DESIGN OF A LOGIC TO SUPPORT LOGISTIC COST EFFICIENT PURCHASING DECISIONS FOR A HARDWARE WHOLESALER

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ราล์ฟ ดอนเนอร์ : การออกแบบตรรกะสำหรับการตัดสินใจสั่งซื้ออย่างประหยัดสำหรับผู้ค้าส่งฮาร์ดแวร์ (DESIGN OF A LOGIC TO SUPPORT LOGISTIC COST EFFICIENT PURCHASING DECISIONS FOR A HARDWARE WHOLESALER) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: ปวีณา เชาวลิตวงศ์, 267 หน้า.

ธุรกิจการนำเข้าสินค้าเพื่อจัดจำหน่าย สินค้าคงคลังคือปัจจัยหลักที่สามารถสร้างมูลค่าเพิ่มได้ แต่การนำนโยบายการบริหารสินค้าคงคลังในลักษณะที่เป็นมิตรกับลูกค้า (สินค้าคงคลังมาก) ถึงแม้ว่าจะสามารถสร้างความได้เปรียบในการแข่งขัน แต่ก็ทำให้ต้นทุนเพิ่มสูงขึ้น ดังนั้นการพิจารณาถึงต้นทุนการสำรองสินค้า กับปริมาณสินค้าคงคลังจึงเป็นเรื่องที่สำคัญอย่างยิ่ง

ในการจัดหาสินค้าเข้ามานั้น ต้องมีต้นทุนการเก็บรักษาสินค้า, ต้นทุนการสั่งซื้อ และต้นทุนการขนส่งสินค้า โดยเปรียบเทียบเพื่อการลดต้นทุนโลจิสติกส์รวม ทั้งนี้ระดับ EOQ หรือปริมาณการสั่งซื้อที่ประหยัดที่ใช้อยู่ ยังไม่เพียงพอสำหรับการคำนวณต้นทุนการขนส่ง เพราะว่าต้นทุนค่าขนส่งขึ้นอยู่กับปริมาณสินค้า ดังนั้นการสั่งซื้อสินค้าหลายรายการ ในซัพพลายเออร์เดียวกัน จึงเป็นเรื่องยากที่จะคำนวณต้นทุนค่าขนส่ง ดังนั้น แนวความคิดนี้คือ จะสามารถคำนวณระดับการสั่งซื้อที่ประหยัด(EOQ) ที่ขึ้นกับต้นทุนการขนส่ง, ส่วนลด และ ระดับการสั่งซื้อที่ต่ำสุด(MOQ) แต่สิ่งที่สำคัญที่สุดคือ จะสามารถหาต้นทุนค่าขนส่งที่แท้จริงได้อย่างไร

การประยุกต์การคำนวณ การสั่งซื้อที่ประหยัด (EOQ) นั้น การพยากรณ์ความต้องการนั้นต้องมีความเสถียร และความแม่นยำ โดยวิทยานิพนธ์ฉบับนี้จะทดสอบว่า ระบบสามารถเลือกรูปแบบการพยากรณ์ แบบอัตโนมัติได้อย่างเหมาะสมหรือไม่

ภาควิชา	ศูนย์ระดับภูมิภาคทางวิศวกรรมระบบการผลิต	ลายมือชื่อนิสิต	....
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KEYWORDS: EOQ / ECONOMIC ORDER QUANTITY / TRANSPORTATION COST OPTIMIZATION / DISCOUNT CALCULATION / MOQ / MINIMUM ORDER QUANTITY / JOINT REPLENISHMENT PROBLEM / JOINT TRANSPORTATION COST / ORDERING COST / APPLIED FORECASTING / PATTERN RECOGNITION / CONTAINER STUFFING / TRANSPORTATION COST FUNCTION

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For trading companies, inventory is the primary enabler of value creation. Applying customer-friendly inventory management policies can constitute a competitive advantage that does, though, usually come along with increased costs. The consideration of costs during inventory related decision making is hence inevitable. For the purchasing of goods, inventory holding costs, ordering costs, and transportation costs need to be outweighed in order to reduce total logistics cost. Since existing economic order quantity calculations (EOQ) do not adequately consider the actual economies and diseconomies of scale that the joint replenishment problems is subjected to, a two-staged heuristic that also considers minimum order quantities and discounts on individual item level is proposed. The centrepiece of this heuristic is, though, the level of detail at which transportation costs are considered whilst simplicity is maintained. As the practicality of EOQ considerations is heavily dependent on schedule stability, a potential improvement of forecast accuracy and robustness by automatic pattern recognition is furthermore evaluated.

Department:	Regional Centre for Manufacturing Systems Engineering	Student's Signature	....
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Gratefully,

Ralf Donner

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1 INTRODUCTION

1.1 The company and its business

Hafele started as a small retail shop for furniture fittings in Nagold, Germany in 1923. A strong focus on international expansion let the company prosper to over 5,000 employees in 38 countries in 2013. Its subsidiary in Thailand was established in 1994 and experienced massive growth since then. Today – 20 years later – Hafele Thailand employs more than 1,300 people and generates annual revenues of around three billion Thai Baht whilst serving about 10,300 customers. The company offers a huge portfolio of products in the areas of furniture fittings, architectural hardware, home-appliances, sanitary, and access control.

1.1.1 The product portfolio

Providing over 20,000 stock keeping units (SKU), the company can be considered to offer the broadest product range within the respective markets in Thailand. With regards to the assortment of the portfolio and its sourcing, the local subsidiaries of Hafele are comparably autonomous. This enables the subsidiaries to cater local markets with specific requirements and to exploit business opportunities that arise in different competitive environments. On this account, Hafele Thailand launched its sanitary and home appliances range, which Hafele Germany does not offer at all. The home appliances, for instance, have been launched due to relatively lower competition with international brands and a high demand that is caused by a rise in condominium developments.

The local adaption alone does, though, not explain the enormous number of SKUs, which is more an effect of the urge to fit the product to the application rather than designing the application to accommodate the product. The complexity can be illustrated by the example of architectural door hinges, which account for around 280 SKUs. Hinges must not only be offered for different door materials, such as wood or glass, but also with variations caused by door weight, opening type (swing door vs.

flush door), door clearance, drilling pattern, number of use cycles (residential vs. commercial use), material requirements, etc.
For products like sanitary items on the other hand it is not so much the function that differs – the customer's choice is rather a design question. Yet, no matter what is the reason for the huge product variety, the high number of SKUs comes along with increased complexity for the management of the supply chain.

1.1.2 The supply chain

1.1.2.1 Upstream

Hafele Thailand characterizes itself as a trading firm and does hence not produce itself apart from bundling of material (BOM), which is why most of the products or at least the BOM components have to be sourced. As indicated in section 1.1.2, the company offers products as diverse as screws, Jacuzzis, and designer fridges – and likewise are the suppliers. The supplier base consists of small, medium, but also large size vendors that are located mainly in Western Europe and Asia. A smaller number of suppliers are domestically located in Thailand. As illustrated in figure 1.1, the suppliers can be clustered into the following groups:

Established European brands went into a distributor agreement with Hafele Thailand, e.g. Blum, Blanco, Hans Grohe. The variety of the portfolio is limited, whilst product values are high.

Asian production companies usually produce products as per Hafele specification. These companies have many other customers apart from Hafele and produce in batches, which is why the lead time is comparably long – usually 90 to 120 days. The negotiation power towards the supplier is limited since in most cases the purchased volume is comparably low due to the high variety of products.

Thai local companies are only supplying very few items. Their major contribution lies in the area of general packaging materials and product specific cartons for BOM packing. Despite the physical proximity of these suppliers, the replenishment times are still considerable long – usually 60 days.

Hafele Germany's warehouse provides backup for non-stock items (customer items). These items are shipped by air freight once a customer has placed an order for them.

Hafele Germany's production sites produce core furniture fittings that are sold worldwide. The production output is split for the different subsidiaries, which is why also long lead times are normal.

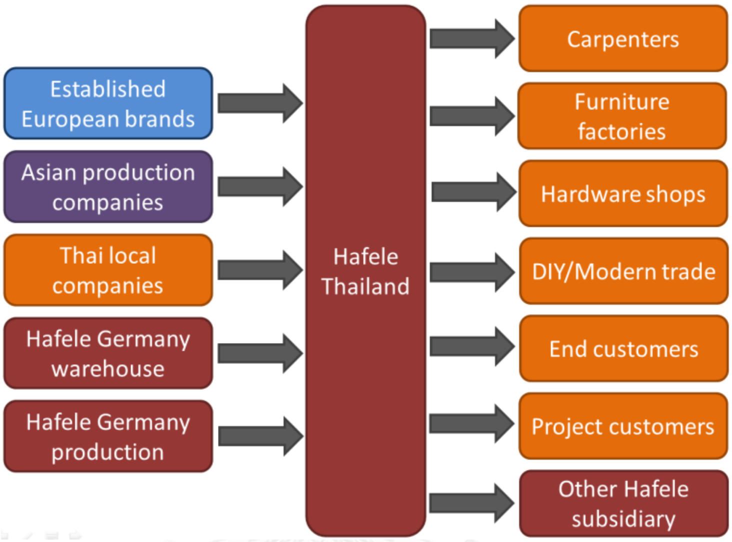

Fig. 1.1: The supplier and customer base of the organization

In total Hafele Thailand is supplied by around 370 companies of which some are only providing a single SKU, whereas others are supplying a few hundred different articles. Table 1.1 gives an indication for the diversity of the suppliers.

Supplier supplying more than 500 SKU	2
Supplier supplying more than 100 and less than 500 SKU	27
Supplier supplying more than 20 and less than 100 SKU	76
Supplier supplying more than 5 and less than 20 SKU	113
Supplier supplying more than 1 and less than 5 SKU	87
Supplier supplying only 1 SKU	68

Table 1.1: Number of suppliers categorized by number of SKUs that they supply

Imported goods are brought in by sea freight FCL 20"/40" and LCL as well as airfreight, whereas airfreight is only used for urgent cases that are non-regular. The typical replenishment time – the sum of lead time and transport time – for sea freight shipments lies between 45 and 130 days depending on the item and supplier location.

1.1.2.2 Downstream

On downstream side Hafele Thailand has around 10,000 active customers that can be classified in the following groups:

Modern trade/DIY (do-it-yourself) stores offer products across all categories. The variety within a product range is though limited since this is not demanded by the end customer and would confuse most of them unnecessarily. Stores open all year and do hence see a rather smooth demand from the end customer, which does, though, not mean that their orders against Hafele are smooth and regular. Moreover, do special offers and promotions cause ripples in the demand. The order profile is:

- Low variety
- Greater volumes
- Short lead time orders
- Penalties for non-delivery
- See rather regular demand

Project customers are developers of condominiums, hotels, or commercial buildings that usually place non-recurring orders with high quantities – for instance a one-time order for 500 toilet bowls to fit all rooms of a hotel. Yet for maintenance and the like, project customers also place regular orders with small quantities. The order profile of this customer group is:

- Low variety
- Greater volumes
- Usually ordering in advance
- Penalties for non-delivery
- Highly irregular (one-time)

Hardware shops are traditional small to medium size stores providing a limited range of products to end customers and craftsmen. The typical order profile of this group is:

- Medium variety
- Medium volumes
- Short lead time orders
- Subjected to seasonality

Carpenters are privately operated small to medium sized businesses that work based on customer orders. These companies do usually not stock materials due to the limited space in their workshops and order their input materials just when they receive a customer order themselves. These businesses do normally close on public holidays and during standard holiday seasons. The aggregated demand of this customer group is, therefore, rather seasonal. The order profile of this customer group is:

- High number of orders
- High product variety
- Small volumes, even looses
- Goods required immediately
- Subjected to seasonality

Furniture factories produce furniture on a larger scale and have hence a rather steady demand for standard products. These factories do not close during holiday seasons – apart from public holidays – and are hence less subjected to seasonality. The order profile of that customer group is:

- Medium product variety
- Medium to big volumes
- Goods required immediately

Private customers have the possibility to purchase goods directly via the internet or in the Hafele owned showrooms**.** The order profile of this customer group is:

- Low variety
- Low volume
- Goods desired immediately

Other Hafele subsidiaries are able to draw on the stock of Hafele Thailand in order to satisfy their customer orders. These occurrences are usually irregular as they only take place in case of stock-outs or special item orders. The order profile is:

- High variety
- Medium volume
- Goods immediately required
- Highly irregular

1.1.3 Customer value proposition

Without owned production, Hafele Thailand is essentially a trading company that purchases goods globally in order to resell them in the Thai market. The organization's right to exist comes from a transformation of order characteristics that it performs for its customers in return for a mark-up. Instead of directly sourcing products from various overseas suppliers, customers are able to obtain everything out of one hand and enjoy delivery to their site. This does not only reduce transaction cost, it also reduces transaction risk as local warranty and aftersales services are available. Yet, the biggest advantage for the customer is that Hafele does not impose minimum order quantities (even a single screw can be ordered) and that lead times are reduced to only one day for at least the stock-range of around 8,000 articles. Figure 1.2 contrasts the order requirements that Hafele faces with those that the organization offers to its customers.

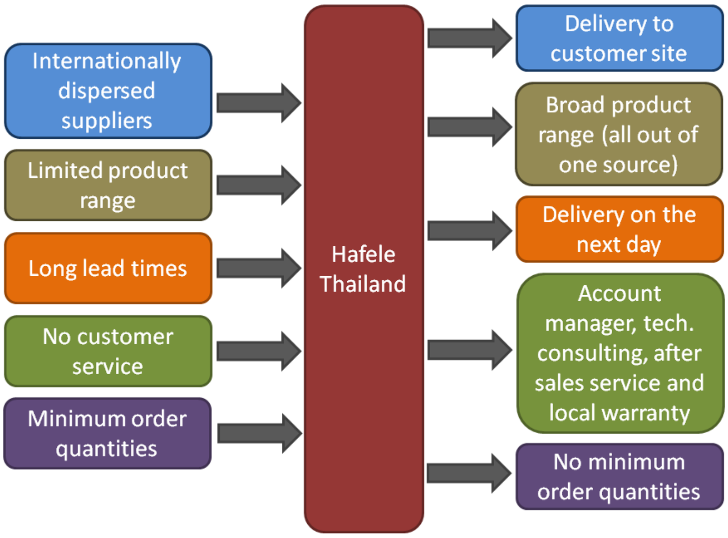

Fig. 1.2: Transformation of order characteristics that is enabled by holding inventory

1.2 Business problem

Offering next-day delivery forces the organization to purchase goods in mere anticipation of future demand and stock them until being despatched upon a sales order. Holding goods over a longer period is expensive and risky, which does hence require proper business justification. In fact, the immediate availability of stock items can be considered as the main driver for the success of Hafele in Thailand over the recent years.

Targeting further business growth within existing markets as well as expansion into new segments, the company's stock range is consistently expanded. Thereby, the number of stock items increased almost linearly by more than 500 SKU per annum for the last five years. At the same time, the revenues generated from stock items have increased significantly, whilst the revenues from non-stock items slightly have declined as figure 1.3 illustrates.

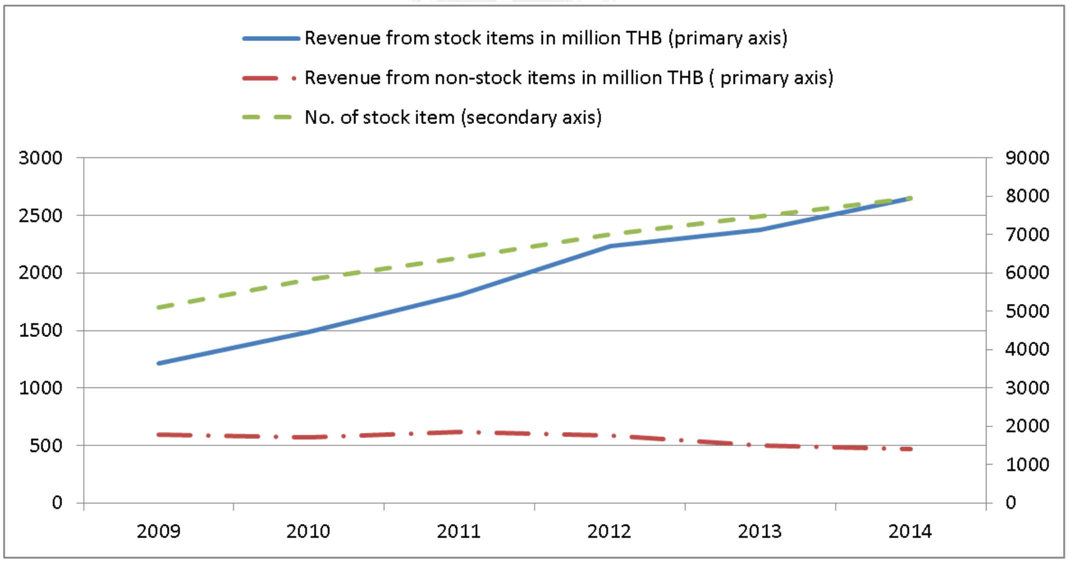

Fig.1.3: Development of revenue and number of stock items from 2009 to 2014

According to Bowman (2013), this trend is not unique to Hafele but can be observed across all industries at an even accelerating speed. Yet, this proliferation of SKUs/ stock items not only comes along with additional revenues, but also with increased complexity for the management of the inventory, its purchasing, and the logistics.

On operations side, costs increase as:

- Total inventory value and, therewith, capital costs increase
- Storage costs increase
- Handling costs for inbound/outbound/intra logistics increase
- Transport economics decrease
- Transaction costs increase (more SKUs cause more orders)

As a consequence, the organization's growth strategy failed to yield additional profits despite the increase in turnover. That is because the operation expenses have increased by 68% from 2011 to 2013 whilst turnover has only increased by 19.5%, which ultimately led to a net profit of 2013 that was 3% lower than that of 2011. Having acknowledged this development, the organization's top management focuses increasingly on cost control, which is also the field of work for this thesis. In line with van Bodegraven and Ackerman (2009), it is thereby not the intent to dam back the SKU proliferation since this is part of the business strategy, but to identify means to counter or at least limit the negative effects.

From the enumeration of the negative impacts of SKU proliferation it transpires that inventory control and, thereby especially, effective purchasing has the highest leverage to reduce costs that are associated with inventory. Yet as mentioned before, the increased number of stock keeping units brings about new challenges for the purchasing itself.

First, with regards to demand forecasting, the higher number of stock items means that also a higher number of items must be forecasted. Thereby, the accuracy of the demand forecast does not only suffer from the fact that many new products are launched for which the demand is still unknown but also from the fact that cannibalization effects between products emerge (Bowman, 2013; Van Bodegraven and Ackerman, 2009). For instance, if the company was previously selling only one model of fridges, then the introduction of a new, additional model will influence the demand for the old fridge as potential buyers might now prefer the new model.

Second, it stands to reason that new items and items affected by cannibalization effects see low/lower demand on individual SKU level, which reduces economies of scale with regards to discounts, transport economies, and handling (Van Bodegraven and Ackerman, 2009). Making cost conscious decisions with regards to what, when and how much to order is, therefore, inevitable for improving the organization's cost position.

1.3 The current purchasing process

The company's purchasing department that is taking care of the inventory planning is aware of the importance of effective inventory management and attempts to consider the cost impact during its purchasing decision making process.

> *A purchasing decision in this context summarizes a decision towards the following characteristics: the items to purchase, their quantities, the time of purchase, the supplier, the delivery place, and the delivery mode.*

However, due to the high number of SKUs and the variety of cost factors to be considered, any manual attempt of optimization is condemned to failure, which is why information technology must be employed.

1.3.1 The current functionality within the ERP system

To support the purchasing department with the decision making, the company's ERP system features a purchase proposal function. Fundamentally, this purchase proposal returns a list of all items with a suggested quantity for immediate purchase as of the day when it is run.

The column "Proposed Qty" in figure 1.4 displays those quantities that are recommended for purchase. The purchaser can then either follow the recommendation by entering the same quantity into the "Schedule Qty" column or can alternate it if he believes that the suggestion is not optimal. Once the review is finished a purchase request can be auto-generated that ultimately leads to a purchase order.

Item Code	Gr.1	Gr.2	UOM	C/Stk Item	Supp Code	Loc/Imp	Proposed Qty		Schedule Qty	
482.97.100	STD	G2	PC	STOCK	0804973	IMPORT	744	0	0	0
556.84.707	STD	G2	PC	STOCK	0805754	IMPORT	420	0	0	0
911.22.271	STD	G2	PC	STOCK	0811567	IMPORT	50	0	0	0
911.76.026	STD	G2	PC	STOCK	0811567	IMPORT	75	0	0	0
553.50.925	STD	G2	PR	STOCK	0811576	IMPORT	186	0	186	0
950.07.602	STD	G2	M	STOCK	0811807	IMPORT	5000	0	5000	0
932.10.051	STD	G2	PC	STOCK	0814013	IMPORT	300	0	300	0
909.87.040	STD	G2	PC	STOCK	0819803	IMPORT	193	0	193	0
820.23.110	STD	G2	PC	STOCK	0820780	IMPORT	40	0	0	0
540.24.927	STD	G2	PC	STOCK	0821054	IMPORT	1	0	0	0
540.91.093	STD	G2	PC	STOCK	0821054	IMPORT	250	0	0	0
545.59.298	STD	G2	PC	STOCK	0821054	IMPORT	37	0	0	0
545.61.028	STD	G2	PC	STOCK	0821054	IMPORT	16	0	0	0
545.61.228	STD	G2	PC	STOCK	0821054	IMPORT	15	0	0	0

Fig. 1.4: Output table by the purchase proposal function

The proposed order quantity for an item is calculated as:

$$Qty_{proposed} = \frac{2\cdot(Q_{M-1}+Q_{M-2}+Q_{M-3})+Q_{M-4}+Q_{M-5}+Q_{M-6}}{39\,weeks}\cdot\frac{t_{repl}+t_{safety}}{7\,\frac{days}{week}} - Qty_{stock} - Qty_{in} + Qty_{res}$$

With:

$Qty_{proposed}$	Proposed order quantity
Qty_{stock}	Current stock quantity
Qty_{in}	Incoming quantity
Qty_{res}	Quantity already reserved for customer
Q_{M-1}	Outbound quantity of last month
Q_{M-2}	Outbound quantity 2 month ago
Q_{M-3}	Outbound quantity 3 month ago
Q_{M-4}	Outbound quantity 4 month ago
Q_{M-5}	Outbound quantity 5 month ago
Q_{M-6}	Outbound quantity 6 month ago
t_{repl}	Replenishment time in days (production lead time + S/F shipping time)
t_{safety}	Safety time in days (90 days for x-items, 60 days for y-items, 30 days for z-items)

Equation 1.1: Current formula for proposed order quantity

The proposal function does also consider the following side conditions:

- Round proposed order quantity to default pack code and pack code hierarchy[1]

[1] A pack code represents a packing unit with a certain quantity, a specific size and volume. Each item may have several pack codes but at least one. For example a knoblock set has the pack codes piece, box, carton, and pallet. One box holds six pieces, whereas one carton holds four boxes (24 pieces). The pallet in turn holds 16 cartons (384 pieces). Order quantities are rounded because ordering loose pieces or a pallet with 15 cartons lacks shipping economics.

- The proposed quantity must be higher than the minimum order quantity (MOQ) required by the supplier
- If the $Qty_{proposed}$ as per the formula is less than 0 (overstock) it is set to 0 (which equals no purchase).

1.3.2 The purchase proposal in application

When using the purchase proposal, the purchaser usually sets a supplier-wise filter in order to process all items that are purchased from that specific supplier and that hence will be combined in one purchase order. Under normal circumstances the purchase proposal for each supplier is run in a 1-week or 2-week cycle. In case a stock-out or an infringement of the safety stock is projected, an email alert is generated that urges the purchaser to run the purchase proposal for the supplier of the affected SKU.

1.4 Research problem

The objective of this thesis is to critically assess the current implementation of the purchase proposal formula and to identify areas of improvement with regards to the business objective of cost reduction. Consequently, an improved or alternative logic shall be developed and adequately described as a blueprint for subsequent IT developments.

Sub-Problem 1:

Suggest on how to improve the current demand forecasting – factually the basis for an adjacent economic order calculation – with regards to forecast accuracy and robustness.

Sub-Problem 2:

Design a purchase proposal logic that outweighs the various cost factors involved in the provision of stock and hence supports cost efficient purchasing decisions.

1.5 Deliverables and delimitations

Within this thesis the logic on how to arrive at a meaningful purchase proposal quantity shall be developed. The actual deliverable is a step-by-step description of how the logic works. The level of detail that the thesis provides shall be adequate to use it as functional specification handed over to the third party IT developer upon which the development is based. Therefore, not only the description but also the illustration with examples must be comprehensive in order to convey the methodology. With regards to input data – especially cost factors – advises are given on how to obtain the data.

As the topics of forecasting and economic order quantity inherently allow for unlimited optimization and extension, which exceeds the time frame and extent of a thesis project, suggestions for additional functions or implementations that can further increase the quality of results shall be given in the recommendations chapter if applicable. The design of the purchase dashboard in which the proposed quantities are displayed and the IT implementation itself shall also not be part of the thesis due to concerns in regards to the time frame and focus of the project.

1.6 Expected benefits

The direct outcome of this thesis has been outlined in the deliverables section.
Yet, it is the actual implementation of this blueprint that is expected to yield the below listed intermediate benefits that ultimately support the business objective of cost reduction.

Higher accuracy of the demand forecast

A more accurate demand forecast helps to decrease overstock whilst ensuring the achievement of targeted service levels. Less overstock means reduced capital cost, better warehouse space utilization, reduced risk of obsolescence and devaluation.

Cost conscious decision making

Cost is the main decision criteria for most business decisions and should hence be the driver for purchasing decisions too. By outweighing inventory costs, ordering, and transportation costs, the following cost benefits can be achieved:

- Savings on freight cost by better utilization
- Capital cost reduction
- Reduction in warehouse space due to lower inventory levels
- Reduction of other inventory cost such as devaluation.
- Reduction of transport cost due to higher utilization

High utilization of transport means will furthermore reduce the ecologic footprint of the organization.

Reduction of workload for purchasing staff

Providing the purchaser with a reliable proposal will reduce the time that is needed to review each item manually and hence release additional capacity.

Personal benefits

From an educational perspective, the application of inventory control, forecasting, and EOQ considerations yields plenty of practical experience and insights into the core of supply chain management. Thereby, also the awareness for practical limitations of theoretical approaches is increased.

1.7 Guiding principle for development

Whilst developing a solution for the stated problem, the feasibility of implementation and the usability during operation shall be the guiding directive.

The ERP system of Hafele is highly customized and new functions can be implemented by request. From previous development experiences it is known though that the mere prescription of the desired outcome is not expedient. That is because deep knowledge of business processes and constraints is not given on developer side, which is why the implementation will not yield satisfying results. It is, therefore, not only necessary to describe the methodology of how to arrive at the solution in deep detail but also to convey the idea on a personal level.

The implementation takes place in Oracle Forms – a JAVA based development environment with the main purpose of data entry and data display for Oracle databases. It must be acknowledged that this environment is obviously not a solver for higher mathematical problems and that the associated developers are not mathematicians in their way of thinking. Therefore, it is ambiguous that complex mathematical formulations as nominated in plenty of literature, e.g. Graves et al (1993), are implementable with the given resources.

With regards to the daily operation, calculation times and server load are factors that also need to be considered during the design. With the number of SKU and the amplitude of parameters that a multi-product-multi-period problem brings along, a chase for the optimal solution might lead to exorbitant processing times that are not proportionate to the gains in yield when compared to quasi-optimal and hence more modest solutions.

Yet, it is not only the feasibility of implementation and the runtime restrictions that call for a clear, simple and straight forward approach but also the needs of later users. Changing working procedures and tools always causes reluctance and mistrust. To overcome this and hence to avoid complete rejection, it is necessary that users can understand what and how the system is actually calculating (Piasecki, 2001). On one side this is done by keeping things as simple as possible and on the other side by ensuring high process visibility – for instance by providing process logs. Such process log is not only useful for engaging the user but it is also extremely valuable during the testing and fine-tuning stage of the implementation.

