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# DISPO 4.0 | Simulation-Based Optimization of Stochastic Demand Calculation in Consumption-Based Material Planning in the Capital Goods Industry

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**Abstract:** This paper presents a digital material planning approach, utilizing simulation-based optimization to select and parametrize article specific demand forecasting methods. Demand forecasts are the basis of material requirements planning in consumption-based material planning, and are an essential lever for efficient inventory and order calculation. Despite their acknowledged potential, digital tools for optimized demand calculation are still lacking in practice. Thus, the goal of the presented approach to provide an application-oriented method to optimally select and parametrize state-of-the-art forecasting methods, based on product-specific demand data. In this approach, a rule-based selection heuristic is combined with static simulation of demand time-series and a metaheuristics-based optimization of forecasting parameters, to provide automatically optimized article-specific demand forecasts. Case studies for two companies in the capital goods industry evaluate and quantify the application potential. The results point to significantly improved, item-specific demand planning.

**Keywords:** demand planning; exponential smoothing; forecasting; parameter optimization; simulation

## 1 INTRODUCTION

Data and information are the *oil of the digital age* [1]. *Kirchner et al.* describe algorithms as crucial in order to be able to process the rapidly increasing amounts of data in a targeted manner [1]. This applies in particular to material requirements planning, which is facing a volatile, global market environment with increasing complexity and is confronted with an increasing amount of information and data [2]. Disruptions due to digitalization, smaller batch sizes, fluctuating demand, globalized supply chains and cost pressure are the key complexity drivers in material requirements planning [3]. Material requirements planning refers to the coordination of the flow of materials into the company and the stock so that the right items are available on time and in the right quality at the right place [4]. The aim of material requirements planning is to ensure that the company's material supply is economically secure in terms of type, quantity, time and quality [5]. The sub-disciplines of material requirements planning are divided into requirements planning, calculation of stock and purchase order calculation [4], see Fig. 1. Each of the mentioned sub-areas can achieve large savings through digitalized processes and employing optimization algorithms [6].

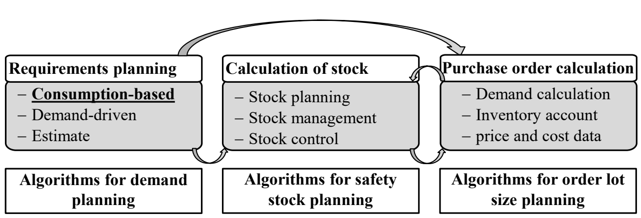


**Figure 1** Sub-disciplines of material requirements planning

This paper deals with the sub-disciplines of requirements planning and specifically with the application of forecasting algorithms in consumption-based material requirements planning. Demand forecasting is about predicting future needs as accurately as possible, taking into account all available information, existing historical data and knowledge of future events [7]. Today, a variety of procedures and complex logics exist in consumption-based material requirements planning to make material requirements planning more efficient. In everyday operations, however, only a very small proportion of mathematical models are used [8]. Forecasting systems require the development of expertise in identifying forecasting problems, applying a range of forecasting methods, selecting appropriate methods for each problem, and evaluating and refining forecasting methods over time [7]. The applicability of forecasting methods depends on the properties of the time series to be forecast, the properties of the forecasting methods, the intended use of the forecasts and the cost-benefit ratios of competing methods [9]. The digitalization and automation of a forecasting system can provide item-specific material requirements planning and spare parts stocking. Accurate demand forecasts lead to an increase in supply security in consumption-controlled material requirements planning, to a reduction in inventories and the resulting warehousing and capital commitment costs, as well as to a reduction in scrapping costs [8]. Consequently, shortages and resulting profit losses can also be reduced and customer loyalty can be secured through improved customer satisfaction [9]. Despite the acknowledged potential, practically available digital planning tools like SAP-APO (**A**dvanced **P**lanner and **O**ptimizer of the Software system SAP) are still lacking autonomous forecast parameter adjustment [10].

This paper presents the development of a digital planning tool for material requirements planning and operational purchasing, which enables an automatic item-specific optimized demand calculation in consumption-based material requirements planning. Using static simulation of sales and demand volumes and a rule-based heuristic as an evaluation criterion, the best possible item-specific forecast values are automatically determined by a *Genetic Algorithm* (GA). The potential benefits of using algorithms in consumption-based material requirements planning for semi-automated forecast calculation are evaluated in two case studies from the capital goods industry. The paper is structured as follows: Following the introduction, chapter 2 introduces the research methodology and goals. Chapter 3 gives an overview of relevant literature, followed by chapter 4 with an introduction of the case-studies used in the method development and evaluation. Chapter 5 presents the developed method, and the concluding chapter 6 discusses the case study results as evaluations of the developed planning method.

