ANALYSIS OF THE PATTERN AGGREGATION IMPACT ON THE DEMAND FORECASTING

Diana Božić, Ratko Stanković, Goran Kolarić

1. INTRODUCTION

In the basic form, a supply chain consists of a company with its suppliers and customers [1]. Extended supply chains have more participants, such as supplier's supplier, service providers, and customer's customer.

Upwards and downwards the supply chain structure, a significant discrepancy in customer demand information between different stages occurs. This phenomenon is known as bullwhip effect or Forrester or whiplash effect [2],[3].

Producers and other participants want to avoid disturbances in their business plans, especially when dealing with short shelf life inventory. For this reason, the right order quantity must be determined, to meet the business plan the best way.

This can be achieved by implementing adequate forecasting method and to periodically verify if the method yields the expected results with reference to the respective demand pattern. The main problem involved is aggregation of demand patterns acquired from different sources.

This paper deals with different time series forecasting methods, and models of demand patterns aggregation used by the respective method.

2. MITIGATING DISTORTION IN SUPPLY CHAIN

Managing supply chain requires trade-offs between efficiency and effectiveness of the participants involved. This can be seen in logistics operations planning which among other issues deal with maintaining the right balance among production, inventory and distribution [4]. Those decisions are based on forecasts that define which products will be required, what amount of these products will be called for, and when they will be needed.

Demand forecasting becomes the basis for mitigating distortions and is used by companies to plan their internal operations and to cooperate among each other to meet market demand. All forecasts deal with four major variables: supply, demand, product characteristics and competitive environment. They combine to determine
what market conditions will be like [1]. Supply is determined by the number of producers of a product and by the lead times that are associated with a product while demand refers to the overall market demand for a group of related products or services. Product characteristics include the features of a product that influence customer demand for the product while competitive environment refers to the actions of a company and its competitors.

When they use this order data to do their demand forecasts, they just add further distortion to the demand picture and pass this distortion along in the form of orders that they place with their suppliers. It represents the phenomenon where orders to supplier tend to have larger variance than sales to the buyer, and customer demand is distorted. This demand distortion also propagates to upstream stages in an amplified form. In return, high inventory levels and poor customer service rates along the supply chain constitute typical symptoms of bullwhip effect. In addition, production and inventory holding costs as well as lead times increase, while profit margins and product availability decrease [5].

Research into the bullwhip effect has identified five major factors that cause the effect: demand forecasting, order batching, product rationing, product pricing, and performance initiatives [1], [5]. These factors interact with each other in different combinations but the net effect is that they generate the wild demand swings. Most of the scientific papers researching bullwhip effect agree that demand forecasting is one of the main causes of this effect [2], [7], [8], [9]. Researchers are mostly examining the influence of different forecast methods such as Moving Average (MA), Exponential Smoothing (ES), Minimum Mean-Squared Error (MMSE), Holt’s and Brown’s methods and kernel regression, in combination with different inventory policy and lead time, on bullwhip effect [2], [7], [8], [9]. In those studies, the same forecast methods for all participants in a supply chain are assumed, using summarized demand data.

3. DESCRIPTION OF THE OBSERVED PROBLEM

In this research, one company acting as the main distributor for East Europe was chosen. The company distributes 38 different medical supplements, from factories in US to wholesalers and retailers. Beside physical distribution, the company has a web shop, selling directly to final customers. The following problems were observed:

- related to factory, raw materials for a medical product are expensive and have a short shelf life;
- factory does not want to hold inventory, neither tolerate big disturbance in supply line or production;
- risk of lost sales or high inventory are on distributors or wholesalers side;
- factory asks sellers to plan quantity for each product at least three months in advance and gives option for the sellers to periodically modify quantity.

Each participant in supply chain has different demand pattern. To solve this problem the company can:

- forecast demand based on summarized sales information (customers data) using any of the forecasting methods;
- summarize forecasted demand values against each customer.

Relationship between trading partners in supply chain is shown in Figure 1.

