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DISPO 4.0 | Digitalization Of Inventory Calculation In Consumption-Based Material Requirements Planning In The Capital Goods Industry

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Abstract

This paper presents a material requirements planning method that determines optimal safety stock levels using a heuristic optimization, based on a deterministic simulation of stock levels. Material requirements planning is a key competitiveness factor in a volatile, global market environment and is becoming increasingly complex due to the availability of more products, product variants and fluctuating demand. Digitalization offers significant potential benefits for this planning domain, however, tools ready for use in industry applications are still lacking, leading to untapped potential in companies. The approach presented herein investigates available safety stock calculation algorithms, develops a heuristic-based optimization method that determines the best fitting algorithm for each product and optimally parameterizes the algorithm. The method utilizes a deterministic simulation as an evaluation function. A case study for a company in the capital good industry is implemented to evaluate the application potential. The results reflect significantly improved service levels with a minor increase in cost.

Keywords

algorithms; calculation of stock; consumption-based material requirements planning; digitalization; heuristic optimization; inventory calculation; safety stock; safety stock planning; simulation

1. Introduction

Data and information are sometimes referred to as the “oil of the digital age". This increasingly applies to material requirements planning, which is confronted with increasing complexity in a volatile, global market environment and the associated increase in data volumes [1]. Disruptions due to digitalization, smaller batch sizes, fluctuating sales volumes, globalized supply chains and cost pressure are major complexity drivers in material requirements planning [2]. Material requirements planning refers to the coordination of the flow of materials into the company and the stock levels so that the required items are available on time and in the right quality, at the right place [3]. 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 [4]. The sub-disciplines of material requirements planning are divided into requirements planning, calculation of stock and purchase order calculation [3], see Figure 1. This paper focuses on the sub-discipline of calculation of stock, specifically on the application of safety stock algorithms in consumption-based material requirements planning. Although many companies view safety stock primarily as a cost driver, safety stocks are the key factor for maintaining a high service level [4]. Optimally defining safety stock levels help on the one hand to increase the service level for the customer, and on the other hand to minimize company-relevant inventory costs [5]. Digitalized, automated planning can achieve significant savings, ensure long-term customer loyalty and improve competitiveness [6], and a variety of algorithms exist in consumption-based material requirements planning to improve its efficiency. However, only a very small proportion of mathematical models are applied in day-to-day operations [7].

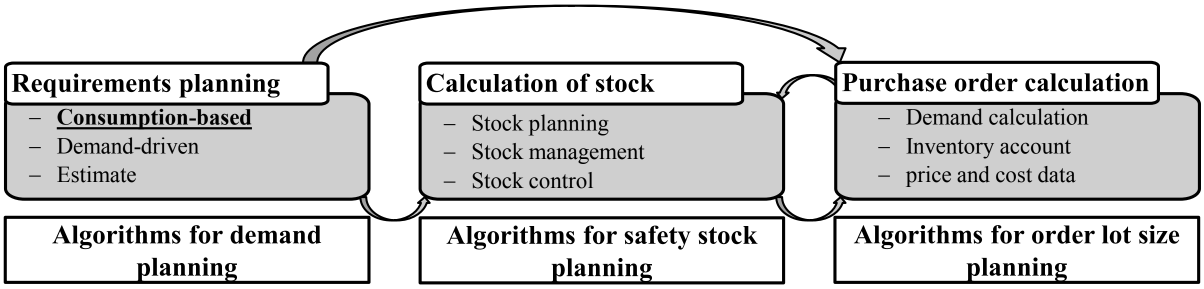

Figure 1: Sub-disciplines of material requirements planning

This paper presents the development of a digital planning tool for material requirements planning and operational purchasing that enables product-specific optimized calculation of stock. The objective is to guarantee the availability of consumption-controlled disposition, considering potential item-specific uncertainties in the supply chain, with the lowest possible safety stocks. For this purpose, a heuristic optimization based on a deterministic simulation is developed as an evaluation function. The potential benefits for optimized safety stock calculation are evaluated in a case study from the capital goods industry. Its relevance for the industry can be justified by the fact that capital goods are increasingly placed at shorter notice and for smaller volumes. Therefore, producers are being demanded short delivery times, a high degree of flexibility and of planning accuracy and this with an increasing variety of articles.

