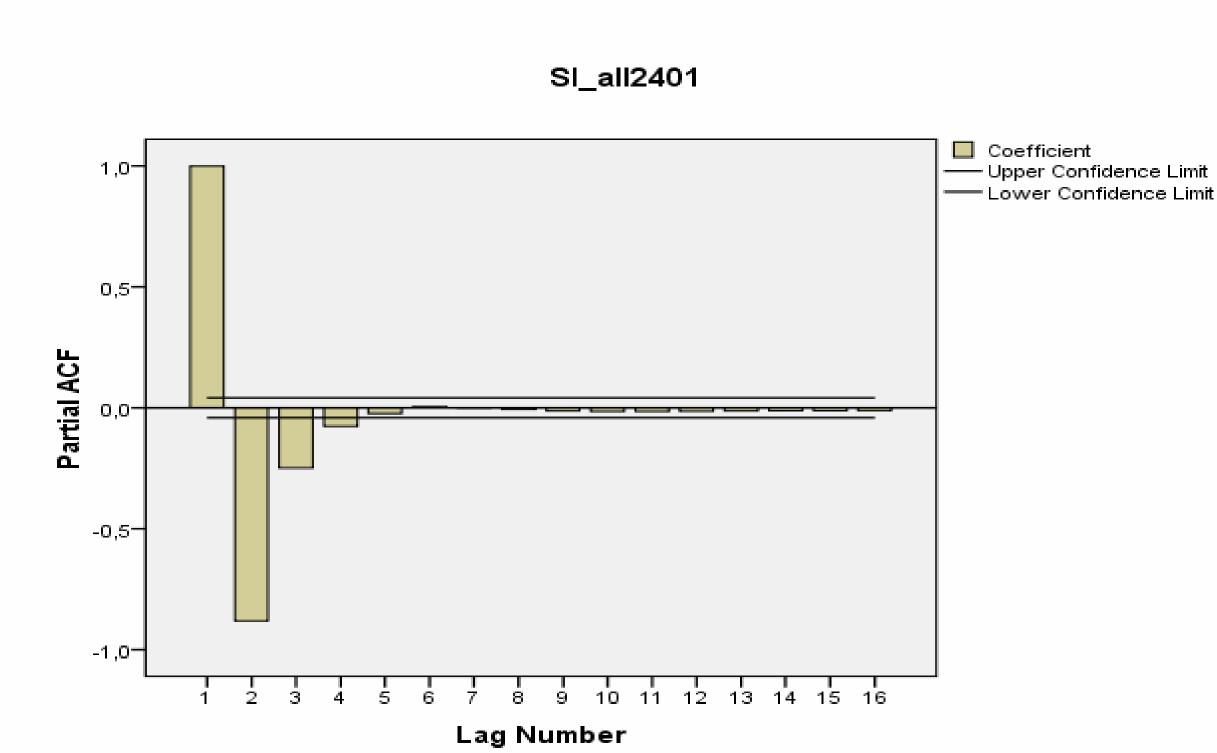

Figure 5. Partial autocorrelation of four stage supply chain data from production phase (2401 observations from 300 time units).

Table 2. ARMA models built with 0.125 interval data from original beer-game setting for production phase (number of observations in integer time units given in parenthesis).

	Co-efficient		Goodness of fit	
Number of observations	t – 1	t – 2	R2	R2 whole sample
100 (12.5)	1.936	-0.938	99.8 %	99.97 %
200 (25)	1.937	-0.939	99.9 %	99.97 %
300 (37.5)	1.937	-0.939	99.9 %	99.97 %
2401 (300.1)	1.918	-0.919	100.0 %	

Table 2 shows co-efficient of two lagging parameters are within the neighborhood of ARMA models built with a larger amount of data. However, the differences among different models are rather minimal.

