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Implementation of a demand planning system using advance order information

1. Introduction

This paper shows the successful application of a supply chain forecasting system in the refractory industry which integrates the knowledge of partially-known advance demand information. This constitutes a flexible demand planning system that enables quick responses to market changes which are immediately reflected by customers' booking patterns. The topic of forecasting under consideration of advance order information is only sparely covered in scientific literature and to the authors' knowledge, no industrial application where a large number of time-series is automatically forecasted in a flexible and data-driven way utilizing advance orders has been reported, so far.

A literature review of available forecasting procedures to incorporate advance demand information is given. On this basis the so-called "additive algorithm" is selected as the most appropriate method for the specific business case, because it enables the forecasting system to react quickly to demand shocks. However, as in the refractory industry demand is volatile because orders can be subject to cancellations and modifications, advance demand information not always improves forecasting performance and therefore has to be used selectively based on the particular forecasting task at hand. Thus, to make this method applicable within an industrial environment a robust procedure which automatically selects the appropriate forecasting method for each forecasting task and upcoming time period has been developed and applied.

For the implementation of the presented method no standard software modules are available. Therefore, an appropriate system architecture for a large scale implementation was put in place combining both the advantages of SAP NetWeaver BI for data preparation and reporting and of SAS Analysis for forecasting. This system architecture is illuminated and the achieved benefits of the demand planning system implementation are discussed.

2. Refractory Industry Background

Although the people of the world's traditional industrialized countries' economies consume an annual 15 – 20 kilograms of refractories per capita (Semler, 2004), the € 13.3 billion per year (Gangloff, 2008) refractory industry is scarcely known by the general public. Refractory is a term given to a class of materials which are produced from non–metallic minerals and possess the capability to withstand heat and pressure. These are products that confer properties like high temperature insulation, resistance to corrosive and erosive action of hot gases, liquids and solids at high temperatures in various kilns and furnaces (Raja, 2006). Figure 1 describes the refractory supply chain by providing an overview of the most important raw materials and the main customer industries.

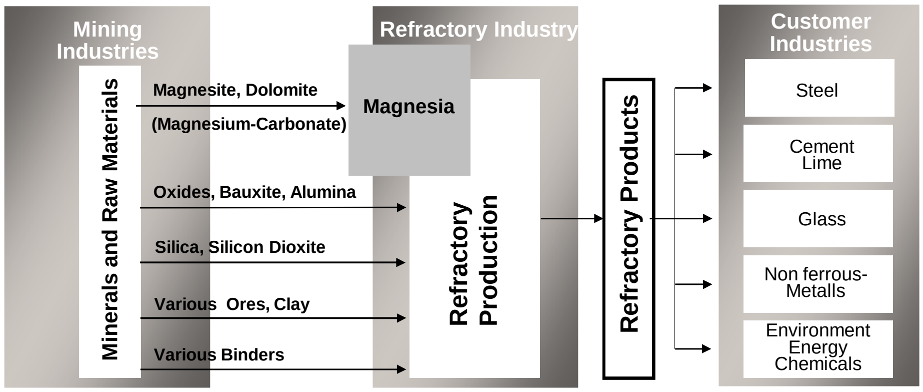

Figure 1: Description of the refractory supply chain

Concerning production of refractories, characteristics of the process industries apply as value is added by mixing, forming and chemical reactions (Fransoo and Rutten, 1994). The outcomes of the production process however are custom–made, distinct items. As the product's distinctive feature of shape is mainly customer specific, the refractory industry can be classified as make–to–order.

3. Aim and Scope of Demand Planning at the Refractory Industry

Forecasting the demand of finished goods or services is the trigger that sets supply chain planning activities in motion by estimating the magnitude, timing and location(s) of future demand. Aim of demand planning is therefore to establish a forecasting process, which supports decision making at the functional areas procurement, production, distribution and sales. Forecasts are the foundation for planning activities on several planning levels, conducted by different organizational units. Therefore a flexible forecasting system, which, dependent on the individual problem, covers multiple dimensions, is needed.

The relationship between forecasting ability and forecasting levels depending on the level of aggregation is investigated in Zotteri et al. (2005). They provide evidence that, even in a specific context, there is no "one best way" in defining the proper aggregation level. This encourages the design of a system which is flexible enough to allow aggregation of all possible combinations of criteria relevant for supply chain planning. Those possible forecasting segments in the refractory industry and thus the multiple possible dimensions of forecasting refractories demand are shown in Fig. 2.