The research hypothesis is that a digital planning method in consumption-based material requirements planning can significantly increase the service level compared to the safety stock determinations practiced today in companies in the capital goods industry. The Design Science Research Methodology according to *Peffers et al.* [8] was applied, supporting both the development of a solution and its communication into application.

The paper is structured as follows: Following the introduction, section 2 provides relevant fundamentals for safety stock planning, while section 3 introduces simulation and optimization for safety stock planning. Section 4 presents the development of the planning method. In the concluding sections 5 and 6, the results are discussed, and an outlook is provided.

2. Background: Safety stock planning

A literature analysis provides an overview of available safety stock calculation algorithms (see Figure 2). Altogether, 16 different methods could be identified. None of the referenced literature considers all algorithms. Figure 3 categorizes the algorithms and outlines their relationships to each other. The algorithms were then characterized and the possible applications in the operational environment of the capital goods industry were evaluated. The procedures marked in dark grey were selected as the most common procedures though a prevalence analysis. Some of these 11 algorithms are already used in Enterprise resource planning (ERP) systems. However, decision-makers in companies lack a basis for deciding which of the safety stock algorithms are most suitable and how to parameterize them optimally and in a product-specific manner.

In real-life settings there are numerous factors that can contribute to uncertainty in material requirements planning [9], such as delivery date deviations, delivery quantity deviations, consumption deviations, supplier quality problems and stock deviations. In order to counteract the occurrence of shortages in materials disposition, safety stocks are used as buffers in materials disposition. Planners have to decide between a high level of service and the associated higher capital commitment and storage costs, and between low stocks and the associated risk of the occurrence of shortages [10].

Algorithms / *References*	Uncertain lead time (Theory of Constraints)	Safety stock with dynamic service-levels	Safety stock with target service-level	Safety stock dynamic with target service-level	Calculation according to service-level	Calculation by using the A-B-C/X-Y-Z method	Dynamic safety stock method	Calculation with a service-level of 100%	Calculation by means of the rough estimate method	Calculation by Lagrange method	Calculation by Percent-Fill Method	Calculation by means of double reorder point	Calculation by means of percentage surcharge	Experience-based method	Square Root Law	Calculation by means of portfolio effect
Becker et al., (2014)				x			x									
Brabänder, (2020)					x				x						x	x
Bretzke, (2020)															x	x
Dangelmaier, (2017)						x										
Gudehus, (2006)	x													x		
Gudehus, (2012)	x															
Heiserich et al., (2011)					x				x			x	x			
Lödding, (2016)			x					x								
Luthra, (2011)									x			x	x			
Nyhuis u. Wiendahl, (2012)			x					x								
Pfohl, (2018)									x			x	x			
Radanasu, (2016)					x				x					x		
Schmidt et al., (2012)	x	x			x				x							
Schönsleben, (2020)					x				x							
Schuh & Schmidt, (2014)	x								x							
Stead, (1990)						x										
Thomopoulos, (2016)					x					x	x					
Wannenwetsch, (2014)									x							
Wiendahl, (2020)					x				x							