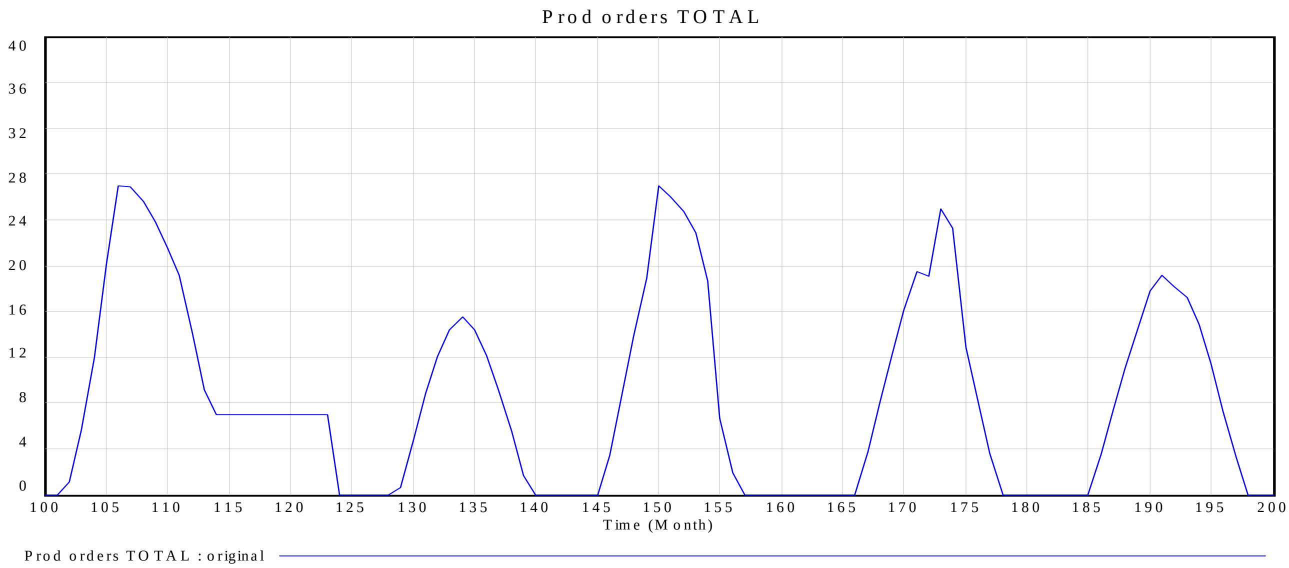

Figure 6. Production orders as ARMA model of wholesaler demand is used in production orders with modifications on operating structure.

Applying advanced forecasting models to tame the Bullwhip effect is challenging because it calls for process transformation (Zhao *et al* 2002, Bayraktar *et al* 2008). In Figure 6 the manufacturing unit reserves forecasted amount of inventory one period before-hand (in order to distribute knowledge from future demand into operative decisions). However, this is not enough. We have used another manufacturing unit, which serves as an emergency inventory, dedicated for sudden upswings of demand. This emergency inventory is served with local short response manufacturing, which continuously replenishes emergency inventory with low lot size (in this case lot size is 7 units, lead time to emergency inventory is 1 time unit, instead of 4). During simulation trials we explored how ARMA model may be built within dynamic environments with respect to time.

4. Advanced Statistical Models

Forecasting demand is a key tool in managing uncertainty. Forecast accuracy depends on the understanding and coverage of parameters as well as the accuracy of historic data available for each variable that may have an impact on the forecast or predictive analytics. The broad spectrum applicability of forecasting includes such diverse verticals as healthcare and energy [2] utilization.

One of the assumptions in the Classical Linear Regression Models relates to homoskedasticity (homo ≈ equal, skedasticity ≈ variance or mean squared deviation (σ^2), a measure of volatility) or constant variance for different observations of the error term. Forecast errors are heteroskedastic (unequal or non-constant variance). For example, in multi-stage supply chains, the error associated with manufacturer's forecast of sales of finished goods may have a much larger variance than the error associated with retailer's projections (the assumption being that the proximity of the retailer to the end consumer makes the retailer offer a better or more informed forecast of future sales through improved understanding of end-consumer preferences). The upstream variability reflected in the Bullwhip Effect violates the basic premise of CLRM, the assumption of homoskedasticity. CLRM ignores the real-world heteroskedastic behavior of the error term ε_t and generates forecasts, which may provide a false sense of precision by underestimating the volatility of the error terms.

