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ANALIZA UTJECAJA AGREGACIJE UZORAKA NA PROGNOZU POTRAŽNJE

ANALYSIS OF THE PATTERN AGGREGATION IMPACT ON THE DEMAND FORECASTING

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Pregledni rad

Sažetak: *Opskrbni lanci su vrlo rijetko u jednostavnom generičkom obliku, već uključuju različite sudionike, koji neovisno provode prognozu potražnje u svojem djelokrugu. Prognoziranje potražnje temeljem podataka o narudžbama umjesto podataka o potražnji krajnjeg kupca (korisnika) u lancu, na sljedećim višim razinama kumulativno generira sve veća odstupanja. Svaki od sudionika opskrbnog lanca tako dobiva drugačije podatke o potražnji što je uzrokovano tim kumulativnim djelovanjem, poznatim pod nazivom "efekt biča". U cilju smanjivanja ovih nepravilnosti, proizvođači obvezuju distributere na dostavljanje podataka o prognozi potražnji na svojem tržištu. Distributeri su pritom suočeni s problemom prikupljanja i obrade heterogenih uzoraka potražnje od ostalih sudionika na nižim razinama. U radu je prikazana analiza agregacije uzoraka koji su korišteni za prognoziranje potražnje primjenom različitih metoda prognoziranja.*

Ključne riječi: *metode prognoziranja na vremenskim nizovima, agregacija uzoraka potražnje, efekt biča, opskrbni lanac*

Review article

Abstract: *Supply chains are rarely in their basic, simple form – they involve different participants who respectively use demand forecasting methods related to their filed. Demand forecasting based on orders received instead on end user demand data will inherently become more and more inaccurate as it moves up the supply chain. Each participant in a supply chain receives different fluctuations data in the orders obtained, which is caused by the bullwhip effect. In order to mitigate these distortions, producers require the distributors to deliver the data on demand forecasting for a certain market. Thus the distributor tries to find the appropriate forecast method. This can be very difficult since the demand patterns of buyers differ. The paper analyses the pattern aggregation used for demand forecasting by applying different forecasting methods.*

Key words: *time series forecasting methods, demand pattern aggregation, bullwhip effect, supply chain*

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 distributers 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.

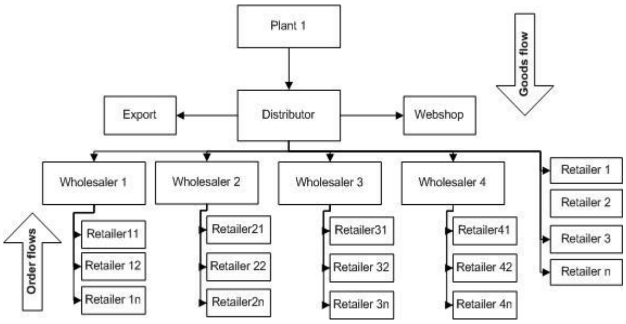

Figure 1. Graphical presentation of the observed production-distribution system

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_{OtF})* is defined as:

$$Q_{OtF} = E_{DD} + SS_D \tag{1}$$

$$E_{DD} = E_{WS1} + E_{WS2} + E_{WS3} + E_{WS4} + E_{R1} + E_{R2} + E_{R3} \ldots\ldots + E_{Rn} + E_{webshop} \tag{2}$$

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:

$$Q_{(p)} = Q_{OtF} + (CS - OS) \tag{3}$$

Here *CS* represents closing stock at the end of the month and equals demand in the month. Quantity of *CS* on distributer 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.

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.

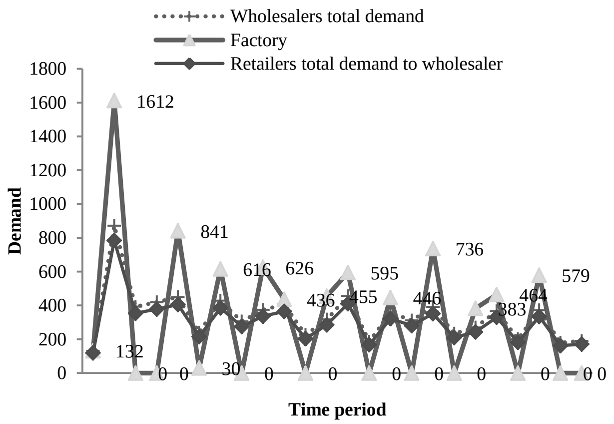

Figure 2. Example of orders placed by trading partner illustrating the bullwhip effect

When the distributer 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.

