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Visualization and Analysis of Customer Provided Forecasts

Visualisierungsstrategien und Analyse von Kundenauftragsinformationen

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Abstract: Demand forecasts can either be provided by customers or manufacturing companies use own common prediction models to estimate the customer demand. This paper provides the first results of a research project with a focus on visualization of forecast uncertainty for customer provided forecasts. The visualization concept described in this paper is developed to analyse systematic and unsystematic forecasting behaviours with respect to periods before delivery. The aim of the developed visualisation concept is to provide support for practitioners in the area of production planning with a special attention on forecast uncertainty in the supply chain. Compared to a classical order analysis the paper shows the advantage of chronological forecast quality monitoring. In future research the visualization concept should be extended to an improved decision support tool in production and supply chain planning.

1 Introduction

The technological and information advancements of the fourth industrial revolution are pushing companies towards improvement of their supplier-customer interrelation, improved communication and information exchange among the supply chain stakeholders. As a result, the need for novel technologies for automated and controlled data flow via EDI-based transactional models and supplier portals has emerged, previously described by Lee and Whang (2000), bringing more challenges for companies to keep improving their production planning and logistics processes. Since the information about the product demand is often uncertain, according to Christy and Kanet (1988), problems such as overproduction, high inventory levels, high overtime hours, additional transportation costs and poor delivery reliability occur. Therefore, manufacturing companies try to improve their forecasting processes in order to make better use of existing resources. Information sharing, such as sharing of sales data, inventory levels and forecasts can potentially improve delivery performance, decrease the outcome of the bullwhip effect by adapting companies planning processes to real demand data (Chandra and Grabis 2005; Lee and Whang 2000).

This paper presents the first results of the research project InnoFIT. The aim of the research project is to develop a concept for the evaluation of advanced forecasting processes. For this purpose, a simulation model and a visualization model are developed. The simulation model is designed to investigate different forecast behaviours and forecast error measures, and the visualization model helps to analyse systematic or non-systematic forecasting behaviour for real industrial or simulation data. Possible outcomes for improved decision-making in production planning can be the development of an analytical model for the adaption of customer-provided forecasts according to the detected forecasting behaviour, and, also, a decision support system for strategic make-to-order versus make-to-stock planning decisions. The developed methods should help manufacturing companies to improve their logistics performance, by achieving better service level with less inventory and with efficient use of resources.

The focus of this paper is to introduce a visualization model for systematic forecasting behaviour analysis and to present its advantages compared to a classical statistical order analysis. The highlight of our research is placed on measuring and visualising the forecast uncertainty and verifying how forecast uncertainty influences the production planning. The representation of the simulation model and its interrelation to the visualisation is left to future research. The visualization model presented in this paper is tested with a fictive data set and advantages are discussed compared to a classical order analysis. It is expected that the visualization model can help researchers and industrial project partners to make better decisions on the most suitable production planning and forecasting processes based on the chronological forecasting behaviour analysis.

2 Literature Review

It has been previously investigated by researchers that with proper forecasting processes companies can reduce uncertainty by understanding the forecasting behaviours of their customers (Danese and Kalchschmidt 2011; Altendorfer et al. 2016). Fildes and Hastings (1994) elaborated a model based on three variables for analysis of forecasting process, in which the forecaster and decision maker, information flows and technical characteristics of the forecast are identified as critical components. Among forecasting techniques Hopp and Spearman (2008) identified qualitative and quantitative forecast methods, and traditional forecasting and prediction methods were investigated in the works of Montgomery et. al (1990). However traditional forecasting methods are not the target of our research. On the one hand, qualitative forecasting methods studied by Syntetos et al. (2009) try to predict future through expert opinions, on the other hand, quantitative forecasting methods, are based on the assumption, that the future can be estimated by including historical data in mathematical models (Ali et al. 2012; Jaipuria and Mahapatra 2014; Gardner 2006; Hopp and Spearman 2008). Therefore, in order to stay competitive in the market, it is important for companies to improve their forecasting processes by adopting different forecasting techniques of both qualitative and quantitative approaches and to lever combined information in order to provide better forecasts and to support decision makers (Danese and Kalchschmidt 2011).

