A New Approach for Forecasting Demand of Functional Products

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Summary: For functional products, which have more stable and predictable demand, it is desirable to have a physically efficient supply chain; whereas, for innovative products, due to the volatile and unpredictable nature of demand, it is desirable to have a responsive supply chain. With ever-changing demand, presence of bullwhip effect, and fluctuating raw material prices, it has become imperative to continuously improve the efficiency of supply chain of functional products by reducing costs. One of the ways to reduce costs in supply chain is to have a better forecast of future demand. This research explores the impact of machine-learning based forecasting approaches on the efficiency of supply chains. We, specifically, looked at three efficiency metrics, viz. forecast accuracy, inventory turns and cash-conversion cycle, to measure supply chain efficiency, and found that the machine-learning based forecasting approaches have a statistically significant improvement in the supply chain performance of functional products when compared with traditional forecasting approaches. We used steel products as a representative of functional products to demonstrate our results.

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KEY INSIGHT

- Machine-learning based forecasting approaches provide statistically significant improvement in the efficiency of supply chains for functional products, when compared with traditional time-series based forecasting approaches. The context of this study is steel products of Jumbo Steel (pseudonym).
- A hybrid forecasting model, combining Neural Network and ARIMAX techniques, performed the best. ARIMAX was good at predicting the peaks, and Neural Networks were good at predicting the small fluctuations in demand.

Introduction

Jumbo Steel is a global steel manufacturing company with global sales and operations in more than a dozen countries with a large employee base. The company made about USD 10 billion in revenue in FY2016-17. Jumbo Steel is one of the largest manufacturers of painted and coated steel products, having strong partnerships with several product brands with uses in building, roofing and walling solutions. It manufactures a wide range of products for construction, building, automotive and manufacturing applications. Some of its major products are coated and painted steel coils for roofing applications, home-appliance steel, and engineered building products. Jumbo Steel has a huge presence in the Asia-pacific region, and have seen strong market growth in ASEAN region in the last few years. In ASEAN, they have operations in Thailand, Malaysia, Indonesia and Vietnam. Thailand is the biggest market of Jumbo Steel in the ASEAN region in terms of annual sales revenue.

Research Objective

Steel products typically fall under the category of "functional" products. Functional products are those that satisfy basic needs and characterized by long life cycle, less product variety, stable and predictable demand, low profit margins, and low inventory risk. With the growth in the region, the company expanded into a retail market segment. This segment is characterized by standardized products and operates within a make-to-stock (MTS) supply chain. The key decision in this case is to know how much of each standardized product to produce. This decision is made in the short-term planning horizon and the demand forecasting has to be accurate to the product family or individual SKU level. Since the demand of functional products can be effectively predicted using the historical data, machine learning techniques, with their ability to learn and improve from the experience or the data they are exposed to, may find a good application in further improving the efficiency of supply chain of functional products. Based on the observational data gathered from Jumbo Steel, we focus on forecast accuracy, inventory turns and cash-conversion cycle as the three supply chain performance metrics and estimate the effects of machine learning techniques on these metrics. In lieu to this, the key question that we aim to answer with this research is – what and how much is the effect of machine-learning enabled demand forecasting methods on functional products' supply chain performance, in terms of forecast accuracy, inventory turns and cash-conversion cycle?

Literature Review

The ultimate goal in any supply chain is to ensure supply is matched with demand (Fisher et al, 1994; Sasser, 1976). For functional products, the demand prediction which was largely based on expert judgments and heuristics earlier, has steadily matured into a science of its own with the evolution of sophisticated tools and techniques bolstered by increased computational power and advances in information technology. For innovative products, expert forecasts and heuristics are still valuable to make a prediction of future sales. Many studies recognize forecasting as a tool of significant capability and management practice (Armstrong, 1987; Cox, 1987, 1989; Fildes, & Hastings, 1994; Makridakis & Wheelwright, 1977; Mentzer & Gomes, 1994; Sanders & Manrodt, 1994; Wright, 1988).