Figure 2: Literature allocation to safety stock procedures

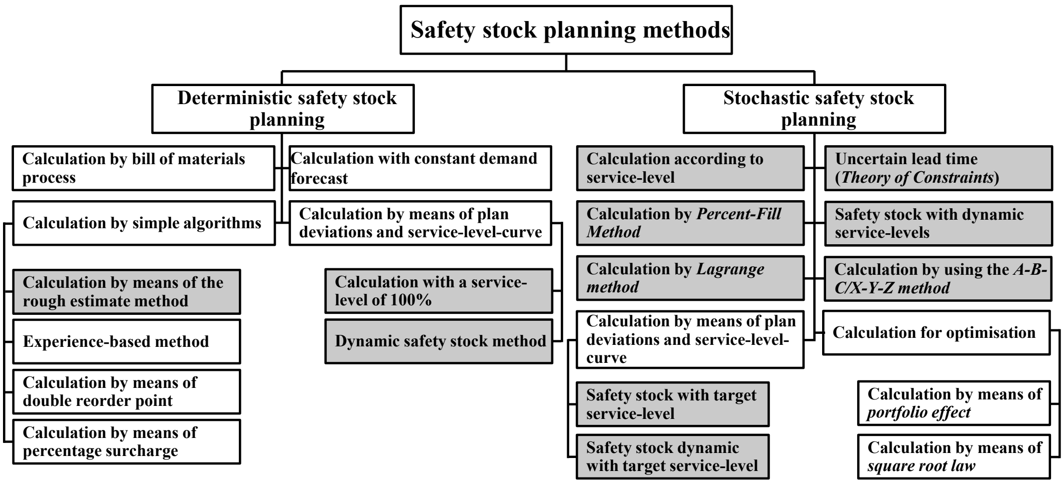

Figure 3: Overview of safety stock algorithms

3. Heuristic optimization, simulation and simulation-based optimization of safety stocks

Optimization is the process of finding the best possible solution for the objective – in this case, maximum service level with minimum inventory – with the help of mathematical operations. The optimization can either be implemented as a mathematical optimization program or as an algorithm that uses an evaluation function to achieve the objective. For complex real systems, some form of simulation is often useful for the evaluation function – in this case, the stock is deterministically simulated over time for the different methods to analyze, how a chosen stock calculation method affects an objective function of stock costs and shortage costs. The static simulation is used to describe deterministic system behavior. In other cases, if the system behavior cannot be predicted deterministically, the behavior results from events over time that influence one another - in such cases, discrete-event simulation is a commonly used [11].

Within optimization algorithms, there are exact procedures that determine an optimum, and optimization heuristics that can determine a good solution for complex practical problems in the practically available computing time [12]. Computation time is especially critical when simulation is used as an evaluation function, as simulation is usually computationally intensive. Metaheuristics are used for practical problems with complex search spaces in which there are many local optima, which are robust to local optima that simple local search procedures, such as hill-climbing procedures, cannot overcome. Rule based heuristics are less universally applicable and require a known optimization strategy, but they are computationally efficient. *Kamhuber et al.* [13] give an example of combining efficient rule-based heuristics, based on human planning expertise, with metaheuristics, in conjunction with discrete-event simulation in production planning. This example demonstrates that a combination or hybridization of the methods can prove to be more useful and advantageous to achieve efficient planning.

In this paper, a heuristic with a static simulation is used as an evaluation function for the selection of the most suitable safety stock calculation. The safety calculation methods are themselves also usually heuristics, that have been established as standard methods in their specific planning domain. Table 1 gives an overview of literature on simulation, optimization and simulation optimization of safety stocks.

Table 1: Literature research on simulation, optimization and simulation-based optimization of safety stocks

Simulation of safety stocks	**Optimization of safety stocks**	**Simulation-based optimization of safety stocks**
Schmidt et al., (2012)	*Gansterer et al.*, (2013)	*Mayer et al.*, (2020)
Gansterer et al., (2013)	*Hernandez-Ruiz*, (2016)	*Claus et al.*, (2018)
Nenni et al., (2013)	*Albrecht*, (2017)	*Bracht et al.*, (2018)
Hernandez-Ruiz, (2016)	*Avci et al.*, (2017)	*Wenzel et al.*, (2017)
Albrecht, (2017)	*Gruler et al.*, (2018)	*Gutenschwager et al.*, (2017)
Avci et al., (2017)	*Ghadimi et al.*, (2020)	*Walmann et al.*, (2016)
Gruler et al., (2018)	*Barrios et al.*, (2020)	*Hanschke*, (2015)
Ghadimi et al., (2020)	*Sourirajan et al.*, (2008)	*Witthaut et al.*, (2015)
Barrios et al., (2020)	*Keskin et al.*, (2015)	
	Schuster-Puga et al., (2016)	
	Park, (2020)	

From the publications in Table 1, the authors highlighted in dark grey were identified as especially relevant publications for this work: *Nenni et al.* [14] evaluate the level of service for safety stocks calculated with different formulas and compare, whether the level of service determined by simulation corresponds to the target level of service of the safety stock level. *Schmidt et al.* [15] deal with the concept of virtual safety stock and evaluate its effectiveness by means of simulation. Freely selected values for lead times, consumption values and their standard deviations function as input data in both works. *Schmidt et al.* use 250 days as the simulation period, which corresponds roughly to the total working days in a year. *Nenni et al.* simulate over 50.000 periods. Due to the uncertainties in demand and replenishment time contained in the models, a single simulation run is not meaningful. For this reason, the simulation results in the papers are arithmetically averaged after 10 or 15 simulation runs. *Nenni et al.* exclusively use the safety stock formula with uncertain lead time (Theory of Constraints), whereas *Schmidt et al.* provide a recommendation matrix for the selection among 9 safety stock algorithms. No real company data is used in each case.