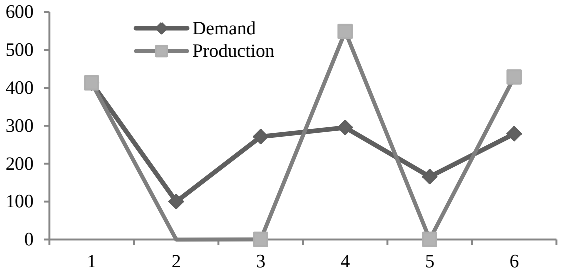

Figure 3. Forecasted demand based on summarized order data

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.

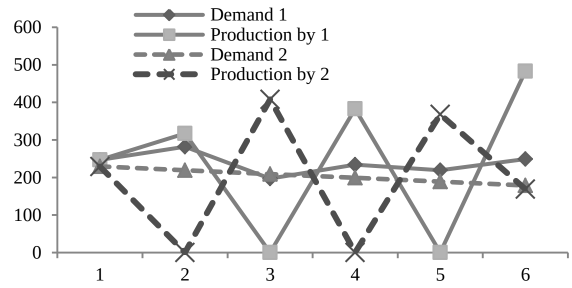

Figure 4. Summarized values of forecasted demand by each wholesaler

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.

Table 1: Methods ranks for wholesaler demand pattern

Rank 1	Method	RMSE	MAD	MAPE
WS1	Single Moving Average	17.61	13.61	72.45%
WS2	SARIMA(1,0,1)(1,0,1)	30.78	24.92	24.23%
WS3	Double Moving Average	14.07	12.03	20.63%
WS4	Double Moving Average	35.79	28.76	67.44%
Rank 2				
WS1	Double Moving Average	20.12	17.90	85.76%
WS2	Single Moving Average	39.32	30.94	37.29%
WS3	Single Moving Average	21.36	16.11	25.64%
WS4	ARIMA(2,1,2)	37.82	30.05	65.60%
Rank 3				
WS1	ARIMA(0,0,1)	22.96	19.45	71.62%
WS2	Seasonal Additive	43.97	40.76	45.43%
WS3	ARIMA(1,1,2)	23.07	19.28	32.02%
WS4	Single Moving Average	44.65	36.06	128.45%

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 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

Methods	Rank	RMSE	MAD	MAPE
ARIMA(2,1,2)	**1**	**70.90**	**56.46**	**19.47%**
Double Exponential Smoothing	4	183.60	116.43	54.25%
Double Moving Average	3	86.73	77.00	31.23%
Single Exponential Smoothing	5	184.73	115.61	55.73%
Single Moving Average	2	85.35	70.66	28.43%

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 distributer has wrongly ordered the quantity of 71 items. This gives no information of whether distributer 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 between observed demand patterns is presented.

Table 3: Correlation between demand patterns of wholesalers

Variable	WS1	WS2	WS3	WS4
WS1	1.000000	0.419835	0.464614	0.615966
WS2	0.419835	1.000000	0.536701	0.492454
WS3	0.464614	0.536701	1.000000	0.758540
WS4	0.615966	0.492454	0.758540	1.00000

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

Variable	Retailers	Web-shop
WS1	0.130436	-0.167629
WS2	-0.110432	0.127863
WS3	0.324240	0.187592
WS4	0.273038	0.130909
Retailers	1.000000	-0.325257
Web-shop	-0.325257	1.000000

