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Simulation-based demand forecast generation to analyze forecast accuracy and its influence on logistical performance

Simulationsbasierte Forecastdaten-Generierung zur Analyse der Forecastqualität und deren Einfluss auf das logistische Potential.

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Abstract: Managers face the problem of different demand models and forecast information for their products. Uncertainty and trends in forecasts influence the logistical performance of the companies and the question which planning method or planning parameter level fits best for the respective product is still open for practitioners. This paper gives an overview about practical inspired demand models to mimic different behaviours of customer provided forecasts, and presents a simulation based forecast generation module to analyse and improve forecast accuracy. The applications of this model presented in this paper show that measuring the forecast accuracy, understanding the forecasting behaviour, and applying respective correction methods is an important issue to be focussed in research.

1 Introduction

In manufacturing companies, demand forecast data is used for the underlying production planning. The demand information can either be self-generated with common forecasting techniques or provided by the customers in a rolling horizon. In a make-to-stock production system, manufacturing companies use classical forecast methods to predict the demand, or the customers provide forecast data in a rolling horizon with periodic order amount updates. In a make-to-order setting manufacturing companies use the customer provided order amounts with a specific due date to plan their production. Norouzi and Uzsoy (2014) highlight that the two mentioned make-to-stock forecast systems are not completely contrary. The authors refer to Chen and Lee (2009) who showed that many commonly used time-series forecast models can be interpreted as special cases of the forecast evolution model. In all mentioned systems the provided information is somehow stochastic, and companies are looking for ways how to deal with the underlying uncertainty. Literature on inventory and production planning shows that understanding, analysing and improving the forecast accuracy has a large improvement potential for production system performance (Enns, 2002; Sanders and Graman, 2009; Metters, 1997; Chen and Lee, 2009). For streamlined production systems and inventory models, analytical models can help to set planning parameters to be more efficient, which means on-time deliveries in the agreed order amount with a minimum of stock levels (Norouzi and Uzsoy, 2014). Nevertheless, for real production systems facing multiple demand uncertainties simulation is an appropriate method to investigate forecast accuracy and its influence on logistical performance. The proposed paper presents results of the research project InnoFIT. The overall project aim is to improve the forecast quality of customer provided forecasts by analysing and visualizing forecast data and developing appropriate mathematical models to correct systematic forecast errors. Due to the project cooperation with four automotive suppliers, the presented demand models and the developed forecast correction models are inspired by real world problems and partly evaluated with real company data.

Contribution one of this paper is the introduction and explanation of a discrete event simulation model module to generate forecast data with systematic and unsystematic forecast effects. The developed simulation model module enables to mimic the evolution of customer provided forecasts over time. In the forecast evolution model, forecasts are not static, but forecast updates appear in a rolling horizon until the due date occur. Such effects can be observed in real data often disturbed with other uncertainty effects. However, to study different information sharing types and their interaction and influence on production planning, framed data sets need to be generated where simulation can be used. Contribution two of the paper shows the output of the mentioned research project where the simulation model module is used in different publications and its contribution to scientific progress is discussed.

This paper is organized as follows. In Section 2 the demand models, the forecast accuracy measures, and one forecast correction method are introduced which are implemented in the simulation model module. Section 3 presents the simulation model application and selected results. Finally, in Section 4 we summarize the results of the presented study and mention some interesting topics for future research.

2 Demand Models and Simulation Model Implementation

To enable a thorough discussion and analysis of customer provided forecast behaviours, a simulation model module that mimics the forecast evolution demand process has been developed and is introduced in this section. The software AnyLogic© is used to build the simulation model. On the one hand, this model can be applied for static forecast data generation to evaluate the forecast accuracy and the improvement potential of forecast correction methods. On the other hand, this model can be applied as simulation module for production planning simulation to evaluate the forecast accuracy and investigate its influence on production order accuracy and key performance indicators such as service level, tardiness, and inventory. The following subsections introduce the forecast evolution demand process which is extended by several practically observed forecasting behaviours. Furthermore, a few forecast accuracy measures, which have been applied in the different studies from the InnoFIT project are introduced. Additionally, one forecast correction method has been developed and is implemented in the simulation model and described in the following section.