The Paper at hand utilizes 11 safety stock algorithms and provides an evaluation based on a company use-case in the capital goods industry and a final *total landed cost* evaluation is carried out.

4. Development of the safety stock optimization method

4.1 Characterization of the case study

The case study was carried out with the disposition-relevant data of a company from the capital goods industry (production of fittings and valves). The company in the case study is embedded in a corporate group and has about 115 employees, an annual turnover of 22.3 million euro, 346 customers from 51 countries, an annual purchasing volume of 11.5 million Euros, 1.780 active suppliers from 61 countries, and uses an ERP as its central IT system. For the case study, the input files are available in a standardized form from the IT systems and are read in via an interface. The optimization method was implemented in a VBA-based MS Excel tool. The objective was to enable users (materials requirements planners, operational purchasers) to plan optimal safety stock levels independently, without requiring expert knowledge in the areas of optimization and simulation.

4.2 Preliminary ranking of algorithms

As the first step, a preliminary priority ranking of the 11 selected calculation methods was determined, independent of the concrete use case and data set. For this purpose, the capabilities of the safety stock algorithms are compared with the requirements from the uncertainty factors of *Wiendahl* [9] in the calculation of stock of material requirements planning. The result of the prioritization is shown in Table 2 (the algorithms are listed with descending priority). At this stage, this prioritization can be used by application companies – depending on the data availability, the best-ranked method can be chosen by the planner. In this paper, this ranking is only an additional orientation, with the final ranking determined via a simulation evaluation presented in section 4.5.

Table 2: Safety stock procedures and operating principle

	Consideration of relative **relationships**	Consideration of uncertainties of the **delivery quantity**	Consideration of uncertainties in **delivery time**	Consideration of uncertainties in **consumption**	Consideration of uncertainties in the **forecast**	Consideration of **probabilities**
Uncertain lead time (Theory of Constraints)	-	-	+	+	-	+
Safety stock dynamic with target service-level	-	-	+	+	-	+
Safety stock with target service-level	-	+	~	+	-	+
Safety stock with dynamic service-levels	-	-	+	+	-	+
Calculation according to service-level	-	-	~	-	~	+
Calculation by using the A-B-C/X-Y-Z method	+	-	-	+	-	-
Dynamic safety stock method	-	-	+	~	+	-
Calculation with a service-level of 100%	-	+	~	+	-	-
Calculation by means of the rough estimate method	-	-	-	-	-	-
Calculation by *Lagrange* method	+	-	-	-	~	~
Calculation by *Percent-Fill* Method	-	-	-	-	~	~

4.3 Data characterization and data preparation for the use case

In the following section, the procedure of data collection as well as the data structure and results are described. As the first step, all data relevant for the application of the algorithms (stock levels, material, disposition master data, consumption data, etc.) are identified based on the 11 selected safety stock methods (see Figure 3) and obtained from the IT systems of the research partner from the capital goods industry. In the process, a total of seven different files in three different file formats (.xlsx, .csv and .pdf) are combined in the VBA-based MS Excel tool by means of an import logic, sorted by article number, and prepared for further use.

The following Figure 4 shows the data required for the heuristic optimization as well as for the subsequent simulation. In addition to the listed information, the article number is imported for each file for accurate sorting.

