Ilmenauer Beiträge zur Wirtschaftsinformatik

Herausgegeben von U. Bankhofer; P. Gmilkowsky;
V. Nissen und D. Stelzer

Volker Nissen, Mauricio Matthesius

Automatic Forecast Model Selection in SAP Business Information Warehouse BPS – an Empirical Investigation

Technical Report No. 2006-04, July 2006

Technische Universität Ilmenau
Fakultät für Wirtschaftswissenschaften
Institut für Wirtschaftsinformatik

Autor: Volker Nissen, Mauricio Matthesius

Titel: Automatic Forecast Model Selection in SAP Business Information Warehouse BPS – an Empirical Investigation

Ilmenauer Beiträge zur Wirtschaftsinformatik No. 2006-04, Technical University of Ilmenau, July 2006

ISSN 1861-9223

ISBN 3-938940-08-5

Anschrift: Technische Universität Ilmenau, Fakultät für Wirtschaftswissenschaften, Institut für Wirtschaftsinformatik, PF 100565, D-98684 Ilmenau.
http://www.tu-ilmenau.de/fakww/Ilmenauer_Beitraege.1546.0.html

Table of Contents

Abstract:

The feature of automatic forecast model selection is empirically investigated in the context of SAP BW Business Planning & Simulation (BPS). The automatic model selection is a software feature routinely used by many companies in their forecasting, for instance in sales planning. Our empirical tests are based on data for time series showing trend, seasonal and trend-seasonal patterns. We use this data first in its 'pure', unaltered form. Afterwards, we add varying amounts of normally-distributed noise to see how this affects the quality of model selection and the forecasting result. We, thereby, mimic real-time data quality which very seldom comes in the form of undisturbed trends, seasonal or other patterns. Our findings indicate that automatic model selection should be used with care, and that some planners should reconsider their rather unreflective attitude towards automatic model selection in practical forecasting.

Key Words: Data Warehouse, SAP Business Information Warehouse, Forecasting, Noise

1 Introduction

Various SAP tools offer forecasting methods as part of their business functionality. Examples include SAP R/3™, SAP Advanced Planner & Optimizer (APO ™), and SAP Business Information Warehouse (BW ™). The forecasting component examined here is the automatic forecast model selection in SAP BW Business Planning & Simulation (BPS). The automatic model selection fits a forecast model to the available historical data while minimizing some error measure, which is Akaike's Information Criterion in the case of SAP BW [AkPa1998, SAP2006].

It is a software feature routinely used by many companies in their forecasting, for instance in sales planning. At first sight, this feature seems to relieve the planner from choosing an adequate statistical forecast model for historical data himself, which can be a time-consuming and difficult task.

Because it is so often applied, one should aim for a good understanding of the strengths and weaknesses of automatic model selection in order to make a well-informed decision when to use it. The experiments outlined briefly in this paper are a contribution to this goal.

2 Methodology

Three basic functions were used in our forecasting experiments performed with SAP BW BPS release 3.5. The empirical tests are based on time series data showing trend, seasonal and trend-seasonal patterns. The total horizon were 96 month of which 48 were treated as historical data and the other 48 were the planning horizon. Figure 1 gives an illustration of the time series patterns that were used.

The data was initially used in an ideal deterministic pattern which should provide a rather trivial task for automatic forecast model selection. Thereafter, varying amounts of normally-distributed noise are added to the historical data in order to see how this affects the quality of model selection and the forecasting result. The additive noise component mimics real-life data quality which can be characterized as a stochastic influence on trend, seasonal or other patterns. Practically, each historical data point *x* of the basic functions was modified in the following way:

$$x' = x + a \cdot N(0{,}1)),$$

where N(0,1) represents a standard-normally distributed random number and *a* is a noise factor that was varied according to *a* = [0 ; 1 ; 2 ; 5]. Thus, we conducted four sets of forecasting experiments for all functions. To remove arbitrary results, at each noise level and for each function 30 runs with different random number seeds for the time series modification were performed.