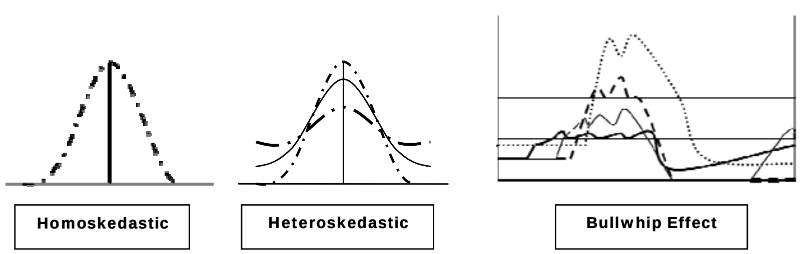

Figure 7. Illustrations pf homoskedasticity, heteroskedasticity and the Bullwhip Effect.

In a homoskedastic distribution, observations of the error term can be thought of as being drawn from the same distribution with mean = 0 and variance = σ^2 for all time periods (t).

[2] See www.cids.ie/Research/DCSES.html

A distribution is described as heteroskedastic when observations of the error term originate from different distributions with differing widths (measure of variance). In supply chains, the variance of orders is usually larger than that of sales and the distortion increases as one moves upstream from retailer to manufacturer to supplier. Therefore, the assumption of heteroskedasticity, over time, seems appropriate as a characteristic that may be associated with demand amplification or the Bullwhip effect.

While variance of error term may change across cross sectional units at any point in time, it may also change over time. This notion of time varying volatility is frequently observed in financial markets and has been the driving force behind recent advancements in time series techniques. These advances from econometrics may be developed into tools for forecasting and risks analytics with a broad spectrum of applications in business, energy, industry, security and healthcare (Datta 2008d), as well as decision support systems and operations management, for example, supply chain management (Datta *et al* 2007).

Impact of Real-Time High-Volume Data from Automatic Identification Technologies (AIT)

Tracking technologies evolved from the discovery of the RADAR at MIT in the 1940's. AIT is slowly beginning to impact information flow in the modern value chain network. Tracking products from manufacturers to retailers may have its origins in the 1970's with the introduction of the bar code to identify stock-keeping units (SKU). Now it is embracing AIT or auto id, for example, use of radio frequency identification (RFID). AIT makes it possible to electronically log product movement in the "digital" supply chain. This information may be available in real-time. However, the standards, such as the electronic product code (EPC), to capture unique identification of physical objects and processes (Datta 2007a) calls for a paradigm shift (Datta 2008c).

Since RFID updates reports every time an individual item or SKU moves from one stage to another stage in the supply chain, or when the item is sold, it is possible to determine the demand for an item in *real-time* rather than wait for batch updates or weekly or monthly buckets to generate a forecast. The granularity of the data from auto id systems may result in very high volume data which may reveal peaks and troughs of demand for the product, hourly or daily. This volatility is lost when data is aggregated in buckets or batch.

Extracting the value from this high volume near real-time data and deciphering the meaning of the implicit volatility may be a boon to business intelligence and predictive analytics, including forecasting.

Indeed many warehouses adopt an inventory policy of ordering products when stock levels fall below a certain minimum amount *s* and order up to a maximum amount *S* [the *(s, S)* policy]. With auto id it is possible to ascertain this at the instant the threshold is attained, thereby, eliminating the likelihood of out of stock (OOS). Hence, it follows that capitalizing on the increased volume of near real-time demand data from auto id may have profound impact on supply chain forecasting.

However, current software with its CLRM engines and clustering approach, does not improve forecasts even with high volume data. The assumption of error terms implicit in CLRM limits the gains in forecast accuracy from high volume data and fails to show return on investment (ROI) from adoption of (new) auto id tools.

It is our objective to justify why deployment of new tools, for example, auto id, calls for adoption of new techniques for data analytics, for example, advanced techniques from financial econometrics. It is safe to state that new streams of data emerging from a multitude of sources, for example, auto id and sensors, cannot yield value or ROI if used in conjunction with archaic software systems running ancient forms of analytical engines that are typically CLRM based, at least, in the forecasting domain.

