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SIMULATION EVALUATION OF AUTOMATED FORECAST ERROR CORRECTION BASED ON MEAN PERCENTAGE ERROR

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ABSTRACT

A supplier-customer relationship is studied in this paper, where the customer provides demand forecasts that are updated on a rolling horizon basis. The forecasts show systematic and unsystematic errors related to periods before delivery. The paper presents a decision model to decide whether a recently presented forecast correction model should be applied or not. The introduced dynamic correction model is evaluated for different market scenarios, i.e., seasonal demand with periods with significantly higher or lower demand, and changing planning behaviors, where the systematic bias changes over time. The study shows that the application of the developed dynamic forecast correction model leads to significant forecast quality improvement. However, if no systematic forecast bias occurs, the correction reduces forecast accuracy.

1 INTRODUCTION

To manage their production facilities, companies usually use forecasts to create production orders. The order generation process is relevant for the logistical performance of a company, which means on-time delivery simultaneously with a minimum of stock. In their hierarchical planning approach of the companies either classical forecast, prediction models are used to predict demand, or they use customer provided forecast, which is usually transmitted and updated in a rolling horizon using Electronic Data Interchange. For both possibilities to estimate the demand, the information quality, i.e., the accuracy of the forecast is critical to efficient production and the competitiveness of the companies. In this paper, we focus on the situation where customers provide and update forecast regularly and investigate the developed forecast correction model for different threshold values, which define whether to apply the correction or not.

To compare different forecast methods, i.e. independent forecast distribution, forecast evolution, and moving average Zeiml et al. (2019) present a simulation model with focus on the modelling of forecast behaviors. The results of the latter paper leads the authors to the development of a working paper that focuses on the analysis of production order accuracy in a biased forecast evolution system and a first evaluation of the performance of the developed static correction model. First preliminary results of this working paper show that for a broad range of demand settings the correction model is beneficial in scenarios with systematic forecast errors.

Nevertheless, this shows that the previous studies are limited in the way that the correction model is either applied or not applied, which brings us to the main contribution of this paper, where a decision model is developed and evaluated for an adaptive correction model. Additionally, both recent papers (Zeiml et al. 2019) and the working paper we assume a stochastic but constant demand setting, which brings us to the second main contribution of this paper, where the performance of the correction model is tested for seasonal demand and changing planning behavior.

The above-explained motivation stated before brings us to the three-research question stated below:

- RQ1: How can an automated decision whether to apply a forecast correction or not be modeled?
- RQ2: What is the performance of the developed automated forecast correction model in scenarios with a forecast bias, and how well is it able to identify scenarios without forecast bias?
- RQ3: What is the performance of the automated forecast correction model for seasonal demand and changing planning behavior?

In RQ1, the decision model and the criterion to apply the forecast correction method or not is developed. RQ2 studies stable demand streams and compares the cases with no forecast correction, continuous forecast correction, and the adaptive forecast correction model. In RQ3, several scenarios with higher and lower demand periods are evaluated, and one scenario with a change in forecast bias is investigated.

2 LITERATURE REVIEW

As stated in the introduction, we focus on the customer-provided forecasts behavior where the demand forecasts are received directly from the customers on a rolling horizon. A general suggestion for an appropriate forecast model is impossible, as the method is related to the forecast generation process (Fildes and Kingsman 2011). Forslund and Jonsson (2007) point on the importance of forecast information and its strong impact on how the forecasts can be used. The latter authors identify collaboration as basic block to increase information quality. In the simulation study of Zeiml et al. (2019), the two different forecast behaviors, independent forecast distribution, and a forecast evolution model are compared to discuss the performance of different forecast error measures in a setting of customer-provided forecasts in comparison to a simple moving average forecast prediction method. The main findings of Zeiml et al. (2019) are the identification of the appropriate forecast error measures for scenarios with and without systematic errors.

Altendorfer et al. (2016) study the effect of forecast errors when material requirements planning is used as the planning method. They find an impact of the forecast errors on required capacity and costs. For a production system with customer provide forecast Enns (2002) investigates the influence of demand uncertainty, and forecast bias. He summarizes that demand uncertainty, and forecast bias are critical to the performance of the production system. He also identified that uncertainty in timing and demand impacts the efficiency of the planning process (Enns 2002). The influence of the timing decision is also studied by Güllü (1996). He analyzes a forecast evolution process for customer provided forecasts and compares a production system without forecast information and with forecast information. Results show a significant improvement in production system performance for the scenario with a forecast update.