2.1 Demand model development

To simulate real forecasting behaviour the following demand model is developed.

2.1.1 Basic forecast evolution model

The idea of this basic forecast evolution demand model is rather simple. Customers provide a constant long-term forecast $\tilde{x}_i$ for due date *i* in the future and start to update this forecast with a due date horizon *H*. This means the first update occurs with $j = H$ where *j* are the periods before delivery, and then each period an update occurs. For a single item with normal distributed update terms this can be written as:

$$\begin{aligned} x_{i,j} &= x_{i,j+1} + \varepsilon_{i,j}\left(\tilde{x}_i, 0, \alpha\right) \\ \varepsilon_{i,j}\left(\tilde{x}_i, 0, \alpha\right) &= N\left(0, \alpha a_j \tilde{x}_i\right) \end{aligned} \tag{1}$$

Whereby $x_{i,j}$ denotes the forecast for due date *i* stated *j* periods in advance and $\varepsilon_{i,j}$ is the normal distributed forecast update for due date *i* generated *j* periods in advance. The parameter a_j is applied to model the stochastic error related to periods before delivery and α is applied to enable an easy change in the level of uncertainty. In the following presented studies the a_j vector is usually kept constant and only α is varied. Note that the original martingale model of forecast evolution as applied in Norouzi and Uzsoy (2014) includes multivariate normal distributed updates with possible relations between the items. This is not included in our simulation model since the focus is more on extending this model by practically observed behaviours. If a pure customer required lead time setting is to be modelled, then only one update occurs with *j* being the customer required lead time. The basic forecast evolution model is used in the simulation studies Felberbauer and Altendorfer (2014), Zeiml et al. (2019), and Zeiml et al. (2020).

2.1.2 Biased forecasts

The basic forecast evolution model assumes that each update includes an information gain, i.e. the new updated value has on average less distance to the final order amount. Since the mean of the forecast updates $\varepsilon_{i,j}$ is zero, the updates can be positive or negative. However practical observations as well as supply chain literature suppose that there might be a customer which provide biased forecast information for example due to rationing (Lee and Whang, 2000). This leads to the following demand model:

$$\begin{aligned} x_{i,j} &= x_{i,j+1} + \varepsilon_{i,j}(\tilde{x}_i, \beta, \alpha) \\ \varepsilon_{i,j}(\tilde{x}_i, \beta, \alpha) &= N\left(\beta b_j \tilde{x}_i, \alpha \tilde{x}_i\right) \end{aligned} \tag{2}$$

The relation between forecast bias and periods before delivery is included with b_j while the level of forecast error is parametrized with β. Note that in the following presented studies the b_j vector is usually kept constant and only β is varied. In this modelling frame the forecast bias can either be positive or negative and it is also possible to model long-term forecast errors, i.e. the long-term forecast might be too high or too low. A simulation model with biased forecasts is investigated in the papers Zeiml et al. (2019) and Zeiml et al. (2020).

2.1.3 Temporary Outliers

A further customer behaviour observed is that planning instabilities in the customer's planning process lead to changes in the demand forecasts that can be high in their amount, but occur only temporary. Such a behaviour is called temporary outliers in our demand model. Note that such temporary outliers imply that again the information quality does not improve with each update. The following modelling is applied:

$$\begin{aligned}
&x_{i,j} = x_{i,j+1} + \varepsilon_{i,j}\left(\tilde{x}_i,\beta,\alpha\right) + P_{i,j}\left(\gamma c_j\right)\lambda_{i,j}\left(\tilde{x}_i,\delta,e\right)\\
&-P_{i,j+v}\left(\gamma c_j\right)\lambda_{i,j+v}\left(\tilde{x}_i,\delta,e\right)\\
&\lambda_{i,j}\left(\tilde{x}_i,\delta,e\right) = N\left(\delta\tilde{x}_i,\delta e\tilde{x}_i\right)\\
&P_{i,j}\left(\gamma c_j\right) = 1 \text{ with Probability } \gamma c_j \text{ and } P_{i,j}\left(\gamma c_j\right) = 0 \text{ otherwise}
\end{aligned} \tag{3}$$