Based on the previous argumentation, it can be concluded that only a solution that can be digested by the organization will be able to provide benefits to it. It is, therefore, mandatory to stand back from complex yet alluring mathematical approaches in exchange for an actually programmable and comprehensible step-by-step approach. An overkill with regards to the pluralism of comparably simple but not essential functions shall be equally avoided in order to keep implementation cost and time at a reasonable level. To ensure this, all functions that are described within this thesis shall be implemented in Visual Basic based Excel Macros that provide a similar range of functions as the actual JAVA environment.

1.8 Methodology and thesis structure

In the prior part of the introductory chapter, the business objective and the research questions with its two sub-problems have been stated. This section shall briefly outline the purpose of each chapter within this thesis. Each of the below listed chapters will be concluded with a summary at the end of the chapter.

Chapter2

A literature research shall be conducted to review existing concepts with regards to the two sub-problems of demand forecasting and EOQ. Beyond that the topics of inventory control and costing shall be explored, as they form the framework respectively the input with which the functionality has to operate.

Chapter 3

The implementation of a beneficial research proposal is not a development from scratch since the basic functionality is already implemented and in use for several years. Therefore, the current implementation shall be critically assessed in chapter 3 to identify areas that need to be improved and areas that can be maintained.

Chapter 4

The focus of chapter 4 will be set to forecasting. At first, the business requirements and the quality of input data shall be reviewed, as this is important for the selection of an adequate approach or approaches if case differentiation is required. Upon that, suggestions on how to deal with the identified cases are given. At this point it shall be pre-empted that automatic pattern matching will be discussed for the forecasting of normal items under the premise of accuracy, robustness and simplicity. To simulate and hence validate the chosen approach, a simulator in Visual Basic has been implemented. For simulation purpose, a selection of quantitative-intrinsic forecasting methods has then been selected and implemented. Based on the actual data and the applied forecasting method, the method of safety stock calculation is then determined.

Chapter 5

Chapter 5 is devoted to the design of the economic order quantity logic. The chapter starts with looking at schedule stability and ways to improve it. The logic for the EOQ itself is developed as a two-step approach starting with the optimization on individual SKU level. The optimized inbound schedules for individual items are forming the basis of a joint replenishment problem, which is intensively discussed. At the end of the chapter suggestions are given on how to determine the cost factors that are needed for the practical application of the EOQ methodology.

Chapter 6

Within chapter 6 the solutions that have been proposed in chapter 4 and 5 shall be validated. Therefore, the functionality of the proposed forecasting method is first tested on standard patterns and on contaminated standard patterns. In a second step a qualitative review of the results for selected real demand patterns is performed. Ultimately, the performance of the proposed solution is evaluated in relation to the performance of the currently implemented forecasting method. Therefore, a both approaches are tested on 600 real life data sets.

Chapter 6 (continuation)

The second part of chapter 6 is dedicated to the assessment of the proposed economic order quantity calculation. It shall be again pre-empted that the solution consists of an individual item related optimization and a joint transport related optimization. The individual component will be evaluated in comparison to existing methods on 1,500 randomly generated test schedules. For the transport cost optimization the literature does not provide adequate counterparts against which the proposed solution could be tested, which is why a qualitative assessment is performed.

Chapter 7

In chapter 7 the key findings of this thesis are summarized again. Next steps with regards to the implementation and in regards to future research will be recommended. Ultimately, the proposed solution will be contrasted with the objectives stated within this introduction.

2 LITERATURE REVIEW

The introductory chapter has identified the different areas that have to be processed in order to arrive at a solution for the stated problem. Existing concepts in the areas of demand forecasting including safety stock calculations and approaches to calculate economic order quantity shall be reviewed within this chapter. At first a brief introduction on inventory control shall be given though.

2.1 Inventory control

2.1.1 Types and purpose of inventory

In the introduction it was emphasized that the immediate ability to deliver is virtually the most distinctive value proposition made by the organisation towards its customers. In order to comply with this promise, inventory must be hold for 8,000 products that are classified as stock items. The term “inventory” summarizes goods that an organization holds in stock in order to sell or to utilize them in any other way for its business. Typically inventory is further classified in three different categories:

Cycle inventory denotes the stock that is used to satisfy normal demand and is hence the main generator of income (Hartman, n.d.). Cycle inventory is usually purchased up on a demand forecast whilst considering economic order quantities.

Buffer inventory (also known as safety stock) is hold to hedge against uncertainties that are inherent in the demand forecast upon which the cycle inventory is purchased.

Anticipation inventory is held in expectation of non-regular orders (Inman, n.d.). This could be the case for expected project orders or planned sales promotions, where a certain quantity needs to be ordered on top of the cycle inventory.

Holding inventory is not free, which is why the inventory level must be consistently controlled at a level that is just enough to satisfy the business requirements. The stakeholders in inventory management within an organization are manifold and with contradicting requirements. Sales prefer to draw on unlimited stocks levels for an unlimited range of products in order to satisfy all possible customer needs. Finance on the other end of the scale opts for low inventory levels in order not to tie up to much of cash (Saxena, 2009). This interest conflict about inventory levels strongly interrelates with the customer service level and is ultimately a decision that has to be taken on strategic level.

The role of the inventory management and/or the purchasing department – whichever is in charge of controlling the inventory levels within the organization – is then to accomplish the strategically targeted service level by taking appropriate purchasing decisions.

2.1.2 Inventory position and review policies

In order to do so, the inventory management must permanently review the stock level of an item with regards to its ability to satisfy future demand. In this comparison future incoming deliveries (outstanding orders against suppliers) but also backorders (order backlog from customer side) must be considered as well. The sum of quantity in stock and incoming orders minus backlogged orders is labelled as inventory position (Axsäter, 2006).

$$Inventory\ position = stock\ on\ hand + outstanding\ orders - backorders$$

Equation 2.1: Inventory position

Logically, an order needs to be placed whenever the inventory position is not strong enough to support the projected demand, which means that the inventory position falls short of a reorder point that is defined as:

$$Reorder\ point = normal\ consumption\ during\ leadtime + safety\ stock$$

Equation 2.2: Reorder point (Toomey, 2000)

The comparison of inventory position versus reorder point can either be done continuously or periodically.

With a **continuous review policy**, the inventory level is permanently reviewed, which factually means that the review takes place whenever an inventory transaction is performed and hence the inventory position changed (Toomey, 2000).

With a **periodic review policy**, the inventory position is reviewed in equidistant time steps, e.g. every day, every week, or every month.

The continuous review comes along with slightly lower safety stock levels as the responsiveness of this policy is higher than that of the periodic review policy because actions are taken immediately. In the periodic case, a certain time elapses until a shortage is noted, which is why safety stock must be kept for the replenishment time plus the time between two reviews (Axsäter, 2006). In case of a continuous review merely the replenishment time must be covered by the safety stock.

However, to review an item's inventory position upon each transaction causes high workload, especially when considering that Hafele performs around 4,000 inventory deductions (caused by the despatch of goods) every day. Axsäter (2006) remarks that the continuous review system is also not advantageous for coordinated ordering of different items from the same supplier. For the reasons, the periodic review policy is most frequently applied in practice. Choosing the time steps between two reviews very short reduces the differences with regards to required safety level. In table 2.1 the advantages and disadvantages for both policies have been summarized once again.

The implementation of either review system answers the question of when to order, it does, though, not answer the question of how much to order. For this purpose, an economic order quantity calculation has to be performed. Based on the normal consumption and under consideration of various cost factors, the EOQ calculation proposes an order quantity. The effort of performing this calculation depends very much on the grade of detail especially with regards to the extent of cost factors that are considered.

Yet, with improvements in IT technology, the complexity that can be solved improved drastically, which is why inventory control emerged from a manual process following basic precepts to a complex and highly comprehensive discipline (Axsäter, 2006).

	Continuous review policy	Periodic review policy
Advantage	▪ Safety stock must be kept for replenishment time only	▪ Less effort ▪ Allows for joint ordering of different products from the same supplier
Disadvantages	▪ High effort since it has to be performed upon each inventory transaction ▪ Difficult to manage as inventory withdrawals are not performed by inventory management	▪ Safety stock must be kept for replenishment time + review period length

Table 2.1: Pro and contra for continuous and periodic review policy

2.2 Demand forecasting

2.2.1 Expected outcome and importance of forecasting

In 2.1 it was shown that the normal consumption is the basis for the reorder point as well as for the EOQ calculation. Yet, the normal consumption – let's call it demand – is normally unknown for future periods, which is why it must be forecasted.

Fundamentally, forecasting is an attempt to predict the future based on available information (Webster, n.d.). With regards to inventory management, the expected outcome of the forecasting is a demand plan that states the expected demand (normal consumption) on item-level for several periods over a certain horizon, see table 2.3 for an example. A demand plan can be considered to be expedient when both, the forecasted quantity and the time of consumption are accurate and when the planning horizon is sufficiently long for the purpose (Chockalingam, 2014).

Period	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8
Forecasted demand	100	200	300	400	500	600	700	800

Table 2.2: Sample demand plan with a horizon of 8 periods

Yet, forecasting is often considered to be more of an art than a science because accuracy cannot be guaranteed no matter how much effort is put in (e.g. Berry, n.d.). In this notion, Toomey (2000) denotes the primary principle of forecasting to be that the forecast will be wrong. Even though this appears to be a rather humorous statement, the severance of wrong forecasts is immense.

Underestimated demand leads to stock-outs and hence missed out sales, customer dissatisfaction and a reduction in goodwill. In this context Fitzsimons (2000) found that customers that experienced stock-outs have a much higher likelihood of switching the supplier for the next purchases when compared to customers that have not been confronted with a stock-out. In another article with the handy title "Stock-outs cause walkouts" Corsten and Gruen (2004) analysed the behaviour of customers when being confronted with a stock-out in a retail environment. Thereby, they found that only around 34% of customers choose a substitute item of the same brand or purchase the item at a later point of time. The remaining 66% either choose an item from another source or cancel their purchase intention for this item entirely. Even though Hafele is not primarily a retailer, one can assume what a carpenter who does not find a product that he urgently needs for a project does, when he is confronted with a stock-out. Thai business habits of not allowing partial shipments worsen the impact, as stock-outs can put an entire order at risk. Therefore, Murray's (2014) claim to classify stock-outs as "one of the worse things that can happen to a business" appears reasonable. Corsten and Gruen (2004) found that an organization can easily achieve 2% sales growth if it manages not to have stock-outs for its best-sellers.

Overestimated demand on the other side of the scale leaves the organization with stock that it might never be able to sell and that hence needs to be written off after some time. However, even if the stock only sits on the shelf, costs are consistently accumulated, what in turn erodes profits.

As both – underestimated demand as well as overestimated demand – bring about negative effects for the business, it is immensely important to get the forecast about right.

2.2.2 Approaches to forecasting

Besides the frequently proclaimed crystal ball, there are numerous ways to arrive at a prediction for the future. On top-level quantitative and qualitative approaches can be distinguished as figure 2.1 depicts. Quantitative approaches are then further split down into quantitative-intrinsic and quantitative-extrinsic approaches. The selection of either of the approaches depends on the availability of historic data and its ability to predict future demand.

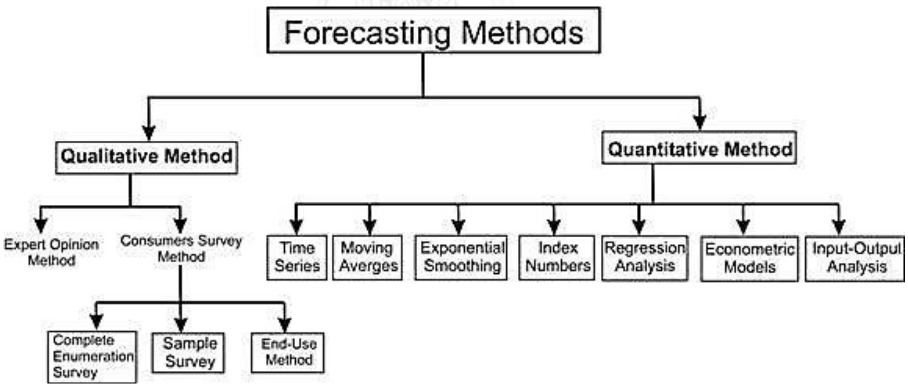

Fig. 2.1: Overview of forecasting methods (Projecttopics.info, 2014)

Quantitative-intrinsic approach

If discrete stochastic demand data for an item is available for a certain number of past periods, it can be used for an extrapolation into the future. The extrapolation of the historic time series is based on statistical/mathematical models and can hence be easily implemented in IT systems. By doing so, "quantitative-intrinsic" models can be applied to thousands of products on periodic basis with little effort, which is why they are most widely used in the practical inventory management (Axsäter, 2006).

Quantitative-extrinsic approach

In some cases the relation between previous demand and future demand can be comparably weak and hence quantitative-intrinsic methods are not expected to provide adequate forecasting accuracy. Yet, if there is a steady relation between product sales and an external factor, a "quantitative-extrinsic" approach can be chosen instead. Toomey (2000) illustrates this with the example of the relation between home appliance sales and the external development of condominium projects. Also in this scenario, a mathematical relation between external input and sales can be modelled within an IT system. In practice, the implementation of such a relation is rather seldom. That is because the data for the condominium development must also be obtained in first place and afterwards carefully reviewed. With regards to the example of home appliances, it is indeed true that the overall market for fridges will grow in case of new housing projects. However, this information is though not sufficient for individual SKU forecasting since there are many products in the markets from which the developer can choose. A "quantitative-extrinsic" approach is more appropriate when a demand projection for a component is derived from the demand projection of parent products (Axsäter, 2006).

Qualitative approach

If there is no previous demand data available, e.g. for new products, or if it cannot be expected that the historic demand pattern will apply to the future, a "qualitative" approach can be taken (Toomey, 2000). Qualitative forecasts are judgements that can either originate from the inside of the organization or from external sources such as market surveys or business analysts (Armstrong and Brodie, 1999).

The different approaches to forecasting do all have advantages and disadvantages. However, considering the mere number of items that need to be forecasted and the effort that would be involved in qualitative forecasting or in the evaluation of extrinsic relations, quantitative-intrinsic forecasting is the preferred choice. This is in line with Toomey (2000), who considers quantitative models with an output on weekly basis as the standard for inventory management. However, Toomey (2000) also suggests that extrinsic or qualitative predictions should be able to overwrite intrinsic forecasts, as these methods provide advantages when it comes to unforeseeable events. Due to the affinity of the targeted application at Hafele to the quantitative-intrinsic approach, further investigations within this chapter focus this approach.

2.2.3 Procedure of quantitative-intrinsic method application

To recapitulate, quantitative-intrinsic forecasting means that based on historic quantitative demand data, the future demand for a product is extrapolated. Hence a quantitative-intrinsic method is fundamentally a mathematical rule or model that transforms previous demand data into an expectation of the future demand. Figure 2.2 and equation 2.3 give an example for how such a model might look like.

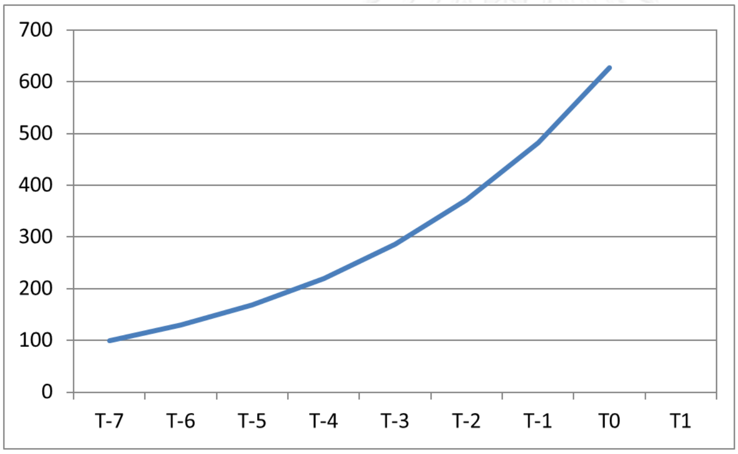

Fig. 2.2: Graph of sample demand history

$$f_{t+1} = 1.3 \cdot a_t$$

Eq. 2.3: Sample model

With this model, the forecasted value for period t+1 (f_{t+1}) is estimated to be 1.3 times the actual value (a_t) of period t – the multiplicative factor of "1.3" is, thereby, called "parameter". In the given example, the mathematical model perfectly fits the historic data. Yet, it is obvious that this model is very specific and hence unlikely to produce good forecasting results for other items, as the mathematical model is selected and parameterized for the underlying data.

Based on the anticipation that what "worked best in the past will most likely work best in the future", Toomey (2000) advises to test different forecasting methods on exactly the same demand history and to select that method that overall performed best in terms of accuracy and reliability. Reliability means that the method delivers consistently accurate results over a longer period (Projecttopics.info, 2014).

Kharin (2010) illustrated the method selection process in figure 2.3. He recommends the identification of forecasting methods that seem auspicious with regards to the application as a first step. This pool of methods is then tested on the same previous data. The method that outperformed the other methods is finally utilized to predict future values. If none of the methods produced adequate results, qualitative forecasting could be considered instead.

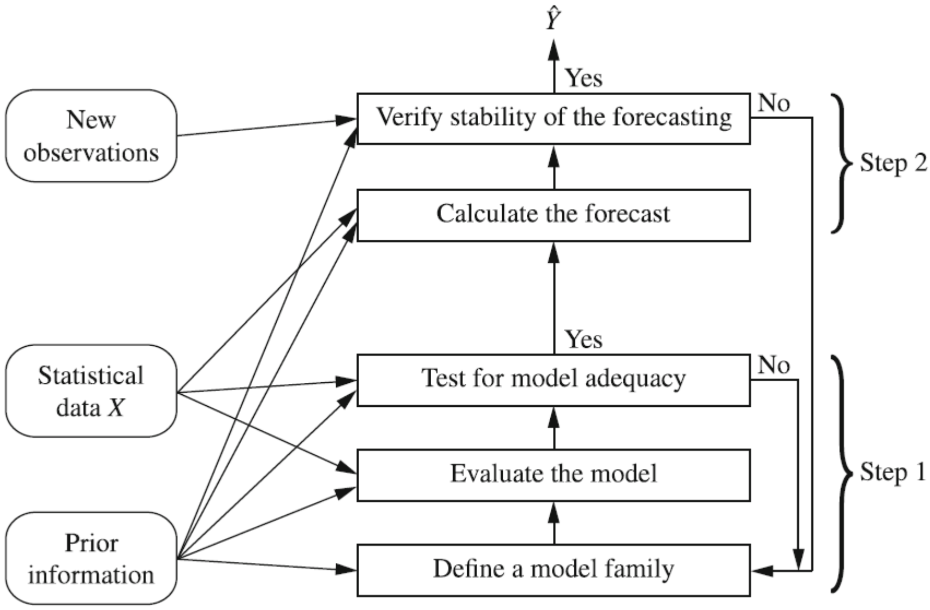

Fig. 2.3: Diagram of forecasting process (Kharin, 2010)

2.2.4 Evaluation of fit

As previously pointed out, different forecasting models shall be applied to the same demand history, which delivers a series of forecasted and a series of actual values with n observations each. To evaluate the accuracy of one method with regards to that of another, commonly the following ex-post indicators are used (Pilinkienė, 2008).

Forecast error

The forecast error e_t is the simple difference between the forecasted value f_t and the actual value a_t for one fitted point (observation for the same period).

$$e_t = f_t - a_t$$

Equation 2.4: Forecasting error

MAPE

MAPE stands for mean absolute percentage error and represents the relative forecast accuracy.

$$MAPE = \frac{1}{n} \cdot \sum_{t=1}^{n} \frac{|e_t|}{a_t} \cdot 100\%$$

Equation 2.5: MAPE

Pilinkienė (2008) classifies forecasts with a MAPE below 10% as "great accuracy", with 10% to 20% as "good accuracy", with 20% to 50% as "sufficient accuracy", and with more than 50% as "insufficient accuracy". Yet, the MAPE calculation faces issues when the actual value (divisor) is zero or very close to zero, as this leads to very high or incalculable MAPEs for the fitted point. A single high value is able to offset the mean significantly, which is why an overall comparison between two forecasting methodologies can be distorted.

MPE

The mean percentage error or MPE represents the offset of the forecast from the means, and can hence be used to detect a bias in the forecast.

$$MPE = \frac{1}{n} \cdot \sum_{t=1}^{n} \frac{e_t}{a_t} \cdot 100\%$$

Equation 2.6: MPE

The MPE's significance with regards to the level of deviation is, though, limited.

MSE

The mean squared error (MSE) measures the dispersion of forecast error. By taking the square of the error value as shown in equation 2.4, large errors in single periods are pronounced, which limits the significance of the MSE (Gentry, Wiliamowski and Weatherford, 1995).

$$MSE = \frac{1}{n} \cdot \sum_{t=1}^{n} e_t^2$$

Equation 2.7: MSE

Taking the root of the MSE delivers the standard deviation that can be used to calculate reliability intervals and that is also used for safety stock calculations.

MAD

The MAD is the mean of the absolute deviation. The MAD provides similar insight as the standard deviation whilst being easier to compute (Axsäter, 2006).

$$MAD = \frac{1}{n} \cdot \sum_{t=1}^{n} |e_t|$$

Equation 2.8: MAD

The MAD is also used in the calculation of tracking signals. Tracking signals are used to “verify the stability of the forecasting”, which was the last stage in the procedure of Kharin (2010). As MAPE and MSE do not indicate the direction of the deviation, tracking signals are used to detect a potential bias.

$$Tracking\ signal = \frac{1}{MAD} \cdot \sum_{t=1}^{n} e_t$$

Equation 2.9: Tracking signal (Toomey, 2000)

If the tracking signal exceeds a certain threshold that depends on the number of observations, the validity of the applied forecasting method shall be reviewed and upon this, the forecasted value should be recalculated (Toomey, 2000). Trigg (1964) proposed a tracking signal that works with exponential smoothing instead of the MAD and hence gives more weightage to recent month.

The selection of an error measure is driven by the purpose for which the forecast is made. For the purpose of comparison, the MAPE is considered to provide the most realistic picture of a method's performance despite its weaknesses with regards to exceptionally small actual values (Gentry, Wiliamowski and Weatherford, 1995). The MSE and standard deviation will be needed for adjacent safety stock calculations.

2.2.5 Forecast vs. actual

Once a model has been selected based on either measure, the model is applied to predict future values. As Kharin (2010) marked in his flow-chart, the forecasted values must be continuously verified to detect potential deviations.

2.2.5.1 Random variation

Even if the fitting might have delivered a model that exhibited outstanding results in the past and truly matches the actual pattern, it must be acknowledged that the actual value for which the forecast was made will be subjected to a random deviation.

$$a_t = f_t + \epsilon_t$$

Equation 2.10: Actual demand is the sum of forecasted demand and some forecasting error

As this deviation is random, its value cannot be predicted. For an infinite forecasting horizon, the sum of the deviation has, though, an expected value of zero (Axsäter, 2006). For limited horizon an estimation of how big the error will be with must be made with a certain confidence. Axsäter goes as far as to say that the estimation of the error is part of the forecast itself.

2.2.5.2 Model risk

The previous discussion mentioned random deviation as a source for forecasting error. After all, the expected value itself can be based on wrong assumptions. In section 2.2.3, the intuitive notion that trends that have been observed in the past will continue in the future, was quoted. However, if this is not the case or if trends have been wrongly interpreted, the selected model itself can be amiss. As we assume that the selected forecasting model/pattern is correct, the “model risk” – as the selection of a wrong model is called – cannot be predicted. Nau (2004) claims that automatic pattern detection as used by forecasting software is a common source for error as these functions are vulnerable to model and parameter risk.

Figure 2.4 illustrates how a model can be wrongly selected based on previous demand pattern. From the demand in the periods T-3 until T, the 4-month a linear trend pattern was selected. However, the actual demand follows a seasonal pattern.

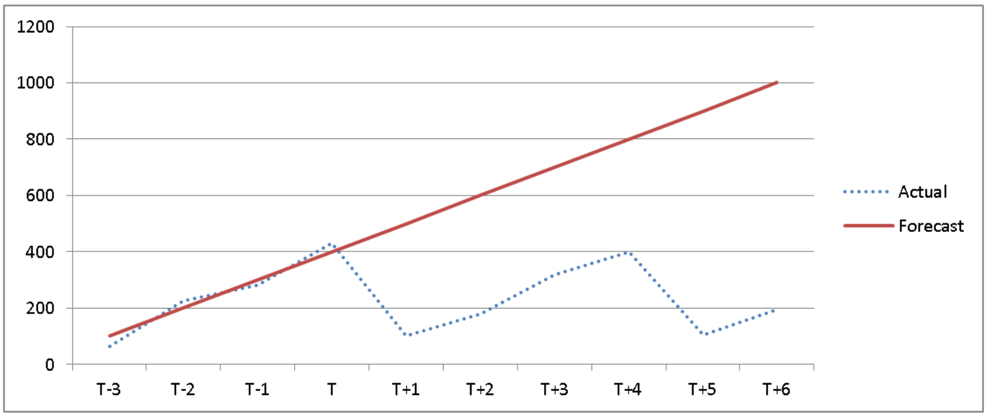

Fig. 2.4: Illustration of model risk

2.2.5.3 Parameter risk

Even if the model/pattern was chosen correctly, the parameters that are required to fit the model to the application might have been selected wrongly. In figure 2.5 the parameter risk is illustrated. Thereby, model and parameters have been again determined from the periods T-3 until T. Even though the model is chosen correctly, the wrongly selected incline delivers systematically wrong results.

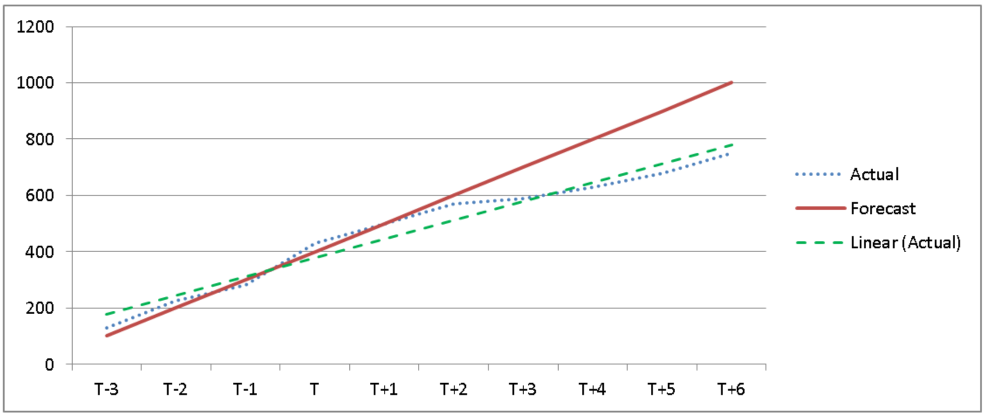

Fig 2.5: Illustration of parameter risk

Nau (2014) claims that estimating parameters based on a longer demand history reduces the parameter risk. However, Nau also emphasizes that including older data might disturb the up-to-dateness, which is also called “blur of history” problem. Even if extensive demand history is available it is often difficult to get the parameters right, as the historical data itself is distorted by random error.

2.2.6 Risk evaluation

2.2.6.1 Assessment of input data

The probabilities of model and parameter risks are heavily dependent on the quality and extent of historic data. Kharin (2010) as well as Broemeling and Tsurumi (1987) stress that data that is contaminated – may it be by outliers, zero values, external events, recording errors or any other extraordinary occurrences – is prone to misinterpretation. This is in line with Toomey (2000) who postulates that the abstinence of extraordinary external events in the past and in the future is a prerequisite for the application of quantitative-intrinsic forecasting. Political crisis, natural disasters, or labour strikes are such events that massively deteriorate the usability of historic data. It is, therefore, necessary to review the validity of historic data prior to its utilization. Beside external events, also recording errors and artificial zero-values should be non-existing. With regards to demand forecasting, the use of shipped quantity as basis instead of actual demand can lead to artificial zero-values (Toomey, 2000). That is because stock-outs erroneously convey the belief of zero demand. However, also extraordinary high one-time orders – which are common for the project business – cause an increase in model and parameter risk. To avoid such exceptional cases that distort the demand data, Toomey (2000) recommends the application of demand filters. Thereby, all values that lie outside of the range of expected demand plus/minus four MAD are considered to be wrong (Saxena, 2009).