## 2 OBJECTIVE, RESEARCH HYPOTHESIS AND RESEARCH METHOD

The objective of the presented research was to develop a method to generate and automate the item-specific planning of consumption-controlled scheduled items. In doing so, it is necessary to consider expert knowledge about forecasting problems, about the application of different forecasting methods, about the selection of suitable forecasting methods as well as about parameterization and optimization of the forecasting methods.

The research hypothesis is that with the proposed planning method, using static simulation and optimization, item-specific material requirements planning for companies in the capital goods industry can be provided automatically, thus significantly improving the forecasting quality and minimizing the cost of material planning.

The research method used was the *Design Science Research Methodology* according to Peffers et al. [11], which combines principle, practices and procedures to achieve a structured, scientific approach in order to develop a solution to an existing problem from industry (demand calculation in materials planning) and then communicate it back into practice.

## 3 BACKGROUND: STOCHASTIC REQUIREMENTS PLANNING

In a literature analysis, an overview of the available forecasting methods was first determined, the algorithms characterized and the possible applications in the operational environment of the capital goods industry evaluated. The analysis of the forecasting algorithms was restricted to time series models of the stochastic requirements planning.

Fig. 2 shows the result of the identified procedures. The procedures marked in grey were selected as the most common procedures after a frequency analysis in the literature and were considered in the planning method developed. These 5 algorithms are already partly used in ERP (***E****nterprise* ***R****esource* ***P****lanning*) systems. However, decision-makers in the companies lack a basis for deciding which of the forecasting methods are the most suitable for the company and how they can be optimally parameterized for specific articles.

Next, an analysis of existing forecasting approaches identified which of the above forecasting methods were being utilized, as presented in Fig. 3. It is shown that authors deal with, describe, or also apply different forecasting methods. However, especially in the case of authors describing multiple methods, no meta-method has been developed, selecting the most suitable forecasting method for each article in the demand planning. The paper at hand aims to provide this meta-method support, enabling companies to utilize the benefits of multiple forecasting methods, with an automatic selection and optimal parameterization.

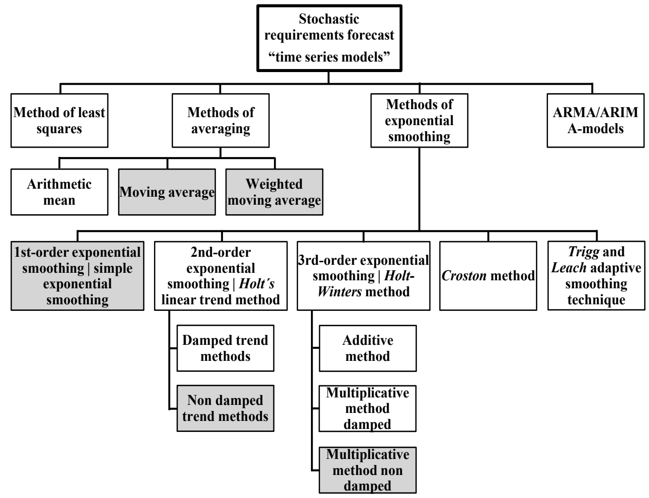


**Figure 2** Overview of time series models of the stochastic requirements planning

Time series data from the historical sales demand in the stochastic requirements planning can show a variety of item-specific patterns. Therefore, it is helpful to divide a time series into several components, each of which represents an underlying pattern category (trend, seasonality etc.) [7]. Roughly subdivided, the following time series types can be identified as shown in Fig. 4.

The literature research revealed that authors do not always agree on which forecasting method is best to use for which time series. A summary from the literature research is shown in the Fig. 5.

Since in practice the item-specific time series (demand patterns) can change over time, and no clear guidelines could be identified in the literature for which time series which forecasting method provides ideal forecasts, this research was initiated with the goal of selecting the most suitable method based on product-specific demand data. Optimization is required for optimal selection and parameterization of the identified state-of-the-art forecasting methods. For complex real-life problems, exact methods often do not apply, and rules-based heuristics or stochastic metaheuristics are chosen. Wari and Zu state that the GA is the most frequently applied metaheuristic for solving optimization problems, being applied in 60% of the analyzed cases. With its 3 operators, they are easily adaptable to specific applications [17, 16].