Lee et al. (1997) identify four sources of information distortion. The “Rationing Game” describes the situation that in shortage situations the customers issue an order that exceeds in quantity what the customer would order in a situation without the constraint. Before delivery the customer cancels the unneeded orders. Cheung and Zhang (1999) show that the order cancellations increase total system costs. The authors find that the influence of cancelations on costs depends on the probability of cancellation and the respective cancellation time.

In comparison to our study, the forecast update is limited to one update two periods before delivery (Güllü 1996). The martingale model of forecast evolution models the improvement of forecast quality with respect to the decreasing time before delivery (Heath and Jackson 1994). Their additive model is applied in the paper to generate the customer-provided forecast data in the forecast evolution scenarios. For a streamlined production system Felberbauer and Altendorfer (2014) compare the forecast-evolution-model with a customer-required-lead-time model and they discuss their performance on costs (inventory, tardiness, and capacity costs), utilization, and service level. Nevertheless, Felberbauer and Altendorfer (2014) do not present an in-depth analysis of the forecast quality.

Zhang et al. (2011) analyze seasonal demand for a stochastic production system. They state that in order to use such a production planning model, production planners should proactively address demand uncertainties and randomness. Matsumoto and Komatsu (2015) investigate demand forecasting by time series analysis for a remanufacturing system. They test two forecasting methods which can cope with seasonal demand and do not need information regarding the time distribution of new products. Both methods used in order to improve the forecast especially considering seasonal effects show the desired results of improvement.

The literature review above shows that many authors are dealing with the parameterization of their production planning methods and coping with uncertainties. Nevertheless, the literature about the adaptation of forecasts is limited. Therefore, the focus of this paper is the development and evaluation of a forecast correction model for demand scenarios with seasonal demand and changing planning behavior.

3 MODEL DESCRIPTION

Next, we describe the forecast generation process, the applied forecast error measures, and the developed correction model with the respective threshold.

3.1 Forecast generation process

The forecast process used in this model has the following structure. We assume that customers provide forecasts on a rolling horizon basis, i.e., forecasts are available for a long forecast horizon into the future and are periodically updated. The long-term forecasts $\tilde{x}_i$ are based on agreement contracts (Shen et al. 2019), which imply regular orders. The index i represents the due date. In this paper, we do not assume for all scenarios constant forecast amounts for periods far in the future, which enables the investigation of different market scenarios. When the due date comes closer, the customers start to update their forecasts for periods before delivery j. The first information arrives $j_{max} = 10$

periods before delivery. For example, $x_{i,j} = x_{i=15,j=2}$=793 means that the forecast amount for due date $i = 15$ two periods before the delivery (i.e., $j = 2$) is 793 pieces. The actual period, where this forecast information was sent, can be calculated by $i - j = 15 - 2 = 13$. In this paper, we analyze two forecast generation methods: original forecast evolution and forecast bias. To parameterize original forecast evolution scenarios, we use the variable α, and for the parameterization of the forecast bias scenario, we use the variables β and b.

3.2 Original Forecast Evolution

The original forecast evolution model is based on the idea of a random walk (Güllü 1996). In this model, each forecast update is modeled by adding a random term to the previous forecast amount, as shown in Equation (1).

$$\begin{gathered} x_{i,j} = x_{i,j+1} + \varepsilon_j(\tilde{x}_i, 0, \alpha) \\ \varepsilon(\tilde{x}_i, 0, \alpha) \sim N(0, \alpha\tilde{x}_i) \end{gathered} \quad (1)$$

This random variable ε is normally distributed with expected value zero and standard deviation $\alpha_j\tilde{x}_i$. The long term forecast $\tilde{x}_i$ for the due dates, i can be constant or variable. The variable α, which determines the standard deviation in the forecast evolution scenario, is constant for all due dates i and all periods before delivery j.