2.2.6.2 Robustness

Fostered by low qualitative input data or not, there is always a potential of unsatisfactory model and/or parameter selection. As soon as trend, seasonality and high noise come together, data can be easily misinterpreted, which is especially true for automatic pattern detection as used in statistical software (Kharin, 2010). Therefore, Chen (1997) recommends the utilization of forecasting methods that are applicable to a broad range of patterns, which is in contradiction with early research. In this context Kharin (2010) – who deeply researched the subject of forecast robustness – remarked that research turned away from the hunt for the most accurate forecasting method towards the hunt for the most robust method. This rethinking resulted from the acknowledgement that theoretically highly accurate methods exhibited significant model and parameter risks when applied to real life problems (Kharin, 2010). In this notion, Huber (1981) suggested the development of models that can better absorb deviations from hypothetical conditions.

2.2.7 Basic patterns

The claim of robustness is coherent. In conjunction with the nominated maxim of simplicity, further investigations shall refrain from sophisticated methods and hence focus on simple methods that are though comparably robust. In their article “How to choose the right forecasting technique” Chambers, Mullick and Smith (1971) assessed forecasting methods across all areas with regards to their practical applicability. For the purpose of inventory control Chambers, Mullick and Smith expect a forecasting method to be able to adapt to trends and seasonality but also to be useable for many items. Toomey (2000) claims that a combination of very basic patterns is usually able to adequately describe demand for longer observations. This implies that only for the modelling of short term observations, more complex formulations might deliver better results.

On bottom level, demand can follow a **linear pattern** that can either be constant, inclining or falling (Toomey, 2000). Axsäter (2006) divides more strictly between demand that exhibits a constant pattern and demand that exhibits a linear trend.

In the case of a constant pattern (equation 2.11), the constant value c might be retrieved by calculating the average over a certain number of past periods. This pattern can usually be found for products that are in the maturity stage of their life cycle and, thereby, especially for consumables (Axsäter, 2006).

$$f_t = c$$

Equation 2.11: Forecasted demand in a constant pattern scenario

A **linear trend pattern** can be denoted as per equation 2.12. Next to the constant value "c" a linear time dependent component is included in the formula.

$$f_t = c + m \cdot t$$

Equation 2.12: Forecasted demand in a constant trend pattern scenario

Non-linear patterns are basically represented by polynomials of n^{th} degree.

$$f_t = c + m_1 \cdot t + m_2 \cdot t^2 + \cdots + m_{n-1} \cdot t^{n-1} + m_n \cdot t^n$$

Equation 2.13: Forecasted demand in non-linear patter of n^{th} degree

A **seasonal trend pattern** or **cyclical pattern** is a recurring pattern that occurs in equidistant time steps. The seasonal fluctuations are considered by a multiplicative weighing factor F_t that basically represents the period's share of the total demand during the seasonal cycle (Nau, 2014). Ft is calculated by dividing the demand of the period by the average demand of the year. If 15% of the annual sales quantity has been sold in December, then $F_{December}$ equals 15/(100/12) = 1.8.

$$F_T = \frac{a_T}{\frac{1}{n} \cdot \sum_{t=1}^{period\ count} a_t}$$

Equation 2.14: Calculation of seasonal factor

Once retrieved, the seasonal factors are multiplied with the values produced by any other pattern – for instance by a linear trend pattern as demonstrated in equation 2.15. Seasonality cannot function as a stand-alone pattern.

$$f_t = (c + m \cdot t) \cdot F_t$$

Equation 2.15: Multiplicative nature of the seasonal demand pattern

2.2.8 Methods for standard patterns

In this section, actual forecasting methods for the different standard pattern types are reviewed.

2.2.8.1 Methods for constant patterns

a) Moving average

The moving average is one of the simplest forecasting methods. It takes the average sales quantity over the last n periods as an expected value for future periods. Thereby, n is a selectable parameter. Taking many month into account (n is high) stabilizes the forecast against fluctuations but also compromises the ability to detect changes ("blur history" problem).

	Existing demand data							Forecast				
Month	x-6	x-5	x-4	x-3	x-2	x-1	x	x+1	x+2	x+3	x+4	x+5
Demand	100	105	102	104	100	98	97	101	101	101	101	101
		(105+102+104+100+98+97) / 6 = 101										

Table 2.3: Demand forecasting example with moving average with n=6

To stronger pronounce the data of recent months, weightages can be assigned, which is known as weighted moving average.

b) Moving median

The median of a data collection is that value which separates the sample into two halfs, one containing values higher than the median and another one only containing value smaller than the median. The median is obtained by sorting all values in ascending order. The median is then the value of the middle rank. If the number of samples (n) is even, then the median is the average of the $(n/2)^{th}$ value and the $(n/2+1)^{th}$ value.

	Existing demand data							Forecast				
Month	x-6	x-5	x-4	x-3	x-2	x-1	x	x+1	x+2	x+3	x+4	x+5
Demand	100	105	102	104	100	98	97	101	101	101	101	101
		97	98	100	102	104	105					
				101								
				Median								

Table 2.4: Demand forecasting example with 6 month median

c) Exponential smoothing

Like the moving average and the median, exponential smoothing delivers a constant forecast for the next n periods. In difference to the previously presented methods, exponential smoothing considers the entire demand history with exponentially declining weightage.

$$f_{t+1} = \alpha \cdot a_t + (1 - \alpha) \cdot f_{t-1}$$

Equation 2.16: Exponential smoothing (Makridakis, Wheelwright and McGee; 1983)

The weightage that is given to recent values can be controlled by the parameter alpha that can be set between 0 and 1. Figure 2.6 illustrates how past periods are weighted in dependence of alpha.

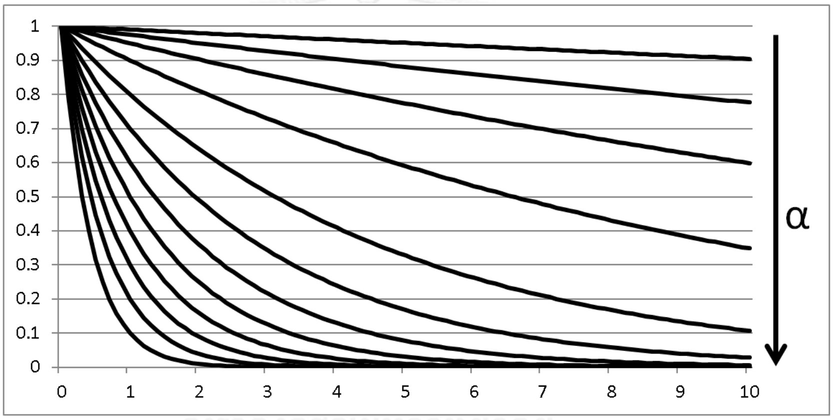

Figure 2.6: Weightage of past periods dependent on the selection of alpha

Choosing alpha too high can lead to instability of the forecast as recent periods are over-pronounced, which is why values between 0.1 and 0.3 are common (Axsäter, 2006).

All three methods do basically forecast a constant value for future periods. With regards to robustness against outliers, the median performs best as the comparison of table 2.5, 2.6, and 2.7 shows.

	Existing demand data							Forecast				
Month	x-6	x-5	x-4	x-3	x-2	x-1	x	x+1	x+2	x+3	x+4	x+5
Demand	100	105	102	300	100	98	97	134	134	134	134	134

Table 2.5: Demand forecasting example with moving average with n=6

	Existing demand data							Forecast				
Month	x-6	x-5	x-4	x-3	x-2	x-1	x	x+1	x+2	x+3	x+4	x+5
Demand	100	105	102	300	100	98	97	101	101	101	101	101

Table 2.6: Demand forecasting example with moving median with n=6

	Existing demand data							Forecast				
Month	x-6	x-5	x-4	x-3	x-2	x-1	x	x+1	x+2	x+3	x+4	x+5
Demand	100	105	102	300	100	98	97	120	120	120	120	120

Table 2.7: Exponential smoothing example with alpha = 0.2

Yet, Chambers, Mullick and Smith (1971) prefer exponential smoothing over moving average and median due to better forecasting accuracy on average.

2.2.8.2 Methods for trend

a) Double exponential smoothing

The previously introduced methodologies aim at rather steady demand as they are not able to capture trends. Double exponential smoothing adds a slope component to the exponential smoothing, which in itself is exponentially smoothed.

$$s_t = \alpha \cdot a_t + (1 - \alpha) \cdot (s_{t-1} + b_{t-1})$$

$$b_t = \beta \cdot (s_t - s_{t-1}) + (1 - \beta) \cdot b_{t-1}$$

with start values $s_1 = x_1$ and $b_1 = x_1 - x_0$

$$f_{t+x} = s_t + x \cdot b_t$$

Equation 2.17: Holt-Winters approach to double exponential smoothing (Holt, 1957)

For exponential smoothing the selection of start values is distinctive for the accuracy that can be achieved. In 1960 Winters added an exponentially smoothed trend component to the double exponential smoothing. This approach is known as triple exponential smoothing.

b) Linear extrapolation

When adding a trend line to a graph in Microsoft Excel, linear extrapolation, which is calculated via the least square approximation, is used.

$$Slope\ \alpha = \frac{n \cdot \sum(x \cdot y) - \sum x \cdot \sum y}{n \cdot \sum x^2 - (\sum x)^2}$$

$$Offset\ \beta = \frac{\sum y - \alpha \cdot \sum x}{n}$$

$$Predicted\ value\ y = \alpha \cdot x + \beta$$

Equation 2.18: Least square approximation (Banas, n.d.)

The advantage of the linear extrapolation via the least square approximation is the ability to capture long term trends whilst exhibiting good robustness against outliners and random fluctuations. If data history is short, though, the linear extrapolation exhibits a high parameter risk.

2.2.8.3 Non-linear trends

a) Exponential extrapolation

In case of an exponential behaviour, an exponential extrapolation shall be applied. Based on two points (x_0, y_0) and (x_1, y_1) an extrapolation as $y = C * e^{kx}$ can be performed. The constants C and k need to be calculated.

$$y_0 = C \cdot e^{kx_0}$$
$$y_1 = C \cdot e^{kx_1}$$

Equation 2.19: Definition of two points that lie on the exponential curve

With a few transformations k can be derived as:

$$k = \frac{\ln(|y_1|) - ln(|y_0|)}{x_1 - x_0}$$

Equation 2.20: Derivation of exponential factor k (Leathrum, 2001)

Inserting k into either of the equations 2.19 delivers the constant C.

$$C = \frac{y_0}{e^{kx_0}}$$

Equation 2.21: Retrieving the constant value for exponential extrapolation (Leathrum, 2001)

b) Polynomial extrapolation

Beside the linear and exponential extrapolation, a number of points can be extrapolated with the help of a polynomial extrapolation. The method of the Lagrange polynomial delivers the polynomial of the lowest degree that satisfies all given data points. The number of data points determines the maximal degree of the polynomial. For the exact calculation it shall be referred to the literature.

For non-linear trend extrapolations – such as exponential, polynomial, or logarithmic extrapolation – a number of data points is required to determine the parameters of the mathematical formula upon which future data points are calculated. Choosing these few data points can be considered as extremely delicate, as unrepresentative samples can offset the curve significantly. Especially polynomials of higher degrees are extremely vulnerable as they tend to drift off and hence badly forecast intermediate values and future. For this reason Gentry, Wiliamowski and Weatherford (1995) recommend to maximally use polynomial of 3^{rd} degree.

However, it appears unlikely that the sales of Hafele follow a higher polynomial pattern or that products experience exponential sales growth over a longer horizon. For short horizons, the approximation of logarithmic or exponential shapes with linear trend functions seems reasonable. For reasons of robustness – this topic will be discussed at a later stage within this chapter – the implementation of non-linear functions shall be waved.

2.3 Safety stock

2.3.1 The purpose of safety stock

Safety stocks are goods that are hold in addition to cycle stock as an instrument to hedge against the risk that the business does not run as planned/forecasted. Divergences can result from all kinds of supply chain risks, whereby especially supply risks and demand risks apply to the business of Hafele. **Supply risks** originate upstream to the focal company and hence summarize all kinds of incidents that disturb the on-time arrival of the ordered goods at the company's distribution centre (Chopra and Sodhi, 2004). **Demand risks** summarize all downstream events that lead to deviations between actual and forecasted demand. This includes unexpected project orders but also minor variations by smaller unrelated orders that are perceived as random.

Safety stock has, therewith, two components – one that hedges against supply risks and one that hedges against demand risks. However, demand risks can usually be further distinguished as disruptions or as delays (Chopra and Sodhi, 2004).

Disruptions are major events that are unlikely but have a severe and long term impact on the operations. The breakdown of a supplier due to bankruptcy is one example.

Delays on the other side are rather small events that only delay the arrival of goods for a certain time.

Apparently, the ability of additional stock to counter the effects of a supplier break down is very limited (Chopra and Sodhi, 2004; Hou and Gopalan, 2014). For this reason, the effects of disruptions have to be mitigated on a higher, strategic level – it shall be referred to contingency management. Therewith the role of safety stock with regards to supply risks is to safeguard against delays.

Demand risks are usually not further classified, as smaller events with high probabilities and major events with smaller probability can be both expected to be events that follow a normal distribution. Deviations are either positive when the actual demand is higher than forecasted, or negative when the actual demand is less than the forecasted demand. With regards to safety stock, only underestimated demand calls for buffering, as overestimated demand does not imply the risk of shortages.

2.3.2 Demand risk

As pointed out in the previous chapter, the random deviation of the demand represents the demand risk. In an infinite horizon, it can be expected that positive and negative random deviations of the demand are outbalancing each other, as the forecast would otherwise exhibit a bias.

$$E\left(\sum_{t=1}^{\infty} a_t - f_t\right) = 0$$

Equation 2.22: Expected value of the random error in an infinite horizon

In comparably short intervals the demand can, though, be subjected to severe swings in value. To illustrate this, a random demand figure ("actual demand") with the mean of 100 and a standard deviation of 10.65 was generated for a horizon of 100,000 periods. The forecasted value for each period equals the mean of 100 pieces. In case that the actual demand of a period exceeds the forecast, the exceeding quantity is deducted from the safety stock. In case that the actual quantity falls short of the forecast, the left-over is added to the safety stock. The starting level of the safety stock is 5,500 pieces. For illustration purpose, negative safety stock levels are permissible. Figure 2.7 illustrates the development of the safety stock level over the 100,000 periods, whereby the stock level for a particular period is calculated as per equation 2.23.

$$stock\ level_t = stock\ level_{t-1} - (a_t - f_t)$$

Equation 2.23: Safety stock level impacted by random deviation

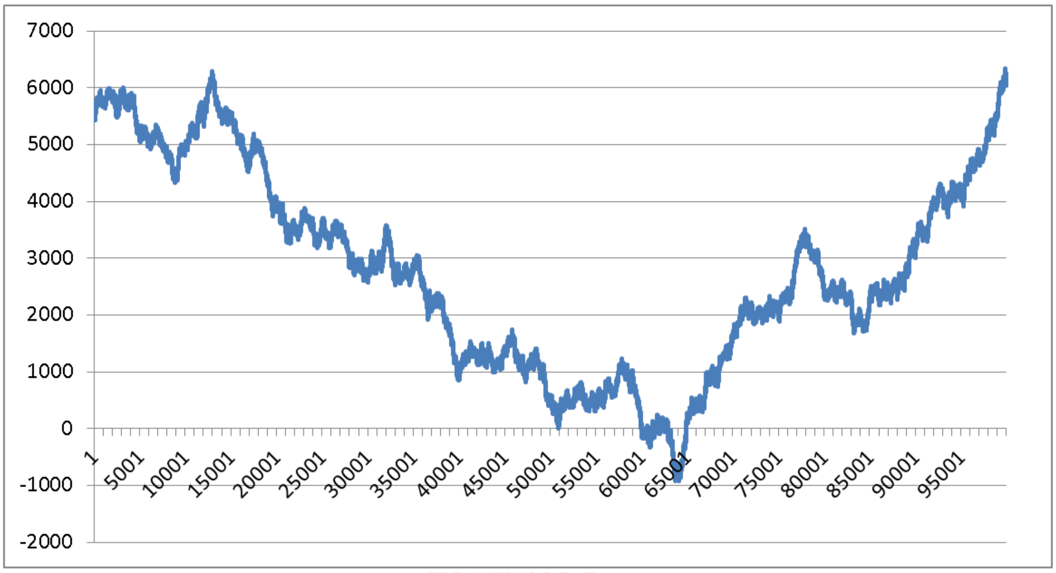

Fig. 2.7: Safety stock level over 100,000 periods for set A

Figure 2.8 shows the same procedure with a new series of random values.

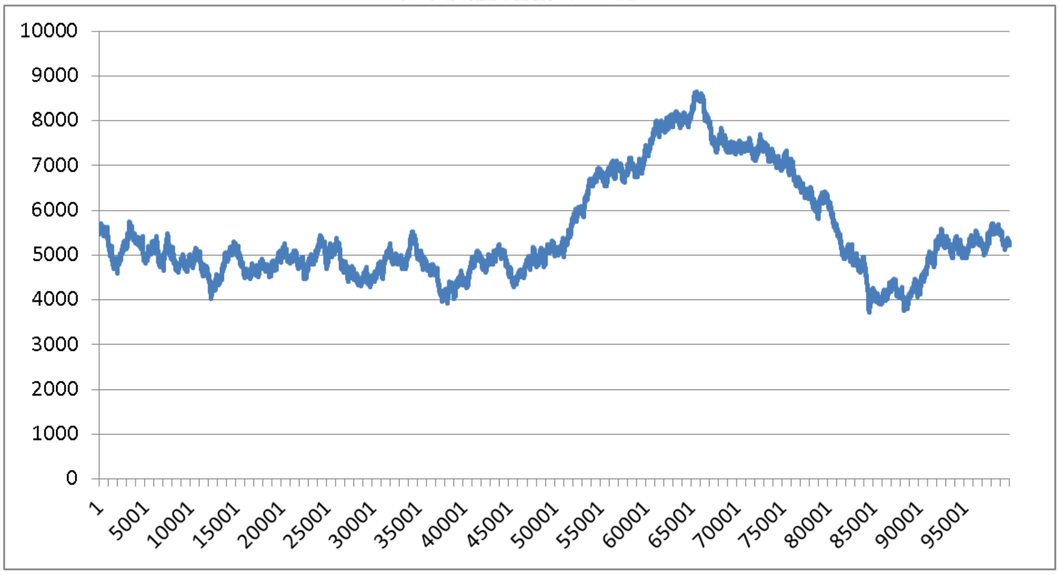

Fig. 2.8: Safety stock level over 100,000 periods for set B

The simulation for both sets shows that even though the level of safety stock ultimately returned to around 5,500 pieces, intermediate fluctuations have been significant. In the first example, a stock-out has been caused by an unfortunate sequence of positive deviations (demand higher than the forecast). It must hence be the target to set the safety stock at a level which guarantees that with a certain probability no stock-outs will occur over a certain period.

2.3.3 Service level

The examples in chapter 2.3.2 have shown how a sequence of random though single-sided deviations can lead to stock-outs. To reduce the probability, adequate safety stock must be carried on top of the cycle inventory. Apparently, higher safety stock levels provide better protection against stock-outs. Yet, the holding of safety stock costs money, which leads to a trade-off between holding cost and so called stock-out costs. The estimation of stock-out costs is very difficult since many rather vague cost factors must be considered, e.g. the loss of good will. Moreover, it is even uncertain how individual customer reacts to a stock-out in the first place. For this reason most organizations prefer to set a certain service level instead, which implicitly is also a cost driven decision (Axsäter, 2006).

The service level can be defined as the probability not to face a stock-out or in positive formulation the probability that all customers can be served (Schalit and Vermorel, 2014).

Obviously, a service level of 100% would be desirable, which is though not feasible, as the far ends of the normal distribution – which is assumed for the random error – never hit zero (Hou and Gopalan, 2014). This means that there is an infinite small probability that an infinite huge order is placed, which in turn would require an unlimited safety stock to hedge against a stock-out. Even though this is rather theoretical, it prevents from a 100% guarantee of customer service.

This theoretic statistical consideration, does though explain why targeting high service levels becomes very expensive. Figure 2.9 shows the safety stock that is required for a certain safety level with regards to the example in section 2.3.2. It is thereby illustrated that increasing the service level by 3% from 95% to 98% would require around 1400 pieces of additional safety stock, whilst a 3% increase from 87% to 90% would only require 500 additional units. Pushing the service level up further would lead to increases in safety stock and cost that might not be justifiable with the gains in customer satisfaction.

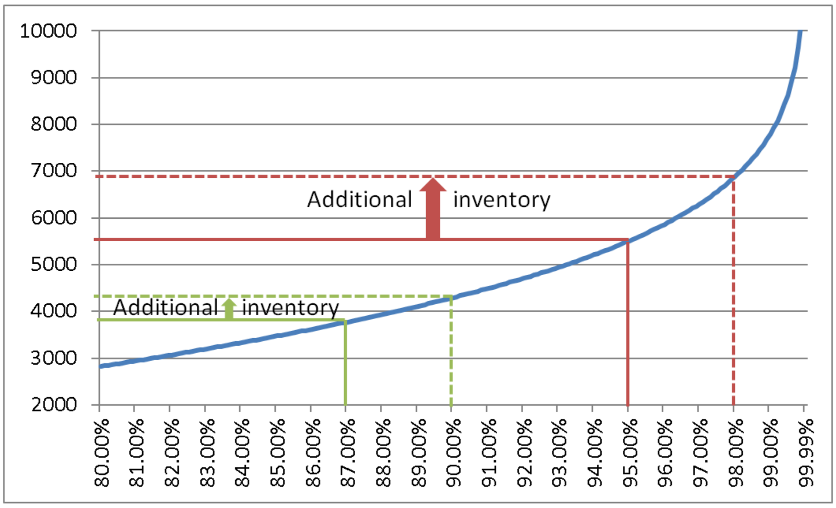

Fig. 2.9: Additional inventory over service level (adapted from Schalit and Vermorel, 2014)

Since the consequences of a stock-out and hence the worth of lifting the service level higher differ from item to item, a determination of the optimal service level on item level seems expedient. For a high number of items this is though impracticable, which is why Schalit and Vermorel (2014) suggest clustering products by ABC analysis or any other differentiation that is relevant to the business. For highly important items, Schalit and Vermorel consider a service level of 98% as feasible and sufficient, whereas goods with low importance are set to levels of about 85%. It shall be emphasized that clustering for the purpose of service level determination does not contradict Hau and Billington (1992) who have criticised the setting of absolute safety times in dependence of a generic item analysis. Safety time is the expression of safety stock in periods of normal consumption, e.g. the safety stock is 3 month of normal consumption. That is because Hau and Billington's criticism is directed against setting safety stock levels that ignore the variation of the demand of individual items and not against the item analysis as such.

2.3.4 Safety stock calculation

In line with Toomey's (2000) recommendation, the service level has been determined as a first step. In a second step, the variation of the demand shall be included in the consideration, as Hau and Billington (1992) require. A standard calculation for this is shown in equation 2.24.

$$Safety\ stock = Z\ \cdot\ \sqrt{\overline{LT} \cdot \sigma_D^2 + \overline{D}^2 \cdot \sigma_{LT}^2}$$

with:

Z	Safety factor
LT	Lead time (replenishment time for Hafele)
D	Demand during lead time
σ_D	Standard deviation of the demand
σ_{LT}	Standard deviation of the lead time

Equation 2.24: Standard formula for safety stock (e.g. Hou and Gopalan, 2014)

The service level is included by the value Z (often called "safety factor", e.g. Piasecki, n.d.), which is the standard normal distribution and can be retrieved from so called Z-tables. In IT software the Z value of a percentage is commonly obtainable by the function "NORMSINV" (Piasecki, n.d.).

Service level	0.85	0.9	0.95	0.975	0.98	0.99	0.995	0.999
Z	1.0364	1.2816	1.6449	1.9600	2.0537	2.3263	2.5758	3.0902

Table 2.8: Z-values for various service level percentages

The purpose of the safety stock is to cover the negative variances (actual demand greater than forecasted demand). As soon as a negative variance occurs and hence the safety stock needs to be touched, the reorder point formula will trigger an order to fill up the safety stock to the original level. As this order will arrive earliest after the lead-time, the safety stock must be able to absorb further negative variances during that waiting time. Thus, the proposed safety stock is dependent on the lead time.

Next to the variation of demand, the formula does also consider variations of the lead time that are the result of low impact demand risks.

2.3.5 Drivers for safety stock

Acknowledging that the prescription for the safety stock calculation (equation 2.24) is based on sheer statistics, there is not much space for “negotiation” for lower safety stock and hence reductions in inventory cost. Therefore, it shall be briefly discussed what are drivers for safety stock.

First, the chosen service level itself should be reviewed. Toomey (2000) emphasizes that understanding the customer is very important for setting the right service level. Whilst underperformance might lead to “walk-outs”, overachievement might not lead to “walk-ins”.

Second, the shorter the lead time, the smaller the safety stock. If it would be possible to just ring up the supplier and get the goods immediately, there would be no need for safety stocks. Reducing lead times by freight expediting is not a viable option as increases in transport cost outweigh the positive effect on inventory reduction (Blumenfeld, Hall and Jordan, 1984). Yet, when compared to production times, the transport time is nevertheless not the primary issue. Critically reviewing the agreed lead times together with the suppliers seems more expedient to achieve improvements. Thus, lead times should already receive high attention during supplier selection and contract negotiations.

Third, the standard deviation of the demand forecast has a massive impact on the safety stock that is required (Chockalingam, 2014). With regards to prerequisites of forecast accuracy, Toomey (2000) mentions that long forecast horizons usually result in higher inaccuracy and that individual SKU forecasting is more prone to error than market forecasting. This is in line with Goetschalckx (2011) who indicates that demand can be aggregated in three dimensions: product group, geography, and time span. In deed the accuracy of the projection for refrigerator sales in Thailand in 2015 will be higher than of the projection for a special model in the Mega Bangna Showroom on the 1st April 2015.

For this reason Simchi-Levi (2013) considers risk pooling to be the “most important concept in supply chain management”. Risk pooling is described as a purposeful aggregation across the Goetschalckyx’s three dimensions to reduce total risk/variability and ultimately the need for safety stocks.

2.4 Economic order quantity

In the prior part of this chapter it was reviewed how to obtain reasonable forecasts and how to define sufficient safety stock levels. Thereby, the basis for an economic order consideration that ultimately delivers the proposed order quantity was provided.
The fundamental principle of the economic order quantity calculation is to balance the costs of placing an order and the costs of holding inventory, in order to reduce to the total acquisition cost.

2.4.1 Review of involved cost factors

Prior to the balancing of the various cost factors that are affected by the purchasing decision, a deeper understanding of their structure shall be gained. Since most cost components are heavily dependent on the organization and logistics setup, the assessment of costs is a rather practical and less academic topic. Literature in this context is rather rare.

2.4.1.1 Inventory holding costs

The term inventory holding cost accounts for all costs and risks (expressed as cost) that occur just because goods are kept in stock. Speh (2009) describes them as the costs of "goods at rest". Holding costs accumulate from the time of put-away until the time of despatch. Therewith, they are variable to the length of storage but invariable to movements (Speh, 2009). As a further sub-classification, Vermorel (2013) recommends to split inventory holding costs into capital cost, storage space cost, inventory service cost, and inventory risks.

Capital costs

Hurlburt (n.d.) called inventory the most valuable asset of a trading company. Yet, the money that has been spent on purchasing the goods is temporarily bound until the goods are sold. For the involved capital the organization has to pay interest on a periodic basis or needs to account for opportunity costs. At first glance those costs should be as high as the company's short term lending rate (Jones and Tuzel, 2009).

However, Vermorel (2013) warns that capital costs are usually underestimated and not covered with the five percent that organizations are typically recognizing. That is because it must be also accounted for opportunity costs and inherent risks in holding inventory. Jones and Tuzel (2009) agree that the inherent risk in the investment into inventory must be considered. Since Vermorel actually suggested a separate subcategory that considers risks, estimating the corporate lending rate as capital cost appears reasonable.