In this formulation, an outlier occurs j periods before delivery with probability γc_j, whereby again c_j includes the link to the periods before delivery and γ defines the level of occurrence probability. The amount of an outlier is normally distributed with mean $\delta\tilde{x}_i$ and standard deviation $\delta e\tilde{x}_i$, i.e. the level of outliers is defined with δ while its stochastic is defined with e. The parameter v indicates for how much periods an outlier occurs (Seiringer et al., 2021).

2.1.4 Demand shifting between periods

Looking at real data sets from the company partners of the research project uncovered a further customer behaviour that is included in our demand model. In this setting, the demands are shifted between the single due dates, e.g., demand for due date i is reduced by a certain amount and demand of due date i+1 is increased by the same amount. Such a behaviour can be based on the assumption of cumulated demand being known by the customers, but the respective due dates may change. The following model includes this behaviour.

$$\begin{aligned}
&x_{i,j} = x_{i,j+1} + \varepsilon_{i,j}\left(\tilde{x}_i,\beta,\alpha\right) + P_{i,j}\left(\gamma c_j\right)\lambda_{i,j}\left(\tilde{x}_i,\delta,e\right)\\
&-P_{i,j+v}\left(\gamma c_j\right)\lambda_{i,j+v}\left(\tilde{x}_i,\delta,e\right)\\
&+\sum_{m\in\{-r,\dots,-1,1,\dots,r\}} Y_{i+m,-m}\left(\psi f_{j+m}\right) l_{j+m}\mu_i - \sum_{k\in\{-r,\dots,-1,1,\dots,r\}} Y_{i,k}\left(\psi f_j\right) l_j\mu_i\\
&Y_{i,k}\left(\psi f_j\right) = 1 \text{ with Probability } \psi f_j \text{ and } Y_{i,k}\left(\psi f_j\right) = 0 \text{ otherwise}
\end{aligned} \tag{4}$$

According to this formulation, a demand shift occurs with probability ψf_j again with ψ stating the general level of amount shifts and f_j stating the relation to periods before delivery. Furthermore, a demand shift can only occur in a range of r periods and the l_j identifies the amount of demand that is shifted. This practical extension finalizes the demand model that is generated in the simulation model to mimic real customer forecasting behaviour.

2.2 Forecast Accuracy Measures

To evaluate the forecast accuracy, several forecast error measures could be applied. In the study of Zeiml et al. (2019) several forecast error measures are introduced whereby the normalized root mean squared error related to j periods before delivery $RMSE_j$ is found to be a good applicable measure for identifying the general forecast accuracy. To evaluate systematic behaviours, the mean-percentage-error MPE_j for j periods before delivery is suggested there. The following equation shows these measures.

$$MPE_j = \frac{\sum_{i=1}^{n}\left(x_{ij} - x_{i,0}\right)}{\left(\frac{1}{n}\sum_{i=1}^{n} x_{i,0}\right)} RMSE_j = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{ij} - x_{i,0}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n} x_{i,0}} \tag{5}$$

In most of the papers presented above these measures have been applied and in some papers a forecast correction method is developed (see next subsection). There also a correction effectiveness is discussed calculated as $E_j = \frac{\left(RMSE_j - CRMSE_j\right)}{RMSE_j}$. Note that $CRMSE_j$ is the normalized root-mean-squared-error when the respective correction is applied.