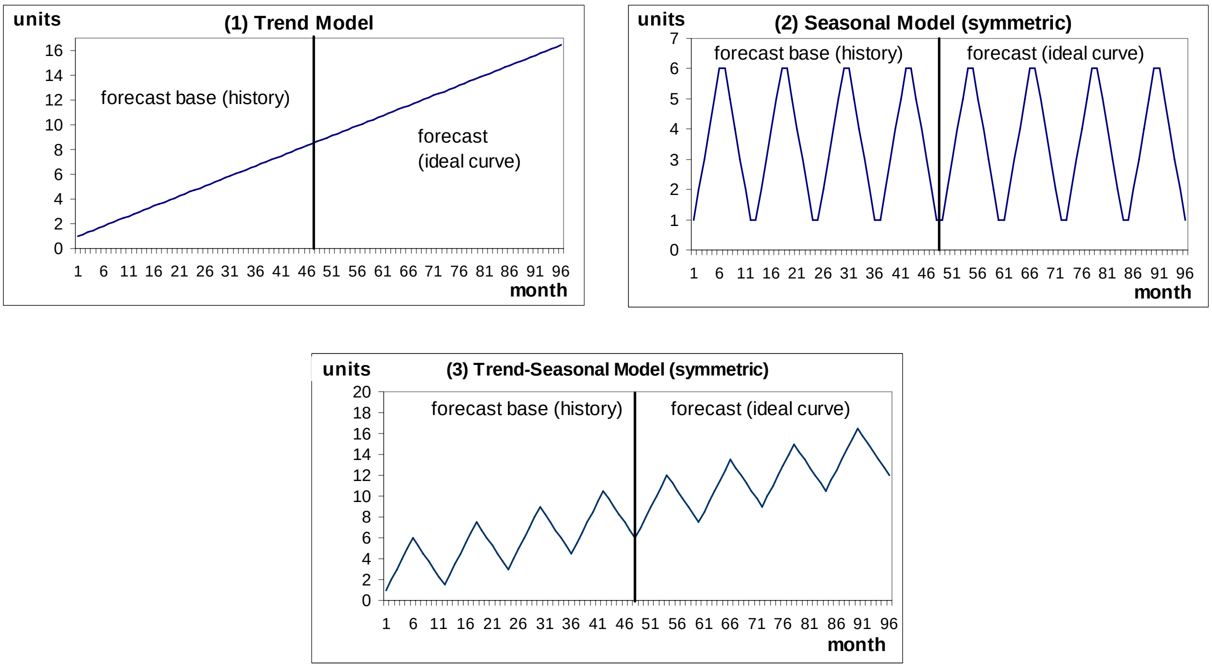


Fig. 1: The basic functions discussed here

3 Results

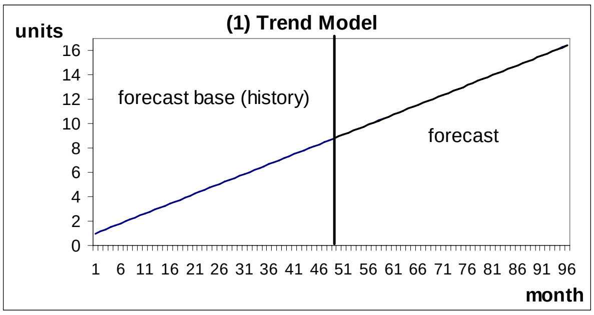
3.1 Initial Experiments

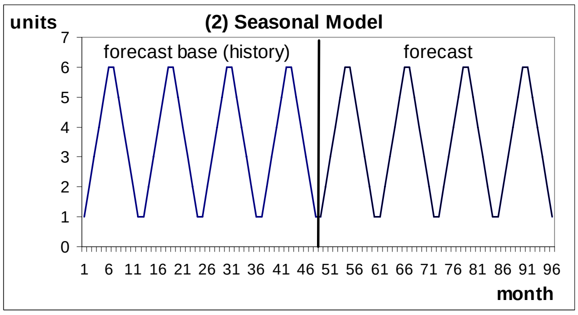
Results are presented in the form of graphs and tables for each function and noise-level. The figures refer to the first run performed in each individual experiment to give a visual impression of the forecasting results.[1] The tables report on data averaged over all 30 runs for each experiment. The mean squared error (MSE) and the mean absolute percentage

1 It should be noted that a figure giving aggregated results is not sensible here.

error (MAPE) are employed as standard forecast error measures. Furthermore, the percentage of correct models chosen by the automatic forecast model selection is given in the tables.

Set 1: Forecasting without noise (noise factor a = 0)





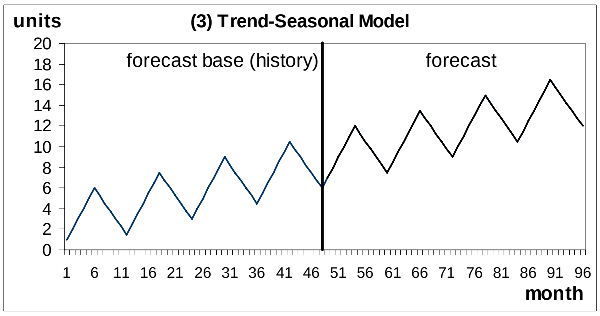


Fig. 2: Results from the first run in each experiment

Function	MSE	MAPE (%)	correct model (%)
(1) trend	0,0	0,0	100,0
(2) seasonal	0,0	0,0	100,0
(3) trend-seasonal	0,0	0,0	100,0

Table 1: Forecast results with original historical data (noise level = 0), avg. from 30 runs

Without noise added, the automatic model selection chose the correct model in every case.