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

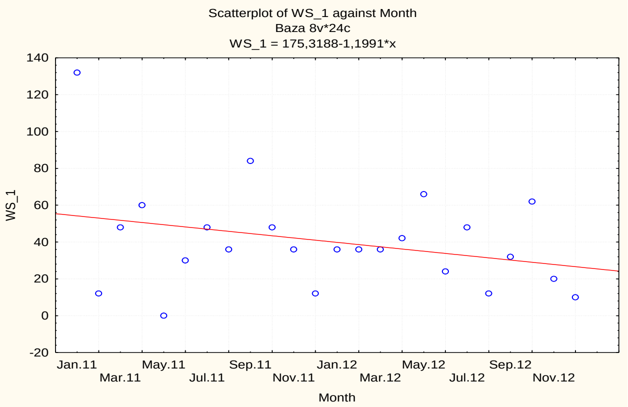

Figure 5. WS 1 trend line

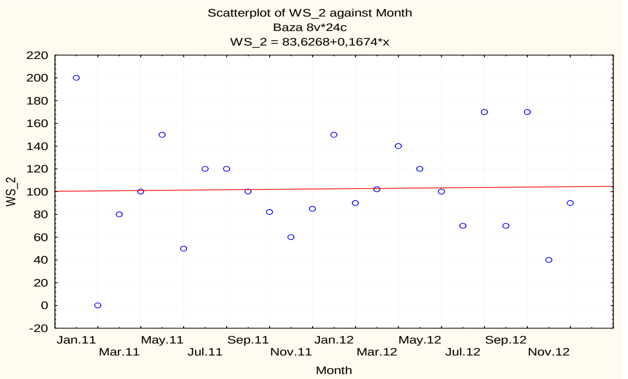

Figure 6. WS 2 trend line

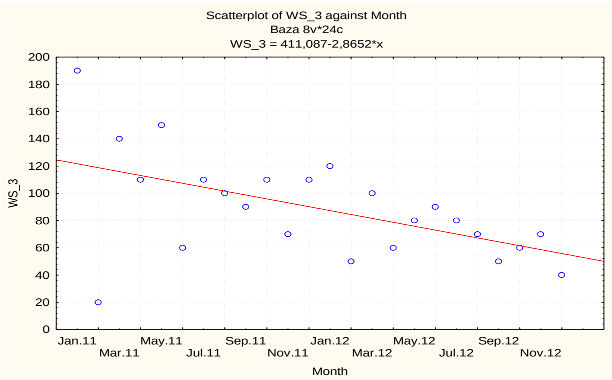

Figure 7. WS 3 trend line

On the other hand, demad 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.

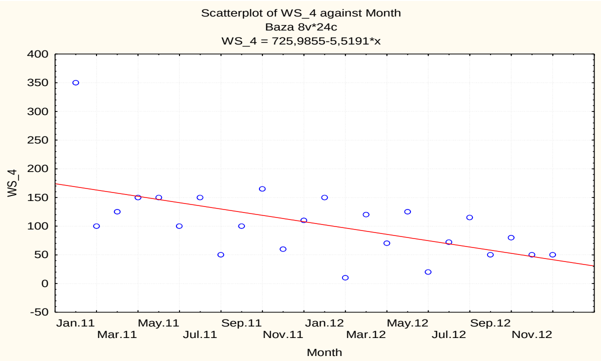

Figure 8. WS 4 trend line

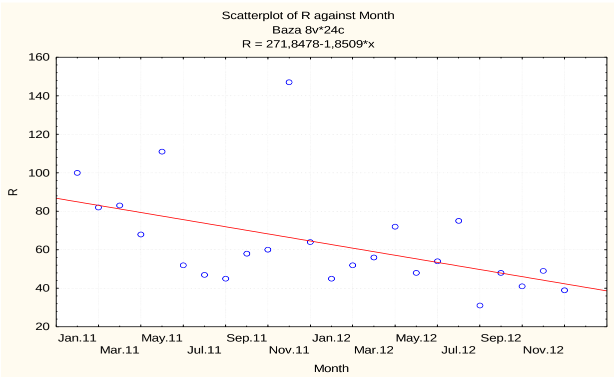

Figure 9. Retailer trend line

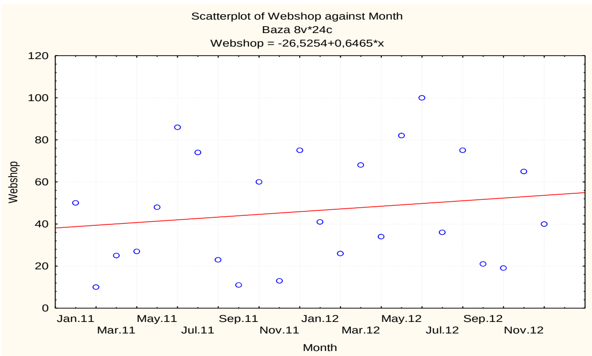

Figure 10. Web-shop trend line

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:

- 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.

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