2.3 Forecast bias correction

Since a forecast bias is a systematic behaviour that a customer shows and this bias can be measured very well with the MPE_j, in Zeiml et al. (2020) a respective forecast correction method is developed that is also included in the simulation model. The following equation shows how forecasts are corrected applying this method:

$$\hat{x}_{i,j} = \begin{cases} \frac{x_{i,j}}{1 + MPE_j} : \sigma_{MPE_j} \le \sigma_t \\ x_{i,j} : \text{otherwise} \end{cases} \tag{6}$$

According to this formulation, the forecast is corrected to $\hat{x}_{i,j}$ by applying the MPE_j whenever the standard deviation of the respective MPE_j is below a certain threshold. This implies that such a correction should only be applied if the bias is stable.

3 Model applications and selected results

In this section the most important results of simulation studies and the respective publications are presented that apply the simulation model module to discuss forecast accuracy effects and the performance of the presented correction model. Note that the contribution of this paper lies in providing a comprehensive view on the potential of applying such a simulation model of forecasting behaviour to tackle different aspects of the respective process.

3.1 Demand model features and its influence on RMSE

Our first results presented in Figure 1 show different demand model features, which are presented in Section 2.1.1-2.1.4, i.e. basic forecast evolution model, biased forecasts, temporary outliers, and demand shifting between periods, and its influence on normalized root mean squared error.

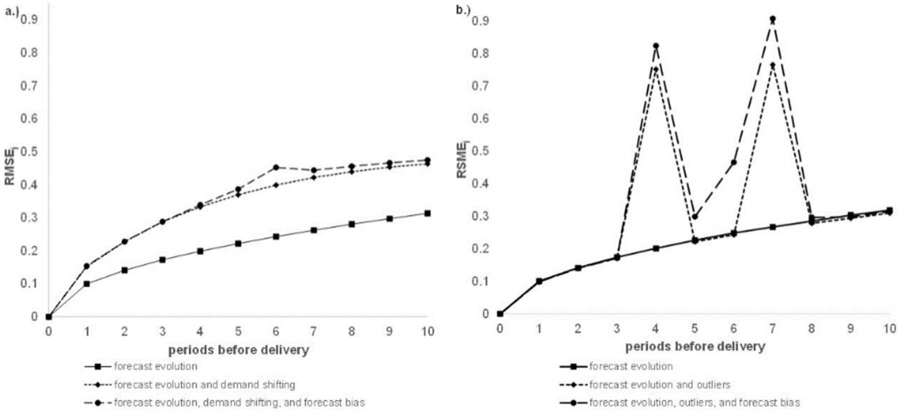

***Figure 1:** Demand model features and its influence on RMSE*

Figure1 show the RMSE with respect to periods before delivery for the demand model features. The forecast accuracy is good if RMSE value is low. Figure1a shows the indicator for basic forecast evolution demand feature and when forecast bias and demand shifting disturbances are added. Figure1b shows RMSE for the demand models with outliers and forecast bias again compare to the basic forecast evolution scenario. Results confirm the intuitive finding that the more disturbances features are present the lower forecast accuracy is and the higher the respective RMSE value. Comparing basic forecast evolution with forecast evolution and demand shifting shows that for all periods before delivery the RMSE value is higher with demand shifting. Additionally, Figure 1a shows for the RMSE values of the scenario with forecast evolution, demand shifting and forecast bias a peak in the respective periods before delivery where the forecast bias occurs $j \in \{4,5,6,7,8\}$. Figure 1b show higher RMSE values in periods where outlier happen $j \in \{4,7\}$ compared to the basic forecast evolution model. When in addition to basic forecast evolution and outliers also the demand model mimics forecast bias results of RMSE is again higher than in the scenario with basic forecast evolution model and outliers.