In supplying the market, the company deals with four wholesalers (WS1, WS2, WS3, and WS4). Beside the contract with the wholesalers, the company sells products directly to retailers and final customer (consumer). So, it is a combination of a four-stage (trading via wholesaler), a three-stage (selling directly to retailer) and a two-stage supply chain (selling directly to consumer).

The order decision system comes from expected demand, upstream. A distributor collects orders from each trading partner and makes its own estimation of market expected demand ($E_{DD}$). According to its own inventory policy, distributor is holding safety stock ($SS_D$) which is equal to forecasted demand in the observed period. Lead time from factory to distributor is two weeks and is continued, while distribution time from distributor to wholesaler, retailer or consumer is fixed, one day. Selling product has shelf life of one year. The order quantity plan is sent to the factory every three months. Final orders to factory are made once a month, or every four weeks.

Final order to factory ($Q_{off}$) is defined as:

$$Q_{off} = E_{DD} + SS_D$$

(1)

$$E_{DD} = E_{WS1} + E_{WS2} + E_{WS3} + E_{WS4} + E_{R1} + E_{R2} + \ldots + E_{Rn} + E_{webshop}$$

(2)

The factory is creating a production plan, which by their business policy must equal demand in the observed period. Total production quantity $Q_{(p)}$ is obtained by the following equation:

$$Q_{(p)} = Q_{off} + (CS - OS)$$

(3)

Here $CS$ represents closing stock at the end of the month and equals demand in the month. Quantity of $CS$ on distributor side is equal to $SS_D$, $OS$ is opening stock at the beginning of the month and is equal to its closing stock in the previous month.

Figure 1. Graphical presentation of the observed production-distribution system
3.1. Analyses of the observed solutions

Retailers and web shops demand is disregarded at the first step of the demand pattern analysis.

What was examined as first was the distortion value without the distributor’s forecasting demand intervention involved. Wholesalers are making their own independent demand forecasting, and the distributor is summarizing quantities and makes orders to the factory.

In Figure 2, an example of orders placed by trading partner is shown, illustrating the bullwhip effect. What can be noticed is that bullwhip effect is present, as expected. The factory has to stop production every two months which brings into question setup cost as well as holding cost of inventory on factory side.

Figure 2. Example of orders placed by trading partner illustrating the bullwhip effect

When the distributor collects orders from wholesalers, he can use two different approaches to create order to the factory. One is to use one forecasting method based on summarized demand data of wholesalers. Another one is to forecast the demand by each wholesaler, and then to summarize values and create an order. In Figure 3 the first case is presented, and in Figure 4 the second one.

Figure 3. Forecasted demand based on summarized order data

Forecasted demand based on summarized order data (Figure 3) was calculated by applying ARIMA. In Figure 4, demand 1 and production 1 present values forecasted by the forecasting method that best suits wholesales demand pattern data. Demand 2 and production 2 show values forecasted by Double Moving Average, as this method was highly ranked for all the observed demand patterns. By analyzing disturbance in supply line based on Figures 3 and 4, it can be concluded that if it is not possible to find the best forecasting method for each demand pattern, orders made from forecasting using summarized data create less disturbance.

Figure 4. Summarized values of forecasted demand by each wholesaler

To find a forecasting method that best suits the demand pattern, it is necessary to constantly monitor changes in demand and to customize methods in use. For the observed problem, few time series forecasting methods were checked and methods were ranked by the forecast accuracy.

When analyzing each wholesaler demand pattern it can be seen that the forecasting method which gives better results by each wholesaler is different. Methods by ranks are shown in Table 1.

As shown in Table, the methods differ, and it is not easy to make decision which method to use, especially with seasonality.