Data input for safety stock calculation

Data input 1	Data input 2	Data input 3	Data input 4
– Material number – Base unit – Safety stock – Planned delivery time – Cross-plant material status	– Material number – Net price – Currency – Price unit – Tolerance for underdelivery	– Material number – Order quantity – Delivery date – Quantity delivered – Base unit – Order date	– Material number – Goods receipt date – Material short text – Quantity
Data input 5	**Data input 6**	**Data input 7**	
– Material number – Forecast for the next 12 months – Forecasting method – Relation – Mean forecast error – Standard deviation of the forecast error	– Material number – Chosen method – Order lot sizes	– Units of measurement	

Data input for simulation

Data input 1	Data input 2	Data input 3
– Safety stocks for calculation methods	– Average lead time – Standard deviation of the lead time	– medium consumption – Standard deviation of consumption

Figure 4: Input data for safety stock calculation and simulation

4.4 Calculation of logistical parameters

After data preparation, relevant logistical parameters for the optimization are calculated from the existing historical and forecast-based input data for each article, as a calculation basis for the safety stock algorithms.

Table 3: Logistical parameters for optimization

Average daily consumption (historical)	Standard deviation lead time (historical)
Average monthly consumption (historical)	Average lot size (historical)
Standard deviation daily consumption (historical)	Maximum monthly consumption (historical)
Standard deviation monthly consumption (historical)	Averaged forecast value (future)
Average lead time (historical)	Standard deviation of the forecast values (future)

4.5 Ranking and selection of safety stock algorithms

Using simulation, the safety stock algorithms are ranked: In the process, a subset of the data set is selected for which all 11 safety stock procedures can be applied for each article (if none or not a substantial share of the dataset is fit for all 11 algorithms, only the supported algorithms are selected and ranked). All algorithms are applied to all articles of the subset (products) and the resulting stock levels are simulated over time (material deliveries and material consumption calculated through a time series analysis) and the article-specific service level is determined for each safety stock procedure. For the simulation, optimal purchase order lot sizes have to be defined – this is achieved via a purchase order lot size optimization method, developed by the authors, which uses a *total landed cost* approach as the objective function of the optimization (all relevant costs are considered) and a deterministic simulation as the evaluation function [16].

Thus, mean lead time, mean consumption, and associated standard deviations of items are imported into the simulation and the warehouse inventory level is simulated for 300 days. The different safety stock levels of the individual algorithms are considered. The algorithms with a combination of the highest resulting service level and a low safety stock level are prioritized. As an example, Figure 5 shows a simulation over 300 days for an item with a mean lead time of 5 days and an associated standard deviation of 3 days. The mean consumption of the example item is 1.000 units per day and the associated standard deviation is 750 units. Figure 5 shows that on days 47, 224 and 242, for example, the stock level would fall to 0 units, meaning that the item would not be available for delivery. The simulation calculates a service level of 96% for this article for a safety stock of 4.829 pieces. The optimal safety stock at a given service level of 98% would be approx. 7.000 pieces, which would be delivered by the procedure with uncertain lead time (Theory of Constraints). Repeating these simulation runs with the subset of the data set plus variation of the items thus led to the decision to prioritize this algorithm.

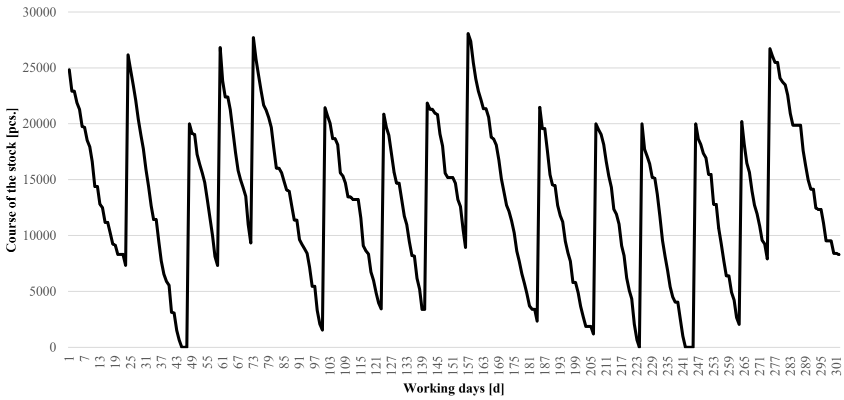

Figure 5: Simulation of the item-specific stock development

The simulation results are translated into a case and data-set specific ranking of the algorithms. The 11 safety stock algorithms have different data requirements, therefore if the necessary data for certain algorithms is unavailable for an article, the next algorithm is tested. The algorithm with the highest available priority is then chosen for each article.