Storage space costs

For the purpose of inventory holding, the organization needs to provide storage space. Irrespective of storing the goods in a rented or owned facility, facility costs arise. The monthly rent or the depreciation of the building should be prorated for the area dedicated to storage. Speh (2009) suggests the calculation on per sqm basis. This seems, though, impracticable for high-rise storage which rather calls for accounting by cubic meter. The cost for the high-rise racking itself must also be considered.

Inventory service costs

Next to the cost for the physical storage of goods, there are also costs evolving from orderly maintenance and management of the inventory. For instance cycle counting is required from time to time in order to comply with accounting standards (Vermorel, 2013). Physical movements like stock transfers or replenishments – but not put-away and picking – must also be accounted for. These services require labour to perform the service but also equipment such as forklifts as support. Both labour and equipment cause further overhead such as utility costs.

Inventory risks

As mentioned in the section of capital costs, the investment into inventory implies risks. Potential shrinkage due to theft, damage, or aging leads to costly write-offs and must hence be accounted for. In this context, Hurlburt (n.d.) observed that the shrinkage and damage costs tend to be higher when stock levels are higher. The value of the goods can also be expected to play a role for shrinkage, whilst the kind of packaging impacts the likelihood of damage. Risk of obsolescence or mere non-saleability might bring about the need to severely discount the goods or even to dispose and hence write them off entirely (RFID Journal, 2009). Slow-movers usually exhibit a higher risk of obsolescence when compared to top-sellers, especially when relating the quantity in danger to the sold quantity. To account for the obsolescence risk, annual inventory depreciations can be considered. From the argumentation above it transpires that inventory risks must be evaluated on item level, as the variety of product characteristics that influence the risk does not allow for clustering. It is recommended to consider the following cost factors:

- Prorated stock adjustments on item level with storage related cause (average adjusted value per month / average monthly stock)
- Annual depreciation as percent of item value prorated to the average storage time

Summary

As the brief discussion has shown inventory costs vary from item to item because of multiple product characteristics that do not allow for clustering. Usually, the inventory costs are given as percentage of product value per annum. Stock and Lambert (1987) as well as RFID Journal (2009) consider values of 25% per annum as realistic, whilst Vermorel (2013) states 18% to 75% (the latter applies to perishable goods).

2.4.1.2 Ordering costs

Fundamentally, ordering costs summarize those expenses that originate before the goods are stored in the warehouse position. They include costs of preparing the purchase order, of administering the freight forwarding, and of the goods receipt and put-away at the warehouse. The freight costs itself is sometimes included and sometimes excluded from ordering cost, which is why it shall be captured in a dedicated section. The ordering cost (or transaction costs) shall be calculated as a simple per order value.

Purchasing costs

Preparing a purchase order, getting management approval, and sending it to the supplier takes time. The more purchase orders are created, the more time is spent. This working time must be captured under purchasing cost. The effort of further communication with the freight forwarded, customs office, warehouse and the like must be considered as well. Additional processing in the accounting department is also necessary in case of additional orders.

Receiving costs

The cost of receiving the goods must be treated carefully. Tasks like the physical put-away to the storage position have to be performed independent of the shipment size and count. Same is applicable for re-palletizing, wrapping, labelling and the like. Yet, the amount of paper work and administration effort increases with the number of shipments. Beyond that, Speh (2009) claims that all general administrative costs of running the warehouse facility – such as security guards – must be considered as well. Speh (2009) also considers the load of IT system and the need of senior management attention as variable cost factors that would be eliminated if the warehouse is closed down. With regards to the economic order quantity, this should be ignored though, as the total shut down of the warehouse is not a valid scenario.

Supplier relation

Even if small order sizes are contractually permitted, a supplier might not be delighted if lot sizes are reduced. It might, therefore, be considered to account for a loss in goodwill.

2.4.1.3 Transportation costs

Beyond the ordering costs, the costs for the physical transport between the supplier and warehouse have to be considered. Fundamentally, transport is subjected to economies of scale and hence a heavily discussed topic in the literature. Existing literature does, though, mostly evaluate the subject from the perspective of carriers or freight forwarders and hence discuss topics like consolidation. From the perspective of freight forwarding customers, transport economics are different but, though, not less important. The objective is to achieve the lowest transportation cost per piece. Yet, the transportation cost function is a discontinuous function, which is why economies of scale do only partially apply. Eventually the stuffing effectiveness – literally speaking the maximum quantity of goods that can be squeezed into a container – has the highest leverage on transport costs. It shall be noted that this only applies to full container shipments where the container utilization is at the responsibility of shipper or consignee.

An only partially filled 40ft container does logically imply higher per piece transport costs than an entirely filled container. As a countermeasure, the order size could be increased to fill the 40ft container or reduced to fit a 20ft container. If a reduction is not possible and an increase to fit 40ft container would cause too high inventory costs, then it might be cheaper to send a 20ft container and the leftover as LCL. These options lead to an unsteady transport cost per piece over quantity curve.

This situation shall be illustrated at an example where the maximum quantity of the item for each container type is known.

	LCL per piece	20ft container	40ft container
Cost	5	300	500
Max quantity	1	110	240

Table 2.9: Example cost for different shipping options

For every quantity the most cost efficient shipping mix can be calculated.

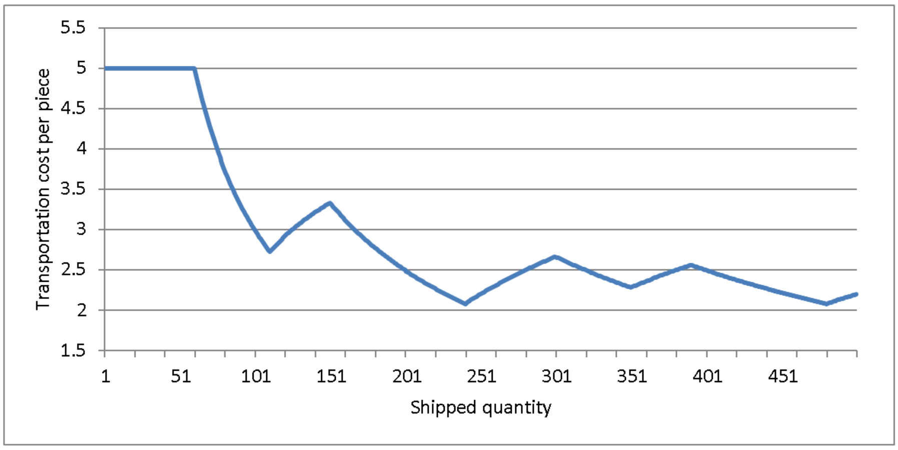

Figure 2.10: Transportation cost in dependence of quantity shipped

As obvious in figure 2.10, some order quantities imply significantly lower transportation costs per piece than others. This circumstance gets entirely neglected by the standard EOQ formulas, as the following review will show.

2.4.2 The traditional approach to EOQ

As outlined earlier, the EOQ calculation aims at balancing inventory costs and ordering costs in order to achieve the lowest possible cost of goods sold (COGS). COGS summarizes all costs that accrue for the provision of goods to the customer, which includes ordering cost, purchase price less discounts, shipping cost, fees, taxes, and inventory costs but not the delivery cost (Presti, 2013).

The traditional approach formulated by Harris in 1913 limits its focus on optimizing the sum of ordering cost and inventory cost (Axsäter, 2006). The model of Harris, makes three main assumptions (ReadyRatios, 2013):

1) The ordering costs are constant and independent of the ordered quantity
2) The demand is constant over the year
3) The full order quantity is delivered once the stock reaches zero
4) Order quantities do not need to be integer values

Example

Assuming an equally distributed annual demand of 12,000 pieces, the required stock could be brought in by a freely chosen number of shipments (n) that take place in equidistant intervals.

If the number of shipments n is selected to be six, every two month a shipment of 2,000 pieces will be received. As the monthly consumption is 1,000 pieces, half of the delivered stock will be left after one month, which is consumed in the second month. The average inventory level is 1,000 pieces. Alternatively, n can be selected as three, which leads to an average inventory level 2,000 pieces, as illustrated by the dashed curve in figure 2.11.

n=3: inventory cost for 2,000 pieces on average and 3 times ordering cost
n=6: inventory cost for 1,000 pieces on average and 6 times ordering cost

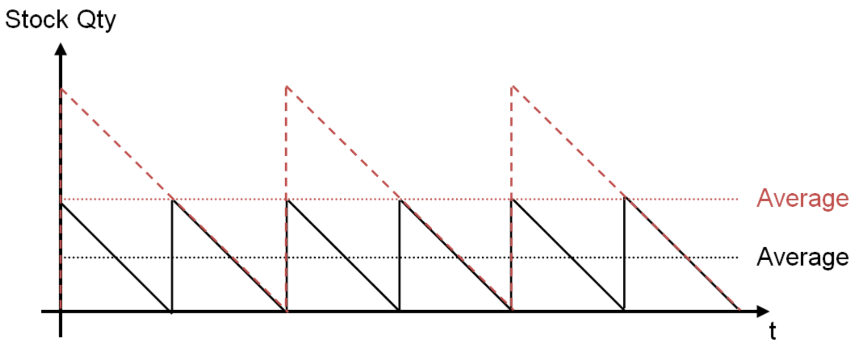

Fig. 2.11: Stock level for 3 and 6 shipments (adapted from Axsäter, 2006)

The question, which of the two options is cheaper can be easily answered by calculating the total cost. However, under the assumptions of Harris, n could be set to any value that is greater or equal to 1. The EOQ calculation proposed by Harris returns the n with the lowest cost by mathematical derivation.

To calculate the inventory holding costs, the cost of holding one piece for one year (H) is multiplied with the average stock quantity, which equals half of the order quantity as obvious in figure 2.12. The order quantity can be expressed as the annual demand (D) divided by the number of orders placed in one year (n).

$$Inventory\ holding\ cost = \frac{1}{2} \cdot \frac{D}{n} \cdot H$$

Equation 2.25: Inventory holding cost function in dependence of n

The ordering costs, yet to contrast with the inventory holding cost, are calculated as the number of orders placed (n) multiplied with the constant ordering cost (S).

$$Ordering\ cost = n\ \cdot s$$

Equation 2.26: Ordering cost function in dependence of n

The total cost is the sum of both cost functions. The inventory holding cost declines with the number of orders, whereas the ordering cost increases with the number of orders.

$$Total\ cost = \frac{1}{2} \cdot \frac{D}{n} \cdot H + n \cdot s$$

Equation 2.27: Total cost function in dependence of n

In order to calculate the minimum, the first derivative of the total cost function is set to zero.

$$f'(n) = 0 = \frac{d}{dn}\left(\frac{1}{2} \cdot \frac{D}{n} \cdot H + n \cdot S\right) = -\frac{1}{2} \cdot \frac{D}{n^2} \cdot H + S$$

This results in:

$$\frac{1}{2} \cdot \frac{D}{n^2} \cdot H = S$$

Equation 2.28: First deviation of the total cost function

Substituting the number of orders (n) again with the demand (D) divided by the order quantity (Q) leads to the following function:

$$\frac{1}{2} \cdot \frac{D}{\frac{D^2}{Q^2}} \cdot H = S$$

This can also be written as:

$$\frac{1}{2} \cdot Q^2 \cdot H = D \cdot S$$

Equation 2.29: Intermediate transformations

With slight transformations, the equation 2.30 for the “economic order quantity” as postulated by Ford W. Harris in 1913 can be retrieved (ReadyRatios, 2013).

$$Q = \sqrt{\frac{2 \cdot D \cdot S}{H}}$$

With:

Q	Optimal order quantity
D	Annual demand
S	Product order cost per order that is independent of Q
H	Holding cost

Equation 2.30: Economic order quantity formula by Harris

The principle can be easily visualized by plotting the inventory holding cost function, the ordering cost function, and the sum function in dependence of n. The value of n for which the total cost function has its minimum, is the optimal number of shipments.

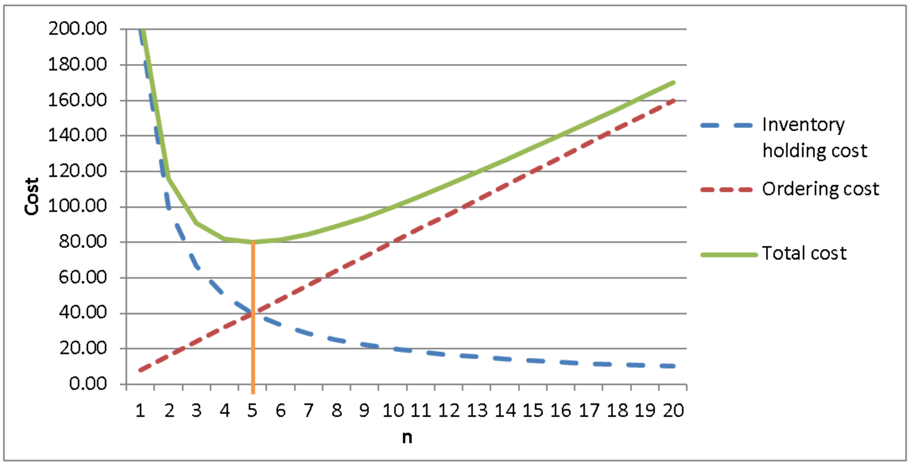

Fig. 2.12: Cost in dependence of the number of orders (n) (adjusted from Dickersbach, 2006)

With regards to practical applications, the economic order quantity model of Harris has several short comings that result from the underlying assumptions.

First, the future demand is considered as constant, which is true for linear constant forecasting models but not for trend or seasonal models.

Second, suppliers usually enforce minimum order quantities. Non-integer values for order quantities or the number of shipments as assumed by Harris are also hypothetical. Apparently, the possible range of n is limited in praxis.

Third, the calculation neglects transport economics and quantity discounts, which impact the optimal quantity. Moreover, does the formula consider only a single item scenario, which does not consider potential consolidation effects.

2.4.3 Alternative approaches

In literature there are many recommendations on how to modify the EOQ calculation of Harris in order to correct some of the short comings, e.g. Piasecki (2001) and Axsäter (2006). However, these improvements do not resolve the limitations that come along with the most fundamental assumption of constant demand. The need for the consideration of time varying demand – also called “dynamic lot sizing problem” – requires entirely different approaches, of which the Wagner-Whitin algorithm shall be introduced after a brief introduction to the matter of rolling horizons.

2.4.3.1 Rolling horizon

Looking at time-varying demand instead of constant demand would fundamentally require the consideration of demand over an infinite horizon. Practically this is not possible, which is why limited rolling horizons are commonly applied. The principle of rolling horizon planning is shown in figure 2.13. Instead of planning for an infinite horizon, a time-limited horizon is evaluated. With the course of time, the limited horizon for the economic order quantity consideration rolls forward (Narayanan and Robinson, 2010).

The planning horizon can be further split into a frozen interval and a free interval. Frozen interval denotes periods that can no longer be influenced, as lead times does not allow for adding or amending orders. For the free interval orders can be placed upon EOQ calculations.

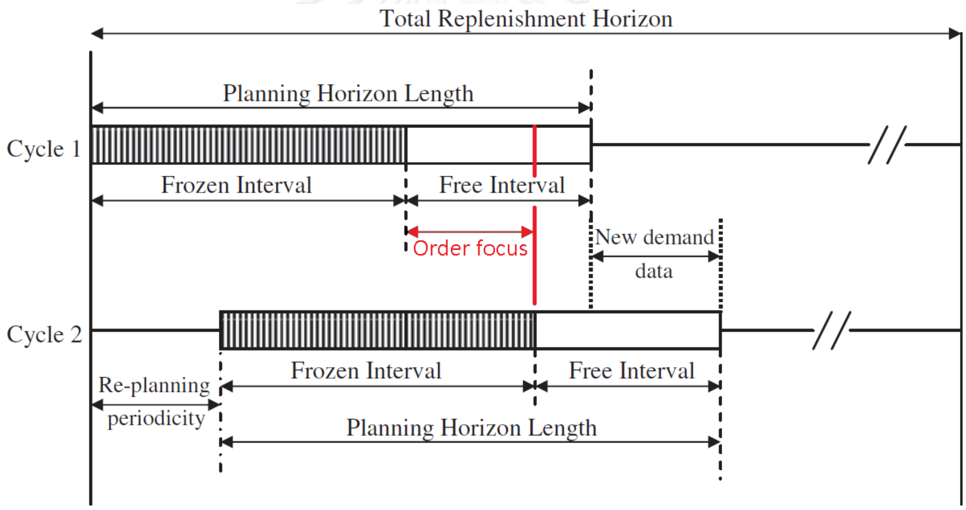

Fig. 2.13: Rolling horizon forecasting (adapted from Narayanan and Robinson, 2010)

Since a periodic inventory review system is applied, a certain time elapses before the planning is reviewed. The frozen interval and the free interval move forward accordingly. As new demand data is available, the frame conditions for the EOQ consideration have changed, which might influence the purchasing decision. Orders that have been placed during cycle 1 and that are not yet frozen may be rescheduled if necessary (Narayanan and Robinson, 2010). Yet, rescheduling also causes effort and ultimately cost. Hence, to allow for maximal flexibility, orders should not be placed unnecessary far in advance in the first place. In cycle 1 merely the orders for the time frame between frozen interval and frozen interval plus re-planning periodicity (“order focus”) must be placed. For the time beyond the order focus, orders can still be placed during the next inventory review.

The length of the planning horizon can be freely chosen, Baker (1977) recommends though a multiple of the time between two inventory reviews. With regards to stability of the system, Narayanan and Robinson (2010) recommend that the planning horizon should not be longer than two times the frozen interval.

2.4.3.2 Wagner-Whitin algorithm

To solve the dynamic lot sizing problem in a finite horizon, the Wagner-Whitin algorithm suggested by Wagner and Whitin (1958) can be used. The basic assumption of this algorithm is that each shipment quantity must be equal to the sum of demand for the next n periods, whereby n is an integer value. It is then evaluated whether combining shipments yields a saving, as order costs are reduced whilst inventory cost increase (Axsäter, 2006). The circumstance that preponing partial shipments does never yield savings, as ordering cost remain the same whilst inventory cost increase, simplifies the problem.
For a more in depth description on how Wagner-Whitin apply dynamic programming to solve the dynamic lot sizing problem, the reader shall be referred to Axsäter (2006) or to Wagner and Whitin (1958) themselves.

2.4.3.3 Heuristic approaches

The Wagner-Whitin algorithm is an exact calculation for the given horizon. The calculation effort significantly increases with the number of periods. Adding side constraints to the problem – for instance minimum order quantities – increases the complexity further. As a result the Wagner-Whitin algorithm is rarely applied in practice (Axsäter, 2006). Instead it is more common to use heuristics instead of optimal solvers. A heuristic approach is applied when the computed way of processing follows the procedure that would be applied in practice when the problem has to be solved manually. The results will thereby not be optimal but in most cases acceptable for the purpose and the spent effort.

2.4.3.4 Silver-Meal heuristic

The Silver-Meal heuristic is a sequential approach that starts at the shipment of the first period. From thereon subsequent shipments are evaluated with regards to the cost impact of combining them with the first shipment (Axsäter, 2006). Shipments are combined until the average period cost increases for the first time.

Example

Ordering cost = 300 per order

Inventory cost = 1 per piece per period

Period	1	2	3	4	5	6	7	8
Demand	90	60	80	70	30	80	60	60

Table 2.10: Silver-Meal example - forecast demand per period

The focus lies on period 1. The average period costs are calculated as:

Period 1 only: (300 + no inventory cost) / 1 period = 300

Combined with period 2: (300 + 60 * 1) / 2 periods = 180

Combined with period 3: (300 + 60 * 1 + 80 * 2) / 3 periods = 173.33

Combined with period 4: (300 + 60 * 1 + 80 * 2 + 70 * 3) / 4 periods = **182.5**

In period 4 the average cost per period increases for the first time. Therefore, a second shipment will be initiated in week 4.

Period	1	2	3	4	5	6	7	8
Demand	90	60	80	70	30	80	60	60
Shipments	230			70	30	80	60	60

Table 2.11: Silver-Meal example – focus on period 1

The same process is repeated starting from week 4.

Period 4 only: (300 + no inventory cost) / 1 period = 300

Combined with period 5: (300 + 30 * 1) / 2 periods = 165

Combined with period 6: (300 + 30 * 1 + 80 * 2) / 3 periods = 163.33

Combined with period 7: (300 + 30 * 1 + 80 * 2 + 60 * 3) / 4 periods = **167.5**

As in period 7 the average cost again increased for the first time, shipments in period 4 to 6 are consolidated. Ultimately, the same happens for period 7 and 8, so that the shipping plan in table 2.12 is recommended

Period	1	2	3	4	5	6	7	8
Demand	90	60	80	70	30	80	60	60
Shipments	230			180			120	

Table 2.12: Silver-Meal example – final results

The overall cost of the proposed solution is:

$$\begin{array}{lr} & (300 + 60 * 1 + 80 * 2) \\ + & (300 + 30 * 1 + 80 * 2) \\ + & (300 + 60 * 1) \\ \hline = & 1370 \end{array}$$

As mentioned earlier, the Silver-Meal heuristic is not aiming at the optimal solution.

In above example the last shipment is inefficiently utilized. Lower cost would have been possible with the schedule illustrated in table 2.13.

Period	1	2	3	4	5	6	7	8
Demand	90	60	80	70	30	80	60	60
Shipments	330					200		

Figure 2.13: Silver-Meal example – optimal schedule

For this schedule the total cost is:

$$\begin{array}{lr} & (300 + 60 * 1 + 80 * 2 + 70 * 3 + 30 * 4) \\ + & (300 + 60 * 1 + 60 * 2) \\ \hline = & 1330 \end{array}$$

This issue Narayanan and Robinson (2010) call “end-of horizon effect”, which denotes that the lack of demand data beyond the horizon leads to comparably poor results. The impact of this effect is reduced for very long horizons (Axsäter, 2006). Baker (1989) estimated that under normal circumstances the minimum cost achieved with the Silver-Meal heuristic is only 1 to 2 % higher than the optimal solution. In above example with very short horizon, the difference is also only 2.9%

2.4.3.5 Other heuristics for inventory cost vs ordering costs

Besides the Silver-Meal heuristic, there are other heuristics that work with the same methodology of combining shipments and assessing the effect. The assessment criteria are, though, different (Axsäter, 2006). Instead of calculating the average cost per period, the least-unit-cost heuristic looks at the average cost per unit. Baker (1989) found that on average the Silver-Meal heuristic does, though, deliver better results.

Based on De Matteis and Mendoza (1968), Axsäter (2006) proposed to follow the finding of the basic EOQ formula of Harris where the lowest total cost is achieved when inventory holding costs equal the ordering costs. Thereby, Axsäter (2006) is aware that with time varying demands and the restriction to integer values, the finding of Harris is no longer valid. However, he still expects reasonable results. The same example that was previously used shall be taken to illustrate this approach. This time, a new shipment is started whenever the inventory costs become higher than the ordering costs.

Period	1	2	3	4	5	6	7	8
Demand	90	60	80	70	30	80	60	60
Shipments	230			70	30	80	60	60

Table 2.14: Heuristic based on cost equality

	Inventory cost	Ordering cost
Period 2	60 * 1 period = 60	300
Period 3	60 + 80 * 2 periods = 220	300
Period 4	60 + 80 * 2 + 70 * 3 = **430**	**300**

Table 2.15: Heuristic based on cost equality – focus on period 1

In period 4, the inventory costs exceed the ordering costs for the first time. Therefore, a new shipment is started in period 4.

	Inventory cost	Ordering cost
Period 5	30 * 1 period = 30	300
Period 6	30 + 80 * 2 vs 300	300
Period 7	30 + 80 * 2 + 60 * 3 = **370**	**300**

Table 2.16: Heuristic based on cost equality – focus on period 4

For period 7 the inventory costs exceed the ordering costs, which is why the shipments of period 4, 5 and 6 are combined. Finally, shipment 7 and 8 are also combined.

Period	1	2	3	4	5	6	7	8
Demand	90	60	80	70	30	80	60	60
Shipments	230			180			120	

Table 2.17: Heuristic based on cost equality – final result

In this example, the result of the heuristic proposed by Axsäter (2006) equals the result of the Silver-Meal heuristic.

2.4.3.6 Comparison of heuristics and optimal solutions

In order to add further side constraints like MOQs or quantity discounts, either of these approaches has to be adapted. With regards to adaptability, heuristics see a clear advantage, as practical procedures can be followed (Axsäter, 2006). Even though heuristics in most case not yield the optimal results, the outcome is sufficiently accurate – especially in face of input data that is nevertheless uncertain. For the proclaimed target of simplicity and comprehensibility, heuristic approaches are recommendable.

2.4.4 Minimum order quantity and quantity discounts

Minimum order quantities and quantity discounts are imposed by suppliers to steer the buyers purchasing behaviour into a direction that is favourable for the supplier and that usually contradicts the economic order quantity with regards to the trade-off between inventory costs and ordering costs (Shah and Dixit, 2005). A minimum order quantity is a quantity that an order must exceed in order to be accepted by the supplier. Quantity discounts are reductions in purchase price if certain conditions are met. With regards to quantity discounts, Graves et al (1993) mention three typical schematics:

I. A schematic in which the price for the entire quantity is reduced if a certain threshold is reached. This schematic is also known as all-unit discount.

II. A schematic in which the exceeding quantity of a certain threshold is discounted

III. A linear model, where quantity and price are connected via a linear function. This schematic is also known as incremental quantity discount.

The literature – e.g. Güder, Zydiak and Chaudhry (1994) as well as Mendoza and Ventura (2014) – considers the all-unit discount and the incremental quantity discount as standard. The comprehensiveness of research in the area of quantity discounts is large – whereby especially the determination of discount structures on supplier side and the trade-off between inventory cost and incremental quantity discount on buyer side are focused (Shah and Dixit, 2005). For instance do Hu, Munson and Silver (2004) suggest on how to adapt the Silver-Meal heuristic to deal with incremental quantity discounts.
With regards to the business of Hafele, the incremental quantity discount is untypical. The all-quantity discount and very rare cases also the exceeding-quantity discount are practically applied. A discount schedule can qualify several breaks of the purchase cost function (Shah and Dixit, 2005).

Example

- If the purchase quantity is less than 5, the price is $10.00/pc
- If the purchase quantity is greater than 4 and less than 20, the price is $9.80/pc
- If the purchase quantity is at least 20, the price is $9.60/pc

In case the order quantity is 4 pc, the total purchase cost is 4pc * $10.00/pc= $40.00
In case the order quantity is 15 pc, the total purchase cost is 15pc * $9.80/pc= $147.00
In case the order quantity is 30 pc, the total purchase cost is 30pc * $9.60/pc= $288.00

The complexity of considering multi-staged discounts in an environment of time-varying demand is significantly higher than that of the standard EOQ trade-off. Not only the perfect solution but also most approximate solutions that are discussed in the literature are very unhandy and difficult to apply in practice. A simple heuristic like the Silver-Meal heuristic is preferable to comply with the self-defined design criteria. Hu and Munson (2002) reviewed the literature for recommendations on which simple heuristic to use for an all-quantity discount scenario. Thereby, the least-unit-cost method has been found to be the method of choice in a handful of comparison tests. In difference to the original least-unit-cost heuristic, the average purchase costs are included into the calculation to add the discount-dependent component.

Reference	*Recommended model(s)*
Benton[14]	MOM
Benton[15]	LUC, MOM
Benton and Whybark[16]	LUC, MOM
Bregman[17]	CCL, DOQ, MOM
Bregman[18]	CCL, DOQ, LUC, MOM
Bregman and Silver[19]	CCL, DOQ, MLPC
Callarman and Whybark[20]	LUC, MOM
Christoph[21]	LUC, MOM
Christoph and LaForge[22]	LUC, MOM
LaForge[23]	IPPB, LUC
LaForge and Patterson[24]	PPB
Lee *et al*[25]	LUC, MWW
Srivastava and Benton[26]	MMOM

Abbreviations: CCL, Chung–Chiang–Lu; DOQ, discount order quantity; IPPB, incremental part period balancing; LUC, least unit cost; MLPC, modified least period cost; MMOM, modified McLaren's order moment; MOM, McLaren's order moment; MWW, modified Wagner–Whitin; PPB, part period balancing.