To extract decisionable information from high volume near real-time auto id and sensor data, the use of techniques like GARCH deserves intense exploration. The fact that GARCH may be a clue to generating ROI from auto id and RFID data is no accident because GARCH *requires* high volume data to be effectively utilized and generate results with higher accuracy levels. Hence, this convergence of auto id data with tools from econometrics may be an innovative confluence that may be useful in any vertical in any operation including security and healthcare, as well as obvious and immediate use in supply chain management. Datta *et al* 2007 and this chapter, has attempted to highlight how to extract the advances in econometrics from the world of finance and generalize their valuable use in decision systems, with a broad spectrum of general applications.

Evolution of such a tool may help analysts and planning managers since a key concern of any manager is the accuracy of the predictions on which their budget is based. The proper allocation of resources for acquisition of personnel and equipment has long been plagued by errors in traditional forecasting. A part of the answer to this problem may be latent in the potential for the combined use of VAR (vector autoregression) with other forecasting techniques. The primary VAR model best suited for the planning function in resource allocation is the standard GARCH model. It is well suited for pragmatic studies involving supply chain, army personnel requirements and defense equipment requirements. Any system that may be modeled using time-series data, may explore how to include GARCH based on the error correction innovation that may improve forecasts. Forecast accuracy of GARCH model may be quantified in a number of different ways. Traditional methods are:

1. Mean Square Error
2. Mean Average Percentage Error
3. Aikiki Information

Once the forecast is developed, the accuracy can be measured by comparing the actual observed values with the predicted values. If the collected data falls within the confidence interval of the forecast model, then the model provides a good fit for the system. Although GARCH is useful in forecasting it is important to realize that it was designed to model volatility and can be applied to positive series but not to economic series.

GARCH Proof of Concept: (a) Spare Parts Inventory Management

Although GARCH models have been almost exclusively used for financial forecasting in the past, we propose (Datta *et al* 2007b) that with appropriate modifications, it may be applicable to other areas. An operation exhibiting volatility may benefit from VAR-GARCH in addition to other techniques, either in isolation or in combination. It is known that in times of conflict military supply chains experience spikes in demand. These spikes and troughs occur over a short period of time and result in losses due to OOS (out of stock) or surplus. GARCH may minimize forecast errors and fiscal losses in some of the following domains:

1. Cost of personnel, supplies, support
2. Planning, programming and budgeting
3. Defense program and fiscal guidance development
4. Force planning and financial program development

In one preliminary study (supported by the US DoD, Institute for Defense Analysis, Washington DC and also mentioned in Datta *et al* 2007) the spare parts supply chain of a military base was examined for inefficiencies. The data for a 9 month period was collected for a spare part for a military vehicle (HumV). Because the US Department of Defense affixes RFID tags on some spare parts from some of its suppliers, the hourly auto id demand data was available for analysis. The historical data was used to develop CLRM and GARCH (1,1) model. In this case, the linear regression model was found to have Mean Square Error (MSE) of 0.20 (20%). By comparison, the GARCH (1,1) model produced a MSE of 0.06 (6.7%). These results are encouraging and the US DoD case lends credibility for exploration of GARCH in forecasting analytics. Although this finding is promising, it needs to be repeated with other forms of data and subjected to rigorous mathematical analysis.

GARCH Proof of Concept: (b) Retail Inventory Management

A pilot implementation using GARCH in a commercial supply chain has been undertaken with real-world retail data from a major US retailer. Preliminary results reveal that using GARCH as a forecasting technique offers some advantages (even with limited data volume) compared to CLRM and ARMA. The retail data are from office supply products for business and home office customers. Thousands of product lines are sourced from different suppliers, globally. In this study, nine different SKU's from three different product classes were chosen for analysis. It is possible that some of the products may suffer from seasonality effects. For each of the 9 products the historical demand data is available for 70 continuous weeks. 52 weeks of history was used to develop projections of demand variability for the subsequent 18 weeks. This projection was compared to the actual observations of demand variability over the 18 week test horizon. Three different techniques were used to forecast the standard deviation. The methods used were CLRM, ARMA and GARCH (Datta *et al* 2007).

Figure 8 shows the performance of each of the three forecasting techniques based on retail data on the 9 products. The error of the forecasted standard deviation is calculated as an average over the final 16 weeks of forecast data. CLRM is outperformed by ARMA and GARCH models for almost all SKU's.