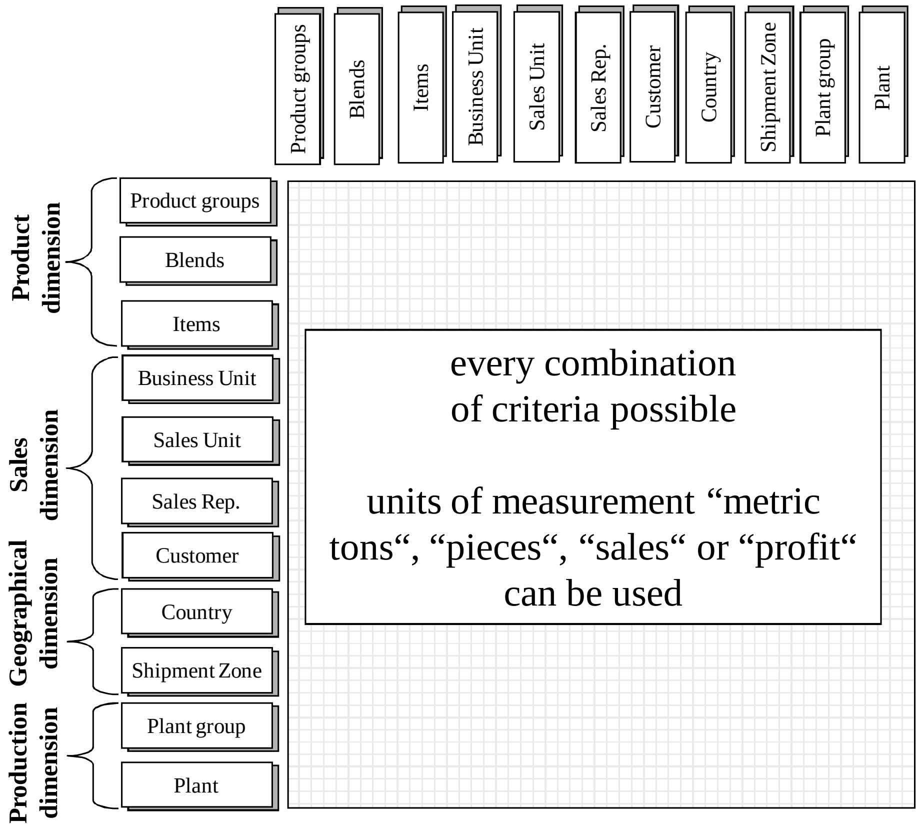

Figure 2: Required forecasting segments in the refractory industry.

Within a demand planning system this can be enabled by applying different characteristics for the aggregation of time series. Based on the combination of those criteria, the magnitude, time and quantity of demand can be calculated in the needed granularity to plan the supply chain. Section 7 describes a software architecture that provides this information in an efficent way. A key requirement for demand planning in the refractory industry is the application of different units of measurement. Depending on the specific question, forecasting is done based on metric tons, pieces, profits, as well as turnover. While the same set of forecasting methods is applicable to the various measurements, this additional dimension increases the number of time series to be analyzed even more. In the business case analyzed, for instance, the demand of about 50 different product groups (aggregated from more than 150 000 different finished products) which are produced at 30 production sites and sold to globally located customers has to be predicted. Clearly, methods which require human inspection are not suitable given the resulting number of different forecasting tasks so that an automatic model selection procedure is needed. Also, because the end–users do not have the necessary mathematical knowledge, a fast and automatic creation of forecasts is necessary.

4. Motivation for the use of advance order information and related literature review

An important aspect of demand planning in the refractory industry is that, due to its make–to–order characteristics, a significant percentage of orders is booked in advance. The level of booked orders is regarded as a strong indicator of business development in many industries and it seems natural to use this information to predict future demands.

In segments where a majority of orders is booked in advance practical experience shows that for upcoming periods this information is often a more reliable source of information for planning than quantitative forecasts which are solely based on historical data. This is the motivation for creating a forecasting method with the aim of increasing forecasting accuracy for predictions of a short– and mid–term time horizon by using the knowledge of already booked customer order data.

The ideas of the procedure take advantage of the so–called "order profile" (Meyr, 2003), which is shown in Fig. 3.

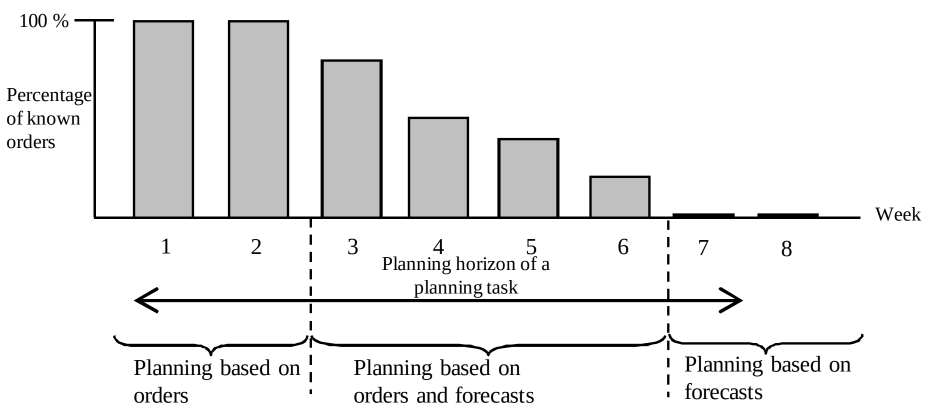

Figure 3: The order profile and its implications on planning.

Based on the percentage of already known orders, planning activities might be founded on orders alone, on a combination of orders and forecasts, or solely on forecasts. Our application and hence this paper deals with this planning activities founded on a combination of orders and forecasts. The main idea is to implement a method where both already available order information and a statistical forecast are combined to predict future demand.