Optimization methods require an evaluation function. In the case of demand forecasting, a time-series consideration is suitable for the evaluation – this can be achieved via simulation. Simulation-based optimization takes into account the consideration of processes dynamically over time, for instance by means of discrete-event-oriented sequence simulation and improves them heuristically rule-based or by metaheuristics on a stochastic basis [18]. In this work, a static-historical time series approach is used, owing to the nature of the forecasting methods and the fact that thousands of articles must be processed, making processing effort and time an important factor to consider.

| *Algorithms* / *Literature* | Simple average | Moving average | Weighted moving average | 1st-order exponential smoothing \| simple exponential smoothing | 2nd-order exponential smoothing (damped trend methods) \| *Holt's* linear trend method | 2nd-order exponential smoothing (non damped trend methods) \| *Holt's* linear trend method | 3rd-order exponential smoothing (additive method) \| *Holt-Winters* method | 3rd-order exponential smoothing (multiplicative method damped) \| *Holt-Winters* method | 3rd-order exponential smoothing (Multiplicative method non damped) \| *Holt-Winters* method | *Croston* method | *Trigg* and *Leach* adaptive smoothing technique | Least square method | ARMA/ARIMA-models |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Abolghasemi*, et al., (2020) | | | | x | | | | | | | | | x |
| *Babai*, et al., (2020) | | | | x | | | | | | x | | | |
| *Bandeira*, et al., (2020) | | | | x | | x | | | | x | | | |
| *Blackwood*, et al., (2019) | | x | x | x | | x | | | | | | | |
| *Claus*, (2015) | x | | | x | x | x | x | x | x | | | | |
| *Claus*, (2021) | x | | | x | x | x | x | x | x | | | | |
| *Doszyn*, (2019) | | x | x | x | | | | | | x | | | |
| *Doszyń*, (2018) | | x | x | x | | | | | | x | | | |
| *Dutta*, et al., (2017) | | | | x | | | | | | | | | |
| *Entrup*, (2018) | | x | x | x | | x | | | | | | | x |
| *FerbarTratar*, et al., (2016) | | | | | | | x | x | x | | | | |
| *Gasparian*, et al., (2018) | | x | x | x | | x | | | | | | | |
| *Gronwald*, (2017) | | x | x | x | | | | | | | | | |
| *Hyndman,* et al., (2021) | x | | | x | x | x | x | x | x | | | | x |
| *Hyndmana,* et al., (2002) | | | | x | x | x | x | x | x | | | | |
| *Jacobi*, (2005) | | | | | | | | | | | | x | x |
| *Jayant*, et al., (2020) | | x | x | x | | | | | | | | | |
| *Kellner*, (2018) | | x | x | x | | x | | | x | | | | |
| *Kolade*, (2019) | | x | x | x | | | | | | | | x | |
| *Kühnapfel*, (2019) | | x | x | x | | | | | | | | | |
| *Lasch*, (2021) | | x | | x | x | x | x | | x | x | | | |
| *Mertens*, (2005) | x | | x | x | x | x | x | x | x | | | | |
| *Mertens*, (2012) | x | x | x | x | x | x | x | x | x | x | x | | x |
| *Nikolopoulos*, et al., (2016) | | | | x | | | | | | x | | | |
| *Patak*, et al., (2015) | x | | | x | | x | x | | | | | | |
| *Razmi*, et al., (2015) | | x | x | x | | | | | | | | | |
| *Schönsleben*, (2016) | | x | x | x | | x | x | | x | | x | | |
| *Schönsleben*, (2020) | | x | x | x | | x | | | | | x | | |
| *Schuh*, et al., (2014) | x | | | x | | x | | | | x | | | x |
| *Segerstedt*, et al., (2020) | | | | x | | | | | | x | | | |
| *Silitonga*, et al., (2018) | | x | x | x | | | | | | | | | |
| *Sing,* et al., (2017) | | | | x | | x | | | x | | | | |
| *Soni*, et al., (2017) | | | | | | | x | | | | | | |
| *Thalles*, et al., (2019) | | | | | | | x | | x | | | | |
| *Thommen*, (2017) | x | x | x | x | | | | | | | | | |
| *Tratar*, et al., (2019) | | | | | | | x | x | x | | | | |
| *Trigg*, et al., (1967) | | | | | | | | | | | x | | |
| *Trull*, et al., (2020) | | | | | | | x | x | x | | | | |
| *Wannenwetsch*, (2014) | x | x | x | x | | x | | | | | | | |
| *Waters*, (2008) | x | x | x | x | | | | | | | | | |
| *Xu*, et al., (2012) | | | | | | | | | | x | | | |
| *Zhu*, (2019) | | | | | | | | | x | | | | x |
| *Abolghasemi*, et al., (2020) | | | | x | | | | | | | | | x |
| **Total:** | **10** | **19** | **19** | **33** | **7** | **18** | **14** | **9** | **15** | **10** | **4** | **2** | **7** |