3.3 Forecast bias

Original Forecast Evolution implies unsystematic forecast errors. The Forecast bias model mimics systematic errors. The forecast bias behavior states that the forecasted amounts from the customers are, on average, significantly too high or too low. In this paper, the forecast bias changes for periods before delivery j and for due date i. This opens various possibilities to investigate different forecast behaviors and changes in the forecast behaviors for different periods. Equation (2) shows how the forecasts are updated in this method.

$$\begin{gathered} x_{i,j} = x_{i,j+1} + \varepsilon_j(\tilde{x}_i, \beta, 0) \\ \varepsilon(\tilde{x}_i, \beta, 0) = \beta b_j \tilde{x}_i \end{gathered} \tag{2}$$

Table 1 shows the parameterization of the Forecast bias scenario for periods before delivery j. For the better analysis of the order behavior scenarios in the result section the parameterization of the systematic forecast, bias is divided into a scaling factor β and the shape factor b_j. Table 1 shows the shape of the predefined planning behavior. In this forecast behavior, there are no changes $j_{max} = 10$ and $j = 9$ periods before delivery. The customer starts the systematic change of the forecast eight periods before delivery $j = 8$. Form periods before delivery eight to six, the customer overbooks his forecast. From periods before delivery five to three, the customer cancels orders again.

Table 1: Forecast bias shape factor $\boldsymbol{b_j}$ with respect to periods before delivery

j	0	1	2	3	4	5	6	7	8	9	10
b_j	0	0	0	-1	-1	-2	2	1	1	0	0

Combining the forecast bias shape factor b_j according to Table 1, with the scaling factor $\beta = 0.05$, and the longterm forecast $\tilde{x}_i = 800$ gives the planning behavior illustrated in Figure 1. In supply chain literature, this specific behavior is also referred to as ration gaming, where customers overbook and cancel afterward. Other different planning behaviors can also be defined similarly, as explained above, using Table 1. Nevertheless, in this paper, we focus on an advanced forecast correction model and do not investigate other planning behaviors.

Figure 2: Forecast evolution of x_{ij} with respect to periods before delivery j, forecast bias shape factor b_j, $\beta = 0.05$, and long term forecast $\tilde{x}_i$.

According to Equation (3), you see the modeling of the forecast process for the combination of unsystematic (*Original Forecast Evolution*) and systematic forecast (*Forecast bias*) errors.

$$\begin{gathered} x_{i,j} = x_{i,j+1} + \varepsilon_j(\tilde{x}_i, \beta, \alpha) \\ \varepsilon(\tilde{x}_i, \beta, \alpha) = N(\beta b_j \tilde{x}_i, \alpha \tilde{x}_i) \end{gathered} \tag{3}$$

Note that β and α can be directly compared between scenarios because they are unscaled. We summarize that α describes the unsystematic noise of the forecast and β Identifies the forecast behavior of booking systematically too much or too little (forecast bias).

3.4 Forecast accuracy

To evaluate the forecast accuracy and later apply the correction model, two forecast error measures (Hopp and Spearman 2008; Hyndman and Koehler 2006; Shcherbakov et al. 2013; Zeiml et al. 2019) are introduced. First, the mean-percentage-error MPEj is introduced to measure systematic effects, and second, the standardized root-mean-squared-error RMSE*j is applied to measure unsystematic effects. The following Equation (4) introduces the respective forecast error measures. According to the definition below, the forecast is more accurate when the forecast error is lower.

$$MPE_{i,j} = \frac{\sum_{k=i+1-m}^{i} (x_{k,j} - x_{k,0})}{\sum_{k=i+1-m}^{i} x_{k,0}} \; ; \; RMSE^*_{i,j} = \frac{\sqrt{\frac{1}{m}\sum_{k=i+1-m}^{i} \left(x_{k,j} - x_{k,0}\right)^2}}{\frac{1}{m}\sum_{k=i+1-m}^{i} x_{k,0}} \tag{4}$$

For both equations, the index i represents the current period in which the forecast errors are calculated based on historical data. Note that both forecast measures are calculated for periods before delivery j. For the forecast error measure calculation, the number of historical data m, which is used to calculate the respective error measures, has to be defined. For the calculation of the error measures for the period i and the respective periods before delivery j the forecast history of all final orders where $i \epsilon \{i+1-m, \dots, i\}$ is used. The two error measures are calculated separately for each period before delivery j. The larger the number of historical data used, i.e., m is higher, the more robust the error measures are. The smaller the number m, the more the forecast measures are sensible against current changes.