The applied procedure is backed by a case study of Kekre et al. (1990) where the used method is called "additive algorithm". Their research was motivated by a consulting project at a printing company and uses simulated data to evaluate the performance of the additive algorithm and a multiplicative approach (the so–called "inflator algorithm"). The basic idea of the additive algorithm is to add a forecast of not yet known orders to the already booked (known) orders, whereas the multiplicative algorithm forecasts the ratio of the sum of unknown plus known orders, divided by the known orders. A serious flaw of multiplicative models is that in periods where no advance data are available forecasts can not be created with this method.

Bodily and Freeland (1988) study six forecasting methods which try to estimate the ratio between already booked orders and the expected total order quantity for a certain period. They also use simulated data and show that the applied procedures outperform the results gained by ARIMA (Auto Regressive Integrated Moving Average) modeling without advance demand information for the given application.

In cases where only a few observations are available and stable seasonal demand patterns occur De Alba and Mendoza (2001, 2006) suggest Bayesian approaches. However, Bodily and Freeland (1988) already noted that Bayesian methods are difficult to employ and demand high mathematical knowledge from a forecaster.

A literature review of forecasting methods which make use of advance demand information is given by Guerrero and Elizondo (1997) and Utley and May (2009). Guerrero and Elizondo (1997) successfully apply regression methods based on additive and multiplicative approaches to forecast a cumulative variable. Using data from the Mexican bank system they show that for the given problem for all lead times satisfactory results can be achieved. The paper of Utley and May (2009) examines the relative performance of four regression models for forecasting total demand when historical time series data for past sales and partial demand data for future orders are available. An ordinary least squares regression model that utilizes a demand ratio approach produced the most accurate forecasts.

Lee and Connors (2006) show that forecasting IBM India's workforce demand can be significantly improved by using partially known demand information and lead times. They illustrate that for their business environment, the inflator algorithm, the additive algorithm, and a hybrid method perform much better than time series models (exponential smoothing) without advance demand information. Similar to the approach stated by Guerrero and Elizondo (1997), the hybrid method is based on linear regression. For the given dataset it slightly outperforms the inflator and the additive algorithm.

Habla et al. (2008) develop a parameter–driven scheme to forecast demand quantities in the semiconductors industry. Their paper shows that for short–term predictions orders–on–hand data can be successfully applied in an industrial environment. They also specify a way of implementing their procedures into practice. They illustrate the system architecture of a prototype application based on MS Excel and VBA (visual basics for applications) programming and use the MS Excel Solver to estimate the parameters.

Common ground of all papers is that the usage advance demand information is encouraged, as for all test settings the forecast accuracy could be improved. Although this generally suggests the use of advance demand information for forecasting whenever available, a detailed analysis of the cited papers reveals serious limitations for an application of the existing methods in the refractory industry.

For many planning segments in the refractory industry the advance order information is not static as cancellations and modifications of booked orders (e.g. shifts over time caused by capacity shortages, modifications by the customers etc.) are common practice. Tan (2008) refers to those segments as "imperfect advance demand information" and presents a statistical approach of how to identify those segments and to calculate the expected order size in a make–to–stock environment. According to Kekre et al. (1990) the improvement of their algorithms are guaranteed for planning areas where it is presumed that the known component of future demand is exact since less of the total demand is predicted using a statistical model. It is also explicitly stated by Lee and Connors (2006) and presumably also assumed in the papers by Guerrero and Elizondo (1997), De Alba and Mendoza (2001, 2006) and Utley and May (2009) that the advance information used in their applications is assumed to be exact. This means that the algorithms were tested in environments where no cancellations or modifications of the advance data occur.

5. Implemented solution method

Given the particular features of the problem at hand, a novel approach based on an additive model was developed. Other than at the methods found in literature the application presented in this paper selects the optimal forecasting model type and the level of integration of advance demand information, depending on the patterns of the particular time series. As the additive algorithm of Kekre et al. (1990) is the basic ground for the approach, its core idea is described. Thereafter the different steps that are necessary for its application are listed.

5.1. Additive algorithm

Let $l \geq 0$ denote periods in general and t denote the current period. Then is AO_l, the total actual demand of period l, known for all periods $l \leq t$. Let O_l^k denote the part of the demand of period l which was already known k $(= 0, \ldots, K)$ periods earlier, i.e. in period $(l-k)$, and $X_l^k (= AO_l - O_l^k)$ denote the residual demand of AO_l, which was not already known k periods earlier. Thus, in general, already booked orders are denoted as O–values and the expected orders, which are the unknown quantities needed to calculate the total demand, are denoted as X–values.