Fig 2.14: Recommended heuristic for all-quantity discount (Hu and Munson, 2002)

In 2004 Hu, Munson and Silver have then reported that the inclusion of the purchase cost diminishes the relevance of other cost factors due to its relative height. Hu, Munson and Silver (2014) do, therefore, recommend to consider the absolute smaller opportunity cost of not taking the discount rather than the purchase cost. In comparison tests, Hu, Munson and Silver have shown that results equal to the optimal solution can be achieved in more than 90% of cases for longer horizons.

2.4.5 Transportation cost

2.4.5.1 Individual item basis

With regards to the inclusion of transportation costs, the unsteadiness of the transport cost function is problematic, whereby the literature concerns about economies and diseconomies of scale. In the original approach, transportation costs have been considered to be constant and independent of the shipped quantity and hence as a part of the ordering costs. Research in the 1970 took transportation costs for multiples of full-truck loads into account, whereby leftover space was ignored (Mendoza and Ventura, 2014). Later works began to include transportation economies as a kind of all-quantity discounts, which faces though trouble to account for diseconomies of scale. Mendoza and Ventura (2014) factor the utilization of transport medium in by assuming that the cost of filling the medium up is lower than shipping the costs by LCL. Eventually, the exact utilization rate of a transport medium for a certain shipment quantity would need to be considered to capture transportation costs adequately. Especially for joint ordering this is a complex issue.

2.4.5.2 Joint replenishment problem

Joint replenishment problems exist when a range of products is purchased from a single supplier. The objective is to minimize the sum of inventory costs, ordering costs and transportation costs. The items are, thereby, linked through the cost sharing with regards to transportation. Narayanan and Robinson (2010) recommend solving joint replenishment problems with a rolling horizon planning approach and hence follow the basic approach of Blackburn and Millen (1982).

Narayanan and Robinson (2010) reviewed the performances of various heuristic methods for a joint replenishment problem. Thereby, a joint ordering cost and an individual item ordering cost has been considered. The joint ordering costs kind of represent the transportation costs that are, though, independent of the shipped quantity. Considering the high dependency of transportation cost on transport mode utilization, the assumption of fixed cost is impractical. The neglect of MOQ quantities and quantity discounts is further reducing the applicability of Narayanan and Robinson's (2010) findings to actual operations.

2.4.6 Review

It was discussed that heuristics do not deliver the optimal solution due to the “end of horizon effect” also “truncated horizon effect” as Van den Heuvel and Wagemans (2005) call it. In return for lower accuracy, heuristics bring about the advantage of simplicity, as they are not only easier to understand and hence easier to implement, but also easier to adapt to certain requirements such as MOQ or quantity discounts. In fact, Simpson (1999) claims that approaches that target optimal solutions do not outperform heuristics in rolling horizon applications. Blackburn and Millen (1980) argue that in certain scenarios in rolling horizons environments, heuristics are even able to deliver superior results. Johansen (1999) analysed the effect of demand uncertainty on the performance of optimal and heuristic methods. Thereby, he only attested superior performance to dynamic programming (optimal solution) for low variations. Wemmerlöv (1989) goes as far as to say that the method choice is rather irrelevant if demand cannot be accurately predicted.

Apparently, for the intended application at Hafele, the advantages of simplicity and adaptability outweigh the disadvantages of occasional inferior performance, which is why heuristics are recommended. With regards to implementation, the joint replenishment problem as discussed by Narayanan and Robinson (2010) appears to be too idealistic since important factors like variable transport costs are neglected. For a proper inclusion of transport costs that considers the utilization of shipment mediums, the literature does not provide adequate solutions – especially for the joint replenishment problem.

2.5 Chapter summary

Within the literature research it was identified that a periodic review system best suits the envisioned application, as it possess advantages for joint ordering. To assess the cost effectiveness of and to plan for joint ordering, demand plans on item basis are required, which can be obtained by evaluating the inventory position in face of future demand.

Since the future demand is unknown, some kind of forecasting is required. Considering that individual item forecasting is required for 8,000 items, preference has been given to the approach of quantitative-intrinsic forecasting. This means that based on previous demand data, future values are calculated by means of a mathematical/statistical relation. If the available historic data is uncontaminated and representing actual demand, and if the future demand will not be impacted by external events, it can be assumed that demand patterns that have been observed in the past will repeat in future. For longer horizons, demand can be adequately described by very basic patterns – e.g. a constant pattern, linear trend pattern, and seasonality – for which standard calculation methods exist. Yet, it cannot be assumed that different products that might even be in different stages of their life cycle can be adequately continued with one and the same method. For this reason it is common practice to apply different forecasting methods on past values and to choose that method for future forecasting that delivered the best results. This does though imply risks that the wrong method or wrong parameters have been selected. It is hence recommendable to use robust methods that deliver acceptable results for a number of patterns, whilst being less vulnerable to contaminations of input data.

For the selected forecasting method, the historic standard deviation can be determined, which is needed to calculated the required safety stock level for a given service level. Based on the demand forecast, the safety stock requirement, and the current inventory position, a demand plan can then be derived, which is in turn the input for an economic order calculation.

The traditional approach to EOQ balances inventory costs and ordering costs. Ordering costs are, thereby, considered as constant and do hence by no means consider transportation costs in adequate manner. Actual transportation costs usually exhibit economies of scale but also diseconomies of scale that provoke an unsteady transport cost function. This fact is completely ignored by the traditional approach to EOQ calculation. However, also non-static and, therefore, time-varying demand cannot be handled by the traditional approach, which is why alternative approaches are required. Most commonly, heuristics that do not deliver optimal but still rather optimal solutions are employed. Usually these heuristics also aim at solving the basic trade-off between inventory costs and ordering costs for a finite horizon. Extensions for quantity discounts and simplified transport costs have been evaluated and proposed in the literature. Those extensions do, though, not satisfy the needs of the targeted application, which is why a more detailed approach is required.

3 CRITICAL ASSESSMENT OF CURRENT IMPLEMENTATION

Within this chapter the logic behind the existing purchase proposal shall be reviewed with the target of identifying areas of improvement and elements that should be maintained.

3.1 Review of inventory policy

The purchase proposal is operated on weekly or two-weeks basis, which indicates a periodic inventory review policy. Considering that the company performs around 4,000 inventory transactions, the periodic review requires by far less effort and additionally provides a better basis for joint ordering.
The negative effects of higher safety stock requirements caused by the virtually prolonged replenishment time are of dissimilar impact for the different items.
For an item that gets replenished within 130 days, the need to keep additional safety stock for 7 days (weekly review cycle) is not severe since the lead time is only considered as square root in the safety stock formula.

$$Additional\ safety\ stock\ ratio = \frac{\sqrt{137}}{\sqrt{130}} = 1.0266$$

Equation 3.1: Factor for additional safety stock in case of 130 day lead time

For an item with a replenishment time of 45 days, an elongation by 14 days (two-weeks review cycle) is an increase by almost one third.

$$Additional\ safety\ stock\ ratio = \frac{\sqrt{59}}{\sqrt{45}} = 1.145$$

Equation 3.2: Factor for additional safety stock in case of 45 day lead time

Yet, as mentioned in the introduction, the ERP system is automatically sending an email alert on daily basis if the reorder point is undershot. Eventually, this can be considered as a quasi-continuous review, as the system evaluates the inventory position in the background at frequent intervals. However, this is only valid as long as the system is reliable enough to work without manual verification.

3.2 Forecast and EOQ calculation

Currently the validity of the proposed order quantities is rather low. As per estimation of the purchasing manager, 90% of all proposed quantities are not those that finally get ordered. It can, therefore, be concluded that the current formula is not reliable enough to consider the review system as quasi-continuous.

Apparently, the formula must have severe short-comings that compromise the quality of the results. The background of these short comings shall be illustrated with the following example.

Example

An x-item with replenishment time of 120 days and a desired safety time of 90 days shall be reviewed.

Month	M_{-6}	M_{-5}	M_{-4}	M_{-3}	M_{-2}	M_{-1}
Sales Qty	119	116	105	112	103	122

Table 3.1: Sample sales history

Currently 200 pieces are in stock. Seven incoming shipments of 80 pieces each are expected in weeks 4, 8, 12, 16, 20, 24 and 42. One pallet contains 25 pieces, which is at the same time the minimum order quantity.

$$Qty_{proposed} = \frac{2 \cdot (Q_{M-1} + Q_{M-2} + Q_{M-3}) + Q_{M-4} + Q_{M-5} + Q_{M-6}}{39 weeks} \cdot \frac{t_{repl} + t_{safety}}{7 \frac{days}{week}} - Qty_{stock} - Qty_{in} + Qty_{res}$$

Equation 3.3: Current formula for proposed order quantity

$$Qty_{proposed} = \frac{2 \cdot (122 + 103 + 112) + 105 + 116 + 119}{39 weeks} \cdot \frac{120 + 90}{7 \frac{days}{week}} - 200 - 560 = 20$$

Equation 3.4: Example – quantity proposed in week 1

The proposed quantity in the list would then be rounded up to be 25 pieces.

3.2.1 Systematic errors and misuse

The current equation for the proposed quantity (equation 3.3) does fundamentally follow the reorder point system as shown in equation 3.5.

$$Reorder\ point = normal\ consumption\ during\ leadtime\ + safety\ stock$$

Equation 3.5: Reorder point formula

Whenever the current inventory position falls below the reorder point, an order is triggered. The inventory position is defined as stock on hand plus incoming stock plus reserved quantity. Reserved quantities are those quantities for which sales orders have been received but which have not yet been delivered. The reasons for this can either be stock-outs or that the customer specified a delivery date in future (common for project customers).

Slightly rewriting the currently implemented formula (equation 3.3) delivers:

$$Qty_{proposed} = \underbrace{Qty_{Monthly} \cdot \frac{t_{repl}}{7}}_{\text{Normal consumption during lead time (replenishment time)}} + \underbrace{Qty_{Monthly} \cdot \frac{t_{safety}}{7}}_{\text{Safety stock}} - \underbrace{(Qty_{stock} + Qty_{in} - Qty_{res})}_{\text{Current inventory position}}$$

Equation 3.6: Reorder point formula rewritten 1

By adding the current inventory positions on both sides, equation 3.7 can be derived.

$$\underbrace{(Qty_{stock} + Qty_{in} - Qty_{res})}_{\text{Current inventory position}} + \underbrace{Qty_{proposed}}_{\text{Shortfall quantity}} = \overbrace{\underbrace{Qty_{Monthly} \cdot \frac{t_{repl}}{7}}_{\text{Normal consumption during lead time (replenishment time)}} + \underbrace{Qty_{Monthly} \cdot \frac{t_{safety}}{7}}_{\text{Safety stock}}}^{\text{Reorder point}}$$

Equation 3.7: Reorder point formula rewritten 2

In equation 3.7 it can now be easily recognized that the $Qty_{proposed}$ as per current implementation just represents the shortfall of the inventory position with regards to the reorder point. The reorder point method in its definition does, though, not prescribe the quantity to be ordered. Its purpose is solely to trigger an order of which the quantity is then determined by some kind of EOQ calculation. The implication of this is that the system is working with a permanent violation of the safety stock, which in turn makes it hyperactive (unstable). If the purchaser would follow the proposed quantity, merely the shortage is rectified. One week later, when the purchase proposal is run again, the inventory position is weakened by the withdrawal of last week's sales quantity. Again the inventory position falls short, which would again trigger an order for the shortage quantity. Ultimately, the organization would end up ordering every week.

We come back to the example, where 25 pieces have been ordered as a consequence of the last review. In the following week of the review, 28 pieces have been sold, which reduced the stock quantity by 28 pieces. Due to last week's order, the sum of incoming shipments has increased by 25 pieces, so that the overall inventory position was reduced by 3 pieces.

$$Qty_{proposed} = \frac{2\cdot(122+103+112)+105+116+119}{39 weeks}\cdot\frac{120+90}{7\frac{days}{week}} - (200-28)-(560+25) = 23$$

Equation 3.8: Example – quantity proposed in week 2

The purchase proposal would now – only one week after the placement of an order – again suggest a purchase of 25 pieces, which would finally repeat every week.

To illustrate the problem, the current system was simulated for a constant trend demand and for a more complex lifecycle demand. Orders have been placed as per proposal.

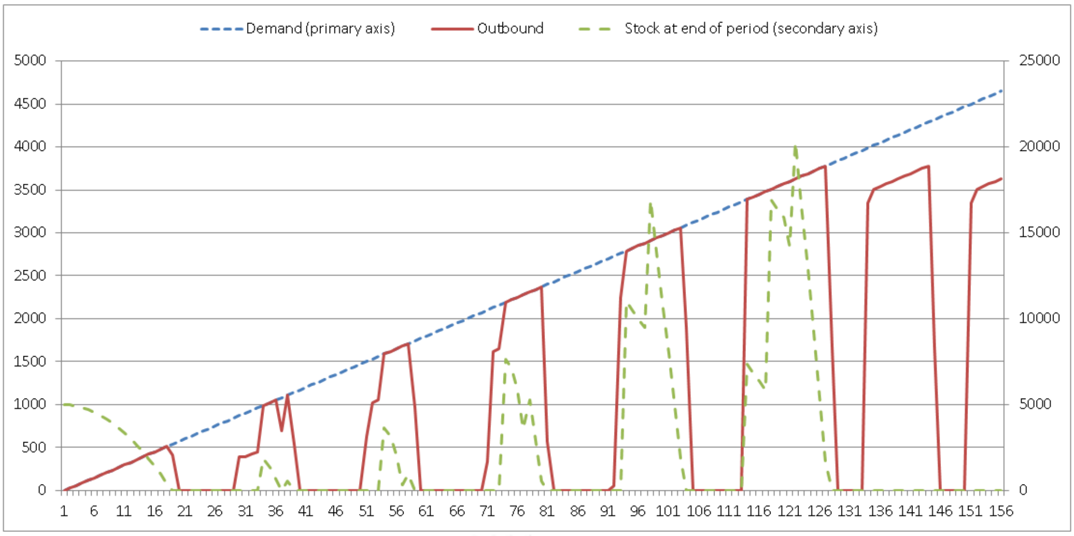

Fig. 3.1: Reaction of current system on constant trend demand

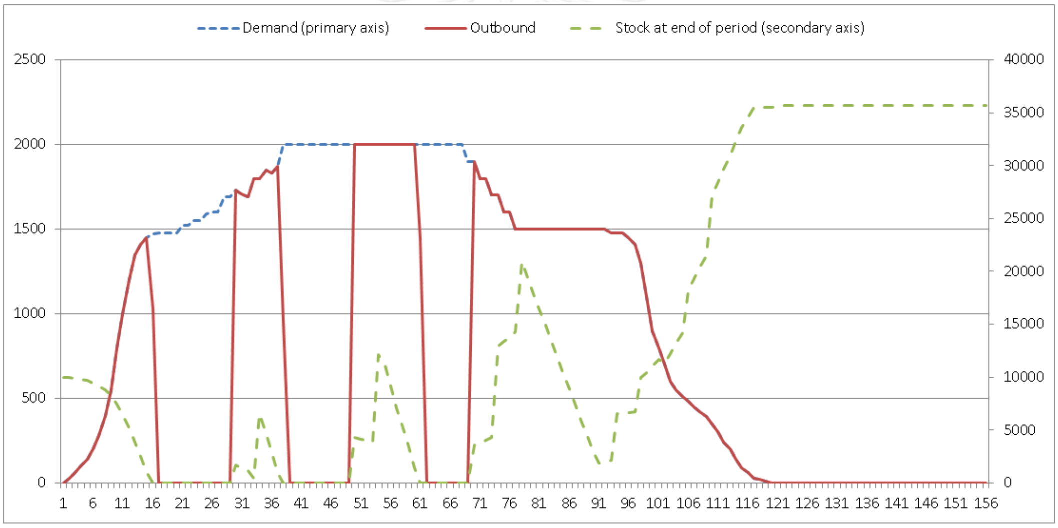

Fig. 3.2: Reaction of current system on lifecycle shaped demand

Both illustrations show that the system in itself is extremely instable since it is highly vulnerable to stock-outs and trend. The effect gets amplified by long lead times but especially by improper application of safety stock that replaces the missing EOQ calculation. In result the actually placed order will most likely not follow the proposal. Instead it can be expected that the safety stock gets compromised by using it as cycle stock. In this case the alert that urges the purchaser to run the purchase proposal would usually get ignored, which ultimately undermines the entire purpose of the purchase proposal.

3.2.2 Negligence of costs during decision making

It was just shown that the purchase proposal merely fills the stock level up to the reorder point and that an EOQ consideration is entirely missing. Howsoever the purchase proposal is used, the resulting financial impact of the purchasing decision is not evaluated by the system. Fundamentally, the purchase proposal provides a good basis for efficient ordering as it is already supplier based, which is expedient for combining shipments and hence generating transport cost savings. However, the items displayed in this list have different lead times and would normally not get despatched at the same time. The desired delivery date for each purchase order is specified by the purchaser in the purchase order. Thus shorter lead times of some articles might be prolonged to match those of items with longer lead times, which nullifies the advantages of shorter lead times for the supply chain.

3.2.3 Demand forecasting

3.2.3.1 Method selection

The proposal formula in its current implementation uses the weighted moving average of the last six month to determine the normal consumption. This function belongs to the class of lagging forecasting methods and is, therewith not able to detect trends. This is not necessarily negative, but surely not suitable for forecasting new products and products in phase-out stage. Figure 3.3 illustrates the lag of goods arrival in the case of 120 days lead time. For the forecasting of new items different approaches have to be found. In general, the application of one forecasting method for all items seems inappropriate. Seasonality is another aspect that is worth to be considered, considering the review of customer types that was performed in the introduction.

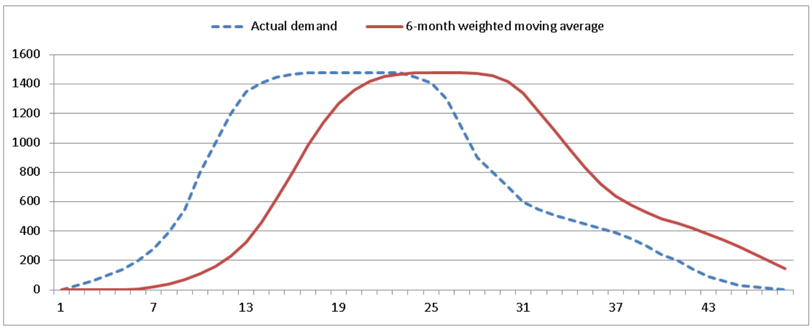

Fig.3.3: Lagging of the 6-month weighted moving average with 120 days lead time

3.2.3.2 One-time orders

Another disadvantage is the fact that the formula bases the demand forecast on the overall sales figures. Yet, Hafele supplies to project customers, which often place one-time orders that should not be considered during future demand forecasting. Currently there is no possibility to include sales intelligence into the demand forecast and, thereby, to add a qualitative component.

3.2.3.3 Available data

The forecasting is based on picked quantity. In case of stock-outs, where the picked quantity is low or even zero, wrong interpretations are the consequence, which might lead to wrong demand forecasts.

3.2.4 Further issues

3.2.4.1 Safety stocks

Beyond the fact that the current calculation works with a permanent violation of the safety stocks, the fact that the safety time is static for all x-items and does not depend on the actual demand fluctuations is suboptimal. As Hau and Billington (1992) have remarked, just because an item is frequently ordered and hence classified as x-item, it does not mean that the required safety stock quantity is high as demand patterns could be still very consistent. Instead, safety stocks should be defined on item basis depending on the variations of the item’s demand. The service level could, though, be defined for product clusters.

3.2.4.2 Ignorance of horizon

In this chapter’s illustration example (section 3.2), seven incoming shipments of 80 pieces each are expected in weeks 4, 8, 12, 16, 20, 24 and 42. The inventory position calculates the sum of current stock and incoming shipments minus the reserved quantity. In fact, the last shipment in week 42 arrives far beyond the forecast horizon and can, therefore, not be considered in the inventory position, as it arrives too late for the demand. This is a frequent scenario for frame contracts, where periodic orders are placed long time in advance in return for lower prices. To solve this issue, it would be required to also look at the period of incoming shipments and demand.

3.3 Chapter summary

Within this chapter it was discussed that the organization is currently employing a periodic inventory review policy, which is advantageous for joint ordering and also handier in regards to the high number of daily inventory transactions.

It was, though, identified that the actual proposal logic in its current implementation has severe short comings that limit its usability. The most serious issue is the fact that ordering the proposed quantity would merely fill up the inventory position to the reorder point, which ultimately leads to weekly ordering or to permanent violations of safety stock levels. The impact is either way negative, which is why the current function can fundamentally only be used as a trigger for manual evaluation.

For this reason, the purchase department is currently re-assessing the proposal for each supplier manually by looking at previous demand history, customer behaviour, shipping cost and the like. As always, and especially when considering the high number of purchase orders that the company issues, manual re-evaluation is subjective, does not include the full variety factors that need to be considered, and is vulnerable to mistakes.

4 APPLIED FORECASTING AND SAFETY STOCK CALCULATION

This chapter will apply the theoretical framework of demand forecasting that was discussed in the literature review to the business of Hafele. Furthermore, the calculation of safety stocks, and the translation of the demand forecast into an order schedule is discussed.

4.1 Operational requirements

Beyond the consideration of the general requirements with regards to forecasting mentioned in section 2.2, the following constraints that are partially specific to Hafele and its business must be kept in mind during the adjacent evaluation and implementation of forecasting techniques.

- To be used in an EOQ calculation the output should be on weekly basis
- The forecast has to be made on individual product level
- The forecast has to be made for 8,000 stock items
- Lead times are with up to 130 days comparably long
- The available historic data is based on picked quantity

4.1.1 Expected outcome

The expected outcome of the demand forecasting and adjacent safety stock calculation is a demand plan on weekly basis since shipments are also scheduled on weekly basis. The volatility of weekly demand can be expected to be significantly higher than of monthly demand, as aggregation effects with regards to time are reduced (Thomopoulos, 2015). This is illustrated in figure 4.1 and 4.2 where the frequency distributions for both weekly and monthly demand of the best-selling knob-lock set are shown.

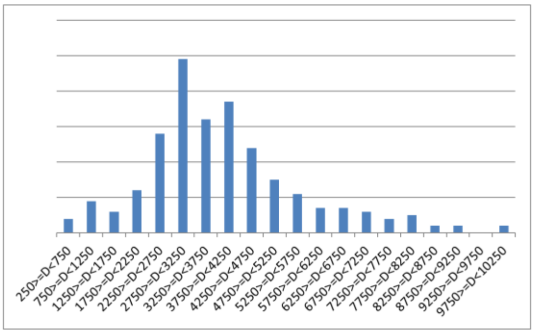

Fig.4.1:Frequency distribution of weekly demand[2]

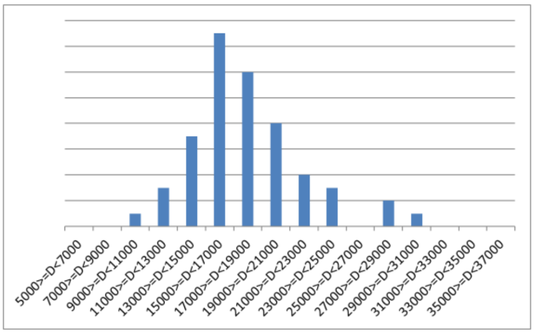

Fig.4.2:Frequency distribution of monthly demand

As expected, the variance of the weekly demand is higher than that of the monthly demand, which increases the difficulty of pattern recognition and hence implies higher demand and parameter risk. In this context Thomopoulos (2015) does also remark that the likelihood to identify seasonal patterns on weekly basis is low. For this reason, the forecasting that is described within this chapter shall be performed on monthly basis. Afterwards, the obtained forecasting result shall be split into weekly figures to match the expected output format.

4.1.2 Individual product forecast

The markets for furniture fittings, architectural hardware and sanitary items are all well established and hence rather stable and predictable, except for times of major political or financial crises, and natural catastrophes like the 2011 flood.
However, for the purpose of purchasing, the demand must be forecasted on individual SKU level rather than on market level. The right quantity of the wrong SKU can still not satisfy the demand. Yet, the demand which an individual product sees is far more volatile than the overall market demand since positive aggregation effects are again lost. Sales promotions or the award of project business for instance are heavily impacting individual product demand but have low impact on overall market size. Figure 4.3 illustrates the fluctuation of the sold quantity for an individual SKU compared to the sold quantity for all furniture handles. It must be noted that “furniture handle total” only represents Hafele’s share of the market.

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[2] The range of the monthly frequency distribution is 4 times the range of the weekly distribution

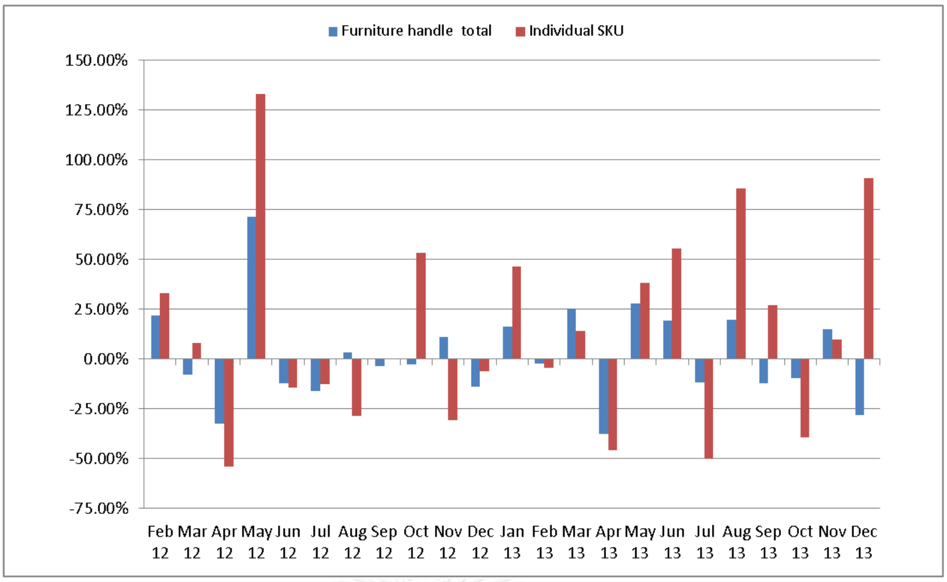


Fig. 4.3: Percentage change of sold quantity in percentage with regards to previous month

The average absolute percentage change of "furniture handle total" is 18% whilst the individual SKU sees fluctuations of "38%", which is hence much harder to predict. Forecasting on individual product level does also mean that forecasts have to be made for 8,000 SKU, which calls for highly automated processes in order to reduce workload.

4.1.3 Forecasting horizon

The forecasting horizon must allow for an adequate application of the EOQ calculation, which means that quite a number of periods beyond the replenishment time have to be forecasted. Products with small demand can be expected to need a longer horizon for a proper evaluation of consolidation effects. Narayanan and Robinson (2010) did, though, recommend that the overall planning horizon should be maximal two times as long as the frozen period for reasons of system stability.
The replenishment time is product specific and varies between 45 to 130 days. Yet, to solve the joint replenishment problems, the horizon of different SKUs should be equal. Since the typical replenishment time is 120 days, the forecasting horizon shall be fixed to 8 months, which is generally considered as medium term.

4.1.4 Source of data

The ERP system holds pick data available for the last 5 years. This means that only the actually sold/utilized data is available. The real demand is unknown.

4.2 Input data assessment and correction

4.2.1 An overview

The base of historic demand that the organization's ERP system withholds is – with over 5 years of recording – comprehensive and hence a good basis for intrinsic forecasting. In a first stage, the usability of the historic data shall be evaluated with regards to the criteria addressed in the literature research.

First, the absence of external influences was a prerequisite to apply intrinsic forecasting. Actually, the 2011 flood and its aftermaths as well as the 2014 political crisis weakened the validity of the data. Beyond that the organization factually committed its own mayhem with the data by frequently running special events and promotions for individual products or product groups without proper recording.

Second, it was claimed that the captured data must represent actual demand rather than sales figures. Yet, the captured data is based on actual pick data from the warehouse and does hence not include lost sales opportunities. For best sellers where stock levels are very high and that as a consequence not faced any stock-outs, this is not so much of a problem. For those items that are medium to slow selling but still classified as stock items, this is indeed a problem that has to be solved.

