Simulation of the control of exponential smoothing by methods used in industrial practice

Professor Dr.-Ing. Frank Herrmann
Hochschule Regensburg - University of Applied Sciences Regensburg
Innovation and Competence Centre for Production Logistics and Factory Planning (IPF)
PO box 120327, 93025 Regensburg, Germany
E-Mail: Frank.Herrmann@HS-Regensburg.de

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ABSTRACT
Demands of customers for products and of the production for parts are being forecasted quite often in companies. The results are used extensively within the operational production planning and control by IT Systems like the SAP system. Hereby preferably methods based on exponential smoothing are being applied. Especially, in industrial practice it is expected that the pattern of the data change over time in such a way, that the parameters of the exponential smoothing have to be changed. In some companies thousands of items require forecasting, which is very laborious. With an adaptive method the parameters are modified in a controlled manner, as changes in the pattern occur. Two adaptive methods used in industrial practice are explained. Simulation experiments over a huge number of periods show when they should be used.

1. INITIAL SITUATION

Forecasts of demands for quantities of products in subsequent periods are carried out several times in a planning process of a company. The fact that the module “Demand Planning” is the most frequently used module within Enterprise Resource Planning (ERP) or Production Planning and Control (PPS) systems in companies, emphasizes that. Other planning functions within ERP or PPS systems use forecasts as well – one example is the use of “alternative planning types”.

In general forecasting methods are chosen for a certain forecasting model. The more accurately a forecasting model describes the actual demand series, the better the forecasting results are. Actual changes in industrial practice can be corrected by adapting the forecasting model and in consequence by changing the forecasting method. Due to the Wold decomposition (Wold 1938) a forecasting model consists – simply speaking – of a linear combination of a sequence of uncorrelated random numbers and a random addend. If there’s a level shift within the forecasting model where one (or more) non-zero coefficients (of the linear combination) are being changed to a different non-zero value, the known forecasting methods adapt in time. Their adaption speed is relatively high when using methods based on exponential smoothing. Such (forecasting) methods are preferably used in ERP or PPS systems and therefore generally in companies. Empirical studies (as Armstrong 2001) show that exponential smoothing outperforms on average complex or statistical sophisticated methods and only sometimes they are worse.

If such a level shift is highly significant, there may be a strong manual adaption of the parameters required – depending on the settings of the exponential smoothing. Because of the enormous amount of forecasts in companies, the number of manual settings required might rise quite fast. Furthermore such a change is to be distinguished from a temporal change, especially from an outlier. That is the reason why so called adaptive methods have been developed where the parameters are being adapted automatically. For an overview see (Mertens and Rässler 2005).

For the investigation the behaviour of the forecasting methods are simulated about a huge number of periods. Such simulations at the IPF show that the results occur by exponential smoothing of the first degree. Since the behaviour of this exponential smoothing is easier to understand as the ones for seasonal data or data with a trend, the paper focuses on this method.

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2. FORECASTING METHODS AND KEY FIGURES

The simplest forecasting method based on exponential smoothing determines the forecast value in period t (p_t) through: $p_t = p_{t-1} + \alpha \cdot e_t$. α is the smoothing parameter and $e_t = y_t - p_t$ the forecasting error. Whereas y_t represents the demand of period t; so: $p_t = \alpha \cdot y_{t-1} + (1-\alpha) \cdot p_{t-1}$.

This exponential smoothing of the first degree is suitable for demands which fluctuate around a mean value. This will be advanced in chapter "Simulations". Before starting with this standard procedure the initial value of the forecast (for the first period) and the smoothing parameter have to be set. That is usually done by analysing a long series of previous demands. This demand series formulates along with a performance criterion an optimization problem. In literature many performance criteria are being proposed; refer to (De Gooijer and Hyndman 2006) for example.

Usually an unbiased forecasting method is required. This means that the expected value of the forecasting errors is zero. The standard deviation of the forecasting errors allows a statement about the safety level with which forecasted demands will occur in the future. That is why it has been examined. In order to achieve steady key figures all forecasting methods are applied on very long demand series – at least over 2500 periods.