For ease of readability the index j will be used instead of k if it is referred to future instead of past periods. Thus, for example, O_{t+j}^j denotes the part of the demand of the future period $(t+j)$, which is already known in the current period t, and O_t^k denotes the part of the demand of the current period t, which was already known in the past period $(t-k)$. Further assume that $\hat{A}O_l^k$ is the forecast for the actual demand AO_l of period l, which has been made k periods earlier, and that $\hat{x}_l^k$ is the forecast for the residual demand X_l^k of period l, which has been made in period $(l-k)$. Then, in order to get – in the current period t – a forecast $\hat{A}O_{t+j}^j$ for the overall demand of the future period $(t+j)$ additively using advance demand information by

$$\hat{A}O_{t+j}^j := O_{t+j}^j + \hat{x}_{t+j}^j \ , \tag{1}$$

one only has to make a forecast for the residual demand $\hat{x}_{t+j}^j$. Kekre et al. (1990) propose to get this by exponentially smoothing the last observation X_t^k, $k=j$, of the residual demand with its latest forecast $\hat{x}_{t-1}^j$ for some smoothing constant $0 < \alpha < 1$ by:

$$\hat{x}_{t+j}^j := \alpha X_t^j + (1-\alpha)\hat{x}_{t-1}^j. \tag{2}$$

5.2. Step-by-step application

Of course, it is not mandatory to use exponential smoothing for calculating $\hat{x}_{t+j}^j$. On the contrary, as at an industrial application fundamental business decisions are based on forecasts, it is imperative to ensure the best possible forecast accuracy. Therefore it is a prerequisite for a successful application to ensure that the best-fitting forecast method is selected.

Thus, not only for each time series to predict, but also for each booking lead time j of the time series, several forecasting models, methods, and potential parameter configurations (e.g. for the value of α above) should be checked by simulating their behavior ex-post for an already known, past part of the time series, i.e. for some $l \leq t$. This has not only to be done for the additive algorithm to predict $\hat{x}_l^k$ first and $\hat{A}O_l^k$ indirectly via equation (1), but also to predict $\hat{A}O_l^k$ directly from the time series AO. Their quality is evaluated and compared using some measure of forecasting accuracy like the root mean square error (RMSE). Out of these tested forecasting alternatives the best one is chosen for the ex-ante forecast of $\hat{x}_{t+j}^j$ and $\hat{A}O_{t+j}^j$, respectively.

Summarizing this procedure, for each times series and order lead time $k(= 1, \ldots, K)$ the following steps have to be executed in the current period t:

1. Simulate several forecasting alternatives (different models, methods, or parameters) to predict $\hat{x}_l^k$ ex post from the past time series X for a sufficient number of periods $l \leq t$.
2. For each of them calculate $\hat{A}O_l^k$ indirectly via equation (1) by adding the forecast for the expected quanitity to the already known quantity.
3. Calculate a unique measure of forecasting accuracy (like RMSE) for all tested forecasting alternatives. The — according to this measure — best alternative will be called the "additive forecast" $\hat{A}O^j$ $(j := k)$.
4. Simulate the same forecasting alternatives as in step 1 to directly ("conventionally") predict $\hat{A}O_l^k$ from the past time series AO.
5. Calculate the same measure of forecasting accuracy for all of the forecasting alternatives of step (4.). The — according to this measure — best alternative will be called the "conventional forecast" $\hat{c}O^j$ $(j := k)$.
6. Depending on this measure choose either the additive or the conventional forecast to predict the future period $t+j$.

6. Examples from the Refractory industry

In the following, examples for the application of this procedure in the Refractories industry are given. It is shown how forecasts for upcoming periods are made and it is demonstrated in Sect. 6.2 how the best forecasting alternative can be selected.

6.1. Forecasting the future

In the Refractory industries, for a period of three to six months ahead the use of advance order information in forecasting demand is considered. These three to six months also correspond with the time horizon needed for raw material sourcing and capacity planning. The analysis of the average order situation of a typical refractories product group is shown in Fig. 4.

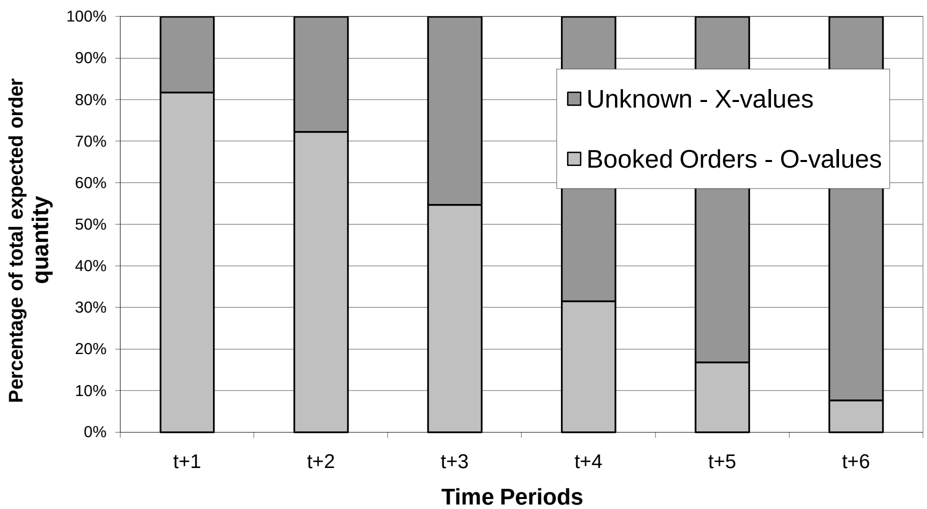

Figure 4: O– and X–values for short–term forecasting.

The time periods $t+1 \dots t+6$ represent months. For the above stated example it is therefore assumed that for the following month $(t+1)$ more than 80 percent of the total quantity to be delivered is already known in terms of booked customers orders.