Set 2: Forecasting with noise factor *a* = 1

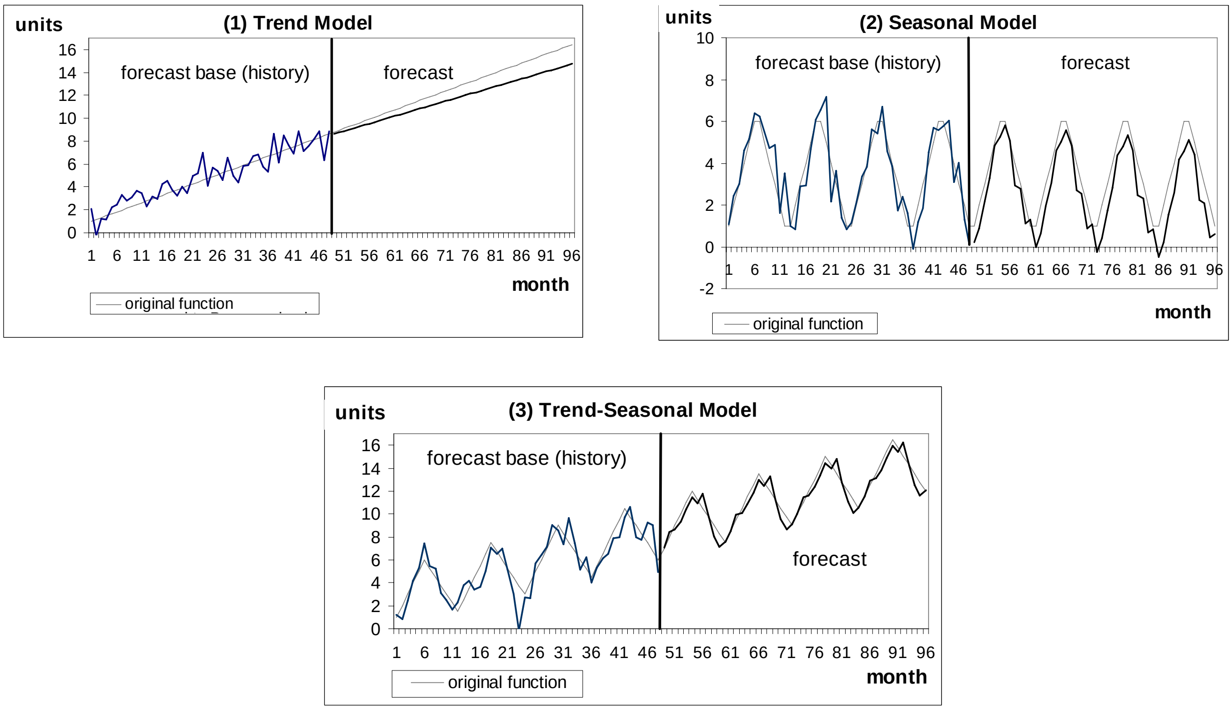


Fig. 3: Results from the first run in each experiment

Function	**MSE** (min, max)	**MAPE (%)** (min, max)	**correct model (%)**
(1) trend	3,1 (0,0 ; 24,0)	8,5 (0,5 ; 32,5)	80
(2) seasonal	0,4 (0,1 ; 2,3)	19,2 (8,9 ; 63,6)	90
(3) trend-seasonal	0,7 (0,2 ; 1,3)	5,7 (2,8 ; 12,6)	100

Table 2: Forecast results with modified historical data (noise level = 1), avg. from 30 runs

For the trend function, the system chose 24 times the trend model, 5 times a trend-seasonal and once a constant model. For the seasonal function, the system chose a seasonal model 27 times and a trend-seasonal model 3 times. For the trend-seasonal function, the trend-seasonal model was chosen in each case.