**Figure 3** Literature assignment to time series models of the stochastic requirements planning

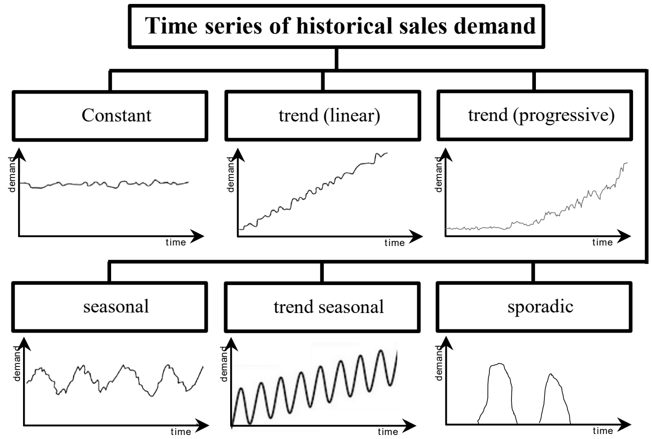


**Figure 4** Time series of historical sales demand (Own representation based on [13,12])

| Forecasting method / Time series of historical sales demand | Constant | trend (linear) | trend (progressive) | seasonal | trend seasonal | sporadic |
|---|---|---|---|---|---|---|
| Simple average | ● | | | | | |
| Moving average | ● | | | | | |
| Weighted moving average | ● | ◐ | | | | ◐ |
| 1st-order exponential smoothing \| simple exponential smoothing | ● | | | | | ◐ |
| 2nd-order exponential smoothing (damped trend methods) \| *Holt´s* linear trend method | ◐ | ● | | | | |
| 2nd-order exponential smoothing (non damped trend methods) \| *Holt´s* linear trend method | ◐ | ● | ● | | | |
| 3rd-order exponential smoothing (additive method) \| *Holt-Winter* method | ◐ | ◐ | ◐ | ● | ● | |
| 3rd-order exponential smoothing (multiplicative method damped) \| *Holt-Winters* method | ◐ | ◐ | ◐ | ● | ● | |
| 3rd-order exponential smoothing (Multiplicative method non damped) \| *Holt-Winters* method | ◐ | ◐ | ◐ | ● | ● | |
| *Croston* method | | | | | | ● |
| *Trigg* and *Leach* adaptive smoothing technique | | ◐ | ● | | | ● |
| Least square method | | | | | | |
| ARMA/ARIMA-models | ● | ● | ● | ● | ● | ◐ |

Legend: ● suitable ◐ limited suitable

**Figure 5** Relationship between time series and forecasting method according to literature study (Own representation based on [14,13,15])

## 4 CHARACTERIZATION OF THE CASE STUDY

The focus of the case studies is the finding that there is a trend that customers in the capital goods industry do not order products based on long-term strategies. Increasingly, products are being ordered through short-term orders. This requires shorter delivery times and a high degree of flexibility. Shorter delivery times mean that the customer in turn reacts with increasingly late order placement and still expects reliable delivery [19]. For the material planning, the implications are that many different articles with varying demand profiles must be considered, making it challenging for human planners to create and maintain article-specific demand forecasting profiles. Since the share of bought-in articles in the Austrian capital goods industry is relatively high, this motivation for an automated digitalized planning support is especially relevant. Two companies considered in the Austrian capital goods industry were included (see Tab. 1).

**Table 1** Case Study - Characterization Company 1 and Company 2

| | Company 1 | Company 2 |
|---|---|---|
| Sector | Fittings and valves production | Automotive industry |
| Employees | 115 (full-time equivalent) | 243 (full-time equivalent) |
| Annual sale | 22,3 m € | 89 m € |
| Customers | 346 from 51 countries | 38 800 from 22 countries |
| Purchasing volume | 11,5 m € | 59 m € |
| Suppliers | 1 780 from 61 countries | 1 258 from 28 countries |
| ERP-system | SAP | Infor M3 |
| Different demand articles (-36 months) | 4 341 items | 17 724 items |

## 5 DEVELOPMENT OF THE DIGITAL PLANNING METHOD

This paper describes how a digital tool for an optimized demand requirement planning of consumption-based items was developed in the capital goods industry. The method is meant to base the selection and parametrization of forecasting methods on quantitative data analysis, i.e. simulation and optimization, thus providing a structured approach, providing consistent results, independent of the experience time and of human planners. The modelling of the tool aims at the highest possible forecasting quality. In doing so, changing market conditions (static vs. dynamic data) are to be considered, with the objective of a future digitalization or automation of the requirements planning.