Table 1 shows an example of the necessary data to start the forecasting process. An exemplary product group of refractories, underlying the demand shock of the 2008 financial crisis, has been chosen for illustration. Here end–of–period data starting in September 2004 is given and for the sake of clarity $j = 1, 2, 3$ is limited to three periods. The current period t for the illustrated example is January 2009. The end–of–period data k is limited to $K = 52$, i.e. $k = 0, \dots, 52$. Until January 2009 the actual values are known and the booked orders for the next periods j are also revealed. For example, at the end of January 2009, order bookings summing up to 8494.6 tons for the next month February are already available.

	$A0_l$	$X^{j=1}_l$	$X^{j=2}_l$	$X^{j=3}_l$	$O^{j=1}_l$	$O^{j=2}_l$	$O^{j=3}_l$
Cal. Month/Year ***(l=t-k)***	Quantity (Tons)	Tons	Tons	Tons	Tons	Tons	Tons
SEP 2004 *(k=52)*	8013.9	2971.3			5042.6		
OCT 2004 *(k=51)*	7819.2	2759.7	3318.8		5059.5	4500.4	
NOV 2004 *(k=50)*	8319.6	4018.7	4317.9	5480.1	4301.0	4001.7	2839.5
DEC 2004 *(k=49)*	8340.7	3100.2	3770.6	4689.1	5240.5	4570.2	3651.6
JAN 2005 *(k=48)*	8131.0	2939.8	3671.7	5359.0	5191.2	4459.3	2772.0
FEB 2005 *(k=47)*	7963.1	3005.4	3543.0	5020.5	4917.9	5072.9	3618.1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
AUG 2008 *(k=5)*	9242.1	821.5	1747.0	4295.8	8420.6	7495.0	4946.3
SEP 2008 *(k=4)*	9124.4	1372.6	2361.8	3887.1	7751.8	6762.7	5237.4
OCT 2008 *(k=3)*	8440.6	1017.2	2147.7	3659.3	7423.4	6293.0	4781.4
NOV 2008 *(k=2)*	9579.5	1586.9	3302.7	4114.8	7992.6	6276.8	5464.7
DEC 2008 *(k=1)*	9039.8	489.5	3560.9	5879.7	8550.2	5478.9	3160.1
JAN 2009 *(l=t; k=0)*	9152.8	445.9	448.5	533.4	8706.9	8704.4	8619.4
Booked Orders for FEB 2009 *($O^{j=1}_{t+1}$)*					8494.6	8430.1	7133.6
Booked Orders for MAR 2009 *($O^{j=2}_{t+2}$)*						7065.4	6805.9
Booked Orders for APR 2009 *($O^{j=3}_{t+3}$)*							5503.1

Table 1: Data structure needed for forecasting with the additive algorithm.

Note that some of the residual values X_l^k could also be negative because within the corresponding product group order cancellations are common. As a next step, forecasts $\hat{x}^j_{t+j}(j = 1, 2, 3)$ are made for the X–value time series in order to get the overall additive forecasts $\hat{A}O^j_{t+j}(j = 1, 2, 3)$ according to equ. (1). This is illustrated in the bottom right–hand column of Table 2. To compare the forecast results $\hat{A}O^j_{t+j}$ obtained by the additive algorithm, the "conventional" forecasts $\hat{c}O^j_{t+j}(j = 1, 2, 3)$ are also made for the actual–time series $AO_{t-k}(k = 0, \ldots, 52)$, which is shown in the bottom left–hand corner.

All forecasts shown in Table 2 are made using the commercial forecasting software SAS Analytics. The forecasting methods are selected automatically using a goodness–of–fit statistic based on the RMSE. This is done for each individual time series. This test of different forecasting methods and the application of the best–performing one, depending on the pattern of a time series, are the main differences to the additive algorithm of Kekre et al. (1990), where exponential smoothing according to equ. (2) is applied to forecast the portion of unknown demand. For all four time series of the stated example ($\hat{X}^1_{t-k}$, $\hat{X}^2_{t-k}$, $\hat{X}^3_{t-k}$ and AO_{t-k}) and their corresponding forecasts ($\hat{x}^1_{t+1}$, $\hat{x}^2_{t+2}$, $\hat{x}^3_{t+3}$ and $\hat{c}O^j_{t+j}$) an additive Winters model (Winters, 1960) has been automatically selected by the forecasting system.

	$A0_l$	X^1_l	X^2_l	X^3_l	O^1_l	O^2_l	O^3_l	
Cal. Month/Year ***(l)***	Quantity (Tons)	Tons	Tons	Tons	Tons	Tons	Tons	
	Time Series $A0_{t-k}$ values	Time Series X^1_{t-k} Values	Time Series X^2_{t-k} Values	Time Series X^3_{t-k} Values				
SEP 2004 *(k=52)*	3.9	971.3			5042.6			
OCT 2004 *(k=51)*	9.2	759.7	3318.8		5059.5	4500.4		
NOV 2004 *(k=50)*	9.6	018.7	4317.9	5480.1	4301.0	4001.7	2839.5	
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.					.	.	.	
.					.	.	.	
DEC 2008 *(k=1)*	.8	489.5	560.9	879.7	8550.2	5478.9	3160.1	
JAN 2009 *(t)*	52.8	445.9	448.5	533.4	8706.9	8704.4	8619.4	
	Conventional Forecast	Additive Algorithm						
	$\hat{c}0^j_{t+j}$		$\hat{x}^j_{t+j}$	+	O^j_{t+j}	=		$\hat{A}0^j_{t+j}$
FEB 2009 *(j=1)*	9051.0	-375.4		+	8494.6	8430.1	7133.6	8119.2
MAR 2009 *(j=2)*	9770.0		106.0		+	7065.4	6805.9	7171.4
APR 2009 *(j=3)*	8926.0			1480.0		+	5503.1	6983.1

Table 2: Scheme of forecast creation using the additive approach.