Set 3: Forecasting with noise factor *a* = 2

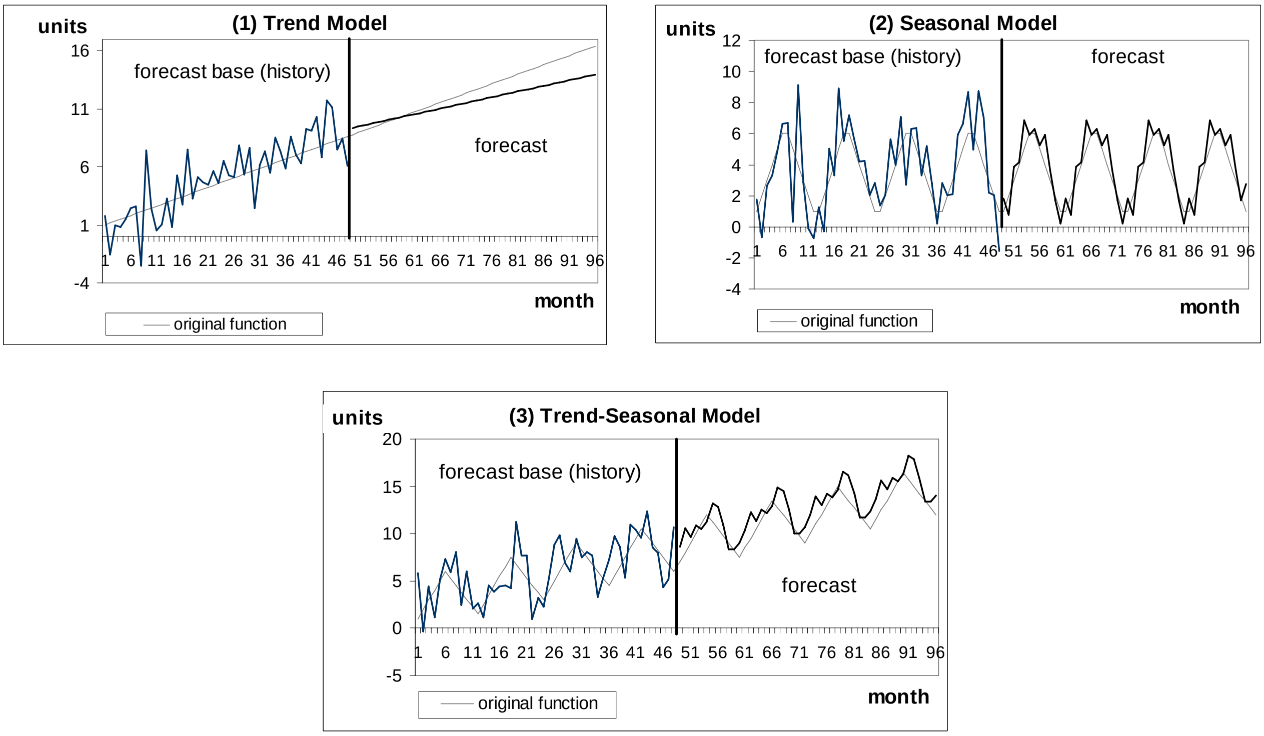


Fig. 4: Results from the first run in each experiment

Function	**MSE** (min, max)	**MAPE (%)** (min, max)	**correct model (%)**
(1) trend	19,3 (0,0 ; 124,3)	25,2 (1,5 ; 73,8)	40
(2) seasonal	1,1 (0,5 ; 2,0)	33,4 (19,2 ; 49,9)	100
(3) trend-seasonal	5,5 (0,7 ; 31,9)	14,4 (5,5 ; 42,0)	80

Table 3: Forecast results with modified historical data (noise level = 2), avg. from 30 runs

For the trend function, the system chose 12 times a trend, 4 times a trend-seasonal and 14 times a constant model. For the seasonal function, the system chose a seasonal model in all cases. For the trend-seasonal function, the trend-seasonal model was chosen 26 times (with 24 times the correct additive model and two times a multiplicative model), while a seasonal and a constant model where both chosen in two cases each.

Set 4: Forecasting with noise factor *a* = 5

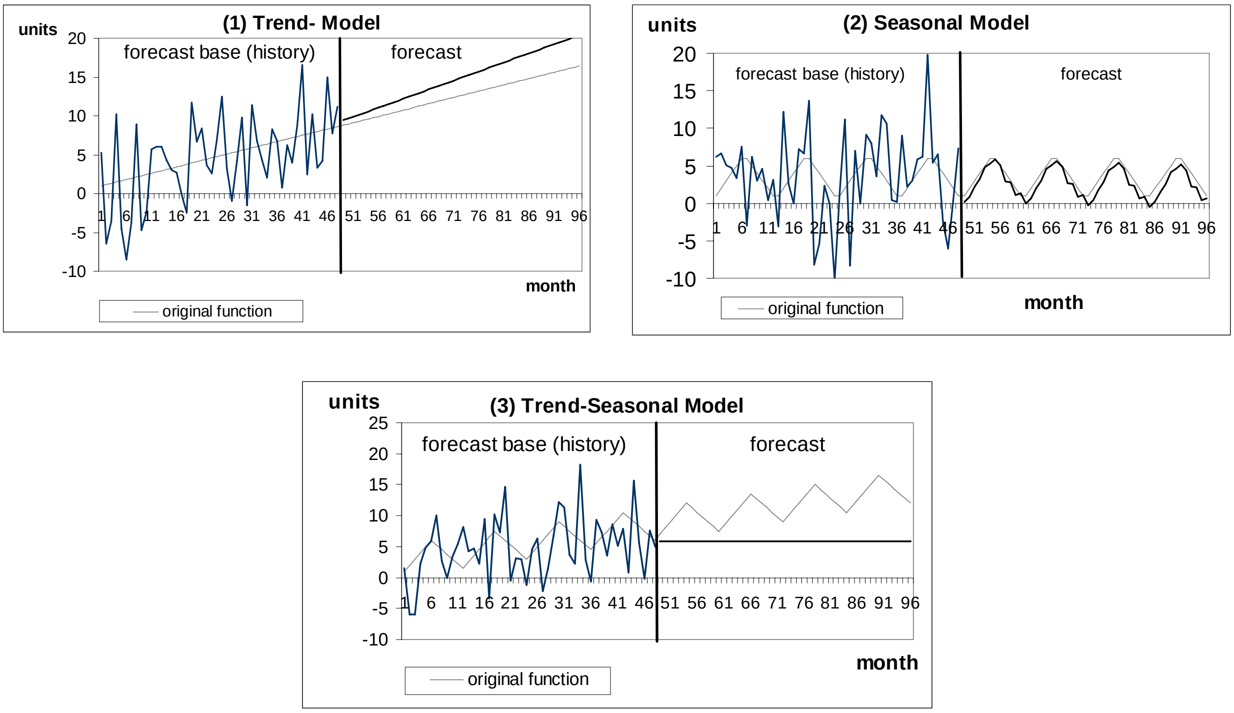


Fig. 5: Results from the first run in each experiment

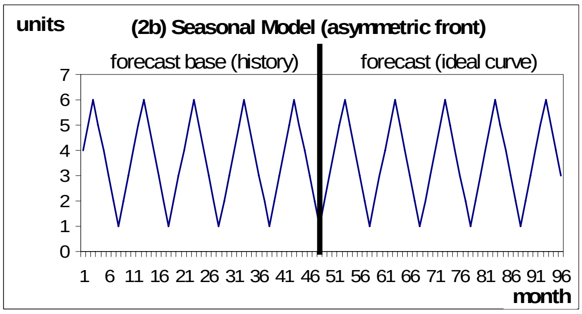
Function	**MSE** (min, max)	**MAPE (%)** (min, max)	**correct model (%)**
(1) trend	44,0 (2,5 ; 168,6)	44,0 (12,6 ; 90,3)	20
(2) seasonal	5,1 (2,9 ; 15,4)	78,2 (55,5 ; 142,4)	27
(3) trend-seasonal	26,3 (2,5 ; 86,3)	35,5 (11,9 ; 76,5)	7

Table 4: Forecast results with modified historical data (noise level = 5), avg. from 30 runs

For the trend function, the system chose 6 times a trend, once a trend-seasonal, once a seasonal and 22 times a constant model. For the seasonal function, the system chose a seasonal model 8 times and a constant model 22 times. For the trend-seasonal function, the trend-seasonal model was chosen in two cases, a seasonal model was chosen 4 times, a trend model 7 times, and a constant model 17 times.