4.6 Application of safety stock calculation

For the sake of economic viability, safety stocks are not to be created for all articles, but only for those with a significant risk of a shortage, the simulation used in section 4.5 is used here again to assess the item-specific risk. All articles are simulated without setting safety stocks first. The simulation results are then evaluated and articles with risk of stock shortages are identified. Next, the optimal safety stock levels for these articles are calculated with the optimal algorithm chosen before for each article (→ section 4.5). For these articles with safety stocks, the simulation is run anew, this time with the optimal safety stock values, to evaluate the successful avoidance of stock-out.

4.7 Optimizing the heuristics based on the simulation results with optimized purchase order lot sizes and safety stocks

In the evaluation, the items with stock shortages are identified and the optimal safety stock levels calculated in the previous safety stock optimization phase are applied to them - no safety stock is defined for items without shortages. It turned out that, despite optimized safety stocks, a safety stock level that was too low was set for some articles, because in some cases there were still understocking costs in the purchase order lot size simulation. Therefore, the heuristics were revised, and, as an example, the "Theory of Constraints" method was given priority over the "Dynamic service-levels" as the more optimal method. As a result, based on the defined heuristics, only items that are at risk of shortage are suggested or issued an optimal safety stock level.

Lastly, another simulation is carried out for determining the *total landed costs*. After this second fine-tuning, optimized purchase order lot sizes and order times are defined for all articles, as well as optimized safety stocks according to demand. The entire procedure is illustrated in Figure 6.

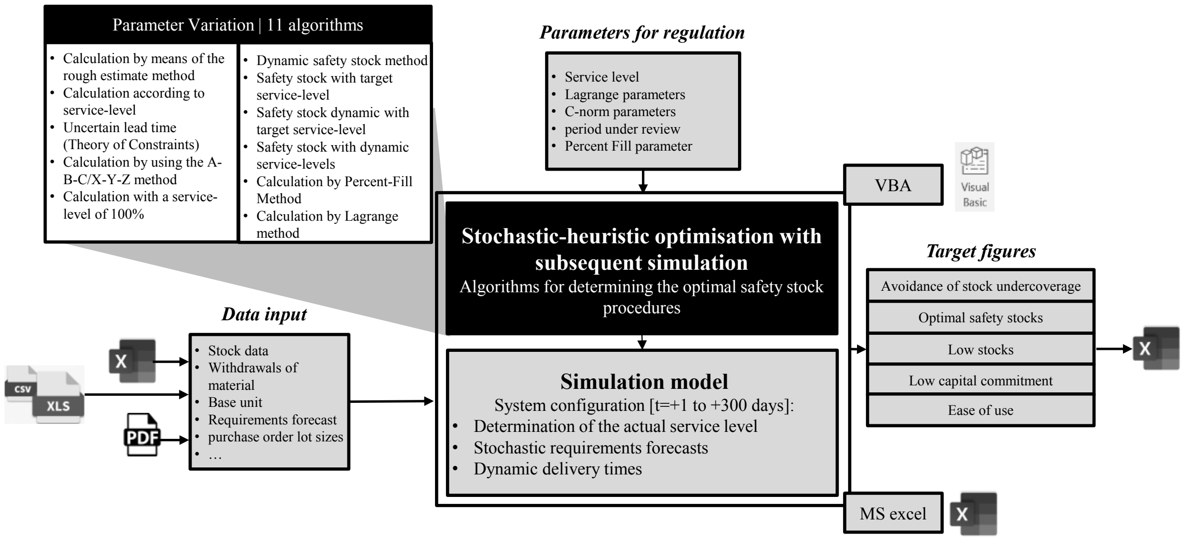

Figure 6: Stochastic-heuristic optimization with subsequent simulation

5. Results and discussion

The results show that using the developed optimization method, different safety stock procedures are identified as optimal for the articles. In this case study, optimal safety stock procedures and safety stocks were determined for 595 articles for which there was a risk of stock shortage, according to the simulation. Of the 11 algorithms considered, 2 were selected by the optimization method. The "Uncertain lead time (Theory of Constraints)" method is used for 76% (452 articles) and the "Safety stock with target service-level" method for 24% (143 articles). The other 9 algorithms have not been selected for this dataset. If the database were expanded from the 595 articles in the application example, other procedures would also be selected, based on the data availability of each article. However, since there is no danger of a stock shortage for these articles, no safety stock was suggested or determined according to the developed optimization method.