3.5 A decision model for forecast correction

Below, the decision model for forecast correction is given. $\hat{x}_{i,j}$ represents the corrected forecast based on the original forecast $x_{i,j}$ provided by the customer and the correction model. The original customer-provided forecasts $x_{i,j}$ are adapted with the mean percentage error MPE_{ij} which is calculated for m historical forecast streams according to Equation 4.

$$\hat{x}_{i,j} = \frac{x_{i,j}}{1 + MPE_{ij}} = \frac{x_{i,j} \sum_{l=i+1-m}^{i} x_{l,0}}{\sum_{l=i+1-m}^{i} x_{l,0} + \sum_{l=i+1-m}^{i}\left(x_{l,j} - x_{l,0}\right)} = x_{i,j} \frac{\sum_{l=i+1-m}^{i} x_{l,0}}{\sum_{l=i+1-m}^{i} x_{l,j}} \tag{5}$$

In this paper, the forecast correction is not automatically applied for each period before delivery j, but we introduce a threshold value δ and a variable $D_{i,j}$ to decide whether to apply the correction or not ($\hat{x}_{i,j} = x_{i,j}$). The variable n defines the number of historical $MPE_{l,j}$ values that are considered for the calculation. The decision variable $D_{i,j}$ represents the coefficient of variation for the last historical n, $MPE_{l,j}$ values. The decision variable $D_{i,j}$ is calculated as follows:

$$D_{i,j} = \frac{\sqrt{\frac{1}{n}\sum_{l=i+1-n}^{i} \left(MPE_{l,j} - \frac{1}{n}\sum_{k=i+1-n}^{i} MPE_{k,j}\right)^2}}{\frac{1}{n}\sum_{k=i+1-n}^{i} MPE_{k,j}} \tag{6}$$

Whenever $D_{i,j}$ value is lower than the threshold value δ, i.e., the forecast correction is applied for the specific period before delivery j. $D_{i,j}$ is calculated at each time point i for the period before delivery j. The application of the forecast correction is decided independently for each period before delivery j. This decision model for correcting forecast answers research question one.

3.6 Simulation model

To evaluate the performance of the developed correction model, we use a discrete event simulation model built in AnyLogic©. The predefined forecast behaviors with systematic and unsystematic forecast errors, the forecast error measures, as well as the forecast correction model, are implemented in the simulation. The runtime of the simulation is 2080 periods, which results in approximately 2050 independent forecast evolutions. The first 30 periods (runtime of 2080 and 2050 complete forecast streams) are neglected from the analysis due to the fact, that for the first thirty final orders no complete historical forecast information is available for the analysis. The simulation is conducted with 20 replications to account for the stochastic behavior of the forecast processes. We assume that the periods are weeks because weekly forecast updates are frequent. With this assumption, the simulation time would lead to an evaluation of forecast streams of 40 times one year. For the calculation of the coefficient of variation, we define the number of historical data to $n = 8$. For the calculation of the forecast error measures, we define $m = 12$. For the determination of these values a preliminary test was conducted, however the analysis of the different values was limited, as this is an extensive topic and suited for future research.

4 NUMERICAL STUDY

The previous section describes the investigated forecast processes, the developed correction model, and the built-up simulation model. The parameters α and β to scale the forecast process enable the investigation of the scenarios A to E, according to Table 2. For all scenarios, the effectiveness of the correction model is discussed. Therefore, different threshold values δ are tested. We test $\delta \epsilon \{0, 0.025, 0.1, 0.4, \infty\}$, where $\delta = 0$ represents the case where no correction is applied and $\delta = \infty$ mimics the situation where correction is always used. Next, different scenarios are introduced.