To evaluate forecasts for this product group, the results of the additive algorithm, the conventional forecast and the "budget forecast" $\hat{b}O^j_{t+j}$ $(j = 1, 2, 3)$ are compared with the actual. The forecast for sales budgets is made yearly by the top management using the consensus method. As shown in Fig. 5, for this product group the additive algorithms clearly outperforms results obtained by conventional forecasts and budget values for all forecast periods.

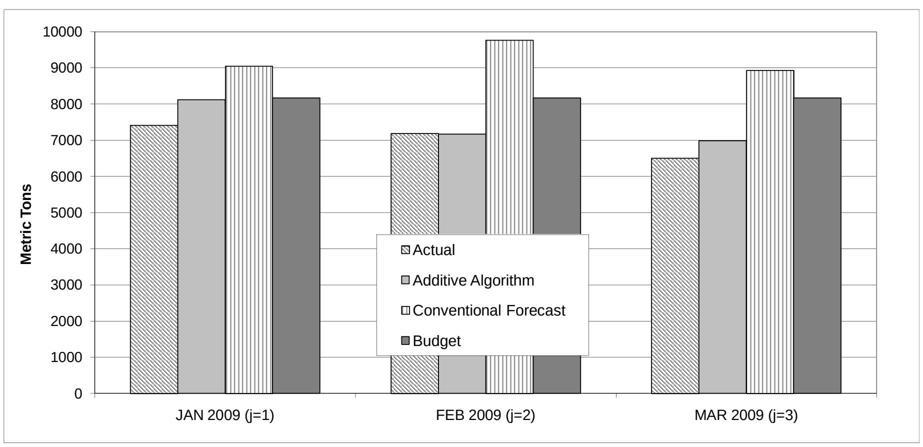

Figure 5: Forecast results $\hat{A}O^j_{t+j}$, $\hat{c}O^j_{t+j}$ and $\hat{b}O^j_{t+j}$ for the actuals AO_{t+j} of a refractory product group using the three different methods additive algorithm, conventional forecast and budget.

The economic downturn due to the global financial crises starting in fall 2008 also affected refractory sales. Budgeting for this example was made in fall 2008 when the extent and impacts of the economic crisis could not be foreseen and thus are not incorporated. Solely based on past data, the conventional forecast is not able to predict such a demand shock. It is shown in Fig. 6 that the conventional forecast evidently follows the demand pattern of the historical time series and that the method using advance order information reflects the economical downturn.

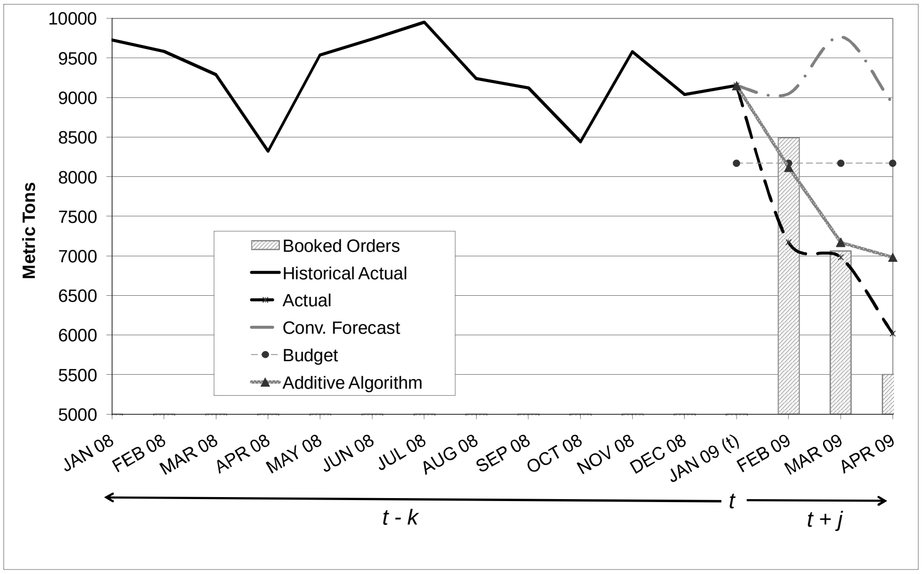

Figure 6: Only the additive algorithm is able to follow the demand pattern in times of demand shocks.

This is consistent with the observation by Kekre et al. (1990) who showed that demand shocks can be successfully predicted using advance order information. By using the additive algorithm the main part of the forecasts for the upcoming periods derive from the already booked orders, where the demand shook is reflected, since a change in buyers' behavior is incorporated immediately.