Third, it was stipulated that no extraordinary external events are expected for the future. Apart from some major project businesses that might come up unexpectedly, there are no reasons foreseen why the demand should not continue as before.

Overall, the expectations with regards to the forecast quality are retrenched due to concerns with regards to the available data. However, even if quantitative-intrinsic forecasting might not the best for all items, the huge number of forecasts to be made calls for “you have to work with what you've got". In this respect, the subsequent part of this section is dedicated to identifying not only further problematic issues with regards to the data, but also ways of treating these problems.

4.2.2 Sample demand patterns

To get an overview of how diverse the demand pattern for different items can be, the sales charts for three stock items are presented within this section. As the organization's number one ranking product in terms of revenue, the knob-lock set of which the sales curve is presented in figure 4.4 could be expected to have rather stable demand.

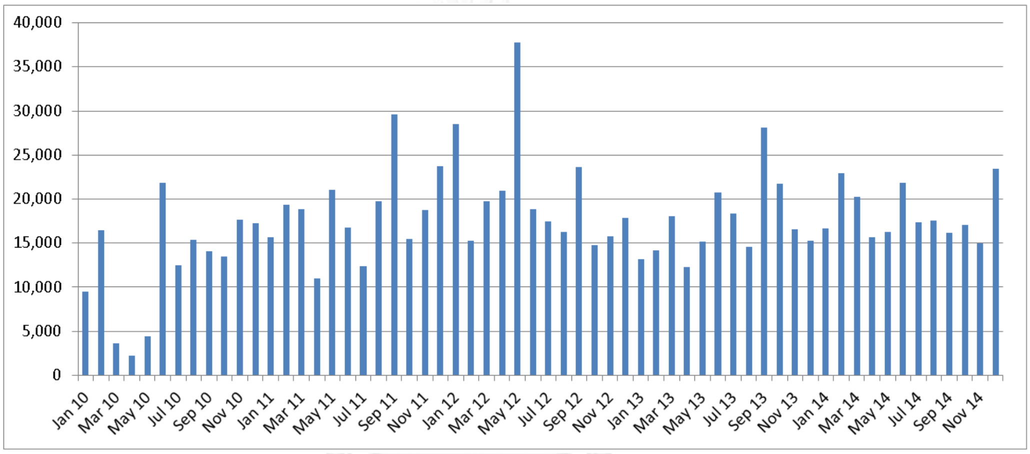


Fig. 4.4: Picked quantity of top selling knob-lock set

However, it can be observed that fluctuations of up to 250% between individual months within a year can be observed. Other items, such as the furniture handle displayed in figure 4.5, show overall lower sales but even higher fluctuations.

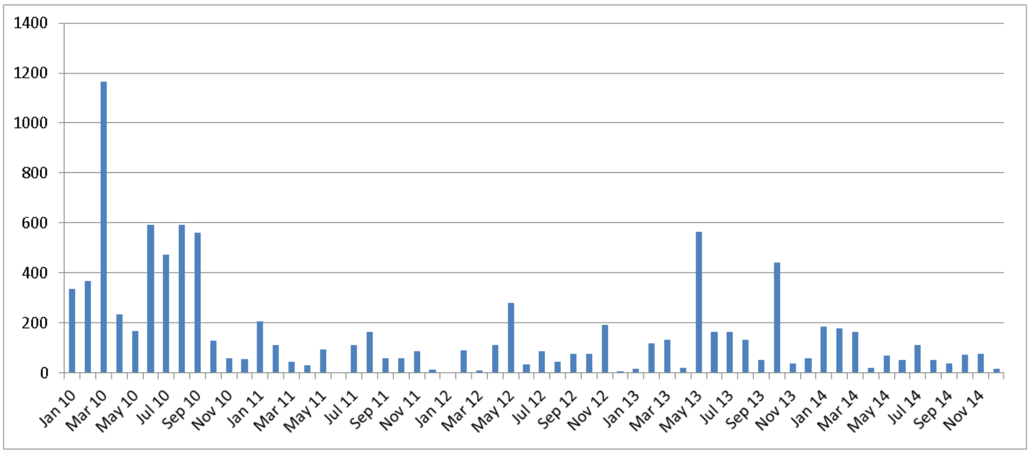


Fig 4.5: Picked quantity of a furniture handle

Even some items with very low and sporadic sales – like the mounting plate in figure 4.6 – are classified as stock items, as they might be necessary to complete a range. Realistically, it seems impossible to predict these highly sporadic sales in anyway since they appear to be entirely random.

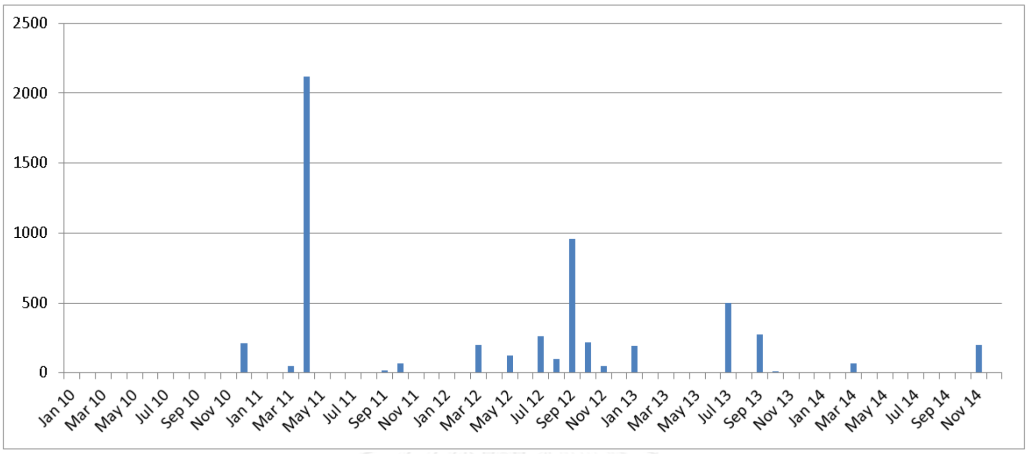
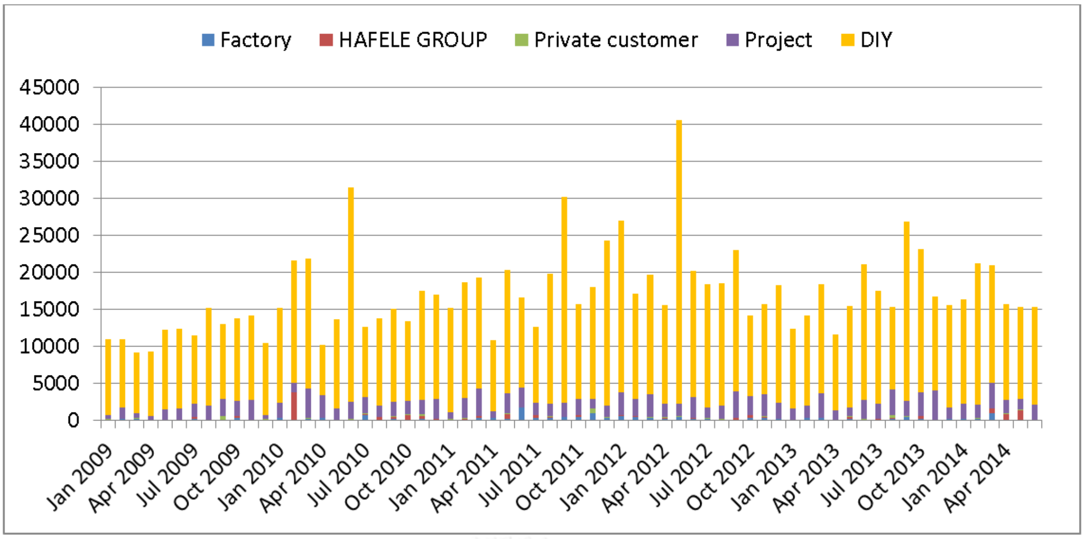


Fig 4.6: Picked quantity of a mounting plate

For items like this (z-items) it should be considered to set a fixed reorder level. Considering that the mounting plate in figure 4.6 has a pallet quantity of around 20,000 pieces that can satisfy the demand over a longer period, the yield of economic order quantity considerations and forecasting seems not to justify the efforts. MOQ requirements imposed by most suppliers – usually at least one pallet – would not allow for much optimization nevertheless. Hence fixing the reorder point for z-items and maybe some y-items appears to be viable option. For other items (x, y, and some z-items), the considerations in the adjacent sections apply.

4.2.3 Demand peaks

The picked quantity of the knob-lock set in figure 4.4 shows that a rather steady demand is regularly distorted by significant peaks. Splitting the ordered quantity into the different customer groups (figure 4.7) clearly reveals that DIY/modern trade customers are the reason for the peaks, as the sum for all other customer group not even exceeds 5,000 pieces.



Fig, 4.7: Split of ordered quantity by customer group for knob-lock set

In a next step it can be found that most of extraordinary quantities that are displayed in figure 4.7 are not a result of an unusually high number of orders, which means that individual orders must have provoked the swings, see figure 4.8.

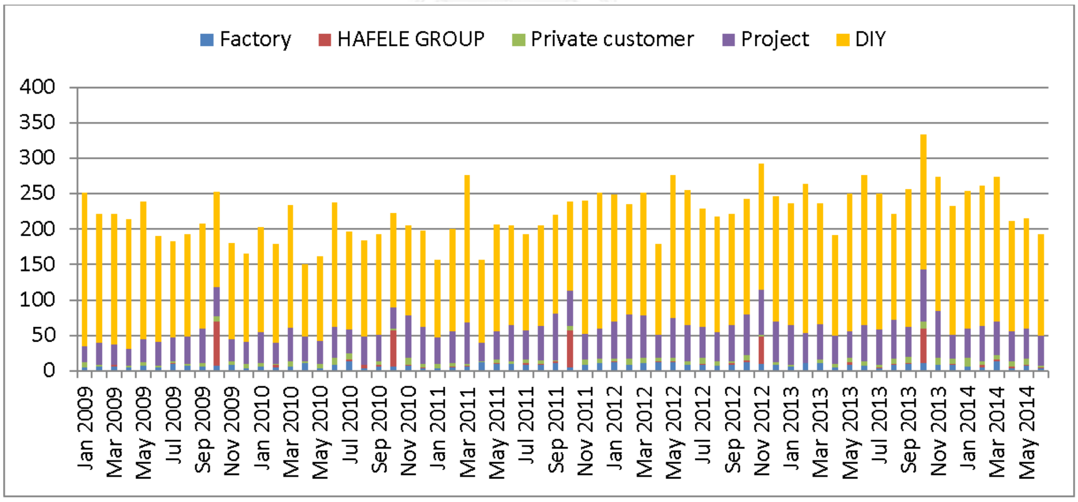


Fig.4.8: Split of order count by customer group for knob-lock set

Plotting the frequency of orders for different order quantities delivers that a low number of orders contains very high quantities. The according frequency distribution is illustrated in figure 4.9.

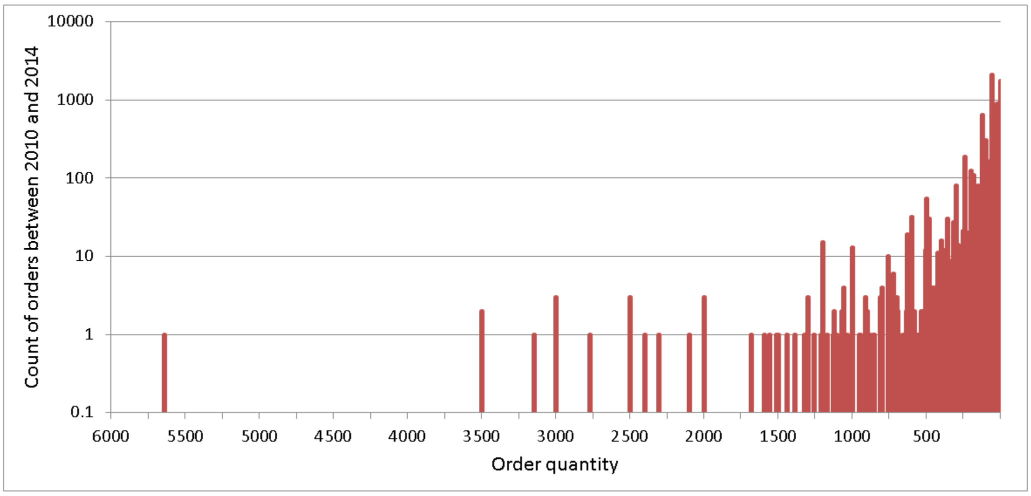


Fig. 4.9: Frequency distribution by order quantity

Moreover, different orders do not automatically mean different customers. Therefore, figure 4.10 shows the accumulated order quantity of different branches of one and the same DIY chain. Since the difference is more than four MAD, it can be expected that something extraordinary has motivated this customer to suddenly order such a huge quantity, which solely accounts for the highest spike in May 2012.

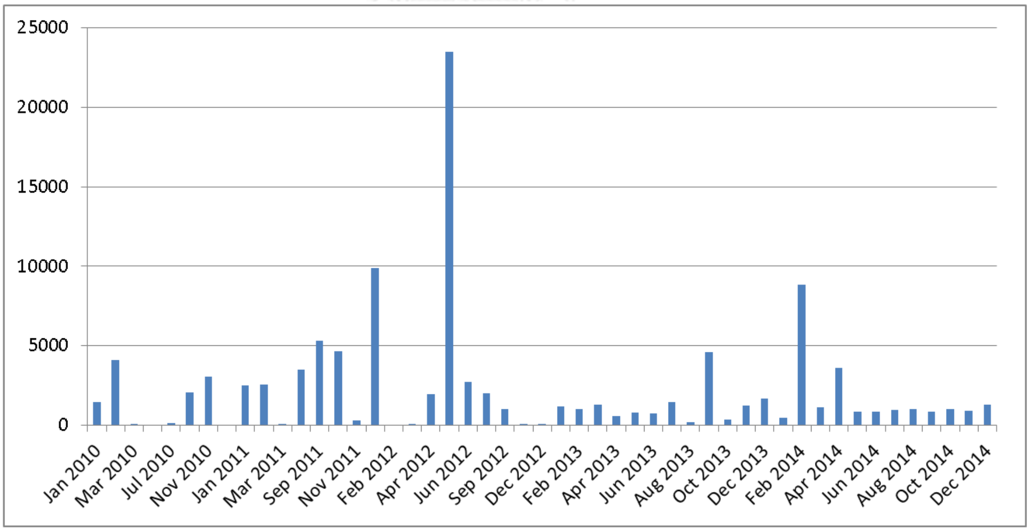


Fig. 4.10: Quantity ordered by a single DIY customer for knob-lock set

A similar behaviour can be observed for many products, which is why it would highly beneficial if upcoming extraordinary orders could be anticipated and in some way included in the forecast in order to initiate appropriate countermeasures. For this purpose customer demand planning – a function to integrate qualitative predictions into the forecast – shall be discussed in section 4.3.

4.2.4 Stock-outs

The data withhold by the ERP system is based on pick data and does hence neglect missed out sales by stock-outs. In retrospect, stock-outs are hard to differentiate from zero demand – especially in case of low demand items like presented in figure 4.6. There are different approaches on how to handle these cases. Some statistical software uses the average of the neighbouring values to replace the missing value, whilst recommending manual replacement due to potential seasonality distortions that can be caused by automatic replacements (NCSS Statistical Software, n.d.).

However, stock-outs might not always lead to sales values that are equal to zero and remain hence undetected. For instance, the delivery of five pieces when the customer requested two hundred has also to be considered as a stock-out, even though the quantity in the history is unequal to zero.

The company's ERP system records the stock level on item level at the end of each day, which is not yet utilized in the context of demand forecasting but could be used as an indicator of stock-outs. During forecasting, those days of a month that have seen a stock-out shall be counted. This number is then used to correct the monthly figure by replacing stock-out days with the 3 months moving average of the non-stock out days. Here, the 3- months moving average is recommended instead of the average of the affected month as it can be expected that there are some irregularities in the sales before and after the stock-out, e.g. backorder are fulfilled that increase the perceived sales. It shall also be noted that in practical stock-outs must not equal a stock level of zero. For instance the availability of one door hinge is not sufficient to equip a door, which is why the effect of non-saleability is still observed. Thresholds should hence be set to some level above zero, e.g. one week's demand.

It should be furthermore considered to use some kind of daily stock level chart for information purpose in the purchase proposal screen. Figure 4.11 illustrates that the chart is likely to provide good insights as safety stock violations and overstocks are easy to identify. This visibility can be expected to significantly increase the awareness of the purchasing staffs.

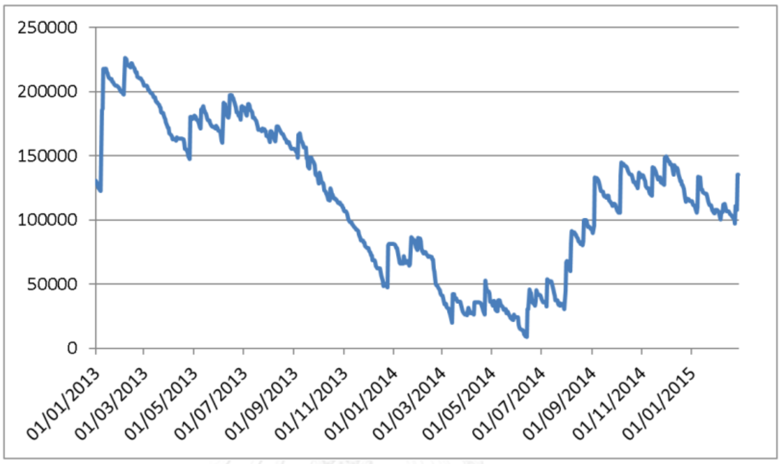


Fig 4.11: Daily stock level at the end of the day of knob-lock set 2013 to 2015

4.2.5 Assumption of trend

With regards to overall revenue, the company grows from year to year. It can hence be expected that also the sales quantities of individual products will be subjected to trend, which calls for forecasting methods that can handle the trend pattern.

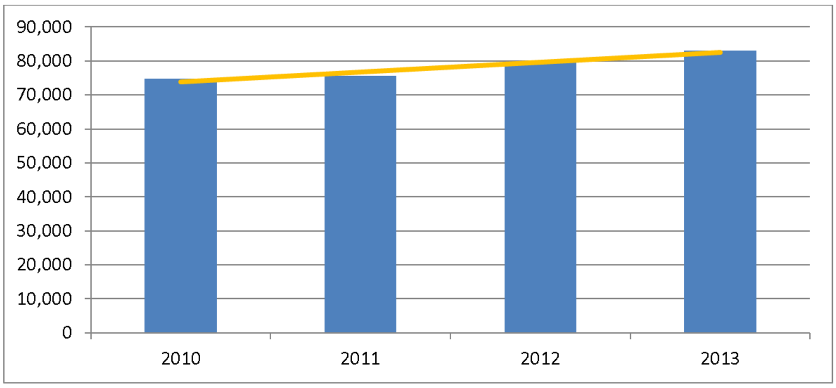


Fig. 4.12: Trend of yearly demand for furniture handles seen by Hafele

4.2.6 Seasonality

The products of Hafele themselves do not have an intrinsic seasonality, as it is neither fancy to give away toilet bowls for Christmas nor are furniture handles especially stylish during summer seasons. However, looking at the revenue chart presented in figure 4.13 some signs of seasonality can be observed.

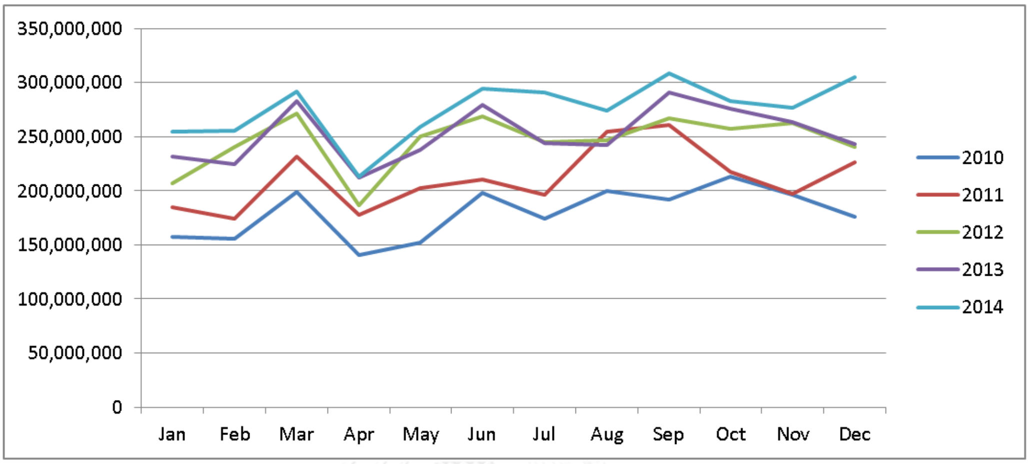


Fig. 4.13: Monthly revenue 2010 to 2014

Since only a small percentage of the revenue is generated from direct sales, ordering practices of intermediaries play a role. Many carpenter shops for instance are closed during Chinese New year in February, which lowers the demand especially for furniture fittings. In April, the Songkran festival, which is the main holiday season in Thailand, takes place. June, July and August are impacted by the raining season, which usually leads to less construction activities and hence reduced demand for architectural hardware. The increase towards the end of the year can be associated with the need to spend budgets on customer side, and with a pursuit of sales targets on Hafele site.

The severity of the fluctuations is also perfectly illustrated by the figure 4.14, which shows how the sales quantity varies over different calendar weeks. Seasonality appears to be a must for consideration during further analysis. The qualitative discussions of the causes for seasonality brought about that seasonality might not be the same for different items and should hence be considered on individual SKU level or at least on product cluster level. In conclusion, the implementation of a seasonality pattern appears mandatory.

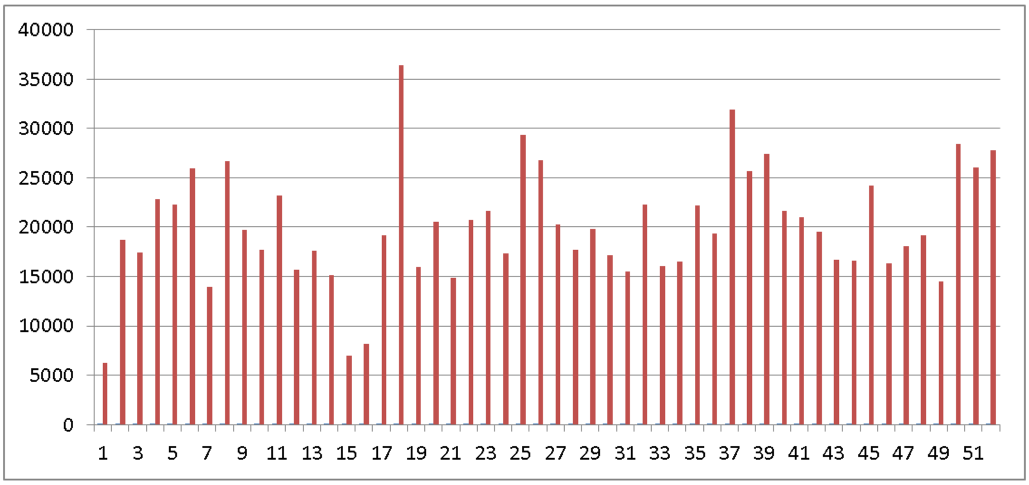


Fig. 4.14: Accumulated sales quantity for the knob-lock set per calendar weeks (2010 to 2014)

4.3 Customer demand planning

4.3.1 Purpose and applicability

The performed data analysis has shown that extreme spikes (low probability but high impact orders) are often caused by purchasing decisions of individual customers that have a big leverage, e.g. DIY customers, modern trade, or project customers. Even though the willingness and/or ability of those customers to share information on official level are rather limited, key account managers frequently have a hunch that orders are in the pipeline. This is especially true for the project business, where often lengthy negotiations take place prior to contract closing.

Currently, there is no provision in the organization’s ERP system to capture this information and to utilize it for the forecasting, which is why customer demand planning (CDM) shall be proposed for implementation. CDM is the inclusion of customer intelligence as a second information source for the forecasting next to statistical data (Chockalingam, 2012). This means that whenever a sales person sees signs of significant unusual demand, this is entered into the system and onwards becomes part of the forecast. If no information is entered, the forecast is purely based on statistical data. Limiting the manual forecasting to meaningful cases adds a qualitative component to the forecast without adding unbearable workload. This function can also be used to plan for special events such as promotions.

4.3.2 Screen layout and functionality

A dedicated screen shall be provided that allows the responsible sales person to make forecasts for his assigned customers. After entering the staff number, the sales responsible can choose from a dropdown menu for which customer a forecast shall be made.

The horizon for manual forecasting shall be 8 months and, therewith, equal to the quantitative horizon. Depending on the replenishment time of an item, it is only possible to enter forecasts well in advance. The frozen period – those months that cannot be changed anymore – are greyed out. For the free interval, it is then possible to enter the projected additional demand on a weekly basis. Thereby, additional consumption must be differentiated into two types:

- Type 1: One-time events, like a project or a sales promotion
- Type 2: Additional normal consumption that cannot be predicted from the demand history, like the launch of an existing product at a DIY chain, or a product introduction that will have a long term impact on the demand of the item

It is important to clearly separate both types of additional consumption as they have to be differently treated with regards to their inclusion into the demand history, see section 4.3.4. To clearly separate both types, and hence to avoid confusion and wrong utilization, separate entry screens shall be provided. Both screens have exactly the same layout while the entered numbers are treated differently.

Beyond the mere entering table for the forecast, the normal consumption of the customer, the demand history, and the sales person's forecast history shall be displayed for information purpose. The normal consumption on customer-item-level shall thereby be calculated by the weighted 6-month moving average, which is the current standard calculation and which is hence what people are used to. It must be noted that the display of normal consumption is only for information and has no impact on the actual calculation.

As promotions are often involving a higher number of SKUs, an upload function from Microsoft Excel must be available. Since such kind of promotions or events is normally not assignable to a distinct customer, a dummy customer shall be created.

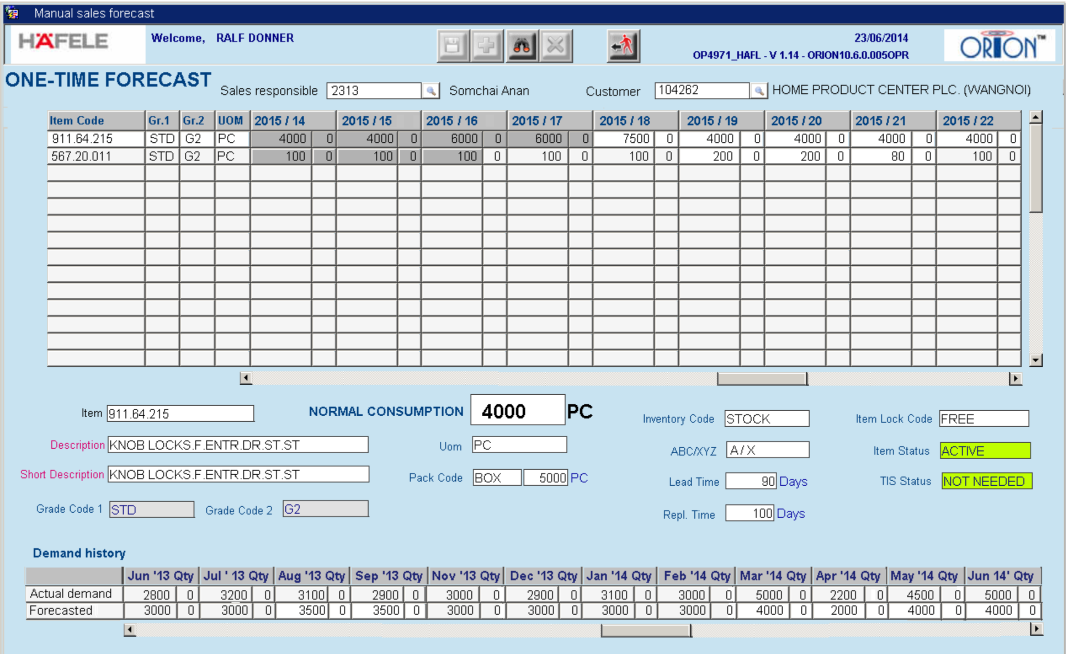


Fig. 4.15: Preliminary design of the manual forecasting screen

4.3.3 Incentive and misuse

The different interests of the various stakeholders in inventory control must be considered at this stage. Since sales persons have a high interest in stock availability in order to treat their customers, the temptation to enter overambitious values is given. To avoid excessive inventory, proper control measures must be implemented. First, the approval of the forecast in the ERP system by the manager should be mandatory. Second, sales management should consider linking sales incentives to the accuracy of forecasts that are made. As these two measures might discourage from manual forecasting, there must also be an incentive to do a forecast. Currently, stock stealing is a contentious point within the organization. Stock stealing means that sales person A makes a forecast for one of his customers, but ultimately a customer of person B issues the sales order before A and hence gets the stock. Therefore, the stock should be soft-reserved for the “owner” of the forecast, which can, though be released by the manager (as per business policy, normal stock reservations are not allowed for x-items). To avoid that the stock idles away, the soft-reservation shall auto-expire within one month, which allows for minor impreciseness in terms of time.