Scenario A is the original forecast evolution behavior that mimics unsystematic forecast errors. In this scenario, we investigate different levels of pure uncertainty by testing the set $\alpha \epsilon \{0.025, 0.05, 0.1, 0.15, 0.2\}$. Scenario B comprises the application of the original forecast evolution with a systematic forecast bias behavior. In order to simulate systematic forecast behavior $\beta \epsilon \{-0.15, -0.05, 0, 0.05, 0.15\}$ is used. In scenario C, scenario B is expanded with a seasonal behavior where the long-term forecast $\tilde{x}_i$ changes with period i. In this scenario $\tilde{x}_i$ is changed in a periodic manner, where the first 26 weeks of a year the long-term forecast is 100%, and the second 26 weeks of the year, the long-term forecast is decreased to 25%. This behavior is repeated for all simulated forty years. Additionally, for scenario C, an increase from 100% to 200% is investigated, while monitoring the effectiveness of the developed correction mechanism. The seasonal demand pattern is common in practice. For example, the automotive industry has demand peaks in spring and lowest sales in the winter month. In scenario D the scenario B is extended by a dynamic forecast bias change β_i. In Scenario B, we used a triangle-shaped planning behavior as shown in Table 1 and Figure 1 and change β_i to 200% of its initial value for the second 26 weeks of the year. The same periodic behaviors are used as in scenario C, where every 26 weeks β_i is increased to 200% and reduced back to 100% after another 26 weeks. In scenario E, original forecast evolution, periodic forecast bias, and seasonal demand are investigated conjunct.

Table 2: Scenario overview

Scenarios	Scenario description	Parameters
A	Original forecast evolution with random step size only	α
B	Original forecast evolution with random step size combined with a systematic forecast bias behavior	α, β
C	Original forecast evolution combined with forecast bias behavior and a seasonal demand behavior	α, β, $\tilde{x}_i$
D	Original forecast evolution combined with a periodic forecast bias	α, $β_i$
E	Original forecast evolution combined with a periodic forecast bias and a seasonal demand behavior	α, $β_i$, $\tilde{x}_i$

In order to compare those different scenarios, we introduce the Correction Effectiveness indicator E to measure the effectiveness of the developed correction procedure. We calculate the $RMSE_j$ of $x_{i,j}$ overall i to get a measure of prediction quality for every time interval j before delivery. That is done for the original uncorrected set of predictions $\delta = 0$ and again for the with various $\delta \epsilon$ {0; 0.025; 0.1; 0.4; ∞} corrected predictions. This way we obtain $RMSE_j(\delta)$ for different δ. As we do all scenarios for those different δ´s, we chose δ_0=0 as the basis for comparison. δ_0 is the situation where the predictions are never corrected, while with δ_∞ all the predictions $x_{i,j}$ are corrected to a new matrix $\hat{x}_{i,j}$ as defined in Equation 5. To get a quality measure for the effectiveness of this correction procedure, we define the correction effectiveness E. This measure can be calculated for all $RMSE_j(\delta)$ for the given thresholds δ as:

$$E_j(\delta) = \frac{RMSE_j(\delta_0) - RMSE_j(\delta)}{RMSE_j(\delta_0)} \tag{7}$$

Figure 2 shows a typical evolution of the Correction Effectiveness E with the timeline towards the delivery date for a solely random walk scenario A. There are two reasons why the correction mechanism keeps constant Effectiveness E while approaching the delivery date (lower *j*) and why E is worse with higher δ:

- Typically, RMSE itself gets smaller towards the delivery date, but this behavior is eliminated in Equation 5 having chosen E as a relative measure.
- The more often correction are applied (high δ) the more often additional random terms are added, which will follow in higher $RMSE_j(\delta)$, leading to an E measure that is worse than without correction.

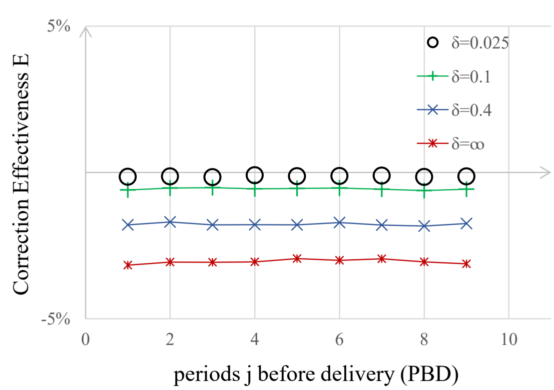

Figure 3: Correction Effectiveness as a function of the periods before delivery for various thresholds

The effectiveness of the correction gives the percentual advantage of the correction compared to the original uncorrected prediction. As lower RMSE indicates a better prediction, a higher E resulting from a lower $RMSE_j(\delta)$ indicates a better performance of the correction procedure and vice a versa. In this formulation $E_j(\delta)$ can be calculated for every period j before delivery. In order to decide on the quality of a complete timeline of predictions, in the following, we use the average correction effectiveness E over all periods j before delivery.