In Table 2, the rankings of forecasting methods by RMSE (Root Mean Square Error), MAD (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error) are shown when forecasting is done using data as the sum of all the wholesalers demands. What must be noted here is that only historical data for two years are used for forecasting. Availability of data issue influences the

Table 1: Methods ranks for wholesaler demand pattern

<table>
<thead>
<tr>
<th>Rank</th>
<th>Method</th>
<th>RMSE</th>
<th>MAD</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Single Moving Average</td>
<td>17.61</td>
<td>13.61</td>
<td>72.45%</td>
</tr>
<tr>
<td>2</td>
<td>SARIMA(1,0,1)(1,0,1)</td>
<td>30.78</td>
<td>24.92</td>
<td>24.23%</td>
</tr>
<tr>
<td>3</td>
<td>Double Moving Average</td>
<td>14.07</td>
<td>12.03</td>
<td>20.63%</td>
</tr>
<tr>
<td>4</td>
<td>Double Moving Average</td>
<td>35.79</td>
<td>28.76</td>
<td>67.44%</td>
</tr>
<tr>
<td>5</td>
<td>ARIMA(2,1,2)</td>
<td>37.82</td>
<td>30.05</td>
<td>65.60%</td>
</tr>
<tr>
<td>6</td>
<td>SARIMA(0,0,1)</td>
<td>22.96</td>
<td>19.45</td>
<td>71.62%</td>
</tr>
<tr>
<td>7</td>
<td>Seasonal Additive</td>
<td>43.97</td>
<td>40.76</td>
<td>45.43%</td>
</tr>
<tr>
<td>8</td>
<td>ARIMA(1,1,2)</td>
<td>23.07</td>
<td>19.28</td>
<td>32.02%</td>
</tr>
<tr>
<td>9</td>
<td>Single Moving Average</td>
<td>44.65</td>
<td>36.06</td>
<td>128.45%</td>
</tr>
</tbody>
</table>

Technical journal 7, 4(2013), 426-430
forecast error. To implement this approach in practice, the usage of historical data of at least five years is suggested. What can be noticed is that the best forecast results for a given demand pattern are achieved with ARIMA (2,1,2).

### Table 2: Ranking of forecasting methods by RMSE, MAD, MAPE

<table>
<thead>
<tr>
<th>Methods</th>
<th>Rank</th>
<th>RMSE</th>
<th>MAD</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA(2,1,2)</td>
<td>1</td>
<td>70.90</td>
<td>56.46</td>
<td>19.47%</td>
</tr>
<tr>
<td>Double Exponential Smoothing</td>
<td>4</td>
<td>183.60</td>
<td>116.43</td>
<td>54.25%</td>
</tr>
<tr>
<td>Double Moving Average</td>
<td>3</td>
<td>86.73</td>
<td>77.00</td>
<td>31.23%</td>
</tr>
<tr>
<td>Single Exponential Smoothing</td>
<td>5</td>
<td>184.73</td>
<td>115.61</td>
<td>55.73%</td>
</tr>
<tr>
<td>Single Moving Average</td>
<td>2</td>
<td>85.35</td>
<td>70.66</td>
<td>28.43%</td>
</tr>
</tbody>
</table>

RMSE of 70.90 tells that average root squared error of the selected forecast method is around 71 items. Thus averagely, by applying ARIMA, the distributor has wrongly ordered the quantity of 71 items. This gives no information of whether distributor has overestimated or underestimated consumers’ needs (as values of miscalculated orders are squared, information whether these were positive or negative values is lost). Therefore, it is highly recommended to consider other error measures, as well as each of them has its own advantages and disadvantages. MAD of 56.46 tells that model tends to slightly over-forecast, with an average absolute error of 56 units and describes well the information that we have miscalculated with RMSE and therefore complements our analysis of the forecast error. The third error measure used is MAPE. MAPE measures the size of the error in percentage terms and for total wholesalers demand and ARIMA it is 0.1947. This means that averagely, by applying ARIMA forecast, ordered quantities are miscalculated by 19.47%.

#### 3.2. Criteria for offered solutions selection

In making decision about demand pattern use for forecasting to lower miscalculated orders and decrease disturbance, it is necessary to analyze correlation between respective demand patterns. If there is no correlation, it will be better not to use the same forecasting method for all wholesalers or to forecast using summarized demand data. In Tables 3 and 4 the correlation coefficients are positive, meaning that ordered quantities are proportional, e.g. if WS3 increases quantity of ordered goods, the same can be expected from WS1, WS2 and WS4.