3.2 Customer-required-lead-time versus forecast evolution behaviour

Felberbauer and Altendorfer (2014) apply a first version of the simulation model module to compare the forecast evolution behaviour, where customers provide a forecast quantity for a specific due date for a long horizon in advance and update their forecast quantities periodically, with a customer-required-lead-time-behaviour, where customers demand stochastic order amounts with a stochastic customer-required-lead-time in advance. In this study the authors assume that the customer required lead times are usually shorter than the forecast evolution horizon, but order quantities do not further change. To compare the influence of both order behaviours for a very streamlined hierarchical production system, a simulation study is performed where among other KPIs the production system overall costs (that are the sum of inventory, tardiness and capacity costs) are discussed.

	Overall Costs											
	forecast quality measure											
	0.13	*0.16*	*0.18*	*0.21*	*0.24*	*0.27*	*0.29*	*0.32*	*0.35*	*0.37*	*0.39*	**Ø**
FEV	12,856	12,899	12,966	13,008	13,082	13,159	13,269	13,382	13,492	13,627	13,762	**13,227**
CRL	12,475	12,575	12,806	13,289	13,881	14,540	15,202	16,036	16,496	16,803	17,929	**14,730**

Figure 2: *Overall costs for forecast evolution (FEV) and customer required lead time (CRL) behaviour with respect to forecast quality (Felberbauer and Altendorfer, 2014)*

Figure 2 shows that for both, forecast evolution (FEV) and customer required lead time order behaviour, the overall costs increase with respect to decreasing forecast quality. In this study the higher the forecast quality measure value the lower the forecast accuracy. Nevertheless, in this study the authors can verify that the hierarchical production planning approach can mitigate the forecast uncertainty better for the forecast evolution behaviour. This means that the average overall costs for all tested forecast quality measures are 11.4% higher for the customer required lead-time behaviour compared to the forecast evolution behaviour. This leads to the insight that for the hierarchical production planning approach more frequent order updates are easier to handle than a very limited number of updates.

3.3 Performance of moving average forecasting if forecast bias occurs

In the paper of Zeiml et al. (2019), the simulation model module is applied to compare forecasts that follow the forecast evolution without bias to forecasts that are biased. Firstly, different forecast error measures are introduced and it is shwon that MPE_j is a good measure to identify systematic forecast errors, i.e. to show if the customer's forecasts are too high or too low with respect to *j* periods before delivery. $RMSE_j$ is identified to be a good measure for evaluating the overall level of forecast uncertainty *j* periods before delivery, however, it also includes the forecast bias induced errors. As stated above, biased forecasts do not imply an information increase with each update and the level of randomness in the stochastic forecast updates significantly influences the value of their respective information. Therefore, it is conjectured that upon a certain level of forecast bias and a certain level of uncertainty, self-generated forecasts, in this setting generated by the moving average method based on the historical final orders, will perform better than the customer provided forecasts. The simulation model module for forecast generation is in Zeiml et al. (2019) applied to generate customer provided forecasts and it is extended by the simple moving average method. The study compares the $RMSE_j$ for customer provided forecasts with different α and β values with the $RMSE_j$ values when the simple moving average method is applied. Figure 3 shows the threshold above which the simple moving average forecasts lead to lower $RMSE_j$ values for biased forecasts (highest forecast bias is 6 periods before delivery) whereby the variable α on the y-axis represents the unsystematic forecast error level and the three lines correspond to different systematic forecast error values β. The scaling factor of the unsystematic forecast error level in this study $a_j = 1$. The respective results show that for high forecast bias values, it is even for very low unsystematic effects better to apply the simple moving average forecast method. From a managerial point of view this is an interesting result as it shows that the forecast bias significantly diminishes the value of demand forecast information. This result motivates the study presented in the next subsection where the performance of a forecast bias correction is evaluated.