6.2. Identifying the best-fitting method

As mentioned previously, the advance demand information is imperfect for many product groups. The application presented in this paper and also the test examples of Kekre et al. (1990) reveal that the performance of the additive algorithm generally decreases with the percentage of booked orders in combination with imperfect demand information. For those planning segments conventional forecasts often outperform the results gained by the additive algorithm for certain (or all) future periods $t+j$. Therefore to forecast those periods a conventional forecast is more accurate.

Thus, a procedure which selects the best forecasting method for each future period individually, was established to enable the practical use of our application. The methodology follows steps (1.) to (5.) of the step-by-step procedure shown in Sect. 5.2. It is named "Integrated Forecast" as it combines the results obtained by the additive algorithm with results obtained by conventional forecasts based on an ex–post analysis of forecast errors.

Table 3 shows how the "Integrated Forecast" can be calculated on the example of a refractory product group with heavily fluctuating, "imperfect" demand information. A prerequisite for the application is that for a sufficient number of periods $t-k$ in the past, e.g., for $k = 1 \dots 12$ as it is shown in Table 3, forecasts are simulated and the results are compared ex post with the already known actual values. For each period $t+j$ the forecasting method to be applied is chosen based on the average RMSE.[1] This follows the idea of the selection of models based on a goodness–of–fit statistic with the extension that the selection is not just done for a whole time series but selectively per booking lead time j. As it can be seen in Table 3, for each booking lead time j the average RMSE is calculated and it is decided whether the additive or the conventional forecast should be used for future forecasts.

		Forecast for j=1		Forecast for j=2		Forecast for j=3	
Period l=t-k (t = JAN 2009)	Actual $A0_l$	Additive Forecast	Conventional Forecast	Additive Forecast	Conventional Forecast	Additive Forecast	Conventional Forecast
JAN 2008 *(k=12)*	19024	19646	18062	14886	20358	24580	20010
FEB 2008 *(k=11)*	17958	17108	17921	20981	17822	24580	20214
MAR 2008 *(k=10)*	18951	22853	20292	16683	20552	25006	20453
APR 2008 *(k=9)*	21871	17893	17725	19617	20552	21911	18730
MAY 2008 *(k=8)*	19907	19571	20283	16982	19037	22682	19782
JUN 2008 *(k=7)*	17720	19650	19909	19891	20266	19692	19020
JUL 2008 *(k=6)*	20566	20675	17844	16139	18708	23344	19065
AUG 2008 *(k=5)*	18477	17868	18798	20205	18103	24897	18967
SEP 2008 *(k=4)*	19956	20139	17903	16637	18190	23302	17495
OCT 2008 *(k=3)*	20034	22598	19810	22028	18140	24893	18427
NOV 2008 *(k=2)*	13775	15995	19936	19797	19860	21071	18190
DEC 2008 *(k=1)*	8710	10912	14743	16626	17235	22720	17160
RMSE		2097	3041	3940	3334	6166	3187

Table 3: RMSE of additive forecasts $\hat{A}O_l^j$ and conventional forecasts $\hat{c}O_l^j$ for different booking lead times $j = 1, 2, 3$.

In contrast to the example presented in Tables 1 and 2, which show another product group, for the particular product group used in Table 3, the additive algorithm outperforms conventional forecasts only for short–term predictions of the next month. For the following month ($j = 1$) on average 95% of the expected orders are already booked. For $j = 2$ the booking rate is 72% but the time series is unsteady because of frequent order cancellations and rescheduling of delivery dates. Therefore the advantage of using the additive algorithm gets lost. A main part of demand for this product group derives from large construction projects which are booked in advance but are often postponed on a short notice. For $j = 3$ a mere 35% of the expected orders are booked. In combination with the unsteady booking pattern, which is typical for this product group, the conventional forecast clearly outperforms the additive algorithm.

[1] In this example the current period t is December 2008.

7. System Architecture

Forecasting methods, which incorporate advance demand information, are sparsely covered in the scientific literature. Therefore, standard software systems suitable for a large scale implementation of those methods are not available. Prerequisite for the application of the additive algorithm is the use of end–of–period data, which has to be filtered and aggregated for all possible forecasting segments as stated in Fig. 2. Therefore a powerful data warehouse is needed. Refractory products show an immense variety in terms of their sales volume development as all kinds of demand patterns such as trends, seasonality, or periodic demand occur. Therefore a system has to apply multiple state–of–the art forecasting techniques including ARIMA–models, which for some applications are superior to common time–series analysis and multivariate regressions (Elliot et al., 2006).

Figure 7 shows the implemented system architecture, which consists of multiple software components.