4.3.4 Inclusion into the quantitative forecasting

If either of the two manual forecast types was entered for a particular week, it shall be added on top of the week's normal consumption that gets calculated from the demand history via quantitative intrinsic forecasting and then split into weekly portions.

	Normal consumption
+	Type 1 forecast (one-time)
+	Type 2 forecast (change in normal consumption)
=	Projected consumption

Based on the projected consumption, the organization is able to build up anticipation inventory to support forecasted business opportunities. Once the actual sale took place, the quantity of the sales order normally passes into the demand history. At this stage the proceeding for the two types of forecast differ, as one-time order forecasts shall – other than additional normal consumption forecasts – not find their way into the demand history.

Thereby, the difficulty of matching actual order quantity and projected consumption arises. This is especially problematic when the actual consumption is lower than the normal consumption. The following rules shall be followed:

- Rule 1: If the sold quantity is smaller than the normal consumption, then the sold quantity shall be taken up into the demand history (case 1). It is assumed that the forecast was wrong.

- Rule 2: If the sold quantity is greater than the normal consumption, then at least the normal consumption shall be taken up into the demand history (case 2).

- Rule 3 (for non-project customers only): Everything that goes beyond the normal consumption plus the type 1 forecast shall be taken up into the demand history (case 3, 4).

- Rule 4 (for project customers only): If the actual demand is greater than the projected consumption, all orders with a quantity greater than 4 MAD are excluded, but the corrected quantity shall not fall below the projected demand. Normal consumption and type 1 forecast are deducted from the corrected quantity. The remaining part is taken on into the demand history (case 5).

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Normal consumption	1000	1000	1000	1000	1000	1000
Type 1 forecast	1000	1000	1000	1000	1000	1000
Type 2 forecast	500	500	500	500	500	800
Sum of actual order qty	800	1300	2300	3000	3000*	3000*
Value that is logged into the demand history	= 800	= 1000	= 1300	= 2500	=1600	=1800

*One order for 400 pieces is greater than 4 MAD and gets, therefore, excluded.

Table 4.1: Examples for the demand history rules

These rules can be implemented by means of if-clauses and are hence suitable for easy implementation.

4.3.5 Summary

The customer demand planning brings about two main advantages:

- Qualitative sales intelligence can be included in the forecast to provide adequate stock to support additional business opportunity. This is especially valuable for:
    - One-time orders
    - New product introductions
    - Quantitatively unpredictable increases in trend, e.g. by launching a product at a new customer

- The demand history quality improves over time, as spikes caused by one-time orders are reduced

4.4 Quantitative-intrinsic forecasting component

The customer demand planning added a qualitative note to the forecasting that will support the forecasting for non-regular cases. Onwards, the design of the quantitative-intrinsic forecasting methodology – which can be considered as the centerpiece of the forecasting module – shall be discussed. With a view to model and parameter risk, the selection of the right method is the essential of quantitative forecasting.

For the method selection it is a common practice to cluster products, e.g. by customer group or by product type. However, contrasting the sales figures for different knob-locks in figure 4.16 reveals that similarities like seasonality are given but that especially the scale (which impacts parameter selection) diverts significantly, particularly for knob-lock type A and B.

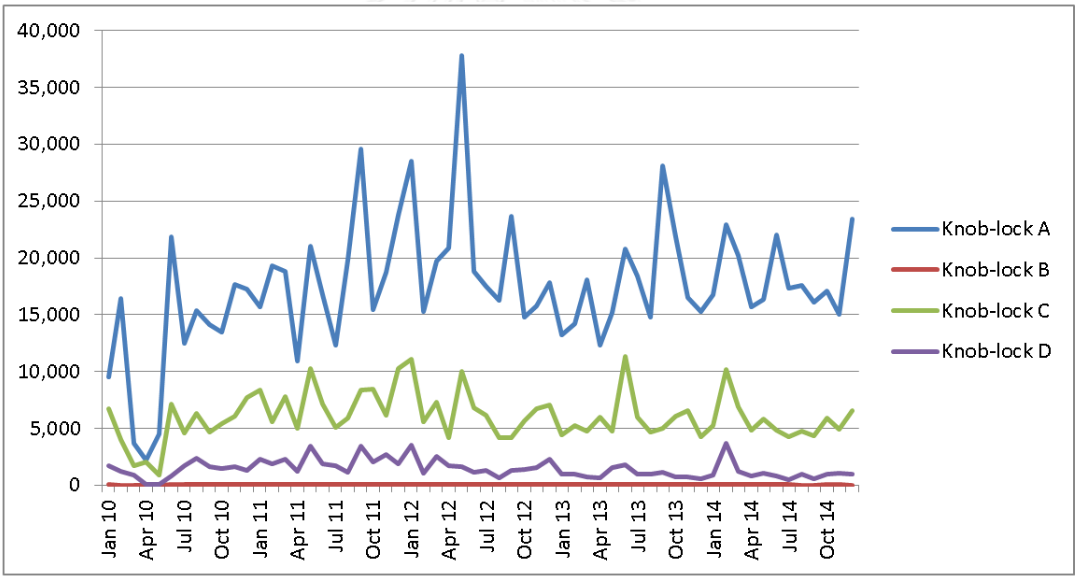


Fig. 4.16: Time series for different SKUs of the same product category

In conclusion, it seems even inappropriate to apply common forecasting methods with common parameters to different items of the same cluster. However, for 8,000 items it is impossible to manually select individual patterns, especially when considering that patterns can change over the time and that hence frequent reviewing is required. For this reason, automatic pattern recognition shall be implemented,

4.4.1 Principle of automatic pattern recognition

Axsäter (2006) and Toomey (2000) stressed both that patterns, which can be observed in the past, are likely to continue in future. Based on this principle, the forecasting method that produced the best results in the past shall be identified and onwards used for the prediction of future values.

Therefore, a selection of forecasting techniques is deployed on past data to forecast more recent but known demand. The various forecasts are then compared with the actual data of the recent past. The method that performed best is then taken to predict the values for the future. Yet, not only the method but also the parameters that provide the best fit must be identified. Figure 4.17 illustrates this process.

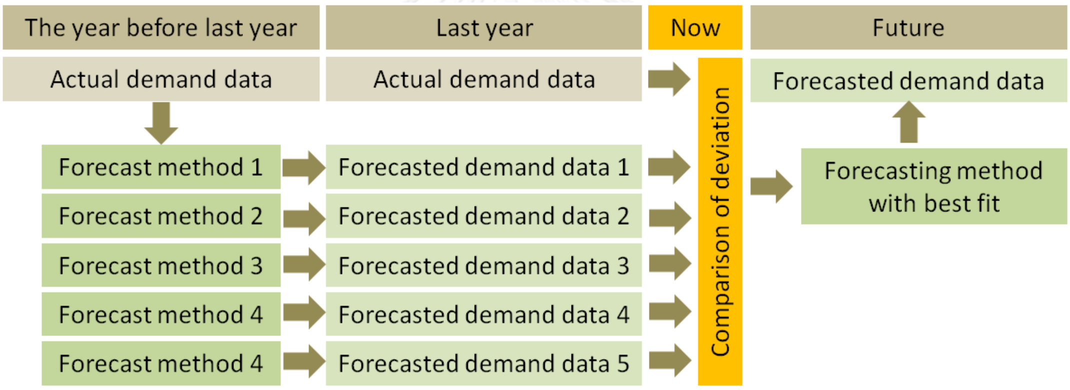


Fig. 4.17: Schematic of pattern fitting

For this purpose a Visual Basic macro was implemented that in a first step selects and displays the forecasting method, which provided the best fit out of the pool of forecasting methods that have been included.

In a second step forecasts for future periods can be made. To allow for an easy assessment of a forecast's reasonability, the forecasted values are plotted in continuation of the graph of historic demand. The solid graph in figure 4.18 shows the historic data, whereas the dotted graph shows the forecast. Such visualization is also recommended for the actual purchase proposal in the ERP system, as it will ensure trust and helps to safeguard when the forecasting drifts off for whatever reason.

As a last step, the implemented simulator calculates the required safety stock, which shall, though, be discussed at a later point within this chapter.

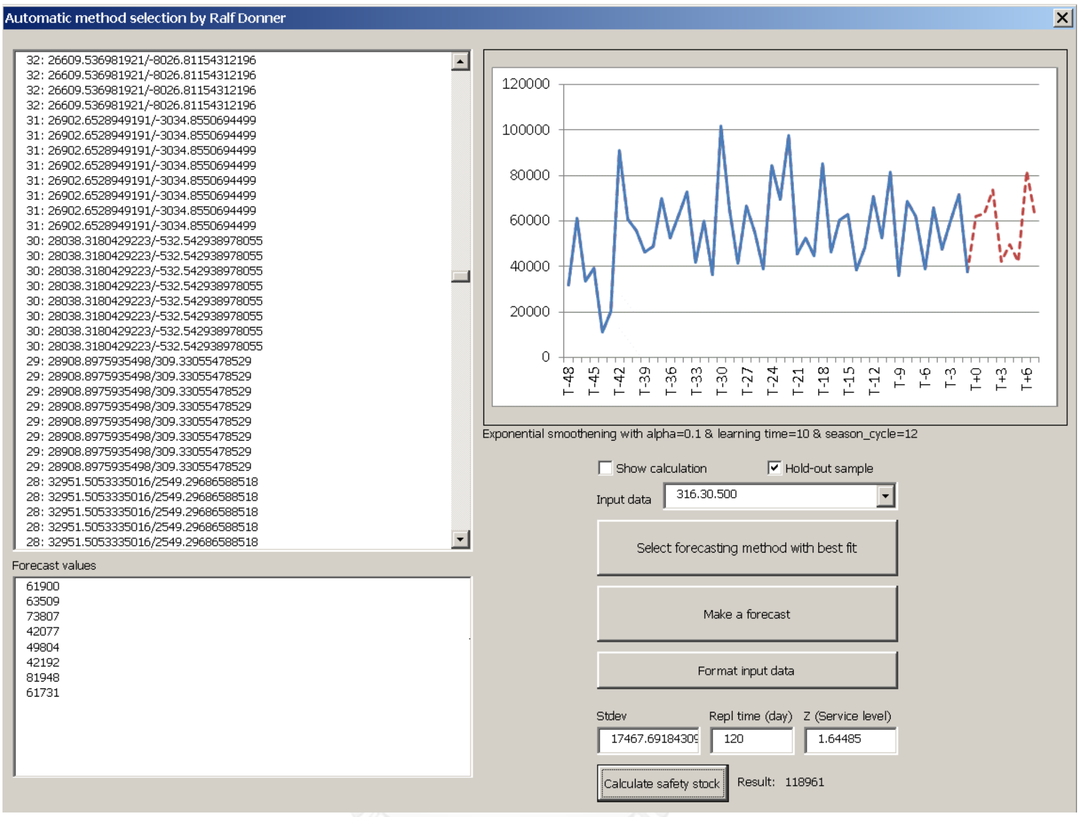


Fig. 4.18: Screenshot of implemented forecasting tool

4.4.2 Selection criteria for automatic pattern recognition

In the previous section it was discussed that the forecast method that provides the best fit is selected. Yet, "best fit" is a qualitative term that needs to be translated into a quantitative measure that can be assessed by an IT function.

4.4.2.1 Difficulty of measure selection

The validity of the forecast output is highly dependent on the criteria upon which the best forecasting method and its parameters are selected. Within the literature research, a small range of different measures like MAPE, MPE, and MAD has been discussed. Yet, benchmarking with existing statistics analysis tools unveils that these softwares offer far more measures to choose from, see figure 4.19.

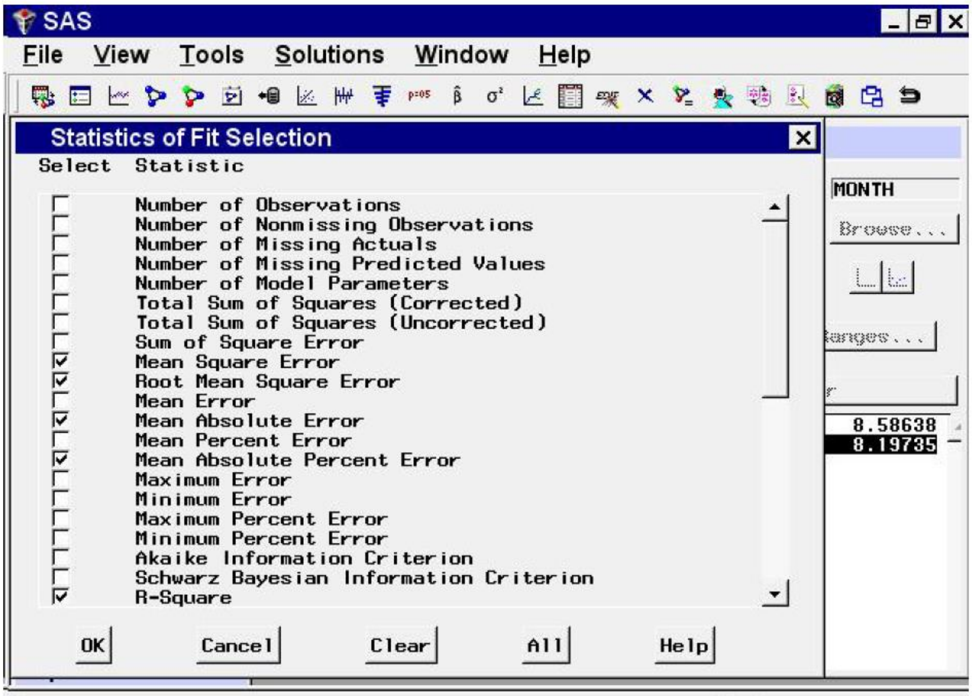


Fig. 4.19: Selection of evaluation measures (SAS Documentation, n.d.)

Upon measure selection, these softwares contrast different forecasting methods with regards to their performance for a specific data history. Figure 4.20 shows the according illustration of the results for two forecasting methods that get deployed on the same data set.

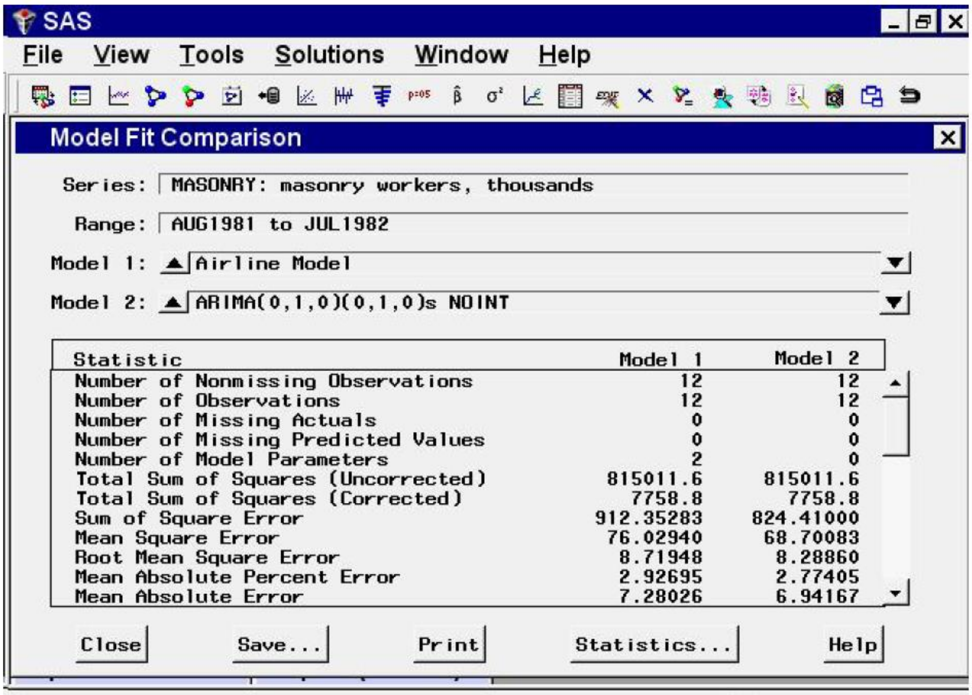


Fig. 4.20: Output of method comparison (SAS Documentation, n.d.)

As long as these measures show all in the same direction it is obvious which method to select. However, in many cases there are contradictions such as that model A performs better in term of measure one whilst model B is ahead for measure two. Already MAPE and MPE often tell another story, which is why the question of which measure to give most credit arises. Frankly spoken, the purchasing department is as per its role description, not a competence center for statistical analysis, and does hence not care too much about the R-square value of a forecast. Factually, the mere forecast values for the required horizon are of interest for the purchaser. This means that the forecast function must not present the statistical test results and ask the user to take decisions upon them, but instead it must automatically select the most appropriate method and apply it to the data. This in turn calls for a single measure to assess the adequacy of a method, which is in line with the requirement of simplicity. As a result it is necessary to identify a single measure that is able to evaluate the methods validity with regards to the business needs and that is robust enough to cope with the quality of historic data that is available.

4.4.2.2 Selection of measure with regards to business purpose

The ultimate target of the forecast is to serve the business, in particular the inventory control and, thereby, the purchasing decision making. Thus, the primary target of the forecasting must be to get that information right that is critical for the purchasing decisions that concern the free interval.

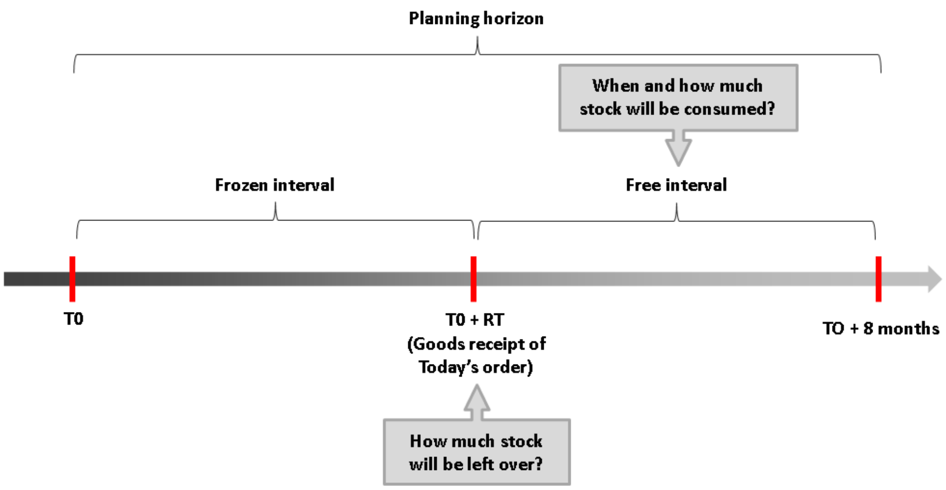


Fig. 4.21: Inventory control related questions

The following two questions are of interest with regards to the purchasing decision:

- How much stock will be left at the end of the replenishment time when the new order will arrive?
- How much stock will be consumed in each week after the replenishment time?

The first question requires contrasting of the current inventory position and the reorder point. The stock at the end of the frozen period that is confined by the replenishment time (T_{RT}) is equivalent to the aggregate of current stock on hand and of the sum of incoming shipments (outstanding orders) during the replenishment time minus the sum of despatched quantity during the replenishment time.

$$Stock(T_{RT}) = stock\ on\ hand(T_0) + \sum_{t=0}^{RT} outstanding\ orders(t) - \sum_{t=0}^{RT} consumption(t)$$

Equation 4.1: Stock level at the end of the replenishment time

The current stock on hand is known. Apart from minor lead time variations the sum of outstanding orders is also known, considering that this period is “frozen” as the lead time has passed. The only variable factor for the determination of the stock at T_{RT} is hence the sum of consumption (demand) in the frozen interval. The exact period in which the demand occurs does, thereby, not play a role as long as the demand takes place within the overall time frame between T_0 (now) and T_{RT}.

It transpires that accurately forecasting the sum of demand is the key to getting the base for further considerations right. It shall, therefore, be stipulated that the forecast accuracy for the sum of n periods is measured instead of for individual periods even if this deviates from common practice. Thereby, n is the count of periods that make up the replenishment time.

4.4.2.3 Assessment process

To receive reliable results it is necessary to assess more than one sample of a forecasting method’s ability to predict the future. Therefore, a running forecast evaluation was implemented, which shall be illustrated with the 3-month moving average for the following example. The replenishment time is 4 month.

Example

Starting with the last demand data that is available (period T-9) the forecast for the next 4 months is performed with the aim of determining the sum error over the replenishment time. The moving average does thereby take only 110 as basis for forecasting since no further values are available.

Period	T-1	T-2	T-3	T-4	T-5	T-6	T-7	T-8	T-9
Demand	190	180	170	160	150	140	130	120	110
Forecast in T-9					110	110	110	110	<<
Sum of actual					540				
Sum of forecast					440				
Error					100				

Table 4.2: Step 1 – forecast based on period T-9

The error is the difference between forecasted sum and actual sum over 4 periods. In a next step the focus period is moved from T-9 to T-8. The moving average for these two periods is 115, which is the forecasted value for the next 4 periods. Again the sum of the forecasted values and the sum of actual values are contrasted, leading to an error of 120.

Period	T-1	T-2	T-3	T-4	T-5	T-6	T-7	T-8	T-9
Demand	190	180	170	160	150	140	130	120	110
Forecast in T-9				115	115	115	115	<<	
Sum of actual				580					
Sum of forecast				460					
Error				120					

Table 4.3: Step 2 – forecast based on period T-8 and T-9

Afterwards the focus is moved to period T-7 where the average of the periods T-7 to T-9 is taken as forecast and sum errors are calculated, see table 4.4.

Period	T-1	T-2	T-3	T-4	T-5	T-6	T-7	T-8	T-9
Demand	190	180	170	160	150	140	130	120	110
Forecast in T-9			120	120	120	120	<<		
Sum of actual			620						
Sum of forecast			480						
Error			140						

Table 4.4: Step 3 – forecast based on period T-7, T-8, and T-9

This process continuous until period T-2 as T-1 is the latest data that is available for comparison, table 4.5.

Period	T-1	T-2	T-3	T-4	T-5	T-6	T-7	T-8	T-9
Demand	190	180	170	160	150	140	130	120	110
Forecast in T-9	170	<<							
Sum Actual	190								
Sum Forecast	170								
Error	20								

Table 4.5: Step 8 – forecast based on period T-2, T-3, and T-4

Yet, the sum forecast errors are comparably small, as the sums are limited to only one period, which might lead to wrong conclusions.

Hold-out sample

As mitigation, the option of "hold-out samples" was implemented with regards to the SAS Documentation (n.d.). This means that the most recent periods are only used for the evaluation of forecasts made in prior periods With regards to the example the periods T-1, T-2, T-3, and T4 are only used to evaluate the forecast that was made in T5 based on the values of T4, T5, and T6.

Yet, expedient, "hold-out samples" is only an option since cutting out the most recent periods might not leave enough periods for the error analysis. For instance if only five periods of historic data are available, cutting out four of them as hold-out sample, would rather harm than help. If this is the case, the errors of the effected periods should be normalized instead.

Focus period	Count of periods for which error sum was calculated	Target periods	Normalized sum error
T-2	1	4	Sum error / 1 * 4
T-3	2	4	Sum error / 2 * 4
T-4	3	4	Sum error / 3 * 4

Table 4.6: Normalization of sum error

As normalizing errors decreases the overall accuracy of the assessment, it shall not be used as a standard. "Hold-out samples" is the preferred option whenever the demand history on-hand allows it. Since 120 days is a typical value for the replenishment time, the threshold for the application of holdout samples should be set to at least one year.

4.4.2.4 Deployment of a measure for accuracy

The recently described process delivered a series of absolute forecasting errors. The values need to be combined in a meaningful way to construct an overall measure, which can be compared with that of another forecasting technique.

When employing the mean percentage error (MPE), the error of each observation is divided by the sum of actuals, leading to a series of percentages that can be either positive or negative. The MPE is then retrieved by dividing the sum of this series by the number of observations. Taking the percentages of errors with regards to the absolute value is reasonable, as this standardizes the results. Yet, the summation of positive and negative values might deliver a result that is close to zero even though huge fluctuations are observed. Fluctuations are, though, a sign that the applied method has reliability problems. As the MPE is not able to detect these fluctuations, its application is not recommend

The tracking signal presented by Toomey (2000) exhibits similar shortcomings with regards to the meaningfulness of its results. A sum of absolute errors that is infinite would result in a perfect tracking signal that is close to zero. It becomes obvious that this measure is only able to detect bias, which is indeed its primary application.

$$Tracking\ signal = \frac{\sum Errors}{\frac{\sum |Errors|}{No\ of\ observations}}$$

Equation 4.2: Tracking signal

MAPE and MAD do both not blind out the absolute deviation, and are hence more reliable measures to assess the accuracy. However, by taking the mean value of the entire series of errors, old values and more recent values are treated as equal. This leads to the frequently discussed “blur of history” effect that does not recognize that patterns and especially parameters slightly deviate over the time.

For this reason, the MAPE was amended with regards to Trigg (1964) who recommend exponential smoothing for tracking signals. Instead of applying the mean to the absolute percentage error, the absolute percentage error shall be exponentially smoothed. For higher values of alpha, sum errors that have been observed in recent history are pronounced, which underlines the importance of “hold out samples” or normalization since otherwise forecasts would appear to be very accurate even if they are not.

A smoothed absolute percentage sum error (SAPSE) was implemented into the testing environment, which provided realistic results in most cases. However, when confronted with stock out situations where the sum of actual values almost vanishes, the percentage calculation goes off course, as small divisors lead to very high errors. If these errors have occurred in recent history and are hence more pronounced due to the exponential smoothing, the reliability of the assessment suffers.

For this reason, the relative component of taking the percentage in regards to the absolute value was removed from the formula. The resulting SASE (smoothed absolute sum errors) exhibits similarities to the MAD. Merely, the mean was replaced by exponential smoothing and deviations are captured on error sum basis instead of individual period error basis. The SASE rectified the problems caused by stock outs. The error caused by the abstinence on standardization with regards to the actual error level via the percentage has shown to be less pronounced than expected, which is why the smoothed absolute sum error was selected as single criteria for the forecasting method selection. The smoothing factor of the SASE was set to be 0.2 since this delivered good results throughout the testing.

4.4.3 Implemented patterns and their constraints

The SASE and the methodology on how to calculate the underlying series of sum errors have been designed in the previous. In a second step, the implementation of actual forecasting methods is required. Thereby, it is not the aim to implement as many methods as possible but rather to provide a range of methods that can cover the basic demand patterns “constant-linear”, “trend”, “seasonality/cyclical”. In case it becomes apparent that more specialized methods are needed to better reflect some observed demand curves, they can still be implemented at a later point of time.

4.4.3.1 Seasonality

A seasonality pattern is an add-on and as such does not occur as standalone pattern. As shown in the literature research, it is usually included as a multiplicative component in demand forecasting formulas.

$$f_t = (c + m \cdot t) \cdot F_t$$

Equation 4.3: Multiplicative inclusion of seasonality factor

Therewith, seasonality factors can be added to each and every forecast method, which is why they shall be discussed in first place. The term "season cycle" shall denote the time between the two cycles in periods (e.g. in a monthly view, the season cycle of a year is 12 periods; in a weekly view, the season cycle of a year would be 52). The seasonality factor F_t has to be calculated for each of the 12/52 periods that the season cycle consists of. The calculation shall be illustrated at the example of a season cycle of four periods, which results in four seasonal factors F_1, F_2, F_3, and F_4.