4.1 Scenario A: Forecast evolution that is driven by a random step size for the predictions only

In order to decide on the usefulness and quality of the correction mechanism, the first approach is made with scenario A. Prediction evolves only by random normally distributed step sizes. The level of randomness is kept fix for all *(i)*, and also starting with a fixed average initial start prediction $\tilde{x}_i$. With various $\boldsymbol{\alpha\epsilon}\{0.025;\ 0.05;\ 0.1;\ 0.15;\ 0.2\}$ we get various matrixes $x_{i,j}$ and their corresponding corrected versions $\hat{x}_{i,j}$ as a basis to get various $RMSE_j(\delta)$ to calculate $E_j(\delta)$ to decide on the quality of the correction procedure. Figure 3 shows the effectiveness of the correction in these cases. As expected with higher δ and higher α the correction effectiveness gets worse, due to the additional randomness that is introduced by these factors. Note that all correction effectiveness values in this setting are negative, i.e. correcting a non-biased forecast stream leads to a worse performance.

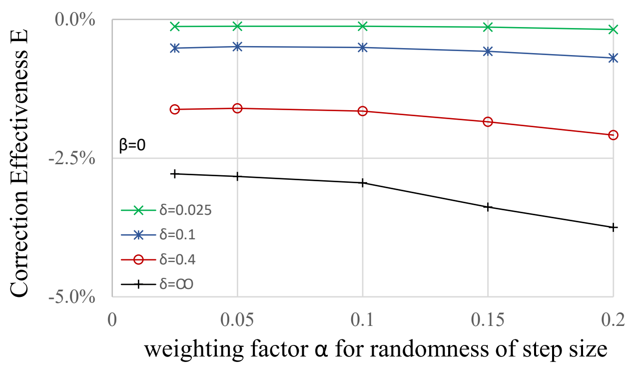

Figure 3: Correction Effectiveness for solely random forecast evolution

4.2 Scenario B: Forecast evolution that is driven by a combination of a given peak like step path (modifying β) and superimposed randomness (modifying α)

Having the weighting factor α for the level of randomness and β for the level of the systematic path deviation of the predictions we modify both in this scenario. α and β are kept constant for all 2080 *(i),* and correction effectiveness is compared to several combinations of these two factors.

Figure 4a shows that the higher the absolute level of the given path (factor β) is, and the lower the randomness (factor α) of this path is, the better the correction mechanism works. These results can be directly summarized to a dependency of the correction effectiveness factor from the ratio β/α (see Figure 4b). The higher the absolute value of that ratio, the better the correction works. This behavior is apparent if there is little noise compared to a primary significant systematic signal, the correction is applied more often, and hence better results are given with higher β/α. Figure 4b shows a light unsymmetrical behavior because we correct prediction resulting from outliers that produce negative predictions, that in our model are carried forward to the next period in (*i*).

Having evaluated the Scenarios A and B, we can answer RQ2: What is the performance of the developed automated forecast correction model in scenarios with a forecast bias, and how well is it able to identify scenarios without forecast bias as follows:

- Using the correction algorithm as described is not useful in cases of only random behavior and even give worse result with high original randomness in the predictions.
- In contrast to that: in cases of repetitive planning behavior with a regular over or under booking in defined periods, the correction procedure is useful. The degree of making a better forecast depends mainly on the ration of the regular repetitive deviation of planning to the random component defined as the ratio β/α. The bigger β or, the smaller α, the more the correction procedure will influence the predictions. In our case an absolute ratio β/α higher than slightly less than 1 starts to give a positive influence on the predictions.
- The correction mechanism works best, if there are sufficient components of β, and it makes situation worse when there are only random components.

a.) b.)