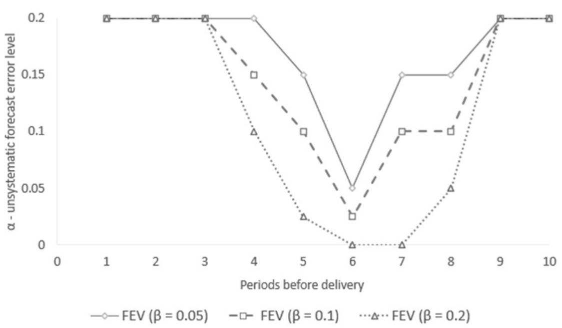

Figure 3: *Simple moving average forecasting compared to forecast evolution method (Zeiml et al., 2019)*

For the pure unsystematic forecast error scenarios, i.e. $\beta = 0$, the simulation results show that customer provided forecasts always lead to a lower $RMSE_j$ in comparison to the simple moving average method. This is an interesting managerial insight, since it implies that whenever there is no systematic forecast bias using the customer provided and continuously updated forecasts is the best choice.

3.4 Forecast bias correction model

Based on the findings of Zeiml (2019) a forecast correction model (see Section 2.3) is integrated in the simulation forecast module to mitigate systematic forecast errors. The correction model is tested in scenarios with and without unsystematic and systematic errors. Zeiml et al. (2020) presents a decision model to decide in a rolling horizon, whether in the current time period the presented forecast correction model should be applied or not. Therefore, the constant forecast data generation module is extended to generate seasonal demand behaviours. Additionally, we introduce the possibility to parameterize a dynamic planning behaviour, where the systematic bias β can also change over time.

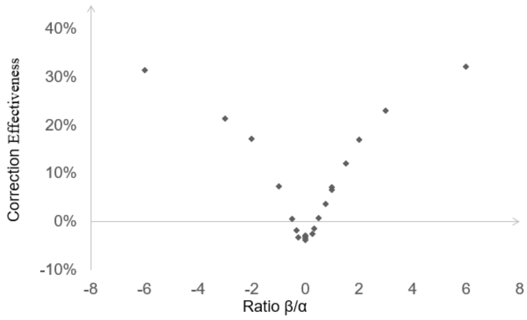

Figure 4: *Correction effectiveness with respect to the ratio of the systematic and unsystematic forecast error β/α (Zeiml et al., 2020)*

To answer the question about the performance of the forecast correction model Figure 4 give some insights. The forecast correction effectiveness measure (Section 2.2) describes the improvement (positive value) or the deterioration (negative value) of the forecast accuracy comparing the situations with and without the correction model. Results show that the ratio β/α influences the correction effectiveness. The higher |β/α|, the better the correction mechanism works. Nevertheless, applying the correction model in situations where the unsystematic error α dominates, leads to an increase of RMSE and on the same time reduces forecast accuracy. Additionally, the study of Zeiml et al. (2020) shows that the developed decision model, whether to apply the correction or not, leads to significant forecast quality improvements, compared to its continuous application.

4 Conclusion

This paper presents the status of the simulation model module for forecast data generation to mimic different customer provided forecast behaviours. Basic forecast evolution behaviour, biased forecasts, forecast with outliers and forecasts with demand shifting are implemented. Additionally, forecast error measures are modelled to discuss the influence of the demand model features and its parameterization. The third feature of the simulation model are correction models to improve forecasts based on the information of historical forecast evolutions. The most interesting results of already published simulation studies, which use the presented simulation model module for forecast data generation, are presented. The highlights of the mentioned papers are discussed concerning the differences of forecast accuracy and their performance of the presented correction model with respect to the customer provided forecast behaviours. The contribution of this paper lies in providing a comprehensive view on the potential of applying the simulation model module for forecast data generation to inspire other researchers to contribute in the area of customer provided forecast. After the InnoFIT project it is planned to share the simulation model module for forecast data generation on phaidra, which is a repository for the permanent secure storage of digital assets. After that, researchers will have free access to the simulation model module to further extend advanced forecasting techniques and forecast correction models for customer provided forecasts. Additionally, the simulation model module will be integrated in a generic and scalable simulation model, to test the developed forecast correction models for more complex production systems.

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