3. ADAPTIVE METHODS

Although there is no consensus as to the most useful adaptive method, the most widely-used one was developed by Trigg and Leach (Trigg and Leach 1967). They apply exponential smoothing of the first degree to the forecasting error and to its absolute value. The forecasting error being $SE_t = \phi \cdot e_{t-1} + (1-\phi) \cdot SE_{t-1}$ and the absolute value $SAE_t = \phi \cdot |e_{t-1}| + (1-\phi) \cdot SAE_{t-1}$ with a common smoothing parameter (ϕ). The tracking signal $TS_t = \frac{SE_t}{SAE_t}$ is now used as smoothing parameter α_t for calculating the forecasting value of time period t + 1; this method is called control (of the smoothing parameter). Trigg shows in (Trigg 1964) that the tracking signal recognizes a structural change within a demand series and for this he recommends a smoothing parameter of $\phi = 0{,}1$. The starting values of these two exponential smoothing methods should be low because of the expected mean forecasting errors of nearly zero. In detail $SE_0 = 0{,}05$ and $SAE_0 = 0{,}1$ have been chosen during the investigation for this article.

Since this method delivers sometimes unstable forecasts, α_t is restricted in various ways, s. (Whybark 1973) and (Dennis 1978). In another approach the smoothing parameter is adapted by the Kalman Filter, s. (Bunn 1981), (Enns et al. 1982), (Synder 1988), for weighted least squares s. (Young 1999, Young et al. 1999, Young 2003) and its using for exponential smoothing s. (Harvey 1990). For further approaches s. (Mentzer 1988), (Mentzer and Gomes 1994), (Pantazopoulos and Pappis 1996) and (Taylor 2004). These adaptive methods were investigated empirically, but no method is superior. Gudehus in (Gudehus and Kotzab 2009) presents an adaptive method which he implemented in a number of consulting projects but which is not analysed in research so far.

Gudehus uses an adaptive calculated smoothing parameter $\alpha_\lambda(t)$ which is calculated at the end of each period t in his exponential smoothing of the first degree for the dynamic mean value forecast in period t $\lambda_m(t) = \alpha_\lambda(t) \cdot \lambda(t-1) + (1-\alpha_\lambda(t)) \cdot \lambda_m(t-1)$ and the dynamic variance forecast in period t

$$s_\lambda(t)^2 = \alpha_\lambda(t) \cdot (\lambda(t-1) - \lambda_m(t-1))^2 + (1-\alpha_\lambda(t)) \cdot s_\lambda(t-1)^2$$

With current variation $\upsilon_\lambda(t) = \frac{s_\lambda(t-1)}{\lambda_m(t-1)}$ and maximal acceptable variation υ_{max} $\alpha_\lambda(t)$ is calculated by

$$\alpha_\lambda(t) = \frac{2 \cdot \min\left(\upsilon_\lambda(t)^2, \upsilon_{max}^2\right)}{\upsilon_\lambda(t)^2 + \min\left(\upsilon_\lambda(t)^2, \upsilon_{max}^2\right)}.$$

Gudehus restricts the effective smoothing range by a lower and an upper limit, i.e. $\alpha_{min} \le \alpha_\lambda(t) \le \alpha_{max}$.

Compared to the aforementioned investigations this paper presents additional types of demand pattern and uses data the IPF received from various companies. There results allow an estimation of the performance of an adaptive method compared to an optimal one.

4. SIMULATIONS

The Wold decomposition mentioned in chapter 1 is a characteristic of so called stationary statistical processes. Within a (weak) stationary statistical process the expected value, the standard deviation and the autocovariance are constant over time and the random variables to the demands in each period are independent of one another; refer to (Tijms 1994) and (Herrmann 2009) for example. Therefore it is not surprising that forecasting methods for stationary statistical processes have been developed.

One such stationary statistical process, called scenario 1 in the following, consists of a constant μ (as mean value) and its the random addend ε_t; i.e. $\mu + \varepsilon_t$ for every period t. Exponential smoothing of the first degree solves the corresponding optimization model with a smoothing parameter close to zero, as shown in (Herrmann 2009) for example.

In scenario 1 the control of the smoothing parameter α provides significantly worse results. Already a constant smoothing parameter of $\alpha = 0.1$ reduces the variance of the forecasting error almost always by at least 9 %. The ideal forecast – hence a very small smoothing parameter – reduces the variance of the forecasting error usually by at least 14%. The mean value of the forecasting error is in the ideal forecast and usually also with a smoothing parameter of 0.1 almost zero. Opposed to the control where admittedly small values exist, but with a high percentage of deviation – typical values are: 0.18, but also values around 1 are possible. That is why the control leads contrary to the standard procedure already with a plausible setting of 0.1 for the smoothing parameter, (which results from a standard recommendation for the smoothing parameter), significantly worse results and should be avoided.

To analyse control, the behaviour of the tracking signal over time is being analysed. At first a smoothing parameter which is small enough to make the forecast equal to the mean value of the demand series, is being considered. An ideal forecasting method has a forecasting error which strongly deviates from zero and an absolute forecasting error which deviates even more from zero. The above-mentioned parameters for the exponential smoothing of the forecasting error and the absolute forecasting error – based on the work of Trigg – do not ensure an ideal forecasting model with the mean value of the forecasting error as a constant value over time. Hence smoothed forecasting errors and smoothed absolute forecasting errors, which differ considerably from zero, occur. Because the forecasting errors and their smoothed values fluctuate around zero, different strong deviations between the smoothed forecasting errors and the smoothed absolute forecasting errors are to be expected in the single periods. Hence it follows that the tracking signal will also fluctuate over time. Empirical investigations with a great number of demand series confirm this analysis.

The development of the tracking signal over 300 periods as shown in figure 1 is representative. The numbers are taken from the periods 1400 to 1699 of a specific demand series. To analyse the degree of the fluctuation, very long demand series – 2500 periods – have been considered. Within these the first 100 periods have not been considered to exclude the influence of less favourable starting parameters for the smoothing of the forecasting error and the absolute forecasting error. Of course the mean values and the standard deviation of the tracking signals of such demand series fluctuate. But due to a high number of demand series the mean values should be 0.2 and the fluctuations 0.15. Figure 2 provides an insight in the rate of the occurring single values by showing the representative percental rate of the tracking signal in left open and right closed intervals of the length 0.1. Although no smoothing parameter is the most frequent, over 70% of the values are greater than 0.1. Hence it is to be expected that when using the control within a great number of periods, a smoothing parameter which is too high will be applied.

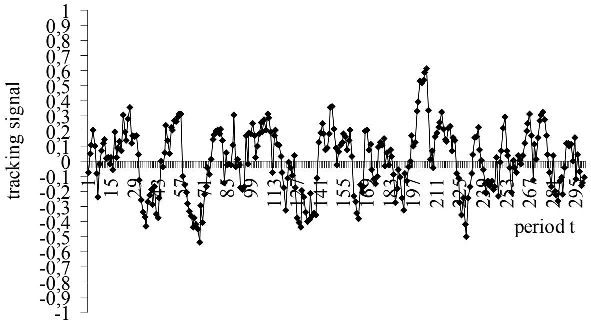

Figure 1: Development of the tracking signal for the periods 1400 – 1699 in an ideal forecast in scenario 1

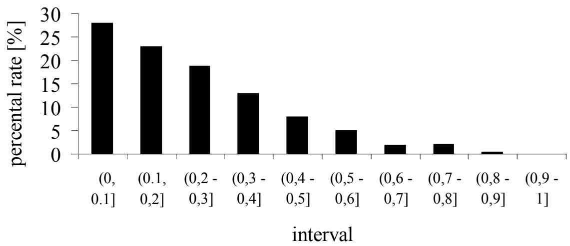

Figure 2: Frequency distribution of the tracking signal in an ideal forecast in scenario 1

A rise of the smoothing parameter in the standard procedure reduces the mean value and also the standard deviation of the tracking signals of such demand series. This explains, that with the control of the tracking signal due to a high number of demand series considered, a similar mean value (0.2) but an around 0.02 lower standard deviation (0.13), occurs. The decrease of the standard deviation which has already been expressed by the reduction of very high and very low tracking signals leads to an modified structure in the representative rate of the tracking signal respectively the control as shown in Figure 3. Because of that the portion of smoothing parameters over 0.1 should be already over 77%. Hence the probability of using a smoothing parameter which is too high even increases. This instability is observed by adaptive methods in general, as said earlier, and they have been criticised for leading to unstable forecasts.

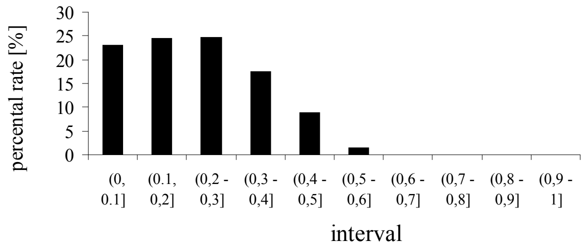

Figure 3: Frequency distribution of the tracking signal in the control in scenario 1

In the procedure of Gudehus the adaptive calculated smoothing parameter $\alpha_\lambda(t)$ has also various values. As Figure 4 shows the highest possible smoothing parameter of one occurs in 32.32% of the periods. Therefore, the results are significantly worse than the ones obtained by control – the variance increases by 48% compared to the control and 72% compared to the standard procedure with an optimal α. Gudehus recommends an upper limit of 0,33 for $\alpha_\lambda(t)$, which causes a constant $\alpha_\lambda(t)$ in nearly every period. In these cases maximal acceptable variation υ_{max} is equal to the ratio of the variance of the demands and the mean of the demands and around 4,03% which corresponds to the recommendation of Gudehus that the value should be 5%. A significant reduction of the mean demand – the variance of the demand remains unchanged – delivers better values if the maximal acceptable variation υ_{max} is still 5%. So, it can be expected that better results are achieved by a limitation of υ_{max}. Experiments confirm this.

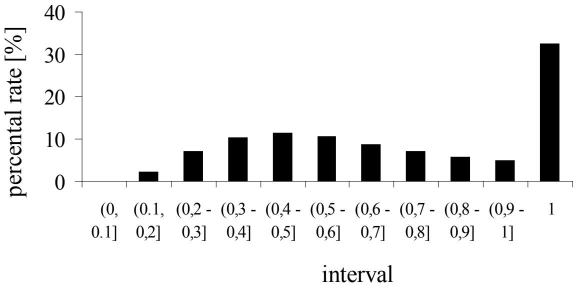

Figure 4: Frequency distribution of the tracking signal in the procedure of Gudehus in scenario 1

In scenario 2 a strong change in the level of the forecasting model occurs at a period T. Due to results in (Trigg 1964) it can be expected that the control delivers nearly immediately values close to the new level. In the standard procedure the speed of adaption increases with an increase of the smoothing parameter (α). So, the adaption speed is in reverse very slow with a α of 0.1 and for very small α the ideal forecast is extremely slow, almost zero. Therefore, the standard procedure delivers after a high number of periods again better values than the control. The results of the procedure of Gudehus are much better than the ones of the standard procedure with a α of 0.1, but still significantly worse than the ones of control. Experiments show that often there exists a α so that the standard procedure delivers the best results.

A reduction of the relative height of the change of the mean value – which has been examined within scenario 3 – reduces this effect. Then the disadvantage of the instability of α is more important, so that a marginal change, especially compared to the standard deviation of the mean value, causes the standard procedure using a smoothing parameter of 0.1 provide better results than the control, but they are a little lower than the improvement of the results in scenario 1. If the standard deviation is high compared to the change of the mean value, a very small smoothing parameter (in the standard procedure) provides even better results, which can often be further improved by a slightly higher smoothing parameter. Whereas this improvement is negligibly small compared to the decline of the key figures when using the control. With a very high smoothing parameter (in the standard procedure) the adaption speed can be increased significantly compared to the control because the tracking signal lies in most cases between 0.7 and 0.8 in some periods after T + 1, which has been proven by a great number of demand series. This approach requires a good recognition of such a strong change in the level of the forecasting model.

According to the research of Trigg (refer to Trigg 1964) the value of the tracking signal should only exceed the threshold of 0.5 when there is a structural change within a demand series which includes a clear level change. Hence the tracking signal in scenario 1 should be between [-0.5, 0.5]. Indeed this did happen during the investigation with the standard procedure the more often, the closer the forecast came to the mean value of the demand series – hence the better the forecast was. With a (very) small smoothing parameter (α) longer fractions of demand series of subsequent demands having a positive or negative forecasting error e_t, compared to a relatively high (α), occur. Or their absolute forecasting errors are higher. This is owing to the fact, that because of the statistical independence of the random values for the single demands, with a rising α it becomes more and more likely, that the forecasting error e_t changes sign and positive and negative forecasting errors balance each other out more often within a relatively short time span. Because of the relatively short memory of exponential smoothing of the first degree, this causes – using a (very) small α compared to a relatively high α – longer sequences with a positive or negative SE_t. Their absolute values are in tendency higher whereas the corresponding SAE_t values are lower. This leads to the occurrence of subsequent demands, which have a higher $|TS_t|$ with a (very) small α than with a high α. That elevates the probability that in one period $|TS_t| > 0,5$ exists. The smallest number of false alarms in the investigations has almost always been with the control. This number has usually already been reached in the standard procedure with a α of 0.2. In reverse the occurrence of a strong level shift has been detected by the control almost as often as by the standard procedure with a very small smoothing parameter during the investigation. The control in scenario 1 rarely provided values of the tracking signal of more than 0.5 in more than two subsequent periods; this could be partly increased quite significantly with a high deviation. For an effective recognition of a significant level shift the tracking signal should be used and its value should be above 0.5 for at least some periods. After that the control should be used to forecast until the new mean value has been discovered. Then, the ideal forecast should be set. A high number of simulation experiments show, that such a manual intervention should lead to an improvement in the standard procedure opposed to the control, which can be compared to the improvement mentioned in scenario 1.

Responsible for the optimality of the constant forecast in scenario 1 is the stochastic independence of the random values to the single demands. In contrast to this, in industrial practice it is often assumed that subsequent demands are related; this was also confirmed by data the IPF received from various companies. Mathematically this relation can be achieved by an autocorrelation through time. In scenario 4 auto correlated random numbers have been created after the method Willemain and Desautles proposed in (Willemain and Desautles 1993). Here a random value is generated by forming the sum of two uncorrelated uniformly distributed random numbers. This sum is transformed to a uniform distribution with the help of simple formulas for the distribution function of two uniformly distributed random numbers. In the next step this uniform distribution is used as a new addend for the next sum which leads to an auto correlation. Using the inverse method this uniformly distributed random series is transformed to a different distribution. For the investigations a normal distribution, with moments that almost entirely avoid negative demands, has been used. Furthermore the moments are identical in every period. That is why there is again a stationary demand series present (refer to (Herrmann 2009)). The resulting demand series have been additionally classified according to which smoothing parameter of the set R = {0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9} supplies the best results through the standard procedure.

Even if 0.9 in the standard procedure delivers the best results, control uses only a few high smoothing parameters (α) over 0.5. Figure 5 visualizes an example with many very high smoothing parameters; the mean value is 0.38, the standard deviation is 0.21 and about one third of the α are higher than 0.5. The investigation prooves, that the standard procedure using a α of at least 0.5 (in R) in scenario 4 provides significantly better results than the control. Often the improvements are considerably over 10% of the variance of the forecasting error – a α over 0.7 (in R) provides improvements of over 30%. The other extreme occurs when an α below 0.1 is best. Then the standard procedure usually provides better results with a α of 0.1 than the control, whereas the improvement is typically much smaller than the one mentioned in scenario 1.

Compared to the control the procedure of Gudehus delivers better results. Normally, they are not as good as the ones by the standard procedure. The procedure of Gudehus delivers the best results if the demand follows a curve which is similar to a sinusoidal curve, which is a special case of autocorrelation. Then, the key figures are much better than the ones of control, but the ones of the standard procedure with the best smoothing parameter in R are normally close to ones of the procedure of Gudehus – often they are even slightly better.

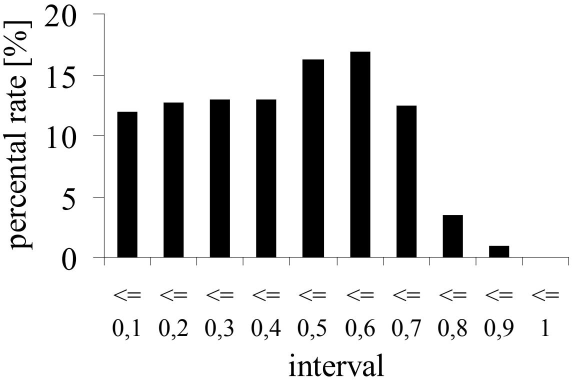

Figure 5: Frequency distribution of the tracking signal with the control – with the standard procedure having a α of the set R α = 0.9 is the best value.

In scenario 4' demand series with α in [0.1; 0.3] as best value in the standard approach are being examined. Such demand series occur when the lag is 1 and the auto correlation coefficient is low. This combination causes the occurrence of several directly succeeding periods, where a high smoothing parameter (greater than 0.5) is suitable (effect 1), because the demands rise or fall in these periods. Or a very low smoothing parameter is suitable (effect 2) because high and low demands alternate in these periods. Figure 6 shows an example. It visualizes the demands of more than 100 subsequent periods. At the beginning and in the middle the first effect occurs and primarily at the end the second one. Within the second effect the short memory of exponential smoothing of the first degree causes the smoothing of the (absolute) forecasting errors to produce small SE_t and relatively high SAE_t values. The control chooses a small smoothing parameter which is preferable. Hence such demand series favor a smoothing parameter which fluctuates over time. The control does not always finds the best parameter over time. Thus the control provides in many cases key figures (primarily the variance of the forecasting error) which are almost as good or even slightly better than the standard procedure with the best possible α. Opposed to any α in [0.1, 0.3] the key figures are usually significantly better; around 10%. Hence the standard procedure should provide increasingly worse results over time, however only with a very high number of periods; this argumentation is confirmed by many simulation experiments. This can be avoided, if the smoothing parameter is adapted periodically according to the last demands. This adaption may happen after a high number of periods. The control is in conclusion especially of advantage, if a manual setting of the smoothing parameter (in the standard approach) is to be avoided. In this scenario the procedure of Gudehus is not an alternative, because it delivers always the worst results.

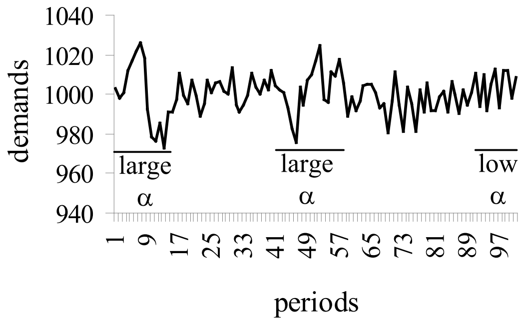

Figure 6: Demand series in scenario 4'

A rising increase of the autocorrelation coefficient causes a growing occurrence of effect 1 and a growing decline of effect 2, so that a growing increase of α delivers the best results. Opposed to that a higher lag causes a decline of effect 1. With increasing lag, demands like in scenario 1 occur in subsequent periods – in the extreme case it is scenario 1. This favors the standard procedure compared to the control and the smoothing parameter in the standard procedure is rather small, confirmed by extensive simulation experiments. It has to be emphasized, that with a rising lag the value of the autocorrelation coefficient becomes more and more irrelevant. The achieved improvement of the results in this way is usually smaller than in scenario 1 which was measured in a lot of simulation experiments.

Up to this point only stationary demand series have been examined. If the adjustments of scenario 2 and 3 happen not only once, but after a certain number of periods (n), the mean value changes over time. This is scenario 5. Respectively the standard deviation can be altered after n periods as well. The adjustments of n, the mean value and the standard deviation may be constant or they can be produced randomly. Through that further scenarios arise.
According to the considerations above, the following two rules and their reversals are valid:

- a rising mean value favors a rising α and
- a rising number of periods favors a declining α.

If these two factors of influence change radically over time, the two (above) effects yet occur. Control provides the better results for the reasons mentioned above. If one of the factors of influence is being kept constant, a smoothing parameter for the standard approach can be found which provides better results than the control. An autocorrelation in such demand series strengthen the common occurrence of effect 1 and 2. Again, in this scenario the procedure of Gudehus is not an alternative.

The effect of a high variance in the scenarios is studied. The experiments show that a rising increase of the variance causes better key figures for the standard procedure compared to both alternatives. Often the procedure of Gudehus profits by high variance. Then, in the scenarios (in general) in which control delivers better results as the procedure of Gudehus, the difference is reduced by a rising increase of the variance.

Finally, real world data are regarded. There are daily, weekly and monthly demand and the time horizons varies between three and ten years. The data are received from retailers and from companies dealing with spare times. As observed in industrial practice, the demand is normally distributed, typically. This is the case for nearly 70% of the real world data. For them, the standard procedure delivers the best key figures as expected by results for scenario 1. Unfortunately, some data sets consist of just a few periods. In these cases, the number of historical data is too small to calculate an effective start value. So, that in some of these cases, around 35%, control delivers the best results. As also observed in industrial practice, demand is gamma distributed for some products, here for around 10%. With the same reason the standard procedure delivers again the best results; for the same reason as above some exceptions occur. The remaining data sets are unsuccessfully tested for typical distributions with SPSS. Due to the analysis it is plausible, but not proven, that these 20% data sets belong to scenario 5. Responsible for this unusual high portion are the demand for the spare times. In most of these cases, around 80%, control delivers better results than both alternatives. In some cases this is caused by a small number of historical data, as argued above. In the remaining cases the standard procedure is best, but the key figures of control is often just a little bit inferior.

Finally, at the IPF exponential smoothing of the second degree has also been examined where the smoothing parameter α has been set to $|TS_t|$. As in the procedures of Holt and Winters one or more additional smoothing parameters occur. In the studies the additional smoothing in the procedure of Holt is set to 10% of α, as recommended in (Herrmann 2011). In addition the third parameter in the method of Winters is set to $|TS_t|$, where suitable (absolute) forecasting errors for the seasonality have to be calculated. The studies show again a high sensitivity of the tracking signal. So, comparable results can be expected, which is proven by a limited amount of experiments.

5. RESULTS AND RECOMMENDATION

Demand series with correlation of subsequent demands (autocorrelation) or changing structure over time (instationary demand series), for which every smoothing parameter should be smaller than 0.5 in the standard procedure, the standard procedure with any smoothing parameter in G = {0.1, 0.2, 0.3, 0.4, 0.5} often only provides better results than the control or at least just as good results, if the ideal choice of the smoothing parameter in G has been made. A random choice of the smoothing parameter in G provides in general far worse results. These demand series of type R therefore favor the control, if a manual setting of the smoothing parameter in the standard procedure is to be avoided (because this is too time-consuming). Regarding actual demand series in industrial praxis, forecasting methods based on exponential smoothing usually achieve even better results, if the parameters, including the starting values, are being determined by solving an optimization problem and the parameter settings are being recalculated after a number of periods like 300 for example. This should also apply to a significant number of demands series of type R. Such an approach is especially suitable for premium products, usually A class parts. It should also be mentioned that latest elaborations on exponential smoothing (refer to (Gardner 2006) for example) may offer even better results. Especially concerning an ABC distribution, there are products where such an effort is too high in comparison to the gain of a reduction primarily of the variance of the forecasting errors. Then the control of demand series of type R should be used. As shown by a large number of simulation experiments, for demand series of type R (except for having to choose a high smoothing parameter) the control is less favorable than the standard procedure. It is also the less favorable alternative with stationary demand series which are statistically independent. For such demand series the standard procedure should be applied principally. Finally, the procedure of Gudehus is just in special cases an alternative to the control. Since it is normally unknown if this is the case, the procedure should be avoided.

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AUTHOR BIOGRAPHY

Frank Herrmann was born in Münster, Germany and went to the RWTH Aachen, where he studied computer science and obtained his degree in 1989. During his time with the Fraunhofer Institute IITB in Karlsruhe he obtained his PhD in 1996 about scheduling problems. From 1996 until 2003 he worked for SAP AG on various jobs, at the last as director. In 2003 he became Professor for Production Logistics at the University of Applied Sciences in Regensburg. His research topics are planning algorithms and simulation for operative production planning and control. His e-mail address is: Frank.Herrmann@HS-Regensburg.de and his Web-page can be found at http://homepages.fh-regensburg.de/~hef39451/dr_herrmann/.