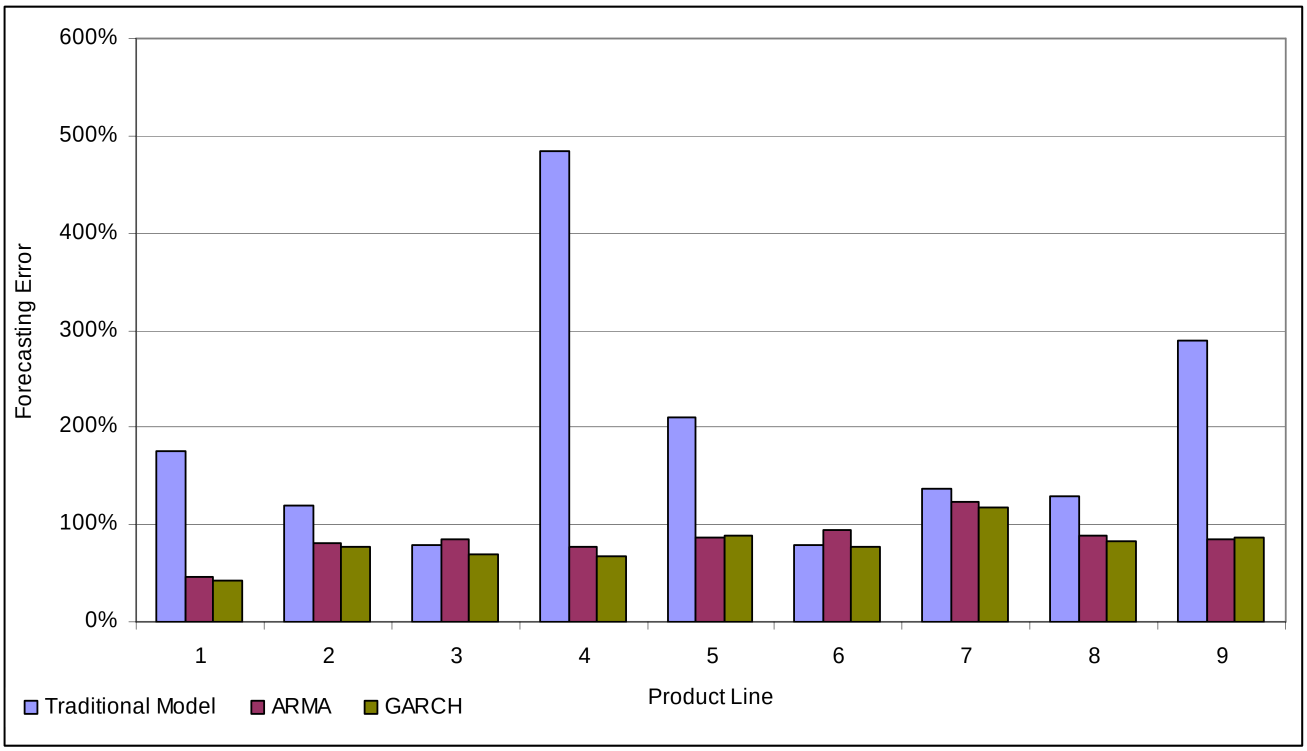

Figure 8: Classical Linear Regression Model (CLRM) is almost always outperformed by ARMA and GARCH tools.