3.2 Additional Experiments with Wrong Seasonal Factors

In addition to the basic experiments described above, we wanted to investigate the influence of the seasonal factor in the seasonal forecasting models. The seasonal factor must be manually customized before using the respective models. This also applies for automatic forecast model selection. Therefore, it is considered interesting to see how wrong choice of the seasonal factor influences forecast quality. Two new asymmetric functions with seasonal patterns were introduced for this purpose which are depicted in figure 6. While the length of a season is 12 month in the symmetric seasonal function used in section 3.1, the length of a season is 10 month in both of the functions used here. However, the seasonal length was deliberately kept to 12 month in customizing when the experiments with automatic model selection described below were conducted.



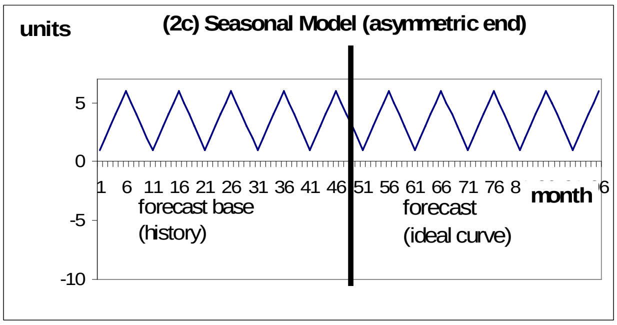
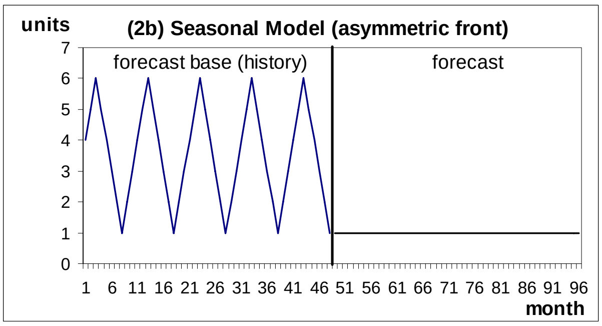


Fig. 6: Seasonal function used in additional series of experiments

<u>Set 5: Forecasting with noise factor *a* = 0 and wrong seasonal factor 12 (instead of 10)</u>



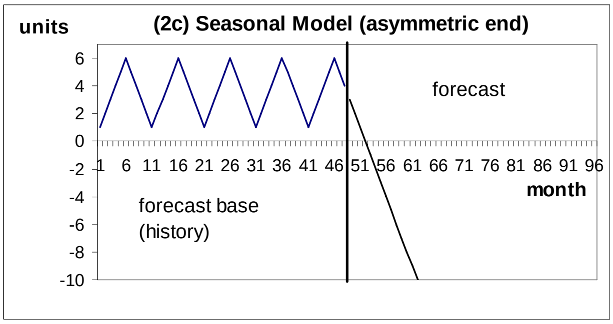


Fig. 7: Results from the first run in each experiment

Function	MSE	MAPE (%)	correct model (%)
(2a) seasonal, symmetric (original)	0	0	100
(2b) seasonal, asymmetric front	8,8	64,2	0
(2c) seasonal, asymmetric end	770,0	850,4	0

Table 5: Forecast results with original historical data (noise level = 0, seasonal factor 12 instead of 10), avg. from 30 runs

It suffices to conduct the experiments for the case without noise to recognize the dramatic influence of setting the seasonal factor correctly. While in the case of function (2b) the automatic model selection frequently chooses the constant model, it is the negative trend model that is chosen for function (2c).

4 Discussion

The performance of the automatic model selection is optimal when no noise is added to the underlying patterns. However, this situation never occurs in practical business forecasting as stochastic influence in historical data is abundant. On a general level, the correctness of the automatic model selection with respect to the underlying function pattern and the forecast quality deteriorates with the amount of noise – a result that can be expected. A closer look at the different noise levels and functions, though, reveals some interesting details.

When the underlying pattern is a trend, the relative performance appears to be the worst. Even with the low noise factor $a = 1$, in 20% of the test cases the wrong model was chosen by the automatic model selection. Moreover, the error measures MSE and MAPE each display results within a wide interval. The maximum MAPE was as high as 32,5 % even at this comparatively low level of noise. This may be interpreted as a significant risk for a bad automatic forecast. The situation is aggravated at higher noise levels.

To a somewhat lesser degree the same applies to the trend-seasonal function, where we find a wide range of MAPE- and MSE-values at the noise level a = 2 and higher. Here, two MAPE-results higher than 40% are found, and in three out of 30 cases the MSE is higher than 25, thus again indicating a performance risk for a purely technical forecasting approach.

When analyzing the performance for the seasonal function, one should bare in mind that the MAPE-value depends on the underlying range of correct function values. As these values on average are smaller for the seasonal than for the trend and the trend-seasonal function, a high MAPE should not be overinterpreted in the seasonal case. The data indicates that the MAPE-error is particularly high at lower turning points of the curve. For the seasonal function, the MSE gives a more reliable account of forecast quality. Here, the performance appears reasonable up to a noise factor of a = 2.