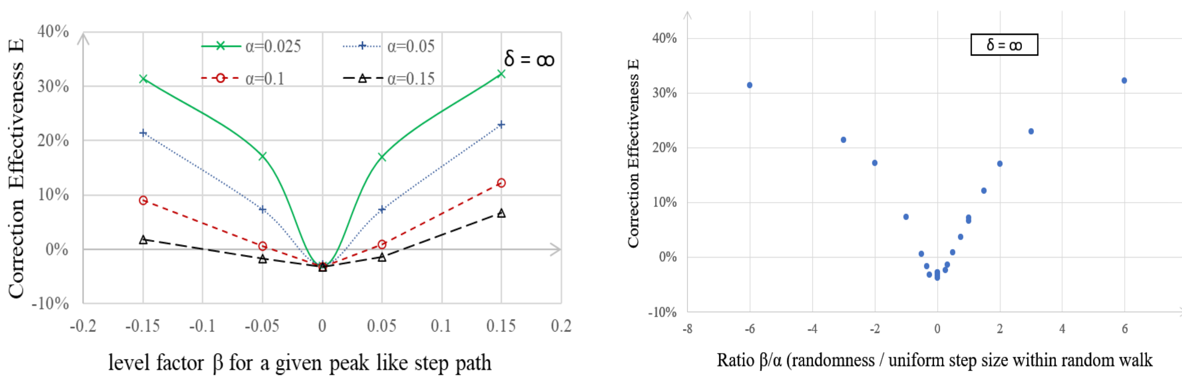

Figure 4: a.) Correction Effectiveness E for the level factor β, and b.) Correction Effectiveness as a function of the ratio β/α

4.3 Scenario C: Forecast evolution with changing demand (changing $\tilde{x}_i$)

In scenario C we changed $\tilde{x}_i$ with rising (*i=1, ..., 2080*) in a periodic manner as described above. This scenario mirrors a typical seasonal behavior that may be agreed upon between customer and supplier for a longer run. In this case, we change $\tilde{x}_i$ every 26 weeks from 100% to 25% or 200% to see the effectiveness

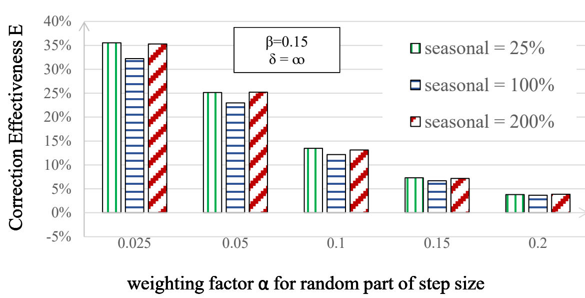

Figure 5: Correction Effectiveness E for different seasonal demand levels and with respect to the randomness factor α

of the correction mechanism in these situations. The quality of the resulting correction depends mainly on the randomness of the prediction (Figure 5). There is only a small dependency from the course of the initial demand $\tilde{x}_i$. This is valid for all δ, though still, δ=∞ gives better results for the predictions when randomness α is comparatively small to the level step path factor β. This can be understood, as the factor for $\tilde{x}_i$ as a factor for seasonality had been chosen to be constant for 26 intervals, a long time compared to the four intervals chosen to build the matrix of $MPE_{i,j}$. Outside this area of four intervals, the demand building factor can be shortened when building $MPE_{i,j}$.

4.4 Scenario D: Forecast evolution with changing planning behavior

In Scenario D, we look at a changing planning behavior on the timeline towards delivery. Starting with $j = j_{max} = 10$ periods before delivery, typically with an average value that is valid for a longer time. The predictions develop towards delivery often in a typical pattern as used in scenario B. And the typical pattern may change, similar to the seasonal demand behavior in its level. In Scenario B, we used a triangle-shaped pattern (see Table 1 and Figure 1) with a defined height of the peak. Additional to scenario B, we change the peak height by 200% depending on the index variable *(i)* along the course of time. The same periodic rhythm is used as in scenario C, where every 26 weeks $\tilde{x}_i$ is increased to 200% and reduced back to 100% after another 26 weeks. Figure 6 gives the corresponding results.

It could be imagined that the situation with half of the year a 100%-peak and another half of the year a 200%-peak should be similar to an average behavior like a year through 150%-peak. However, it is different. The peak within RMSE is considerably higher for the periodic change in peak heights. This is due to the additional random aspect added by these repeated periodic changes. Additionally, the effectiveness of the correction mechanism decreases, which is, as seen before, typical for increasing randomness.