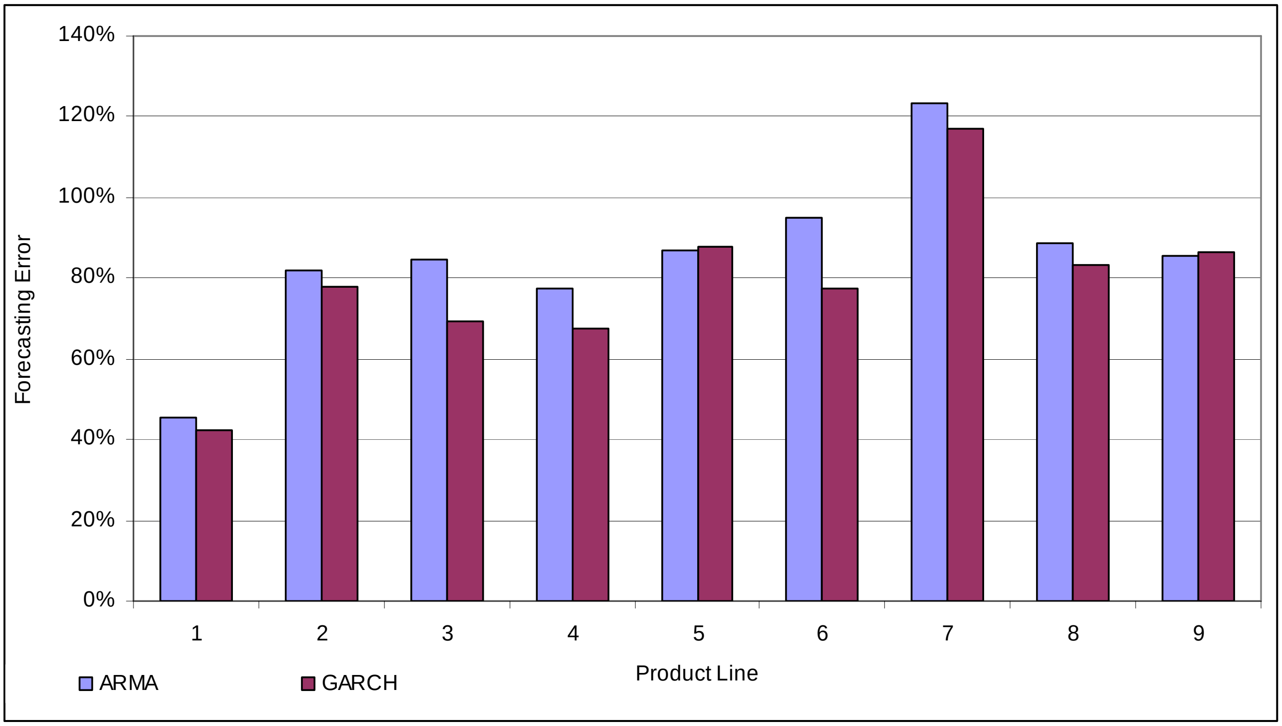

Figure 9: Comparing autoregressive techniques: ARMA vs GARCH (same data set but excluding CLRM)

The results suggest that GARCH may be better (or as good as) across different SKU's. GARCH outperforms ARMA for a number of products. For the eight favorable tests, an average improvement of 800 basis points was observed. The product-dependent variability of GARCH performance may be linked to seasonality or other factors (accuracy of input data). Further testing with granular data (hourly or daily) and higher volume data per SKU may increase the accuracy and benefits from using the GARCH technique in forecasting.

It is not difficult to extrapolate that high volume item level retail sales or inventory data (per minute or by the hour) may be available with the diffusion of item level tagging using RFID or radio frequency identification tags. The volume of the data may increase exponentially if embedded sensors are deployed to enhance security and/or detect movement of any physical object from any location. Businesses dealing with short life cycle products (electronics, semi-conductor industries) may explore how these advanced techniques may help to reduce the volatility of supply-demand since the ability to re-address sales or marketing issues are often limited if the shelf-life of the product is merely a matter of a few months (laptops, MP3 players, cell phones).

5. Temporary Conclusion

Making sense of data may benefit from high volume data acquisition and analysis using GARCH and VAR-MGARCH (Datta *et al* 2007) techniques in addition to and in combination with other tools for forecasting and risk analysis. In this work, we explored the possibility of using advanced forecasting methods in a context of supply chains. It remains unexplored if concomitant business process transformation may be necessary to obtain better results. The proposed advanced forecasting models, by its very construction requires high volume data. Availability of high volume data may not be the limiting factor in view of the renewed interest in automatic identification technologies (AIT) that may facilitate acquisition of real-time data from products or objects with RFID tags or sensors. Although speculative, it stands to reason that use of advanced forecasting methods may enhance profitability from IT investments required to acquire real-time data. However, understanding the "meaning" of the information from data is an area still steeped in quagmire but may soon begin to experience some clarity if the operational processes take advantage of the increasing diffusion of the semantic web and organic growth of ontological frameworks to support ambient intelligence in decision systems coupled to intelligent agent networks (Datta 2006). To move ahead, we propose to bolster the GARCH proof of concepts through pilot implementations of analytical engines in diverse verticals and explore advanced forecasting models through integration with real-world business data, processes and systems.

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