Chambers et al (1971) elaborated three major categories of forecasting techniques: qualitative, time series data-based, and causal models. Functional products which are more like commodity, are much more suitable for quantitative time-series based models and need very little judgment to forecast demand (Fisher, 1997). As far as steel as a functional product is considered, Xuan and Yue (2016) highlight several approaches in use for demand forecasting in the steel industry. The most common approach is econometric analysis (Linda, 2014; Gao and Wang, 2010; Olsson 2008), which considers steel demand to be driven by macroeconomic factors like GDP per capita.

Traditional demand forecasting approaches can use only a handful of factors that affect the demand to make a forecast. Some of these factors are trends, seasonality, cyclicity, etc. On the other hand, machine learning based forecasting approaches can combine AI learning algorithms with big data to analyze and account for unlimited amounts of causal factors simultaneously (Chase, 2017). Several researches have been conducted to identify the best forecasting approach for functional products. Some of these approaches use time-series based forecasting, while others use multiple variables, including macroeconomic indicators along with historical time series data. There is still little knowledge on the effectiveness of machine learning based forecasting approaches on the supply chain performance. In this research, we aim to bridge this gap.

Methodology

The retail market segment Thailand business unit (BU) of Jumbo Steel is the fastest growing market segments within the company globally, growing at the rate of over 5% by volume year-over-year. It is characterized by many product types which are representative of entire Jumbo Steel product portfolio. The majority of the steel products for this BU are Make-to-Stock, i.e. standardized products. Therefore, such a pilot study will be a good candidate to later generalize the results for functional products overall.

Data collection

Jumbo Steel operates in four different market segments, viz. Retail, Project, Manufacturing and Home Appliances, each having different characteristics that impact the demand. We collected the historical sales data of Jumbo Steel in the Thailand market for the four market segments. The frequency of the data was monthly, and the range was last six years (year 2012 to 2017).

The macroeconomic data in this research is collected from the Global Economic Monitor database of World Bank. This database lists out various economic indicators, per region or country, such as consumer prices, high-tech market indicators, industrial production and goods and services trade. We collected this data for Thailand to study the influence on demand forecast for that country. The database consisted of monthly value of 30 macro-economic indicators for the last six years (2012-2017).

To calculate some of the financial and supply chain performance metrics information, we collected the data from their yearly financial reports. One limitation of this source of information is that the financials for Jumbo Steel are reported on a global basis, and not for individual business units. For this research, since our business unit of interest was Jumbo Steel (Thailand), we translated the financial figures (i.e. sales, COGS, etc.) from global to Thailand using the ratio of sales volume of steel they sold.

As discussed above, the observational data collected from Jumbo Steel is linked to their supply chain performance while using the traditional forecasting approaches. To make an effective comparison, we needed to generate their financial and supply chain performance data in case they had used the machine-learning forecasting approach. The data is generated for the same period as their collected observational data. To generate this data, we have used the following steps:

- Collect global financial performance information from financial reports database

- Convert global revenue to Thailand BU's revenue using ratio of sales volume

- Calculate observed inventory levels, receivables, payables for Thailand BU are generated using same ratio to revenue as global data. For example, the ratio of inventory-to-revenue of Thailand BU is same as ratio of inventory-to-revenue of global business

- Use the observed inventory levels to calculate observed values of IT and CCC

- Generate inventory levels based on accuracy of each of new forecast approaches. The type of forecasting approaches used are discussed in the next section.

- Use the generated inventory levels to calculate values for IT and CCC for each of the forecast approaches.

While we perform our study on steel products of Jumbo Steel, we would like to understand the effect of different forecasting approaches on the general category of functional products. Therefore, we formulate the following null hypothesis:

H0: Compared with traditional time-series based forecasting approaches, machine-learning based forecasting approaches have no significant improvement in the efficiency of supply chain.

With our analysis, we found that we can reject this null hypothesis. The details are provided in the results section.

Results

The observational data in the form of historical sales of Jumbo Steel exhibits trend and seasonality patterns. The selection of traditional forecasting approaches is based on their ability to handle such time-series related factors and generate forecasts. The two traditional forecasting approaches that were selected were Holt-Winter's method and damped trend method.

The machine learning based forecasting approaches can take into account many factors due to their ability to handle complex interdependencies and non-linearity. The three shortlisted macroeconomic indicators, viz. core CPI, foreign reserves and terms of trade, are also used along with the historical sales to create forecast models. The selected modelling techniques to develop the forecast models are ARIMAX and feed forward back propagation Neural Networks (NN). While ARIMAX is a linear modeling technique, NN is able to take into account the non-linearities in dependant variables.