Customer demand uncertainty and forecast bias in a production environment play a significant role on customer delivery and service levels, specifically, with decreased demand uncertainty the service levels improve (Enns 2002). It was investigated by Danese and Kalchschmidt (2011) and Altendorfer et al. (2016) that forecast errors have substantial effects on the unbiased customer-provided forecasts in a material requirements planning (MRP) setting. Furthermore, Xie et al. (2004) investigated the impacts of forecasting errors on service level, production and inventory costs, including the total cost, with demand uncertainty. Having investigated the relevant literature, we identified that there is no clear differentiation between forecast uncertainties for customer provided forecasts and forecast predictions, especially with relation to systematic and non-systematic forecast error implication. Therefore, we intend to cover this research gap and to investigate forecast uncertainty for customer provided forecasts.

Souza (2014) identified descriptive, predictive and prescriptive analytics techniques for supply chain management and identified a model for independent and dependent demand forecasting. In our approach we try to highlight predictive category with an emphasis on demand forecasting for adaptation to our visualization model. The visualization model described in this paper aims to analyse the historical customer forecast behaviour, forecast history and forecast error measures, and it is described in detail in the Section 3. For the visualization development, a combination of both high-level and low-level visualization libraries were investigated (Satyanarayan et al. 2016).

3 Visualization Model Description

Data-Driven-Documents (D3.js) is a non-traditional visualization framework for the web, which provides efficient manipulation of document object model (DOM) of a browser based on data with the use of combined web technologies (Bostock et al. 2011). One of the biggest advantages of D3.js library is the possibility of cross-platform performance and deployment of highly customisable visualizations. Due to aforementioned advantages, the D3.js library was chosen for the basis of the visualization model development.

The visualization model, which is comprised of a developed web tool, is designed to provide visualizations of fictive or real industrial data, collected from the project partners. The visualizations should help to make initial assumptions about the data based on the chronological visualization of the error measures and classical order analysis, as well as to make suggestions for improved forecasting and production planning decisions. The data structure, which is used for the visualization model, is shown in the Table 1 below.

The notation described is used for the forecast data, the error measure calculation and the visualizations. The current time period is defined by calculating i-j, and periods before delivery are defined by variable j. Moreover, $x_{i,j}$ indicates the forecasted order amount (or demand forecast) and $x_{i,0}$ indicates a final order amount. Periods before delivery is calculated by the difference between *ForecastPeriod* and *ActualPeriod*. *ActualPeriod* is the transmission period, during which the customer sends the forecast.

The *ForecastPeriod* indicates the due date, for which the order delivery is planned, *Product* indicates the name of a product, and the *OrderAmount* indicates the customer order amount. The notation of variables described here applies also to the notations of error measures described in this paper. For each $x_{i,j}$ the expected due date i can be calculated. The due date i is defined as the sum of current period and the periods before delivery. When the *ForecastPeriod* is equal to *ActualPeriod*, then the *OrderAmount* of that period is the final order amount that is planned to be delivered. From the Table 1 below, the order amount of 620 pieces (pcs) is the final order amount of the Product 1, so the difference between *ActualPeriod* and *ForecastPeriod* is 0, i.e. the periods before delivery are equal 0; while the next order amount of 640 pcs is the forecasted order, one period (week) before delivery (or one period before the due date). The notation of "period" was used to make the data structure more flexible for future visualizations, in order to adapt visualizations with respect to, for instance, weeks, months, or years and to appropriately filter and render visualizations with a timeline overview. Most company partners in the research project get the customer provided forecasts in a similar structure as it is described in this paper. The forecast data of companies is updated in a rolling horizon manner without storing the chronological forecast behaviour. Therefore, one of the first steps of the research project was to set a storage feature that can save the historical forecast data for further data visualization and analysis.

Table 1: *Web-tool data structure*

Product	**ActualPeriod**	**ForecastPeriod**	**OrderAmount**
Product1	10	10	620
Product1	10	11	640
Product1	10	12	814

The visualization model is developed with the use of web programming languages, D3.js and a MySQL database, which is stored in an online web hosting environment of St. Poelten University of Applied Sciences. The data in a defined format (Tab. 1) is uploaded in a CSV format via the web tool into a database system. The overview of the visualization model structure is shown in the Figure 1 below. The data is visualised and manipulated with D3.js by binding data element properties to DOM of a browser. A web storage API solution "localforage" was chosen to store data on the client to facilitate data load on the DOM. In overall, there are three levels in the visualization model structure: first is the data storage and preparation, when the data is converted in the database into the required format for further processing; second is the data processing, when the data is filtered and transformed on the client; and finally, data visualization using visualization frameworks (D3.js, DC.js, crossfilter.js). The convenience of using the client-based data storage and data manipulation is the higher data load efficiency and increased scalability of visualizations, since all data is accessed remotely on the web pages without the need of data extraction from the database each time it is visualised.