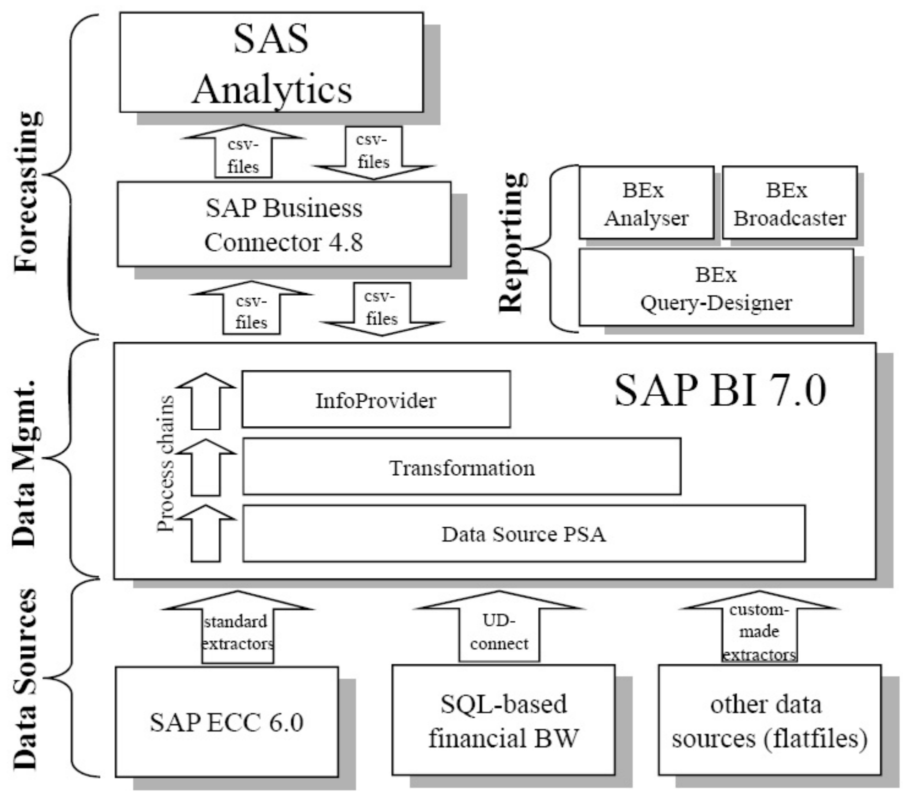

Figure 7: Applied architecture of the planning system.

The aggregation of the time series is done using filter transactions. This is the user interface to define the aggregation level and the planning horizon. From a technical point of view these aggregation levels are characteristics, which are grouped in dimensions and have several hierarchies. Key figures such as quantities, sales, or profits are assigned to the characteristic combinations (Jones, 2008).

The most noteworthy technical innovation of this project is the procedure for data preparation necessary to enable the forecasting concept using orders–on–hand data described in section 5.2. Due to the immense volume of data involved, the needed AO, O–values and X–values are pre–calculated, assuring data consistency on all possible characteristic combinations. Otherwise, a system had to aggregate and calculate its way through several hundred–thousand order positions for each forecast. This pre–calculation is made in a complex staging process, which consists of the following steps:

1. gather customer order data, which form the AO–values, and end–of–period data for the O–values.
2. filter relevant order positions by order type, schedule line type and rejection reason.
3. fill transactional data with attributes, which correspond to the forecasting segments stated in Fig. 2. This step is necessary as current master data attributes and organizational structures have to be applied.
4. calculate the key figures "weight", "quantity" in pieces and "sales" in home currency.
5. allocate the individual data sets to the respective planning months $t - k$ and the booking lead time $t + j$.
6. aggregate each combination of characteristic values and time stamps for both customer order data and end–of–period data.
7. AO– and O–values are merged by filtering datasets with matching characteristic combinations and timestamps and finally X–values are calculated.

8. Impact

The use of advance order information helped estimating the impact and effects of the economic crisis for problems in various functional areas within the supply chain and allows better and faster decisions. The application with data of the refractory industry shows that also for segments with imperfect advance demand information, the additive algorithms clearly outperforms conventional forecasts for a short–term time horizon and for most of the planning segments. Even without the full functionalities of the system in place, decisions based on forecasts paid off the investment within a few months. This could be proved by tracking the results of decisions made based on forecasts such as:

- anticipatory sourcing of raw materials based on forecasts led to price advantages compared to last–minute spot–market buying.

- based on forecasts, the optimal allocation of customer orders to the production plants could be improved significantly, resulting in a six-digit € sum of cash–flow relevant cost savings.

- stock levels could be decreased by a seven–digit € value using forecasts as a foundation for safety stock calculations.

9. Conclusion

This paper contributes in drawing the attention of both researchers and practitioners on the use of advance demand data in forecasting. It shows that by using modern information technology in combination with an easy to understand algorithm, forecasting accuracy can be increased for many planning segments in an industrial make–to–order environment. In contrast to the cases stated in related literature, a system, which is flexible enough to forecast in multiple dimensions and to cope with various different demand patterns, such as seasonality, is described. A main advantage of the applied algorithm is that demand shocks can be foreseen because changes in the demand pattern are reflected by already booked customer orders. However, the application also shows that forecasts using advance order information can not be applied automatically for all planning segments and time periods. The performance of the algorithm generally decreases the further the planning horizon and the more unreliable advance demand information is.

For the use in industrial practice, it is imperative to ensure that for each forecasting segment and each booking lead time j the most appropriate forecasting method is chosen. Therefore, a methodology is proposed which compares forecast errors of past time periods and automatically selects the probably most accurate forecast method. To identify situations where forecasting with advance demand information always outperforms conventional forecasts and to analyze general prerequisites for an advantageous behavior of the additive algorithm would be a promising area for future studies.

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