However, it is worth mentioning that the performance in the seasonal (and the trend-seasonal) case very much depends on the customized seasonal length for the planning object in SAP BW. Our experiments with slightly wrong seasonal length factors in section 3.2 led to very bad forecast results. Even without noise the automatic model selection then generally does not find the correct forecast model. The necessity to enter the correct seasonal length in advance of the forecast limits the practical value of any forecasting tool. This is <u>not</u> an SAP-specific problem, though. One should also consider that in business practice the length of a season may vary over time and often differs for different planning objects, once more demonstrating the necessity to closely monitor and supervise automated planning.

For any pattern, the automatic model selection generally fails at the high noise factor a = 5, both in terms of the model chosen and the forecast quality achieved. Frequently, the automatic model selection chooses the constant model in this situation as no particular pattern can be identified by the system.

Great errors at all noise levels often occur when the automatic model selection chooses a model that does not correspond to the true underlying patterns in the historical data. When classifying this choice as “wrong” prior knowledge of the original function is required that the system does not have. From a purely statistical point of view, based on the available historical data in the individual run, the system’s choice is therefore justified. This demonstrates the limits of a technical approach to forecasting when really business knowledge is necessary to help deciding the right forecast model, tune it's parameters or manually adapt the results.

Many companies routinely use automatic forecast model selection, for instance in sales planning, where the number of planning objects is very high. The argument is often that manual planning requires a high effort. A lack of statistical knowledge is another important reason why planers turn to automatic model selection instead of analyzing the data themselves. Our results remind us that a blind trust in the results of a tool can lead to suboptimal performance.

5 Conclusion

The results presented here may be interpreted as a warning for practical planners not to automate where their individual business knowledge can help to improve the forecast. Automatic model selection is useful where the variance of historical data around clear statistical patterns is relatively small and the importance of the forecast results is not exceptionally high. In all other cases, the planers knowledge and skills are important input in forecasting. This suggests that some company planners should reconsider their rather unreflective attitude towards automatic model selection in practical forecasting.

References

[AkPa1998] Akaike, H.; Parzen, E.: Selected Papers of Akaike Hirotugu. Springer, New York, 1998.

[SAP2006] SAP AG: SAP Help Portal: SAP BW BPS Automatic Model Selection, http://help.sap.com (1-18-2006)

Appendix: Results from Section 3.1 in Detail

Results for noise factor *a* = 1

Run	Trend Pattern		
	MSE	MAPE	Model Selected
1	1,06592	6,941	Trend
2	0,03094	1,329	Trend
3	0,49743	5,070	Trend-Saisonal(add)
4	5,58502	16,072	Trend
5	0,57456	5,655	Trend
6	11,61895	22,154	Trend
7	0,89792	6,564	Trend
8	1,73970	8,105	Trend
9	0,83292	6,874	Trend
10	23,97934	32,512	Trend
11	7,37418	18,644	Trend
12	0,00598	0,457	Trend
13	0,80402	6,013	Trend-Saisonal(add)
14	0,01174	0,734	Trend
15	0,38939	4,415	Trend
16	0,09957	2,222	Trend
17	5,80633	15,280	Trend
18	0,06667	1,603	Trend
19	3,56007	13,605	Trend
20	0,01821	1,064	Trend
21	4,27370	12,323	Trend
22	0,87435	6,147	Trend
23	0,74405	5,761	Trend-Saisonal(add)
24	0,31089	4,300	Trend
25	0,10591	1,945	Trend
26	1,84825	9,281	Trend-Saisonal(add)
27	0,63221	5,601	Trend-Saisonal(add)
28	1,34632	8,618	Trend
29	16,52433	24,733	Konstant
30	0,07515	1,662	Trend

Run	Seasonal Pattern		
	MSE	MAPE	Model Selected
1	1,02551	36,199	Trend Saisonal (add.)
2	0,28231	14,200	Saisonal
3	0,16251	15,313	Saisonal
4	0,32475	17,372	Saisonal
5	2,32180	63,603	Trend Saisonal (add.)
6	0,27164	19,395	Saisonal
7	0,14998	9,217	Saisonal
8	0,20963	17,457	Saisonal
9	0,13170	14,004	Saisonal
10	0,30576	18,188	Saisonal
11	0,58594	21,988	Saisonal
12	0,23443	16,448	Saisonal
13	0,27422	14,901	Saisonal
14	0,24004	15,336	Saisonal
15	0,53748	27,293	Saisonal
16	1,49762	24,350	Trend Saisonal (add.)
17	0,11092	12,468	Saisonal
18	0,31036	19,918	Saisonal
19	0,18559	15,129	Saisonal
20	0,20408	13,129	Saisonal
21	0,08937	11,109	Saisonal
22	0,32329	18,578	Saisonal
23	0,11094	8,944	Saisonal
24	0,31995	17,787	Saisonal
25	0,19780	14,033	Saisonal
26	0,51454	31,919	Saisonal
27	0,14129	13,259	Saisonal
28	0,23365	19,320	Saisonal
29	0,22909	17,543	Saisonal
30	0,20543	17,485	Saisonal