Figure 1: *Visualization model structure*

4 Numerical Study

In this section the error measure description as well as the visualizations for a numerical example using a fictive data set are presented. The notations for the used forecast error measures are introduced first, and afterwards the visualizations are discussed.

4.1 Classical Order Analysis

The graphical representation of the classical order analysis is shown in the Figure 2. This kind of order analysis is usually conducted in companies for the descriptive analysis of the final customer orders. In inventory management literature the distribution of the final orders appears relevant to the parameterization of the inventory model for a make-to-stock system. From the visual analytics perspective, Figure 2 is a scatterplot graph with an average line. The graph shows the weekly distribution of final order amounts with respect to the due date, and the line denotes the mean of all final orders. Discussions on seasonality are also possible with this plot. Additionally, various descriptive statistical measures, such as mean, median, maximum and minimum order value, standard deviation, coefficient of variation and 99%/95%/75% quantiles, are calculated based on the final orders. Nevertheless, in a make-to-order environment, where the replenishment lead-times or production lead-times are relevant, this kind of analysis is limited. Therefore, in this visualization the information about the forecast uncertainty is not visible, which is relevant for an efficient production planning.

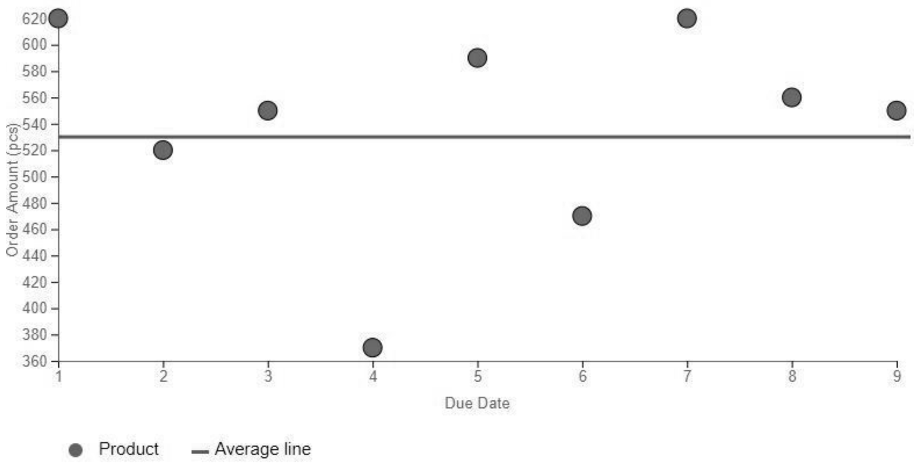

Figure 2: *Final order amount (classical order analysis) visualization*

4.2 Delivery Plan Matrix

The previously stated problem (Section 4.1) brings us to the following representation of the customer provided forecast data, investigated previously by Jodlbauer (2016). The term *delivery plan*, used in this paper, represents the overview of forecasted and final orders with respect to actual periods. The delivery plan matrix in Figure 3 represents the weekly chronological forecasting behaviour of a customer, where the columns represent the forecast transmission date (actual periods are calendar weeks 1-10), i.e. the period from which the forecast calculation starts; and the rows represent the forecast periods. The diagonal of the matrix is comprised of the final order amounts. Above the diagonal the backlog can be seen, but there is no backlog in our example, whereas below the diagonal the customer provided forecasts are shown. For instance, for calendar week 5 (CW5), actual week 5, forecast week 5, the final order amount is 590 pcs. The row on the left from the final order amount shows the chronological forecasting behaviour for the respective due date of CW5. This means that one week before delivery the forecast for due date CW5 was 803 pcs., which shows that the customer cancelled 213 pcs one week before delivery. The presented process also applies for previous weeks and various due dates. The colouring range of the matrix helps to see the forecasting behaviour with respect to periods before delivery. Analysing a row of the matrix shows that when the colour of elements changes from dark to bright means that the customer decreased order amounts, while vice versa means increase. The matrix has advantages for a detailed discussion of single customer-provided forecasts, but it is limited for the discussion of the forecast quality and the systematic forecasting behaviour.