The methodological core of the optimization is a *Genetic Algorithm* (GA), which improves the method-specific forecast parameters in each case. The GA uses a simulation-based optimization of monthly sales forecast for each method. A rule-based heuristic then compares the sales predictions to actual sales for historical data, determining the forecasting error and using the latter to select the most suitable forecasting method. In this developed digital planning method, the ***M**ean **S**quared **E**rror* (MSE) is used as an evaluation criterion for the forecasting error. The optimally parametrized method for each article is then used to forecast medium-term future sales.

The digital planning method was implemented in *MS (Microsoft)-Excel* with *Visual Basic for Applications* (VBA). It comprises the following steps:

1. General settings for the forecasting methods
2. Data preparation and data processing
3. Importing prepared data
4. Forecast optimization and calculation
5. Export of results

### 5.1 Parameterization of the Planning Method

In the first step, the planning method is parameterized and set up for the specific use case, using the *MS-Excel* Solver. The forecasting methods are then parameterized in the following steps:

- Setting the number of periods of sales history that should be considered
- Setting the number of forecast periods (the further into the future, the less reliable is the result – 12 months should be the maximum)
- Setting the maximum optimization runtime per item – this is a termination criterion for the *Genetic Algorithm* GA optimization and thus determines the runtime of the entire planning method
- Setting the relevant periods to calculate the forecasting error MSE
- Limit predictability: Input for which articles no forecast will be provided, due to too high forecasting errors MSE for historic sales data (the error threshold can be set by the planner and the identified articles are labelled "*Non-predictable items*")
- Forecasting method *weighted moving average* additionally allows the setting of the "number of periods for averaging" or the reduction factor.
- exponential smoothing of the 1st and 2nd order as well as the *Holt-Winters* procedure allow the setting of the limit values of the respective forecast parameters to prevent unusual values, e.g., a potential result of overfitting, that could lead to high-risk parameters
- Finally, the five currently available forecast algorithms are parameterized with the GA. For each method, the values for the parameters "surplus" and "shortage" can be defined before the calculation.

### 5.2 Data Preparation and Data Processing

For the relevant input data, a distinction is made between the following two different data sets:

- Input data needed for the forecast calculation.
- Input data required for the preparation of the user-specific result files (warehouse and supplier data).

It must be ensured that the input data corresponds to the specified data formats to enable automated processing of the data without reprocessing the data records. The time series of the historical sales figures are automatically prepared according to the settings from *section 5.1*. This generates a clear time series monthly for each article from a data set of several hundred thousand article withdrawals.

In addition, "replacement articles" are read in. These are articles that will no longer be needed in the future or that will be replaced by another article (discontinued item). No forecast is issued for these articles by the planning method. This automated data preparation takes about one minute for the dataset in the use-case.

### 5.3 Importing Prepared Data

The data prepared in *section 5.2* (item number, item name, time series, base unit etc.) are automatically read into the planning tool, in separate tables for each forecast method. In the two case studies, the *forecast error **M**ean **S**quared **E**rror* (*MSE*) is used because it penalizes and minimizes the largest deviations the most. In planning, these large deviations are especially costly when there is no sufficient safety stock.

### 5.4 Forecast Optimization and Calculation

After completing the preparatory steps, the forecast calculation of all five implemented forecast algorithms is compiled. The following is a list of the actions executed in this planning step:

a) Forecast parameter(s) is/are optimized by using *Genetic Algorithm* (GA), considering the product specific constraints
b) All results (forecast values, parameters, forecast errors etc.) are gathered in a result sheet
c) Identification of "*Non-predictable items*"
d) The forecast result with the lowest forecast error (*MSE*) is transferred to the result sheet for each article
e) Export of results (.csv files and *MS-Excel* based result analysis)

The following five forecasting methods are executed consecutively:

1. *Holt-Winter* method or *3rd-order exponential smoothing* procedure (multiplicative, non-damped)
2. *Holt´s linear trend method* or *2nd-order exponential smoothing* procedure (non-damped)
3. *1st-order exponential smoothing* procedure or *simple exponential smoothing*
4. *Moving average*
5. *Weighted moving average*

PARAMETER OPTIMISATION AND FORECAST CALCULATION: HOLT-WINTER METHOD

| MINIMIZATION Ø FORECAST ERROR MEAN SQUARED ERROR (MSE): | MAD 40.85 | MSE 2888.68 | MAPE 1.84 | STABW.S 37.21 |
|---|---|---|---|---|

Current item 157
Alpha (HB) 0.05
Limit values (NB) 0.01 1.00
Overlap 1.00
Shortfall 2.00
Beta (HB) 0.83
Gamma (HB) 0.18
Item display 157
Start display

| CW | Sales history | Sales forecast | Error value | Absolute error value | Quadratic error value | Absolute error value |
|---|---|---|---|---|---|---|
| -36 | 26.0 | 26.0 | | | | |
| -35 | 144.0 | 26.0 | 118.0 | 236.0 | **55696** | 164% |
| -34 | 20.0 | 32.4 | -12.4 | 12.4 | **154** | 62% |
| -33 | 4.0 | 31.7 | -27.7 | 27.7 | **769** | 693% |
| -32 | 8.0 | 30.2 | -22.2 | 22.2 | **494** | 278% |
| -31 | 102.0 | 29.0 | 73.0 | 146.0 | **21304** | 143% |
| -30 | 17.0 | 94.7 | -77.7 | 77.7 | **6032** | 457% |
| -29 | 70.0 | 123.6 | -53.6 | 53.6 | **2871** | 77% |
| -28 | 11.0 | 79.7 | -68.7 | 68.7 | **4726** | 625% |
| -27 | 78.0 | 67.8 | 10.2 | 20.5 | **420** | 26% |
| -26 | 8.0 | 60.5 | -52.5 | 52.5 | **2758** | 656% |
| -25 | 80.0 | 47.8 | 32.2 | 64.3 | **4141** | 80% |
| -24 | 1.0 | 40.5 | -39.5 | 39.5 | **1563** | 3953% |
| -23 | 49.0 | 39.6 | 9.4 | 18.7 | **351** | 38% |
| -22 | 20.0 | 18.3 | 1.7 | 3.3 | **11** | 17% |
| -21 | 6.0 | 8.4 | -2.4 | 2.4 | **6** | 41% |
| -20 | 0.0 | 0.0 | 0.0 | 0.0 | **0** | 0% |
| -19 | 0.0 | 0.0 | 0.0 | 0.0 | **0** | 0% |
| -18 | 12.0 | 0.0 | 12.0 | 24.0 | **576** | 200% |
| -17 | 82.0 | 0.0 | 82.0 | 164.0 | **26896** | 200% |
| -16 | 71.0 | 0.0 | 71.0 | 142.0 | **20164** | 200% |
| -15 | 0.0 | 0.0 | 0.0 | 0.0 | **0** | 0% |
| -14 | 96.0 | 0.0 | 96.0 | 192.0 | **36864** | 200% |
| -13 | 40.0 | 0.0 | 40.0 | 80.0 | **6400** | 200% |
| -12 | 2.0 | 4.5 | -2.5 | 2.5 | **6** | 124% |
| -11 | 47.0 | 17.8 | 29.2 | 58.4 | **3408** | 124% |
| -10 | 24.0 | 24.1 | -0.1 | 0.1 | **0** | 1% |
| -9 | 48 | 33.9 | 14.1 | 28.3 | **799** | 59% |
| -8 | 32 | 45.0 | -13.0 | 13.0 | **169** | 41% |
| -7 | 4 | 54.4 | -50.4 | 50.4 | **2544** | 1261% |
| -6 | 50 | 58.9 | -8.9 | 8.9 | **79** | 18% |
| -5 | 50 | 93.2 | -43.2 | 43.2 | **1863** | 86% |
| -4 | 104 | 69.7 | 34.3 | 68.6 | **4702** | 66% |
| -3 | 53 | 78.9 | -25.9 | 25.9 | **671** | 49% |
| -2 | 21 | 83.3 | -62.3 | 62.3 | **3884** | 297% |
| -1 | 148 | 83.7 | 64.3 | 128.6 | **16539** | 87% |
| 1 | | 92.8 | | | | |
| 2 | | 136.1 | | | | |
| 3 | | 96.8 | | | | |
| 4 | | 99.0 | | | | |
| 5 | | 101.6 | | | | |
| 6 | | 104.8 | | | | |
| 7 | | 105.6 | | | | |
| 8 | | 152.3 | | | | |
| 9 | | 107.4 | | | | |
| 10 | | 108.5 | | | | |
| 11 | | 110.0 | | | | |
| 12 | | 112.2 | | | | |

**Figure 6** Calculation worksheet *3rd-order exponential smoothing* or *Holt-Winter* method 1/2

The forecast calculation and, for parameter-dependent methods (1) - (3), additionally the forecast parameter (smoothing parameter $\alpha$, trend parameter $\beta$, seasonality $\gamma$) optimization is carried out per item number. The calculation and optimization are carried out in sequence, article per article. The forecast parameters (e.g. for *exponential smoothing*: alpha, beta, gamma) are optimized by the *Genetic Algorithm* (GA) according to the stored parameter "Maximum optimization runtime" as well as the stored GA settings per article. The solver and integrated GA [20] provided in *MS-Excel* were automated in *VBA* and adopted with the corresponding settings (convergence, mutation, population size etc.) as well as the solver objective function, constraints and variable parameters.

The forecast is calculated and optimized for each article and each of the five forecast methods according to the stored constraints (limits, surplus, shortage, number of periods for averaging, reduction weighting).

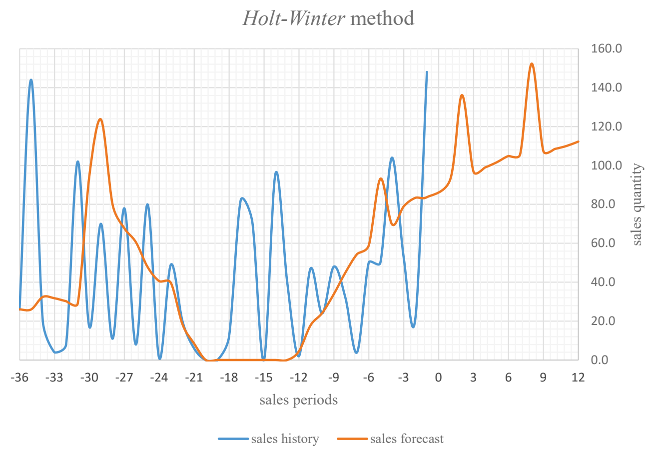


**Figure 7** Calculation worksheet *3rd-order exponential smoothing* or *Holt-Winter* method 2/2

The calculated results are the basis for a rule-based heuristic and the evaluation of the "optimal" forecast method and the associated "optimal" forecast values.

For the case studies, a "limit of predictability" was empirically determined for each company over several data sets. In this process, no forecast is to be issued for items that have very high uncertainties. This is a pre-emptive effort to avoid wrong decisions. The uncertainty is defined as the relation between the forecast error ***M**ean **S**quared **E**rror* (MSE) and the historical consumption of the article and a defined relation value per case study.

From the five generated forecast results, the rule-based heuristic selects the forecasting method with the lowest forecast error (MSE) for each article. After several empirical tests, the period considered for the forecast error (MSE) was made adjustable for the selection of the optimal, item-specific forecast algorithm. In the case studies, the forecast error (MSE) of the past 12 months was used for the evaluation, although at least 36 months of past data were available. Experience has shown, however, that complex forecasting algorithms such as exponential smoothing learn over time (seasonality, trend etc.) and that the forecasting error (MSE) is successively reduced by the learning effect. This distinguishes the simple forecasting methods (*moving average* and *weighted moving average*) from the more complex mathematical methods. The item-specific optimal forecast algorithm, the monthly rolling future forecast values as well as one of the forecast errors *MSE*, *MAD (**M**edian*

***A**bsolute **D**eviation)* or *MAPE (**M**ean **A**bsolute **P**ercentage **E**rror)* to be selected for optimization and the standard deviation of the forecast error are transferred to the result sheet. The calculated forecast errors *MAD* and *MAPE* as well as the standard deviation of the forecast are used as input for additional digital tools developed by the authors for the calculation of stock [21].

When transferring the rolling monthly future forecast values to the result sheet, depending on the parameterization (see *section 5.1* "*Rounding for general cargo items*") and the article-specific base unit of measure, the forecast results are rounded commercially or output as a two-digit decimal number. Especially with low forecast quantities in the single-digit range (e.g., spare parts), rounding leads to the output of values that are too high compared to the forecast values determined. For this reason, the decimal places in the integrated "Round" function are always added up and only shown in the result sheet when a whole number is reached. This avoids rounding errors in the forecast shown.

Finally, there is a result sheet in which for each article from the input database, except for the "replaced articles", an optimal forecasting procedure from the five considered forecasting algorithms as well as the corresponding forecast values are shown. Depending on the system performance/server performance and the data volume of the input file, the execution of the forecast calculation can take several days to compute. As parameterized in *section 5.1*, a maximum optimization time of several seconds per item (3 seconds is recommended, based on the analysis of optimization quality vs. time for the use-case datasets) is available for parameter optimization per forecast method.

### 5.5 Export of Results

To ensure that the item-specific forecasts can also be directly integrated into the company's daily routine, practical company-specific requirements were formulated for the preparation of the result reports.