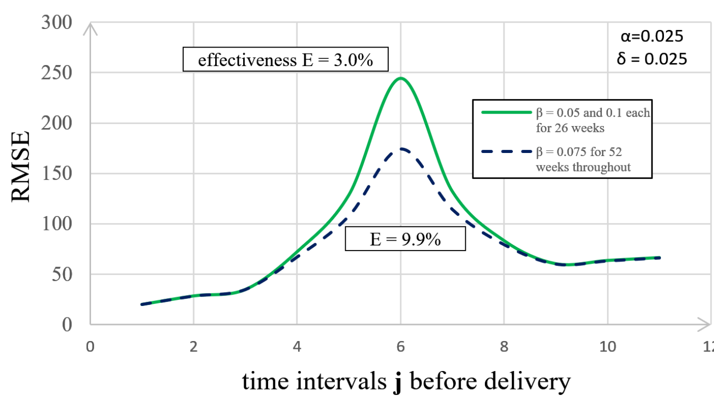

Figure 6: RSME for a periodic prediction behavior compared to a stable nonperiodic prediction behavior

4.5 Scenario E: Forecast evolution with seasonal demand and changing planning behavior

As the last scenario, we looked at the influence on the Correction Effectiveness by changing α (randomness) and β (step path variation) in their level height and with a given seasonal (changes of the initial demand in i) or periodic (changes in prediction bias level in j) behavior. We found by analyzing the calculations that higher randomness gives fewer gains by the correction algorithm and using the correction always ($\delta=\infty$) is better than using a small threshold value. On the other side, calculations show that it is the other way around with β. High absolute β gives better corrections than lower. Again, also in this variation of parameters, a higher threshold value gives better results. Having evaluated the Scenarios C, D, and E, we can answer RQ3 - What is the performance of the automated forecast correction model if seasonal demand occurs and forecast bias is not stable? – as follows:

- With a lower random aspect of the forecast (low α), the correction algorithm works more effectively if at least a part of the prediction has a systematic bias component β in the size of the noise component α. With no such systematic component, predictions get worse.
- In the case of a higher systematic part of the forecast bias (high β), the gains by the correction algorithm get better.
- Both aspects lead to a higher ratio of β/α. This ratio indicates the possibility to distinguish between random noise and meaningful information, thereby allowing better correction through the algorithm.
- These general findings do not change in a complex situation. Using the correction algorithm in more complex situations leads to better predictions. However, it has to be taken into account that the additional changes in time and level of parameters introduce more randomness and, therefore, a decrease in correction effectiveness.

5 CONCLUSION

In this paper, a discrete event simulation model is developed to investigate the performance of a decision model for the application of a forecast correction. The forecast generation process models systematic and unsystematic forecast errors for a system with periodic forecast updates. The forecast error measure mean percentage error is used to set up a forecast correction model to mitigate systematic forecast errors. Additionally, to answer RQ1, we introduce a decision model that can be used to adaptively use the correction model, which is a significant contribution compared to past publications where either the correction model is applied continuously or not. We test the correction model for different levels of systematic and unsystematic forecast errors, seasonal demand scenarios, and scenarios where the planning behavior changes with time. Answering RQ2, the study shows that the correction model is advantageous in all our scenarios where there is a systematic bias of a comparable value as the pure random component and its correction effectiveness was up to 30%. Notably, in scenarios where the systematic effect was significantly higher than the unsystematic error, the effectiveness of the correction model is best. We find that the adaptive correction model is not beneficial in situations without systematic error. Concerning the performance of the forecast correction model in situations with demand disruptions and unstable forecast bias, i.e. RQ3, results confirm in our case its benefit which was up to 17% also in complex situations and it's increasing effectiveness: the higher the ratio of systematic error compared to the unsystematic error is (β/α) the better are the results. Nevertheless, the numerical study shows that in case of systematic bias it is better to run the correction model more often, than not. For further research, the risk of applying the correction model especially the importance of the ratio β/α should be discussed in more detail and we will provide a more comprehensive study on different demand patterns and planning behaviors.

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