Run	Trend–Seasonal Pattern		
	MSE	MAPE	Model Selected
1	**0,44567**	**4,611**	Trend-Saisonal
2	**0,52123**	**4,853**	Trend-Saisonal
3	**0,94871**	**7,477**	Trend-Saisonal
4	**1,04413**	**8,074**	Trend-Saisonal
5	**0,54695**	**5,315**	Trend-Saisonal
6	**0,17051**	**2,759**	Trend-Saisonal
7	**1,12222**	**7,782**	Trend-Saisonal
8	**0,27478**	**3,866**	Trend-Saisonal
9	**0,50306**	**4,965**	Trend-Saisonal
10	**1,33515**	**9,135**	Trend-Saisonal
11	**0,26141**	**3,707**	Trend-Saisonal
12	**0,69457**	**6,065**	Trend-Saisonal
13	**0,31833**	**4,061**	Trend-Saisonal
14	**0,44700**	**4,812**	Trend-Saisonal
15	**0,34919**	**4,560**	Trend-Saisonal
16	**0,27447**	**3,468**	Trend-Saisonal
17	**0,61403**	**5,113**	Trend-Saisonal
18	**0,62603**	**5,053**	Trend-Saisonal
19	**0,23483**	**3,619**	Trend-Saisonal
20	**1,32149**	**8,543**	Trend-Saisonal
21	**0,40026**	**4,672**	Trend-Saisonal
22	**0,21667**	**3,391**	Trend-Saisonal
23	**0,15436**	**2,914**	Trend-Saisonal
24	**0,49595**	**5,633**	Trend-Saisonal
25	**0,34411**	**4,622**	Trend-Saisonal
26	**0,82554**	**7,094**	Trend-Saisonal
27	**1,30436**	**8,415**	Trend-Saisonal
28	**0,38043**	**4,467**	Trend-Saisonal
29	**2,88131**	**12,593**	Trend-Saisonal
30	**1,32055**	**8,980**	Trend-Saisonal

Results for noise factor $a = 2$

Run	Trend Pattern		
	MSE	MAPE	Model Selected
1	1,68616	7,663	Trend
2	13,21740	21,548	Konstant
3	124,31386	73,766	Trend
4	31,42319	38,680	Konstant
5	31,48483	38,729	Konstant
6	20,39307	28,693	Konstant
7	26,01444	34,116	Konstant
8	24,99286	33,191	Konstant
9	3,07243	13,215	Trend
10	33,76257	40,507	Konstant
11	29,50883	37,296	Trend
12	0,02461	0,928	Trend
13	12,87381	22,882	Trend-Saisonal (mult.)
14	0,04662	1,463	Trend
15	24,15378	32,412	Konstant
16	26,44686	34,501	Konstant
17	23,23333	30,565	Trend
18	27,84694	35,722	Konstant
19	14,25858	27,225	Trend
20	0,07591	2,171	Trend
21	23,62451	31,913	Konstant
22	3,50127	12,301	Trend
23	2,99868	11,556	Trend-Saisonal(add)
24	1,24311	8,598	Trend
25	27,61843	35,526	Konstant
26	7,39184	18,561	Trend-Saisonal(add)
27	2,52870	11,202	Trend-Saisonal(add)
28	5,36710	17,210	Trend
29	15,29980	23,528	Konstant
30	21,32281	29,652	Konstant

Run	Seasonal Pattern		
	MSE	MAPE	Model Selected
1	0,94077	32,339	Saisonal
2	1,32301	42,202	Saisonal
3	0,83012	26,593	Saisonal
4	0,69137	32,188	Saisonal
5	0,77223	26,570	Saisonal
6	1,11377	31,179	Saisonal
7	0,59889	19,181	Saisonal
8	1,22902	37,627	Saisonal
9	0,99917	27,560	Saisonal
10	0,46769	27,305	Saisonal
11	1,22499	33,896	Saisonal
12	1,40517	44,988	Saisonal
13	2,03091	33,549	Saisonal
14	1,00856	37,340	Saisonal
15	1,60968	32,671	Saisonal
16	0,69855	27,678	Saisonal
17	0,88728	28,835	Saisonal
18	1,23254	32,627	Saisonal
19	1,51099	49,881	Saisonal
20	0,98275	25,029	Saisonal
21	1,77784	34,806	Saisonal
22	1,35135	38,449	Saisonal
23	1,62746	43,830	Saisonal
24	1,13543	36,153	Saisonal
25	0,47266	24,480	Saisonal
26	1,54063	36,692	Saisonal
27	1,71556	45,248	Saisonal
28	1,22132	30,213	Saisonal
29	0,54563	26,301	Saisonal
30	1,26005	37,747	Saisonal