#### Figures 5-8 show the trend line for each of the sales.

**Table 4: Correlation between demand patterns of wholesalers and retailers and web-shop**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Retailers</th>
<th>Web-shop</th>
</tr>
</thead>
<tbody>
<tr>
<td>WS1</td>
<td>0.130436</td>
<td>-0.167629</td>
</tr>
<tr>
<td>WS2</td>
<td>-0.110432</td>
<td>0.127863</td>
</tr>
<tr>
<td>WS3</td>
<td>0.324240</td>
<td>0.187592</td>
</tr>
<tr>
<td>WS4</td>
<td>0.273038</td>
<td>0.130909</td>
</tr>
<tr>
<td>Retailers</td>
<td>1.000000</td>
<td>-0.325257</td>
</tr>
<tr>
<td>Web-shop</td>
<td>-0.325257</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

When considering WSs, it can be seen that WS4 and WS2 show highest deviations in order quantities. Also, when considering individual WSs orders, there is statistically significant correlation (p < 0.0500) among WS1, WS2, WS3 and WS4. All of the correlation coefficients are positive, meaning that ordered quantities are proportional, e.g. if WS3 increases quantity of ordered goods, the same can be expected from WS1, WS2 and WS4.

### Table 3: Correlation between demand patterns of wholesalers

<table>
<thead>
<tr>
<th>Variable</th>
<th>WS1</th>
<th>WS2</th>
<th>WS3</th>
<th>WS4</th>
</tr>
</thead>
<tbody>
<tr>
<td>WS1</td>
<td>1.000000</td>
<td>0.419835</td>
<td>0.464614</td>
<td>0.615966</td>
</tr>
<tr>
<td>WS2</td>
<td>0.419835</td>
<td>1.000000</td>
<td>0.536701</td>
<td>0.492454</td>
</tr>
<tr>
<td>WS3</td>
<td>0.464614</td>
<td>0.536701</td>
<td>1.000000</td>
<td>0.758540</td>
</tr>
<tr>
<td>WS4</td>
<td>0.615966</td>
<td>0.492454</td>
<td>0.758540</td>
<td>1.000000</td>
</tr>
</tbody>
</table>
On the other hand, demand pattern from retailers and web-shop seems not to have significant correlation with the above mentioned WSs and behaves independently on the customers market. Figures 9 and 10 show the trend line for each of the sales. It can be seen that most of the sales have negative trend line and are ordering/selling less and less goods. Only WS2 and Web-shop are increasing the quantity of ordered goods, but when overall orders are considered, common trend is still negative, meaning that the increase in orders from WS2 and Web-shop are not enough to compensate decreases made by other sales.

- using aggregated sales information in forecasting demand rather than forecasting each customer’s demand individually decreases the final forecasting error, an error involved in forecasting each wholesaler’s demand can be compensated by the other error of the opposite sign (i.e. forecast error for one wholesaler is -5 and forecast error for another wholesaler is +3, the result is total error -2)(i.e. if for one error it is -5 and for other +3, these two errors give the total error of -2);
- as the model becomes more complex by increase of assortment or the number of wholesalers it is easier to deal with the summarized data;
- training programs for staff are more convenient to be adopted when involving a single method.

5. REFERENCES


Contact:
Diana Božić, Ph. D.
E-mail: diana.bozic@fpz.hr

Ratko Stanković, Ph.D.
E-mail: ratko.stankovic@fpz.hr
Faculty of Transport and Traffic Sciences
University Campus, Borongajska cesta 83a
HR-10000 Zagreb

Goran Kolarić, M.Sc.
Polytechnic of Varazdin
J.Krizaća 33, HR-42000 Varazdin
E-mail: gkolakovic@gmail.com

4. CONCLUSION

Research results show that the demand patterns aggregation has a significant impact on the accuracy of the demand forecasting. Furthermore, it is shown the demand forecasting based on summarized sales information (customers data) yields better results due to the following issues: