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DISPO 4.0 | Simulation-Based Optimization of Stochastic Demand Forecast of Intermittent Material in the Capital Goods Industry

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Abstract: This research introduces a digital planning method tailored to intermittent demand, leveraging simulation-based optimization to select and parameterize forecasting techniques for individual items. Accurate demand forecasting is crucial for optimizing inventory and order quantities, especially in spare parts planning, where demand is often intermittent. Despite the recognized value of digital solutions in this area, practical implementation of optimized forecasting tools for intermittent demands remains limited. To address this gap, the proposed approach offers a practical methodology for systematically selecting and configuring forecasting techniques specifically suited to irregular demand patterns. The method combines a rule-based heuristic with a static simulation of demand time series and metaheuristic-based optimization to calibrate forecasting parameters. The outcome is an automated, item-specific forecast tailored to the characteristics of intermittent demand. The approach is validated through two practical case studies from the capital goods sector, demonstrating its effectiveness in enhancing forecast accuracy and improving intermittent item planning.

Keywords: Croston's method; demand planning; forecasting methods; intermittent demand; parameter optimization; spare parts

1 INTRODUCTION

The optimization of inventories is crucial for companies in order to minimize inventory and capital tie-up costs [1]. It is also essential to minimize scrapping costs and profit losses due to shortages [2], while at the same time ensuring a high level of delivery reliability [1]. Spare parts warehouses in particular play an important role, as they minimize downtimes, can deliver stocked spare parts quickly and avoid downtime costs [1]. High inventories in turn cause costs and account for around a third of all company values [3]. Companies therefore must manage a balancing act between security of availability and inventory costs [2].

In order to remain competitive in a volatile business environment, companies must be able to make timely decisions based on precise demand forecasts derived from existing data [4]. Data and information processing is crucial [5] and algorithms are the key to the efficient utilization of large data volumes [5]. In everyday operational planning, usually only a limited number of mathematical algorithms are applied, as there is a lack of ready-to-use methods for selection and case-specific parameterization [6].

Stochastic demand forecasts [7] - so-called time series models - are classified as quantitative forecasting methods [8]. Time series models are always based on the analysis of historical data in order to predict future demand [8]. Historical material consumption data form the basis for determining future requirements by means of suitable forecasting algorithms [9]. This is referred to as customer-anonymous sales planning [10]. The primary target of this sales planning is to predict future requirements as precisely as possible by incorporating all available information [11] and analyzing demand patterns [12]. Modern forecasting algorithms support companies to optimize planning, manage risks and estimate future material requirements [7].

This practice-oriented research describes the further evolution of a digital planning method for optimized sales forecasting in the capital goods sector, which builds on the authors' existing publications [13-15]. The further development of the method is intended to investigate the use of forecasting algorithms for intermittent material demands in the capital goods sector [14].

2 OBJECTIVES

The aim of this research is the development of an item-accurate planning for items with intermittent requirements in the capital goods industry. This encompasses expertise in forecasting challenges related to intermittent requirements, the use and selection of appropriate forecasting algorithms, their parameterization and optimization, and an evaluation based on real company data [14]. The following research questions are answered by our contribution:

1) Do stochastic time series-based forecasting algorithms specifically designed for intermittent demands achieve better forecasting results for intermittent material demand than general forecasting algorithms designed for constant, trend or seasonal demands (see Fig. 2)?
2) How can a digital, user-friendly planning method be designed to make time series models described in the literature and developed specifically for intermittent material requirements practically usable for the capital goods industry?

3 BACKGROUND STOCHASTIC DEMAND FORECAST

Intermittent demands are characterized by irregular patterns and longer phases without demand [12] as well as sudden demands and represent a material category that is difficult to forecast [16].

The literature contradicts the prevailing assumption in practice that intermittent material demands cannot be reliably predicted [16]. The *state-of-the-art* already provides specialized forecasting algorithms for intermittent material requirements [17]. Intermittent forecasting algorithms were first identified and analyzed, followed by an evaluation of

their potential applications within the operational context of the capital goods sector (see Fig. 1). The methods highlighted in blue represent the most frequently cited techniques, identified through frequency analysis, and were integrated into the developed planning approach [14]. Some of these forecast methods are already in use in IT systems. Nonetheless, a systematic approach to identifying the most appropriate forecasting techniques and their optimal parameterization is currently missing in corporate planning [14, 13].

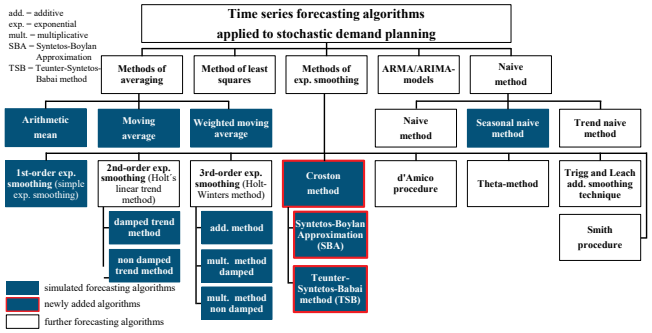


Figure 1 Overview of time series forecasting algorithms applied to stochastic demand planning - (Own representation based on [13, 14, 18, 19])

The consideration of the different types of time series patterns is initially one of the most important aspects in the selection of suitable forecasting methods [20]. When analyzing the development of demand, it is necessary to break down the time series into several components in order to produce accurate forecasts [10] (see Fig. 2).

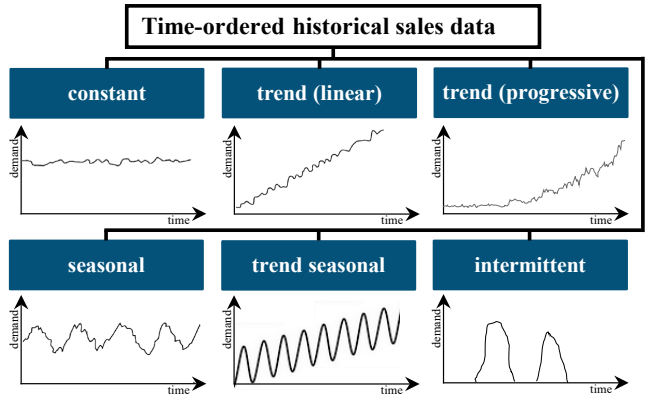


Figure 2 Overview of time-ordered historical sales data [14]

According to the literature review (see Fig. 3), there is no unified expert opinion on the best forecasting technique for specific time series types [14]. Therefore, the optimizing planning method presented here is intended to guide planners to the best possible selection and parameterization of the methods by analyzing the demand curves of all items.

Intermittent material requirements - such as for spare parts in the capital goods industry - require specific forecasts. In contrast to well-researched approaches for fast-moving items, this area has so far received little attention from the literature, which indicates a clear demand for research [21].

Forecasting technique \ Time-ordered historical sales data	constant	trend (linear)	trend (progressive)	seasonal	trend seasonal	intermittent
Saisonal naïve method				●		
Arithmetic mean	●					
Moving average	●					
Weighted moving average	●	◐				◐
1st-order exponential smoothing procedure	●					
2nd-order exponential smoothing procedure (non-damped)	◐	●				
2nd-order exponential smoothing procedure (damped)	◐	●				
3rd-order exponential smoothing procedure (add.)	◐	◐	◐		●	
3rd-order exponential smoothing procedure (mult., non-damped)	◐	◐	◐	●	●	
3rd-order exponential smoothing procedure (mult., damped)	◐	◐	◐	●	●	
Croston method						●
Syntetos-Boylan Approximation (SBA)						●
Teunter-Syntetos-Babai method (TSB)						●

Legend: ● suitable ◐ limited suitable

Figure 3 Relationship between time-ordered historical sales data and forecasting technique according to literature study (Own representation based on [14])

4 CHARACTERIZATION OF THE CASE STUDY

To assess the method's effectiveness, planning-relevant data from two Austrian capital goods manufacturers were used in the evaluation. This topic is highly relevant for the industry, as capital goods are now often ordered with shorter lead times and in smaller volumes. Consequently, manufacturers face rising demands for short delivery times, enhanced flexibility, and precise planning - all under conditions of increasing product variety [14].

	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 in 51 countries	38.800 in 22 countries
Purchasing volume:	11,5 m €	59 m €
Items (active):	12.462 items	17 517 items
Suppliers:	1.780 in 61 countries	1.258 in 28 countries
Period under review:	-36 months sales history	-36 months sales history
Forecast period:	+12 months rolling	+12 months rolling

Figure 4 Case Study – Characterization both Companies [13, 14, 15]

The term "capital goods" covers goods that are not intended for final consumption but are used in the intermediate production of other goods. In other words, goods that produce goods themselves [22].

5 EXTENDED DIGITAL PLANNING METHOD

The digital planning tool was implemented leveraging Microsoft Excel and VBA (*Visual Basic for Applications*) for digitized and (partially) automated requirements calculation for optimized sales planning for items from two Austrian capital goods manufacturers. This tool is intended to make best practices usable and facilitate the traceability of decisions [13, 14]. The tool is modeled to deliver the highest achievable forecast quality by adapting to evolving market dynamics [14].

Using static simulation and a rule-based heuristic as evaluation criteria, this planning method is used to select the best possible forecast procedures for specific items and parameterize them automatically using a *Genetic Algorithm* (GA). The benefits of using quantitative forecasting techniques for semi-automated sales planning within the capital goods sector are examined in two use cases, with detailed discussion in Chapter 6. Fig. 5 below provides an overview of the digital planning method.

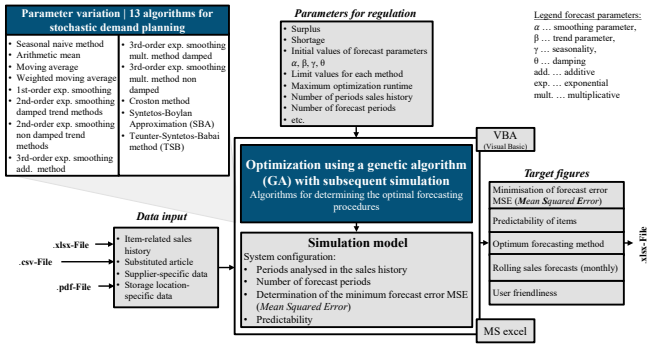


Figure 5 Schematic of the digital planning method based on simulation and optimization (Own representation based on: [23])

This planning method is intended to free the forecasting of future item-specific requirements from the experience of individuals, make best practices generally usable and facilitate the traceability of decisions down to item level based on a simulation model. The modeling aims to achieve the highest possible forecast quality [15]. The planning method involves the following seven steps (see 5.1 to 5.7).

5.1 Data Preparation and Processing

According to *Syntetos*-classification (based on the two coefficients *Average Demand Interval* (*ADI*) and the square of the *Coefficient of Variation* (CV^2)) material requirements can be categorized into different material classifications [19]:

- *Smooth*: steady demand with little fluctuation. [$CV^2 \leq 0.49$ und $ADI \leq 1.32$]
- *Intermittent:* irregular demand in which the order quantities remain largely constant. [$CV^2 \leq 0.49$ und $ADI > 1.32$]
- *Erratic*: high variability in frequency and order quantity. [$CV^2 > 0.49$ und $ADI \leq 1.32$]
- *Lumpy*: infrequent, irregular orders with strongly fluctuating quantities. [$CV^2 > 0.49$ und $ADI > 1.32$]

Table 1 Material classification according to *Syntetos* for both companies

Syntetos material classification	Company 1		Company 2	
	# Items	Percent	# Items	Percent
Lumpy	6.918	55,6%	10.798	61,6%
Erratic	623	5,0%	585	3,3%
Smooth	353	2,8%	817	4,7%
Intermittent	1	0,0%	12	0,1%
Not classifiable	4.567	36,6%	5.305	30,3%
Total:	12.462	100,0%	17.517	100,0%

The classification reveals that most items in both companies are assigned to the *Lumpy* category. This underlines the challenges associated with the high variance and irregular demand intervals in demand forecasting.

The first step is to prepare the data. This process includes a standardized reference to historical data records, the identification of missing values, the filtering of item-specific time series and other pre-processing tasks [11]. Different data sources are imported from the IT systems and processed automatically [15].

5.2 Configuration

This second step determines the parameterization and initial configuration of the individual algorithms and takes into account the setting of the parameters relevant to forecasting and optimization (surplus, shortage, initial values of forecasting parameters, limit values etc.) [15].

In the case study, 12 monthly periods were forecast using 36 monthly periods from the sales history. In a separate worksheet for each forecasting method, the monthly quantities per item are saved as the basis for the following steps [15].

5.3 Calculation

As part of the calculation or optimization of the forecast error (MSE), the sales history for all 13 methods is transferred to the calculation item by item. All forecast methods (see Fig. 1) are calculated for each item and the item-specific forecast result and the corresponding forecast error are saved in the worksheet for each method [15].

The forecast algorithms *Croston method*, *Syntetos-Boylan Approximation* and *Teunter-Syntetos-Babai method*, which were incorporated during the further development of the simulation-based optimization (see Fig. 5) for intermittent demand, are briefly described below.

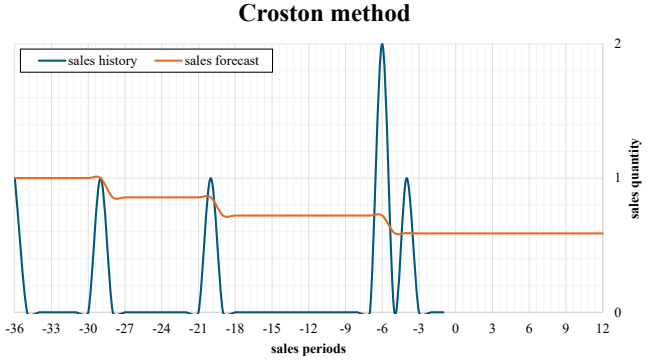


Figure 6 Sales history and sales forecast (*Croston method*: item handle)

The method named after *Croston* (see Fig. 6) is the established approach for forecasting intermittent material requirements and is still recognized as the standard method in this area today [24]. It was the first method to estimate the quantity required and the interval between the requirements separately and enabled a much more accurate forecast compared to the *Moving average* [25]. Over time, various extensions of the *Croston method* have been developed. These include the *Syntetos-Boylan-Approximation* (SBA),

which reduces systematic overestimates of the classic *Croston method*, see Fig. 7 [19]. Another further development is the *Teunter-Syntetos-Babai* (TSB) method, which combines the strengths of the SBA- and *Croston-method*, see Fig. 8 [18]. In addition to frequency and quantity, the *TSB-method* also considers the probability of future demand, thereby improving the accuracy of the forecast.

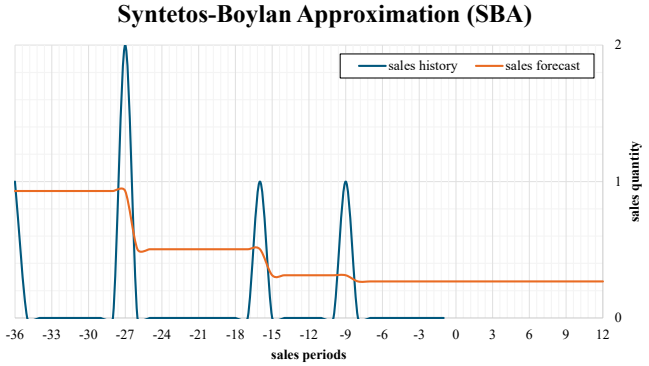


Figure 7 Sales history and sales forecast (*SBA method*: item threadbolts)

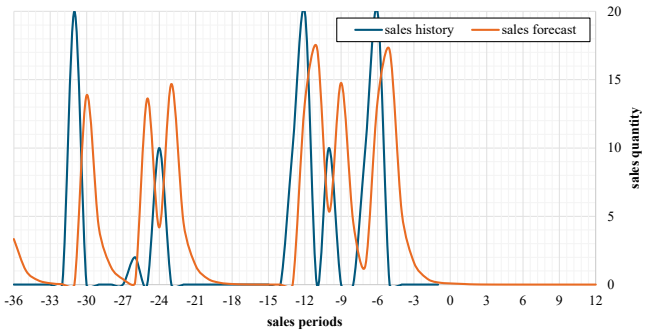


Figure 8 Sales history and sales forecast (*TSB method*: item sight glass)

Initialization of the solution uses optimized parameters: $\alpha = 0.2$ (smoothing), $\beta = 0.5$ (trend), $\gamma = 0.5$ (seasonality), and $\theta = 0.8$ (damping) [15].

5.4 Optimization

The stochastic, combinatorial optimization of the forecast parameters (α = smoothing, β = trend parameter, γ = seasonality, θ = damping) using GA is performed for the *Methods of exp. smoothing* (see Fig. 1). The other methods don't provide any forecast parameters to be optimized. MS-Excel GA is applied for parameter optimization. The GA minimizes the target function represented by the forecast error, transferring the variable cells and the constraints, including the associated settings for the algorithm, for example the runtime and termination criteria [15]. After the preparations, the forecast is calculated as follows:

1) The forecast parameter(s) is/are optimized using a *Genetic Algorithm* (GA).
2) All results (forecast values, parameters etc.) are summarized in a result sheet.
3) Identification of "non-predictable items".
4) The forecast yielding the minimal error is recorded in the results sheet.
5) The results are being exported.

The developed digital planning method enables the calculation of up to 13 forecasting procedures.

5.5 Simulation Parameterisation

The evaluation of the optimal item-specific simulation-based optimization (see Fig. 5) is based on the optimized forecast error [14]. Our approach for optimized demand planning allows one of the following ten standard evaluation methods (*MSE*, *MAD*, *MAPE*, *standard deviation*, *WAPE*, *MASE*, *BIAS*, *TS*, *rMAD* and *rMSE*) to be used to parameterize the simulation.

5.6 Simulation

In practice, the evaluation of the output of real systems is often executed using simulation [26]. The main objective is to determine the forecast quality, which compares the forecast values calculated using the corresponding method with the historical consumption values that have occurred, to be able to draw conclusions about the respective forecast quality. The *MSE* (*Mean Squared Error*) was chosen for the evaluation, as squaring gives greater weight to larger forecast deviations. The *MSE* is determined as follows [10, 12]:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_{t+h|t})^2, \quad (1)$$

where $\hat{y}_{t+h|t}$ - forecast value for period t, y_t - real demand value, n - number of samples of the period.

The simulation compares all implemented (13) forecast methods for each item and chooses the one with the lowest *Mean Squared Error* per item (see Tab. 2).

The new methods (*Croston*-, *SBA*- and *TSB-method*) for predicting intermittent demand were identified as optimal according to *MSE* in 9.8% of the items in company 1 and 14.8% of the items in company 2. Company 2 tends to use more new methods than company 1, which is plausible as the data collected there mainly relate to spare parts with predominantly intermittent patterns. The new methods were developed for precisely this type of demand pattern. Only a small proportion of spare parts remain *non-predictable*.

The optimization potential of the respective forecast error is ~48% and ~38% on average based on an evaluation for the data set of the two case studies. However, it should be noted that the forecast parameters (α, β, γ, θ) are only optimized in nine out of 13 methods. The nine parameter-optimized methods are recommended for about ~57% or ~70% of the items.

Table 2 Results of the item-specific simulation-based optimization

Implemented algorithms for stochastic demand planning	Company 1		Company 2	
	# Item	Percent	# Item	Percent
Seasonal naive method	230	1,8%	580	3,3%
Arithmetic mean	60	0,5%	188	1,1%
Moving average	3.336	26,7%	3.139	17,9%
Weighted moving average	1.454	11,7%	1.373	7,8%
1st-order exp. smoothing procedure	226	1,8%	325	1,9%
2nd-order exp. smoothing procedure (non-damped)	1.056	8,5%	1.579	9,0%
2nd-order exp. smoothing procedure (damped)	570	4,6%	949	5,4%
3rd-order exp. smoothing procedure (add.)	517	4,2%	2.158	12,3%
3rd-order exp. smoothing procedure (mult., non-damped)	2.843	22,8%	4.198	24,0%
3rd-order exp. smoothing procedure (mult., damped)	615	4,9%	391	2,2%
Croston method	523	4,2%	1.294	7,4%
Syntetos-Boylan Approximation (SBA)	278	2,2%	545	3,1%
Teunter-Syntetos-Babai method (TSB)	424	3,4%	747	4,3%
Non-predictable items	330	2,7%	51	0,3%
Total	12.462	100%	17.517	100%

5.7 Optimization Results

The use of the digital planning method for optimized demand forecast shows that complex *Methods of exp. Smoothing* (see Fig. 1), optimally parameterized, often achieve better results (see Fig. 9) than the *Seasonal naive method* often used in practice, in other words, updating the demand of previous periods. The application of the *Genetic Algorithm* (GA) for the parameter optimization of the *Methods of exp. smoothing* enables an average reduction of ~48% or ~38% of the MSE depending on the company.

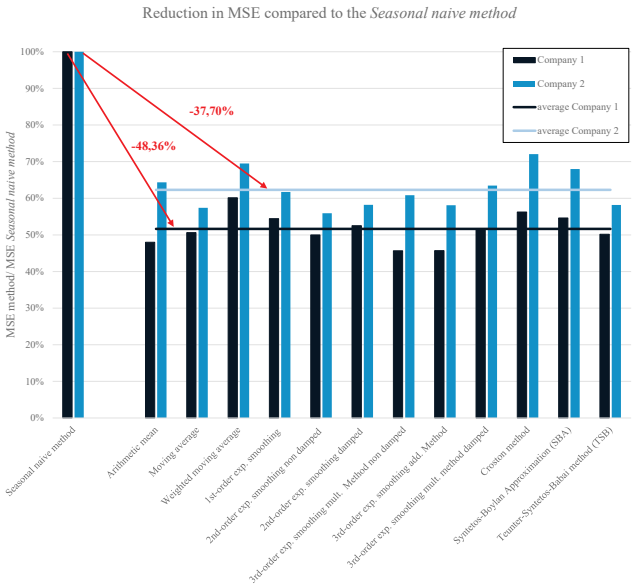


Figure 9 Reduction in MSE compared to the Seasonal naive method

Tab. 2 shows that there is no single optimal forecasting method for the capital goods industry, but that optimal algorithms are emerging for specific items. However, this only represents a snapshot of the forecast calculation for two companies. The optimal forecasting methods change over several planning horizons, as sales figures develop dynamically. Only around ~32% of the items retain the same best forecasting method over three forecasting periods (months).

At the end, an item-specific output of the optimization results, adapted to the case study, is generated.

6 CONCLUSIONS

In practice, the consumption of the past 12 months is often extrapolated as requirements for the future 12 months (*Seasonal naive method*). The digital planning method presented here was able to achieve a reduction in the MSE of ~38 % - ~48 % and thus a significant improvement in forecasting accuracy by using a mix of 13 forecasting algorithms in two case studies (see Fig. 9). The data analysis (see Chapter 5.1) shows that the majority of the items (> 55 %) have a *Lumpy* classification - rare, irregular orders with strongly fluctuating quantities - which cannot be reliably forecast using simple forecasting methods such as the *Seasonal naive method*.

The following answers can be given to the research question posed in Chapter 2:

Question 1: The newly implemented forecasting methods specially designed for intermittent demand patterns (*Croston-*, *SBA-*, *TSB-method*) were able to reduce the MSE by up to ~11 % and ~9 % on average and thus increase the forecast quality accordingly. Since the majority of the items are classified as *Lumpy* (see Chapter 5.1), no general superiority of new forecasting algorithms over classic algorithms can be determined. Nevertheless, the higher forecasting accuracy shows its advantage for intermittent requirements.

Question 2: A digital planning method for the automatic application of established forecasting methods was successfully developed. By linking simulation-based approaches, heuristic parameterization and the use of an appropriately parameterized GA, it was possible to realize an item-accurate, practical material requirements planning approach.

Overall, the digital planning approach for intermittent demand is convincing due to its high specificity (item-specific forecast), comprehensibility and empirical foundation. This is offset by an increased computational effort, a dependence on static simulations and a certain sensitivity to data quality.

As an outlook for future research, higher sophisticated forecasting methods with *Machine Learning* (ML) could be developed and their opportunities and risks evaluated.

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7 REFERENCES

[1] Ball, M., Barnhart, C., Dresner, M., Hansen, M., Neels, K., Odoni, A. R., Peterson, E., Sherry, L., Trani, A., & Zou, B. (2010). Total delay impact study: a comprehensive assessment of the costs and impacts of flight delay in the United States

[2] Claus, T., Herrmann, F., & Manitz, M. (2015). *Produktionsplanung und -steuerung: Forschungsansätze, Methoden und deren Anwendungen*. Springer Berlin Heidelberg. (in German) https://doi.org/10.1007/978-3-662-43542-7

[3] Gioia, D. G., Felizardo, L. K., & Brandimarte, P. (2023). Simulation-based inventory management of perishable products via linear discrete choice models. *Computers & Operations Research, 157*, 106270. https://doi.org/10.1016/j.cor.2023.106270

[4] Kolade, O. J. (2019). Demand Forecasting and Measuring Forecast Accuracy in a Pharmacy, Universität Danubius. *Oeconomica, Audoe, 15*(3), 157-169.

[5] Barton, T., Müller, C., & Seel, C. (2018). *Digitalisierung in Unternehmen, Von den theoretischen Ansätzen zur praktischen Umsetzung*, Springer, Worms, Wildau, Landshut (in German) https://doi.org/10.1007/978-3-658-22773-9

[6] Wischmann, S., & Hartmann, E. A., (2018). *Zukunft der Arbeit, Eine praxisnahe Betrachtung*, 1st edition, Springer Vieweg, Berlin. (in German) https://doi.org/10.1007/978-3-662-49266-6

[7] Rostami-Tabar, B., Greene, T., Shmueli, G., & Hyndman, R. J. (2025). Towards Socially Responsible Forecasting: Identifying and Typifying Forecasting Harms, 1-43.

[8] Gasparian, M. S., Karmanov, M. V., Kiseleva, I. A., Kuznetsov, V. I., & Sadovnikova, N. A. (2018). Modeling of the demand forecasting. *International Journal of Civil Engineering (IJCIET), 9*(12), 163-173.

[9] Pfohl, H.-C. (2018). Logistiksysteme, Betriebswirtschaftliche Grundlagen, Springer, Darmstadt. (in German)

[10] Schuh, G., & Schmidt, C. (2014). *Produktionsmanagement - Handbuch Produktion und Management 5*. 2nd edition, Springer, Aachen. (in German) https://doi.org/10.1007/978-3-642-54288-6

[11] Hyndman, R. J., & Athanasopoulos, G. (2021). Forecasting: Principles and Practice: A comprehensive introduction to the latest forecasting methods using R. Learn to improve your forecast accuracy using dozens of real data examples, 3rd edition. OTexts, Melbourne. https://otexts.com/fpp3/

[12] Meyer, J. C., Sander, U., & Wetzchewald, P. (2019). *Bestände senken, Lieferservice steigern- Ansatzpunkt Bestandsmanagement*, 3. Auflage, FIR an der RWTH Aachen. (in German)

[13] Schmid, A., Sobottka, T., Luther, S., & Sihn, W. (2022). Demand Planning Falcon – Zielgenaue, stochastische Bedarfsvorhersagen mit einer neu entwickelten digitalen Planungsmethode. *Industrie 4.0 Management, 2022*, 47-50. (in German) https://doi.org/10.30844/IM_22-6_47-50

[14] Schmid, A., Kamhuber, F., Sobottka, T., & Sihn, W. (2022). DISPO 4.0 | Simulation-based optimization of stochastic demand calculation in consumption-based material planning in the capital goods industry. *Tehički glasnik, 16*(3), 328-335. https://doi.org/10.31803/tg-20220504151004

[15] Schmid, A., Kamhuber, F., Sobottka, T., & Sihn, W. (2022). DISPO 4.0 - Simulationsgestützte Absatzprognoseoptimierung in der Investitionsgüterindustrie. *Proceedings Langbeiträge ASIM SST 2022, ARGESIM Report 20*, 73-80. (in German) https://doi.org/10.11128/arep.20.a2017

[16] Pinçe, Ç., Turrini, L., & Meissner, J. (2021). Intermittent demand forecasting for spare parts: A critical review. *Omega, 105*, 102513. https://doi.org/10.1016/j.omega.2021.102513

[17] Babaveisi, V., Teimoury, E., Gholamian, M. R., & Rostami-Tabar, B. (2023). Integrated demand forecasting and planning model for repairable spare part: An empirical investigation. *International Journal of Production Research, 61*(20), 6791-6807. https://doi.org/10.1080/00207543.2022.2137596

[18] Teunter, R. H., Syntetos, A. A., & Zied Babai, M. (2011). Intermittent demand: Linking forecasting to inventory obsolescence. *European Journal of Operational Research, 214*(3), 606-615. https://doi.org/10.1016/j.ejor.2011.05.018

[19] Syntetos, A. A., Boylan, J. E., & Croston, J. D. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society, 56*(5), 495-503. https://doi.org/10.1057/palgrave.jors.2601841

[20] Hanke, J. E., & Wichern, D. W. (2013). *Business forecasting*, 9th edition. Prentice Hall/Pearson Education International.

[21] Hasan, N., Ahmed, N., & Ali, S. M., (2024). Improving sporadic demand forecasting using a modified k-nearest neighbor framework. *Engineering Applications of Artificial Intelligence 129*, 107633. https://doi.org/10.1016/j.engappai.2023.107633

[22] Hache, E., & Sander, H. (1997). *Expert-Lexikon Bilanzierung - 1333 Begriffe, systematisch und von A - Z praxisnah erläutert*. Expert-Verl., Renningen-Malmsheim. (in German)

[23] März, L., Krug, W., Rose, O., & Weigert, G. (2011). *Simulation und Optimierung in Produktion und Logistik: Praxisorientierter Leitfaden mit Fallbeispielen*. Springer, Heidelberg, Lindau, Dresden. (in German) https://doi.org/10.1007/978-3-642-14536-0

[24] Singh, A. K., Simha, J. B., & Agarwal, R. (2024). Prediction of Intermittent Demand Occurrence using Machine Learning. EAI Endorsed Trans IoT, 10. https://doi.org/10.4108/eetiot.5381

[25] Croston, J. D. (1972). Forecasting and stock control for intermittent demands. *Operational Research Quarterly (1970-1977) 23*(3), 289. https://doi.org/10.2307/3007885

[26] Weinzierl, T. (2024). *Grundlagen des parallelen wissenschaftlichen Rechnens: Ein erster Leitfaden zu numerischen Konzepten und Programmiermethoden*, 1st edition. Springer Vieweg, Cham. (in German) https://doi.org/10.1007/978-3-031-49082-8

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