Run	Trend–Seasonal Pattern		
	MSE	MAPE	Model Selected
1	**2,60383**	**12,086**	Trend-Saisonal
2	**2,04312**	**10,061**	Trend-Saisonal
3	**1,79527**	**10,023**	Trend-Saisonal
4	**4,17795**	**16,150**	Trend-Saisonal
5	**31,86015**	**41,985**	Konstant
6	**0,68157**	**5,515**	Trend-Saisonal
7	**4,48743**	**15,561**	Trend-Saisonal
8	**1,09975**	**7,735**	Trend-Saisonal
9	**2,01088**	**9,926**	Trend-Saisonal
10	**6,64394**	**19,619**	Trend-Saisonal (mult.)
11	**1,04584**	**7,415**	Trend-Saisonal
12	**2,77979**	**12,134**	Trend-Saisonal
13	**1,27273**	**8,119**	Trend-Saisonal
14	**1,78745**	**9,623**	Trend-Saisonal
15	**4,93797**	**14,671**	Trend-Saisonal (mult.)
16	**1,09818**	**6,935**	Trend-Saisonal
17	**2,45559**	**10,225**	Trend-Saisonal
18	**2,42036**	**9,921**	Trend-Saisonal
19	**0,93892**	**7,236**	Trend-Saisonal
20	**5,28624**	**17,085**	Trend-Saisonal
21	**1,60132**	**9,343**	Trend-Saisonal
22	**0,80607**	**6,443**	Trend-Saisonal
23	**27,05624**	**41,113**	Saisonal
24	**15,15981**	**26,038**	Konstant
25	**1,37650**	**9,244**	Trend-Saisonal
26	**3,30521**	**14,194**	Trend-Saisonal
27	**5,21861**	**16,834**	Trend-Saisonal
28	**1,52007**	**8,929**	Trend-Saisonal
29	**25,49440**	**39,160**	Saisonal
30	**1,27032**	**7,682**	Trend-Saisonal

Results for noise factor *a* = 5

Run	Trend Pattern		
	MSE	MAPE	Model Selected
1	**6,23087**	**17,284**	Trend
2	**25,45077**	**33,609**	Konstant
3	**55,40556**	**49,917**	Trend
4	**37,98957**	**43,628**	Konstant
5	**75,00339**	**65,133**	Konstant
6	**36,38022**	**42,465**	Konstant
7	**29,81594**	**37,377**	Konstant
8	**2,45028**	**12,593**	Trend
9	**14,32754**	**27,881**	Trend
10	**31,45400**	**38,704**	Konstant
11	**25,84088**	**33,961**	Konstant
12	**42,92413**	**47,028**	Konstant
13	**44,52818**	**48,085**	Konstant
14	**31,62894**	**38,843**	Konstant
15	**33,41011**	**40,236**	Konstant
16	**83,26203**	**69,065**	Konstant
17	**116,08888**	**71,520**	Trend
18	**30,18544**	**37,680**	Konstant
19	**51,22284**	**52,279**	Konstant
20	**13,45253**	**20,363**	TrendSaison(add)
21	**168,61037**	**90,308**	Trend
22	**32,72225**	**39,704**	Konstant
23	**34,37649**	**40,974**	Konstant
24	**57,59768**	**55,998**	Konstant
25	**38,48487**	**43,980**	Konstant
26	**36,21257**	**42,342**	Konstant
27	**38,68170**	**44,119**	Konstant
28	**30,74989**	**38,139**	Konstant
29	**53,55148**	**50,457**	Saisonal
30	**41,71569**	**46,217**	Konstant

Run	Seasonal Pattern		
	MSE	MAPE	Model Selected
1	3,45542	87,806	Konstant
2	3,00310	65,011	Konstant
3	3,95707	56,067	Konstant
4	3,60889	57,790	Konstant
5	4,63277	104,286	Konstant
6	5,47723	81,213	Saisonal
7	2,94132	67,789	Konstant
8	2,93131	73,426	Konstant
9	3,51884	89,008	Konstant
10	4,08307	97,706	Konstant
11	10,18622	115,372	Saisonal
12	3,74251	72,490	Saisonal
13	7,36529	76,493	Saisonal
14	11,46060	76,439	Konstant
15	2,93155	73,446	Konstant
16	3,05431	63,449	Konstant
17	5,84075	77,614	Saisonal
18	15,35774	142,424	Saisonal
19	3,10676	79,813	Konstant
20	6,31490	86,885	Saisonal
21	2,91917	71,986	Konstant
22	11,33827	75,582	Konstant
23	5,10134	62,387	Saisonal
24	4,08523	55,508	Konstant
25	3,89479	56,351	Konstant
26	3,49427	58,450	Konstant
27	3,11203	79,935	Konstant
28	3,41935	58,918	Konstant
29	3,61056	90,639	Konstant
30	3,75389	92,985	Konstant

Run	Trend–Seasonal Pattern		
	MSE	MAPE	Model Selected
1	39,34681	48,032	Konstant
2	17,70820	28,639	Konstant
3	52,09198	56,543	Saisonal
4	86,26156	76,485	Trend
5	35,54889	45,057	Konstant
6	9,70740	25,231	Trend-Saisonal
7	3,85859	14,937	Trend
8	4,03108	13,340	Trend
9	5,09661	17,084	Konstant
10	25,72936	36,451	Konstant
11	19,73715	30,701	Konstant
12	45,39850	52,450	Konstant
13	41,50709	50,072	Saisonal
14	46,25896	54,694	Saisonal
15	11,47320	22,227	Konstant
16	20,43638	33,868	Saisonal
17	46,29675	52,111	Konstant
18	35,70361	45,182	Trend
19	2,55638	12,245	Konstant
20	47,97790	54,231	Konstant
21	28,18788	38,707	Konstant
22	28,83631	39,304	Trend
23	2,54644	11,869	Trend
24	2,53797	12,560	Trend
25	6,22520	20,568	Konstant
26	50,82646	56,137	Konstant
27	23,61516	34,465	Konstant
28	10,87667	21,640	Konstant
29	9,51651	20,670	Trend-Saisonal
30	29,99016	40,346	Konstant