A .csv-file with all results for each article is generated. This is normally used as input to parametrize the warehouse management systems installed in the company. In addition, a company-specific result report can be generated. By importing two supplementary input files, item-specific storage data (stock value and stock quantity across all warehouses, safety stock etc.), scheduling data (item owner, replenishment time, order point etc.) and supplier-specific data (main supplier, supplier item number, price etc.) are automatically added to the item-specific forecast. Mathematical data, as listed in the .csv-result report, are reduced to a necessary minimum. The objective was to enable material requirements planners and operational purchasers to continue working with the result report directly in *MS-Excel*. This result report can be used both for internal company communication and for communication with suppliers. Due to the extensive supplementary input data for this report and the complex linking of the data with each other (identification of the main supplier, consolidating stock data across all warehouses etc.), this last calculation in the case studies takes anywhere from one to several hours.

## 6 CONCLUSION

The developed digital planning tool for an optimized requirements planning was verified using the example of two case studies (see chapter 4).

The limitation of this research relates to the (Austrian) capital goods industry and the utilization of five forecasting methods, as the development and evaluation of the digital planning method was carried out on basis of two companies from the capital goods industry (see chapter 4) and five different forecasting methods (see section 5.4). The following distinction is made between the two companies in the case study. In company 1, 4341 articles from material planning are considered, which subsequently flow into the processing of a small batch production. In company 2, in total 17.724 articles from material planning are considered, which are purely spare parts and subject to a corresponding spare parts planning. The developed planning tool, also implemented in a software tool "*Demand Planning Falcon*", is suitable for both series production and spare parts planning. Tab. 2 shows the selected optimized forecasting methods for the two use-cases and the differences, due to the different time series of the articles considered, become apparent.

During the development of the planning tool, it was found that the naive *moving average* forecasting method most widely used in practice, mainly due to the low implementation and maintenance effort, is replaced with complex *exponential smoothing procedures*. Essential for this result is also the item-specific optimization of the forecast parameters by means of *Genetic Algorithm* (GA). This allowed the complex forecasting methods to be optimally adjusted and applied according to the item-specific characteristics. However, it is also evident from the case studies that each of the forecasting methods is required for optimal item-specific forecasting and is applied in the case studies. The results in both cases identify *3rd-order exponential smoothing* as the most frequently chosen method. This can be explained by pronounced seasonality of many of the involved articles – in company 1 resulting from products for the agricultural technology. In company 2 strong long-term sales trends lead to *2nd-order exponential smoothing* being chosen for many articles.

**Table 2** Results of the forecast calculation per item

| Implemented forecast algorithms | Company 1 | | Company 2 | |
|---|---|---|---|---|
| *Moving average* | 345 | 7,9% | 4 969 | 28,0% |
| *Weighted moving average* | 737 | 17,0% | 2 | 0,0% |
| *1st-order exponential smoothing procedure \| simple exponential smoothing* | 581 | 13,4% | 2 310 | 13,0% |
| *Holt´s linear trend method \| 2nd-order exponential smoothing procedure* (non-damped) | 650 | 15,0% | 3 926 | 22,2% |
| *Holt-Winter method \| 3rd-order exponential smoothing procedure* (multiplicative, non-damped) | 1 665 | 38,4% | 6 372 | 36,0% |
| *Non-predictable items* | 255 | 5,9% | 43 | 0,2% |
| *replacement articles*: no forecast | 108 | 2,5% | 102 | 0,6% |
| Total: | 4 341 | | 17 724 | |

The use of different forecasting methods ensures that the respective, item-specific time series are considered more efficiently. This is a process improvement compared to sales planning based on a single forecast method (e.g. *moving average*) [22].

The applied *Design Science Research Methodology* shaped the research procedure: The starting point is an existing problem from industry, from which an objective and a research hypothesis were derived (see *chapter 2*). Based on theory research on the current state of the art (see *chapter 3*) and a specification of the problem in the capital goods industry (see *chapter 4*), a solution to achieve the objective was developed (see *chapter 5*). The results from the developed planning method were demonstrated and evaluated in terms of applicability using real company data and subsequently communicated back to the industry. During the evaluation and communication, suggestions for improvement of the developed digital planning method were identified. The resulting necessary adaptations in the adjustment of the objectives or in the design and development of the digital planning method were run through in several loops.

The research outlook comprises the following elements: Identifying and implementing continuous improvements by monthly application of the planning tool (*Demand Planning Falcon)* at the application partners. An expansion to other forecasting methods (see Fig. 2) to sustainably increase the quality of forecasts is planned. In addition, the results are used as input for further research projects within the framework of the research project *DISPO 4.0*. These include the digitalization of *calculation of stock* using safety stock algorithms [21] and the digitalization of *purchase order calculation* using order lot sizing algorithms [23]. The results of the *Demand Planning Falcon* enable significantly improved, item-specific demand planning and are a first step towards the automation and digitalization of the *requirements planning* of consumption-based material requirements planning.

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