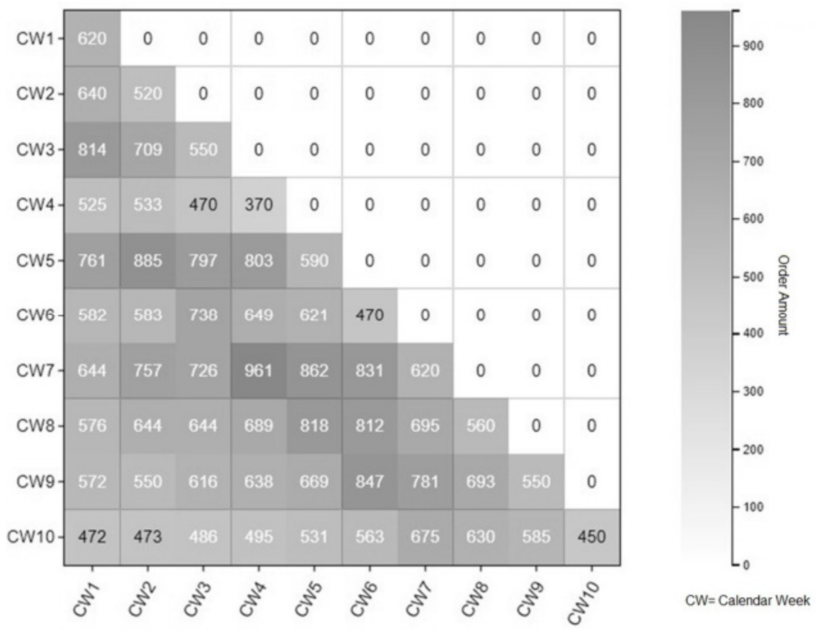

Figure 3: *Delivery plan matrix visualization*

4.3 Delivery Plans Graph

The delivery plans graph in the form of a scatterplot is used to analyse the forecast quality, and it shows the historical final and forecasted orders distribution with respect to the due date on a weekly basis. The brighter circles indicate the final orders and the darker circles indicate the forecasted orders. Due to the limited number of time periods analysed in the fictive data set, the number of forecasts per due date (darker circles) increases. This would not be the case, when analysing real data. Additionally, in this example, the final order amounts are always lower than the amounts of forecasted orders, which indicates a systematic overbooking behaviour in the forecasting. The graph presents a range of forecasts for a specific due date. For example, for the due date 8 the forecasts in the range 500 to 800 pcs can be seen. The graphical representation in Figure 4 provides a quick overview about the forecast quality. However, the analysis of the chronological forecasting behaviour is not possible in this graph, which brings us to the next visual representation.

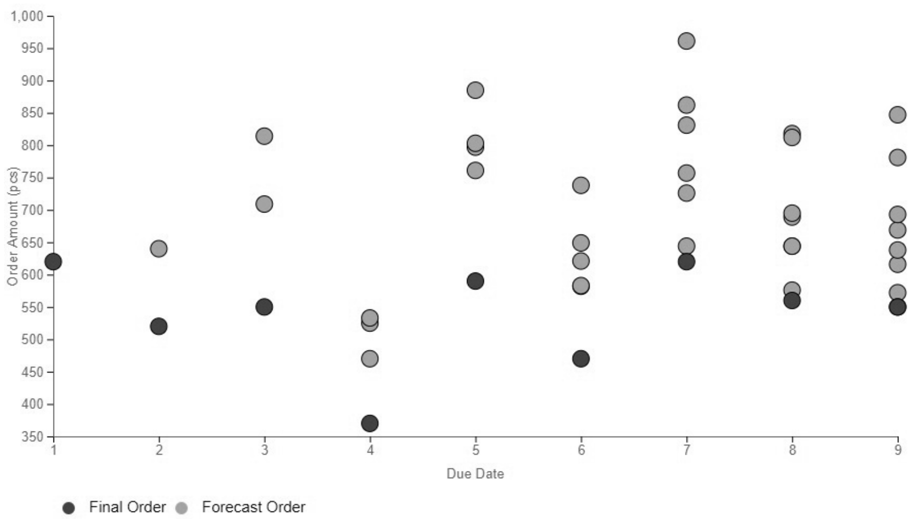

Figure 4: *Final order and forecasted order amounts with respect to the due dates*