The combined consideration of calculation of stock (safety stock method) and purchase order lot size calculation (purchase order calculation method) increases the service level (availability of goods). For all simulated 595 articles with understocking costs (out of 4.066 articles in total), a stock-out could be avoided for almost all articles (476 articles). For 119 articles, a stock-out could not be avoided due to the nature of the initial state at the beginning of the planning period: For those articles, errors in the material requirements planning in the period before the considered planning period have led to a stock level of zero at the start of the planning period, which led to unfulfilled demand right after the start. In principle, this phenomena cannot be avoided.

It must be noted that the increase in the availability of goods through safety stocks is at the expense of warehouse and capital commitment costs, as shown in Table 4. Only costs represented through figures, data and facts in financial accounting records were able to be evaluated. For example, a possible customer fluctuation due to insufficient delivery capability could not be evaluated financially. Through this targeted and optimal application of safety stocks, it was possible to guarantee the service level and the associated availability of goods for those articles with understocking costs (apart from those 119 articles) with a minimal increase in costs of ~0.6 percentage points.

After applying the last (2nd) phase of fine-tuning, the combined optimization of purchase order lot sizes and safety stocks, the *total landed cost* shows higher total costs for this combination compared to a procurement optimized only for purchase order lot sizes, without optimized safety stocks (see Table 4). From the point of view of the *total landed cost* objective function, the optimization result has thus even slightly deteriorated due to the combined optimization, while it has improved from the point of view of the safety stock optimization objective function (service level 99,9% with the lowest possible safety stocks). Since the *total landed cost* approach only considers actual costs incurred and does not consider, for example, the negative effects of a stock-out on customers who could reorient themselves to other suppliers, it is reasonable to suggest refining the objective function from an overall optimization point of view - i.e., the entire material requirements planning.

Table 4: Total landed cost (TLC) consideration before and after optimization of safety stocks

	TLC consideration **before** optimization of the safety stock level	TLC consideration **after** optimization of the safety stock level
Stock shortage costs	15.691 EUR	6.811 EUR
Storage costs	60.855 EUR	62.543 EUR
Capital commitment costs	329.794 EUR	339.317 EUR
Total landed cost (TLC)	406.340 EUR	408.672 EUR

6. Conclusion and outlook

The method was developed using an extensive case study and data set from the capital goods industry. It is based on established calculation methods for purchase orders and safety stocks. In principle, it is therefore suitable for most companies that operate complex material requirements planning. The benefits increase with an increasing number of articles as well as risk factors and other complexity drivers, all of which can be found in the capital goods industry – this is where the digital (partial) automation of planning can prove to be most valuable.

The results show that with the targeted use of digitalization in the calculation of stock of consumption-controlled material requirements planning, the service levels can be significantly improved. In addition, the interaction and interdependence of the main disciplines of calculation of stock and purchase order lot size calculation in materials disposition is also presented. The relevance of data quality and structure in companies was also demonstrated while the study was underway.

Further research work will be aimed at the development of an integrated material requirements planning method, comprising requirements planning, calculation of stock and purchase order lot size calculation. This will include investigating the hierarchy between planning goals and working towards a less sequential planning process in the interest of pursuing an aligned material requirements planning optimization.

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Biography

After graduating in 2007, **Alexander Schmid** (*1977) developed and was responsible for the department of supply chain management at *Knorr-Bremse GmbH*. Since Oct. 2013, Dipl.-Ing. Alexander Schmid has overseen various teaching activities in the areas of supply chain management and logistics at the *Vienna University of Technology* and is employed as a research assistant at *Fraunhofer Austria.*

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Wilfried Sihn (*1955) Prof. Dr. Wilfried Sihn has been active in the field of applied Research for more than 30 years, taking part in more than 300 industrial projects. His areas of expertise include production management, corporate organization, enterprise logistics, factory planning, order management, life-cycle management, maintenance, modelling and simulation, and business process reengineering.