The following table summarizes the forecast accuracies from the different forecasting approaches used in the study.

Method	Forecast Accuracy
Damped Trend	81.3%
Holt-Winter's	84.1%
ARIMAX (1,1,0)	88.9%
ARIMAX (3,0,0)	89.1%

NN (5,2)	89.4%

To test the hypothesis on effect of forecasting approach on supply chain performance, we have built regression model as follows:

$$Y = a + bX + e$$

Where Y is the supply chain performance indicator (forecast accuracy, inventory turns and cash-conversion cycle), a is a constant, X is a binary variable which is 0 when traditional forecasting approach is used and 1 when machine learning based forecasting approach is used, b is the coefficient of variable X, and e is the i.i.d. error term. For our null hypothesis to be true, coefficient b would have to be zero.

From our analysis, we found that a, $b \neq 0$ at 95% significance level, which proves that machine-learning based forecasting approach improved the forecast accuracy, inventory turns and cash-conversion cycle of Jumbo Steel. The table below summarizes our findings.

SC metrics	Observed	Traditional time-series based	Machine-learning based
Forecast accuracy	50-60%	81-84%	88-89%
Inventory turns	1.29	1.41	1.46
Cash-conversion cycle	262.9	243.5	241.3

Conclusion

The direct measure of any forecasting approach is the forecast accuracy. In this study, we used two traditional time-series based and three machine-learning based forecasting based forecasting approaches. From the regression results, it is evident that the machine-learning methods perform better than the traditional time-series based methods for predicting demand of functional products. The improvement is around 6.4% on average. Better forecast accuracy will lead to better planning in supply chain, which will enable firms to reduce costs, such as inventory costs and manufacturing costs, and thus improve efficiency.

As another measure of efficiency of supply chains, we looked at two other metrics, one financial and one non-financial. The financial metric we evaluated was cash-conversion cycle (CCC). Based on our hypothesis testing, we conclude that using traditional quantitative forecasting approach (Holt-Winter's method in this study), Jumbo Steel could reduce their cash conversion cycle by around 19 days. This is largely impacted by the reduction in Days of Inventory Outstanding (DIO) due to improved forecast accuracy of Holt-Winter's technique from the observational forecasting method currently used by Jumbo Steel. Since the machine-learning based forecasting approach (ARIMAX and NN) had even better forecast accuracy than the traditional Holt-Winter's technique, the reduction in DIO in this case was more than 21 days from the baseline. A reduction in the cash conversion cycle has a direct impact on improving the working capital of any business. A higher working capital is an indicator of a better financial health of any firm.

The other non-financial metric we looked at was Inventory Turns (IT). As with CCC, our hypothesis testing revealed that using traditional forecasting approach (Holt-Winter's method) improved the IT by 0.12 turns, while the machine-learning based forecasting (ARIMAX and NN) approach improved the IT by 0.17 turns from the baseline. Higher IT means the firm is able to manufacture and sell the inventory faster over a period of time. Low IT means there is inefficiency in the supply chain as the firm has to incur holding costs of excess inventory.

Bullwhip effect (BE) is another cause of inefficiency in supply chains. BE is more prevalent toward the supplier and manufacturer end of the supply chains. Several past studies demonstrate that machine learning based forecasting approach will help to reduce the costs in supply chain, especially in cases where it is difficult for parties to collaborate and freely exchange the information. Through our study, we have provided a quantitative proof that machine learning based forecasting approaches do improve the supply chain performance in the case of Jumbo Steel, who was faced with distorted demand as was evident from the observational data.

Limitations and future work

In this research, we used steel products as a representative of functional products. We propose to include other commodity-type standardized products in a similar study to make a much broader claim. The impact on efficiency of supply chain performance can also be extended to other metrics such as fill rate, service level, etc. A similar study could be performed on the effect of machine learning based forecasting approach on innovative products. The forecasts made for such products currently rely very heavily on expert judgements. The research could be guided towards understanding how these expert decisions can be "learnt" by the ML technique to generate accurate forecasts.

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