4.4 Mean Forecast Bias

Mean forecast bias (MFB) visualization representation is shown in the Figure 5. MFB indicates the error measure of customer's over- or under-booking behaviour with respect to periods before delivery *j*. The formula used for the calculation and visualization is defined as:

$$MFB_j = \sum_{i=1}^{n} x_{i,j} / \sum_{i=1}^{n} x_{i,0} \text{ for all } j \in J \tag{1}$$

. Note that we also visualise other common forecast error measures, such as mean absolute deviation or mean percentage error, but MFB is the most promising measure for the discussion of forecast behaviour. In the Figure 5 we can see that the forecast quality is quite good from 9 to 6 periods before delivery. Then the customer starts overbooking between periods 5 till 2. Closer to the due date the customer decreases order amounts. The described behaviour is a problem for production planning, when a production company should order sub-materials with a respective lead time. If we assume that the manufacturing company has as lead time between 2 and 3 periods, Figure 5 shows that all orders would systematically be 40% above the actually required demand. The identified forecasting behaviour is a rational choice in the supply chain. In this example, the customer reserves the capacity to ensure delivery and then partially cancels the orders later. The identified systematic behaviour could either be used to discuss the forecasting behaviour with the customer, or, if the customer does not want to change his behaviour, the manufacturing company could adapt the customer provided forecasts according to the identified systematic behaviour.

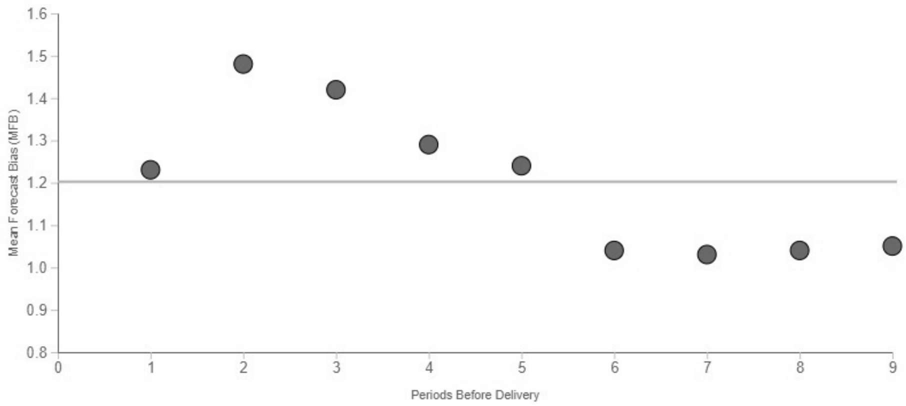

Figure 5: *Mean forecast bias (MFB)* with respect to periods before delivery.

5 Conclusion

This paper provides the first results of a research project in the direction of data visualization of forecast uncertainty for customer provided forecasts. The visualization concept described in this paper is developed to present forecasting behaviour and forecast quality with respect to periods before delivery. We found out that most of the company partners do not store the forecast data in a way, which enables analysing chronological forecast uncertainty. Additionally, we investigated that classical order analysis is very limited with respect to the forecast quality and its interrelation to production planning. Therefore, the delivery plan matrix was introduced, which represents the chronological forecasting behaviour of a customer. The delivery plan graph (Fig. 4) provides an overview of the forecast quality but still neglects the chronological forecasting behaviour. Therefore, the mean forecast bias with respect to periods before delivery was introduced, which enables the discussion of systematic forecasting behaviour and, as a result, can be used to improve the collaboration between suppliers and customers. For the visualization model further work is needed to integrate more forecast error measures and to implement interactive visualization techniques such as data-rendering, data-filtering, and clustering, which could also require in-depth investigation of the visualization tools mentioned in this paper as well as other additional tools. In the future research a simulation model will be developed to generate forecast data that mimics different forecast behaviours. In detail, two demand models are planned to be investigated, i.e. independent forecast distribution and a forecast evolution model, in order to discuss the value of customer-provided forecasts in comparison to a common forecast prediction method. As a result, an analytical model can be developed for the adaption of customer provided forecasts according to the investigated forecasting behaviour to provide improved decision support in production and supply chain planning.

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