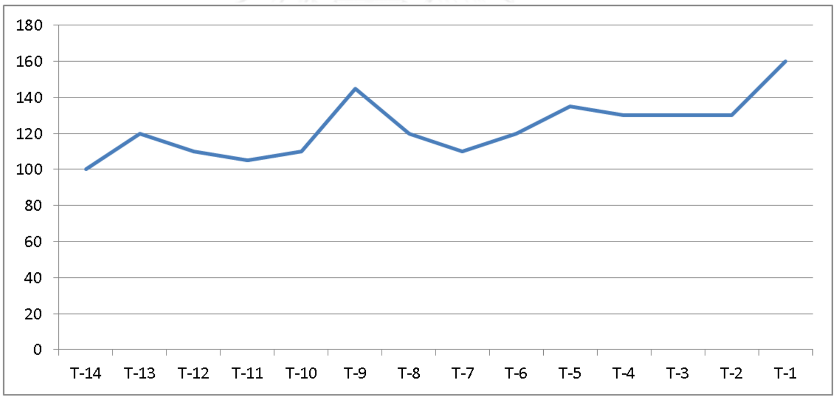


Fig. 4.22: Illustration of sample demand data for seasonality calculation

The according data values are displayed in table 4.7.

P	T-14	T-13	T-12	T-11	T-10	T-9	T-8	T-7	T-6	T-5	T-4	T-3	T-2	T-1
D	100	120	110	105	110	145	120	110	120	135	130	130	130	160

Table 4.7: Sample demand data for seasonality calculation

The demand in figure 4.22 obviously exhibits a seasonal behaviour. In table 4.8 the different periods have been assigned to a season. The most recent period T-1 is set to belong to season 4 (the last season). That is because the first period to be forecasted can then start as season 1.

P	T-14	T-13	T-12	T-11	T-10	T-9	T-8	T-7	T-6	T-5	T-4	T-3	T-2	T-1
D	100	120	110	105	110	145	120	110	120	135	130	130	130	160
S	3	4	1	2	3	4	1	2	3	4	1	2	3	4

Table 4.8: Allocation of periods to seasons

The sum of demand for all periods that belong to a particular season is taken and then divided by the count of periods to retrieve the average (Tibben-Lembke, 2003).

$$\bar{D}_{S1} = \frac{D(T-4) + D(T-8) + D(T-12)}{3} = \frac{130 + 120 + 110}{3} = 120$$

$$\bar{D}_{S2} = \frac{D(T-3) + D(T-7) + D(T-11)}{3} = \frac{130 + 110 + 105}{3} = 115$$

$$\bar{D}_{S3} = \frac{D(T-2) + D(T-6) + D(T-10) + D(T-14)}{4} = \frac{130 + 120 + 110 + 100}{4} = 115$$

$$\bar{D}_{S4} = \frac{D(T-1) + D(T-5) + D(T-9) + D(T-13)}{4} = \frac{160 + 135 + 145 + 120}{4} = 140$$

Equation 4.4: Calculation of average season demand

The average season demands are then divided by the mean of the average season demands.

$$F_1 = \frac{\bar{D}_{S1}}{\overline{\bar{D}_{S1} + \bar{D}_{S2} + \bar{D}_{S3} + \bar{D}_{S4}}} = \frac{120}{\frac{120 + 115 + 115 + 140}{4}} = 0.9796$$

$$F_2 = \frac{\bar{D}_{S2}}{\overline{\bar{D}_{S1} + \bar{D}_{S2} + \bar{D}_{S3} + \bar{D}_{S4}}} = \frac{115}{\frac{120 + 115 + 115 + 140}{4}} = 0.9388$$

$$F_3 = \frac{\bar{D}_{S3}}{\overline{\bar{D}_{S1} + \bar{D}_{S2} + \bar{D}_{S3} + \bar{D}_{S4}}} = \frac{115}{\frac{120 + 115 + 115 + 140}{4}} = 0.9388$$

$$F_4 = \frac{\bar{D}_{S4}}{\overline{\bar{D}_{S1} + \bar{D}_{S2} + \bar{D}_{S3} + \bar{D}_{S4}}} = \frac{140}{\frac{120 + 115 + 115 + 140}{4}} = 1.1429$$

Equation 4.5: Calculation of seasonality factors

The seasonal factors can now be included into any forecasting function. However, not only the forecast should consider seasonality but also the demand data should be seasonality corrected before to its utilization. The process is illustrated in figure 4.23. First, the input data is deseasonalized by dividing the demand of the period with the period's seasonality factor. Second, the forecasting method is applied to the season-free historic data. Third, the output of the forecast is seasonalized again with the seasonal factor relevant to the forecasted period.

Fig. 4.23: Procedure of seasonalization

This principle can basically be applied to all forecasting methods if the consideration of seasonality is desired. If not needed, seasonality factors can be set to the value 1.

Limitations

It must be noted that adding a seasonality component to forecasts – which are based on very short demand history – produces a superb fit, which is though problematic. That is because the historic pattern will be remodelled by the seasonal factors, which delivers a superior SASE. Yet, the ultimate forecast will almost be a copy of the demand history. If the length of the demand history equals the season cycle, it will even be an exact copy, which is in practice very unrealistic. To avoid this, seasonality shall only be considered in cases where the demand history is longer than two times the season cycle.

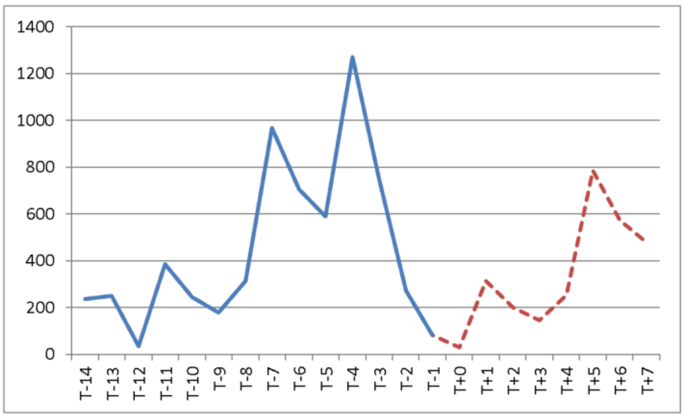


Fig. 4.24: Accidental application of seasonality pattern in case of short demand history

4.4.3.2 Constant value forecasting methods

Moving average

The moving average as one of the most standard methods for the prediction of constant values is a must have. The number of periods over which the moving average is calculated is variable.

As announced in the section about seasonality, the quantity of each input month is divided by the applicable seasonal factor prior to taking the moving average. The result of the moving average is then multiplied with the seasonal factor of the period that is forecasted. In the following example, the 3-month moving average of the periods T-1, T-2, and T-3 is taken to forecast the demand for T0, T+1, T+2, and T+3. The seasonal factors are those from the example in the last section.

P	T-6	T-5	T-4	T-3	T-2	T-1	T0	T+1	T+2	T+3
D	110	120	135	130	130	160	?	?	?	?
S	3	4	1	2	3	4	1	2	3	4

Table 4.9: Example for 3-month moving average with seasonality

$$MAVG_{T0} = roundup\left(\frac{\frac{160}{F_4}+\frac{130}{F_3}+\frac{130}{F_2}}{3}\cdot \boldsymbol{F_1}\right) = 139$$

Equation 4.6: Calculation of the moving average forecast for T0

$$MAVG_{T+1} = roundup\left(\frac{\frac{160}{F_4}+\frac{130}{F_3}+\frac{130}{F_2}}{3}\cdot \boldsymbol{F_2}\right) = 131$$

Equation 4.7: Calculation of the moving average forecast for T+1

$$MAVG_{T+2} = roundup\left(\frac{\frac{160}{F_4}+\frac{130}{F_3}+\frac{130}{F_2}}{3}\cdot \boldsymbol{F_3}\right) = 131$$

Equation 4.8: Calculation of the moving average forecast for T+2

$$MAVG_{T+3} = roundup\left(\frac{\frac{160}{F_4}+\frac{130}{F_3}+\frac{130}{F_2}}{3}\cdot \boldsymbol{F_4}\right) = 159$$

Equation 4.9: Calculation of the moving average forecast for T+3

Weighted moving average

For the weighted moving average, the results of the divisions of the periods' demands and their seasonal factors are multiplied with the weighing factor W_{-1}, W_{-2}, and W_{-3}.

$$WMAVG_{T0} = roundup\left(\frac{\frac{160}{F_4} \cdot w_{-1} + \frac{130}{F_3} \cdot w_{-2} + \frac{130}{F_2} \cdot w_{-3}}{w_{-1} + w_{-2} + w_{-3}} \cdot F_1\right)$$

Equation 4.10: Weighted moving average for T0

Moving median

In a similar way the median was implemented. Demand figures get divided by the seasonal factors and are then sorted by size. The median value is retrieved and then multiplied with the seasonal factor of the forecasted period.

Exponential smoothing

Exponential smoothing was implemented to complete the range of constant linear functions. The calculation follows the standard calculation that was presented in chapter 2. Thereby, the oldest value of the data series is used as start value. As frequently recommend in literature, an option to not update the forecast in case of zero-demand is available. Beyond this a parameter "learning time" was implemented. This means that a certain number of periods at the beginning of the data series are only used for learning the pattern but not for evaluating the sum error. This can for example be useful if the item saw very small demand during its product introduction, which is not representative for the actual demand, see example in table 4.10.

P	T-14	T-13	T-12	T-11	T-10	T-9	T-8	T-7	T-6	T-5	T-4	T-3	T-2	T-1
D	10	20	30	50	110	145	120	110	120	135	130	130	130	160
	Learning period				Evaluation period									

Table 4.10: Learning period

4.4.3.3 Trend methods

As so far only trend method, double exponential smoothing was implemented following the calculation in the literature. The second oldest value of the data series is set as start value for alpha. The start value for the trend factor beta is set to the difference between the two oldest values. Similar to exponential smoothing also the double exponential smoothing is equipped with the not updating option in case of zero values.

Triple exponential smoothing was not implemented, as the seasonality is already covered by the seasonal factor schematic that is applied to all functions.

4.4.4 The procedure in brief

Once a demand history was selected by the user, the option of “hold out samples” is automatically selected if the length of the demand history is at least two times the length of the forecast horizon. This data history requirement is also applied to decide whether to enable the option of seasonality inclusion or not.

In the next step, the four constant models and the double-exponential smoothing as trend model are applied to the data history. Each of the functions can be tested with or without the consideration of seasonality, if the item’s data history is sufficiently long. Furthermore, each method requires additionally a set of input parameters. Table 4.11 gives and overview of the various parameters that are applicable to the different methods. Within the literature there is no dedicated approach on how to set these parameters, which is why trial-and-error is frequently recommended, especially for alpha and beta of the double-exponential smoothing (Hung, n.d.). Therefore, the parameterization within the simulation software was also implemented as trial-and-error, which requires the test of a high number of method/parameter combinations.

Each trial run returns the SASE of the tested combination. The model/parameter combination that delivers the lowest SASE it ultimately selected to predict future values.

Method	Type	Parameters	Type
Moving average	Constant	Number of month to be included Season cycle (if any)	Integer Integer
Weighted moving average	Constant	Number of month to be included Weighing factors Season cycle (if any)	Integer Array of Double Integer
Moving median	Constant	Number of month to be included Season cycle (if any)	Integer Integer
Exponential smoothing	Constant	Alpha Season cycle (if any) Non-update for zero values Learning time	Double Integer Boolean Integer
Double exponential smoothing	Trend	Alpha Beta Season cycle (if any) Non-update for zero values Learning time	Double Double Integer Boolean Integer

Table 4.11: Overview of currently implemented models and their parameters

4.5 Safety stock

The function of automatic pattern recognition delivers the model and the parameters that provided the best fit with the historic data in terms of sum error. As it must be assumed that the selected model is adequately representing the actual pattern, model and parameter risk are expected to be zero.

Yet, the forecast must be expected to be subjected to random error, which is why safety stock must be kept to hedge against this error. The calculation of the safety stock that was presented in the literature research is a straight forward approach, which uses the standard deviation to describe the variation of the forecast.

$$Safety\ stock = Z \cdot \sqrt{\overline{LT} \cdot \sigma_D^2 + \overline{D}^2 \cdot \sigma_{LT}^2}$$

Equation 4.11: Standard formula for safety stock (e.g. Hou and Gopalan, 2014)

4.5.1 Standard deviation

The standard deviation for a sample is calculated as per equation 4.12.

$$\sigma_D = \sqrt{\frac{1}{n-1} \cdot \sum_{t=1}^{n} (E(a_t) - a_t)^2}$$

*Equation 4.12: Corrected sample standard deviation (*Encyclopedia of Mathematics, 2014)

Thereby, $E(a_t)$ is the expected value of a_t, which in theory is the arithmetic mean of the series of actual values. Yet, for the targeted application, the expected value of a_t is the forecasted value f_t that is in most cases different from the mean. Hence the difference between expected value and actual value equals the forecast error.

As demonstrated in the assessment process in section 4.4.2.3, a forecast for the future n periods is made in each period. In result several series of forecast errors can be calculated that in some way have to be combined to an overall standard deviation (see example in table 4.12). Applying the typical calculation as per equation 4.12, the standard deviation would be calculated as the square root of the sample-corrected mean of the squared forecast errors. This way of calculating the standard deviation would weigh old and recent errors equally, which in some cases can lead to high safety stocks. The logarithmic function in figure 4.25 illustrates this scenario. In this illustration, the double exponential smoothing produced significant errors in older history. With more recent data the double exponential smoothing did, though, perform better, which is why this method was actually chosen.

Fig. 4.25.: Error development at the example of logarithmic function

The recent forecast errors in figure 4.24 are comparably small and can be expected to remain small in future periods, considering the shape of the graph. Giving equal weightage to older and newer error data distorts the validity of the result. Therefore, a sample corrected standard deviation shall be calculated for each focus period. The obtained values are then exponentially smoothed with the standard deviation of the oldest focus period as starting value – see table 4.12 for an example.

Considering that the forecasting method was selected based on an exponentially smoothed absolute sum error, using exponentially smoothing for the standard deviation is a consistent approach. To remain consequent, the smoothing factor shall be set equal to the selected smoothing factor of the SASE.

Example
Method: 3 month median; Forecast horizon: 4 periods

						Hold-out sample				
Period	T-9	T-8	T-7	T-6	T-5	T-4	T-3	T-2	T-1	σ_D
a_t	100	110	120	130	140	150	160	170	180	
Focus period = T-9										
f_t		100	100	100	100					31.62
$(f_t-a_t)^2$		100	400	900	1600					
Focus period = T-8										
f_t			105	105	105	105				36.51
$(f_t-a_t)^2$			225	625	1125	2025				
Focus period = T-7										
f_t				110	110	110	110			42.43
$(f_t-a_t)^2$				400	900	1600	2500			
Focus period = T-6										
f_t					120	120	120	120		42.43
$(f_t-a_t)^2$					400	900	1600	2500		
Focus period = T-5										
f_t						130	130	130	130	42.43
$(f_t-a_t)^2$						400	900	1600	2500	
Exponential smoothing (alpha = 0.2)										37.4

Table 4.12: Example for calculation of standard deviation

4.5.2 Average demand and standard deviation of lead time

The second part of the safety stock calculations considers the supply risk with regards to lead time variations. For each incoming shipment from a supplier, the lead time shall be recorded. The deviation shall be calculated, whereby the contractually agreed lead time shall be taken as expected value. As the supplier might have improved over time, exponential smoothing could be used for this case as well. This would also simplify the recording as only the smoothed value has to be stored.

The average demand that has to be multiplied with the standard deviation of lead time is suggested to be calculated as the sum of demand over the forecast horizon divided by the number of periods.

4.5.3 Z-Value

The importance of stock availability has been outlined several times throughout this thesis. Ultimately, the decision for the Z-value – respectively the service level – has to be taken on strategic level though.

Therewith, all factors that are needed to calculate the safety stock as per equation 4.11 have been gathered, which is why the generation of the just-in-time inbound schedule is the next step that shall be discussed..

4.6 Just-in-time inbound schedule

The previous functions produced a demand forecast for the next 8 months and defined a target safety stock level. Within this chapter the demand schedule shall be converted into a just-in-time (JIT) inbound schedule. This plan specifies the latest point of time when goods have to arrive in order to comply with the forecast and the safety stock requirement.

The purchasing department works on weekly basis, which is hence also mandatory for the JIT inbound schedule. Yet, the demand plan has been calculated on monthly basis to profit from the smoothing effect of time-wise aggregation. Thus, in a first step it is necessary to convert the monthly demand plan into a weekly demand plan.

4.6.1 Weekly demand plan

Within the discussion about seasonality, it was illustrated that significant differences in demand are observed not only across different months, but also across different weeks. Furthermore it was identified that the main cause for differences are official public holidays and typical holiday seasons of various customer groups. Since it is also difficult to mathematically split months into weeks, the approach that is illustrated by the following example shall be proposed.

Example

The forecast delivered a projected quantity of 4,000 pieces for June, 5,000 pieces for July, and 5,550 pieces for August, which shall be split into weekly demand. The example will focus on the calculations for July.

Based on a calendar that also considers non-public holidays, the number of working days for each month shall be counted (Time and Date, 2014). The weightage for the different week days shall be applied as per table 4.13.

Week day	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Holiday
Value	1	1	1	1	1	0.5	0	0

Table 4.13.: Weightage of week days

This results in 22.5 days for June, 23 days for July and 21.5 days for August. The same is done for each calendar week, whereby the count is split by month, see table 4.14. The prorated demand for each week is then calculated as shown in equation 4.13.

$$Demand_{W27} = \frac{Demand_{June}}{22.5\ days} \cdot 1\ day + \frac{Demand_{July}}{23\ days} \cdot 3.5\ day$$

Equation 4.13.: Calculation for weekly demand

July 2014								Day count				Prorated
Week	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total	Jun	Jul	Aug	demand
27	30	1	2	3	4	5	6	4.5	1	3.5		939
28	7	8	9	10	11	12	13	4.5		4.5		978
29	14	15	16	17	18	19	20	5.5		5.5		1196
30	21	22	23	24	25	26	27	5.5		5.5		1196
31	28	29	30	31	1	2	3	5.5		4	1.5	1253

Table 4.14.: Prorated demand by week

The outcome of this procedure is a demand plan on weekly basis.

4.6.2 Weekly just-in-time schedule

Within this section a weekly demand schedule shall be converted to a just-in-time inbound schedule. This means basically to calculate when and how many pieces have to be brought in to satisfy the demand. If cycle inventory is still left over from previous periods, this shall be consumed first. Bringing in new goods shall be deferred to the latest possible point in time – just-in-time – in order to save on inventory costs. The basic principle is illustrated in figure 4.26.

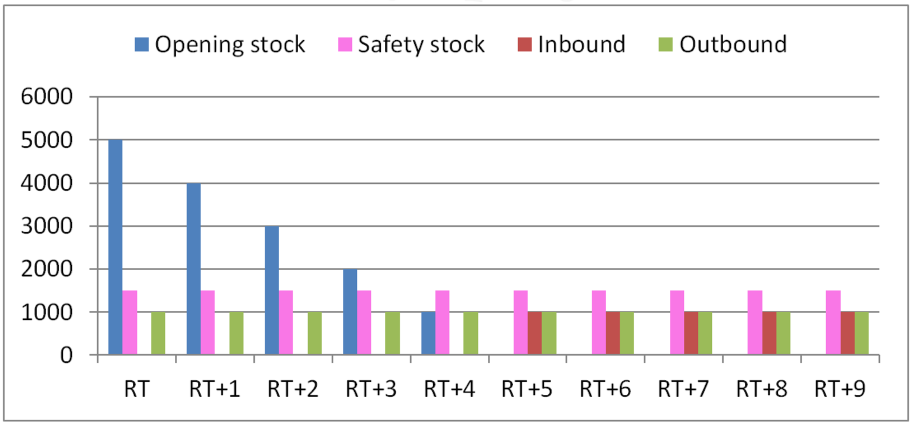


Fig. 4.26: Illustration for JIT inbound of goods

At present time it is only possible to schedule shipments that will arrive after the replenishment time (RT). What happens in the frozen period before RT cannot be influenced anymore and must be accepted as given.

With regards to section 4.4.2.2 the following two questions shall be recapitulated:

- How much stock will be left at the end of the replenishment time […]?
- How much stock will be consumed in each week after the replenishment time?

To answer the first question, the demand over the replenishment time, the incoming shipments over the replenishment time and the current stock – all in all the inventory position with regards to the replenishment time – have to be evaluated. Fundamentally, this calculation is rather straight forward – only potential demand shortages during the lead time must be treated specially. The literature review has confirmed that a fraction of the customers who face a stock-out will cancel their order. This means the unsatisfied demand of a week shall neither be ignored nor be fully added to the demand of the next week. A parameter "walk out percentage" shall be introduced, which captures the percentage of the unfulfilled demand that is lost due to order cancelation. The setting for this parameter needs to be calibrated based on experience but shall be set as 50% for further explanations. Based on this parameter the carried over demand (order backlog) can be calculated for each period.

Example

An earlier forecast for an item with a replenishment time of six weeks projected a weekly demand of 300 pieces and recommended a safety stock of 500 pieces. Upon this forecast orders of 600 pieces every second week have been placed.

Week	W-7	W-6	W-5	W-4	W-3	W-2	W-1	W0	W+1
Target safety stock	500	500	500	500	500	500	500	500	500
Forecasted demand	300	300	300	300	300	300	300	300	300
Demand carried over	0	0	0	0	0	0	0	0	0
Total demand	300	300	300	300	300	300	300	300	300
Targeted opening stock	800	800	800	800	800	800	800	800	800
Opening stock	800	1100	800	1100	800	1100	800	1100	800
Outbound (-)	300	300	300	300	300	300	300	300	300
Closing stock	500	800	500	800	500	800	500	800	500
Order backlog	0	0	0	0	0	0	0	0	0
Inbound (+)	600	0	600	0	600	0	600	0	600

Table 4.15: Perfectly balanced planning as of week "W-7" for "W0"

Now at the beginning of week “W0” unexpectedly a frame contract with a customer for 300 pieces monthly on top of normal consumption was made with immediate effect. This value was entered via the manual forecasting function (no effect on safety stock). The updated stock projection as of week “W0” shows heavy backlogs for the next weeks. However, nothing can be done against this since orders that are placed now will arrive earliest within W+6 and will be available in stock at the beginning of W+7.

	Replenishment time							
Week	W0	W+1	W+2	W+3	W+4	W+5	W+6	W+7
Target safety stock	500	500	500	500	500	500	500	500
Forecasted demand	600	600	600	600	600	600	600	600
Demand carried over	0	0	50	25	313	157	379	190
Total demand	600	600	650	625	913	757	979	790
Targeted opening stock	1100	1100	1150	1125	1413	1257	1479	1290
Opening stock	1100	500	600	0	600	0	600	??
Outbound (-)	600	500	600	0	600	0	600	??
Closing stock	500	0	0	0	0	0	0	??
Order backlog	0	100	50	625	313	757	379	??
Inbound (+)	0	600	0	600	0	600	??	??

Table 4.16: Planning basis in W0

The focus lies now on avoiding further shortages in W+7 and beyond. In the example the targeted opening stock for W+7 is 1,290 (demand plus safety stock) and the projected closing stock at the end of W+6 is 0 (quantity left over at the end of the replenishment time). By placing an order of 1,290 pieces in period W0 the desired opening stock of W+7 of 1,290 pieces can be achieved. For the following weeks the planned inbound volume is set to be equal the forecasted demand.

		Planning Horizon						
Week	W+6	W+7	W+8	W+9	W+10	W+11	W+12	...
Target safety stock	500	500	500	500	500	500	500	500
Forecasted demand	600	600	600	600	600	600	600	600
Demand carried over	379	190	0	0	0	0	0	0
Total demand	979	790	600	600	600	600	600	600
Targeted available stock	1479	1290	1100	1100	1100	1100	1100	1100
Opening stock	600	1290	1100	1100	1100	1100	1100	1100
Outbound (-)	600	790	600	600	600	600	600	600
Closing stock	0	500	500	500	500	500	500	500
Order backlog	379	0	0	0	0	0	0	0
Inbound (+)	1290	600	600	600	600	600	600	600

Table 4.17: Inbound shipments for planning horizon in W0

Generalization

The example has shown that the incoming shipment for the period T+RT (first period after the replenishment time) has to adjusted the stock level to satisfy the safety stock requirement and to bring in the stock for the projected demand of period T+RT. Equation 4.14 can be used for calculation.

$$Inbound_{T+RT} = Target\ safety\ stock - Closing\ stock_{T+RT-1}$$
$$+Demand\ carried\ over_{T+RT} + Forecasted\ demand\ T_{T+RT}$$

Equation 4.14: Inbound for the first period after the frozen period

For subsequent periods no further adjustment of the stock level has to be performed, which is why for these periods the JIT inbound quantity equals the forecasted demand. Equation 4.15 is applied.

$$Inbound_{T+RT+n} = Forecasted\ demand\ T_{T+RT+n}$$

Equation 4.15: Inbound for all subsequent periods

4.7 Chapter summary

In preparation for the selection of an approach to forecasting, operational needs and the quality of historic demand data have been reviewed. Thereby, it has been identified that purchasing individual SKUs on weekly basis implies a low degree of agglomeration and hence rather unsmooth demand. In this respect, the review of available demand data has revealed significant distortions like one-time events, zero-values, severe random error, and skewness, which has retrenched the expectations towards quantitative-intrinsic forecasting. With regards to the high number of SKUs and frequency of inventory reviews, is has been realized that there are no other viable options, which is why the quantitative intrinsic forecasting has been focussed.

Yet, to improve the data basis for forecasting in the long term, a manual forecasting functionality has been proposed which can help to prevent the transition of one-time events into demand history. Additionally, the inclusion of inventory ledger data to identify and hence trigger the correction of stock-outs has been proposed.

In accordance with the literature research, a pattern recognition functionality has been developed that automatically selects forecasting model and parameters on individual item basis. Within this functionality several predefined model/parameter combinations are tested on historic data, whereof the winner is used for future forecasting. The smoothed absolute sum error over the replenishment time has been chosen as sole selection criteria, as the accuracy with regards to this measure is most decisive for the inventory position and hence severely impacting the purchasing decision.

Based on the selected forecasting model, the standard deviation that is required for the proposed safety stock calculation can be determined. Therewith, the safety stock requirement has been detached from items x/y/z classification, which is henceforth merely setting the service level. By doing so, safety stock levels are dependent on the variations in item demand, which is far more reasonable than an equal treatment of all items irrespective of the individual item variation.

Ultimately, the transformation of monthly and hence more stable demand figures (agglomeration effects) into weekly inbound figures has been proposed using a calendar day accurate conversion method.

5 APPLIED EOQ CALCULATION

5.1 General outline

The forecasting based on automatic pattern recognition that was developed within chapter 4, delivers just-in-time inbound schedules for a group of items. Table 5.1 illustrates this exemplarily. These JIT inbound schedule in turn are the input for the economic order calculation that will be developed within this chapter.

	…	W17	W18	W19	W20	W21	W22	W23	W24	…	
Item A	Frozen period	100	100	100	100	100	100	100	100	…	End of horizon
Item B		150	160	170	180	190	200	210	220	…	
Item C		220	200	180	160	220	200	180	160	…	
Item D		80	90	100	110	500	130	140	150	…	
Item E			100	80	120	80	100	80	120	…	

Table 5.1: Sample multi-item JIT inbound schedule

The purpose of the economic order consideration is to review the just-in-time schedule with regards to overall acquisition cost and to make adjustments where needed and feasible in order to save costs. As this is not a mere academic exercise, the totality of costs that are influenced by the purchasing decision must be considered. The three major cost components are inventory costs on per piece/per period basis, ordering costs on per shipment basis, and transport costs on per shipment/per transport unit basis. A suggestion on how to obtain these costs is given at the end of this chapter. For the development of the logic knowledge of exact cost figures is not required.

The literature review in chapter 2 has shown that the existing EOQ methodology is limited in its way of handling transport costs. The negligence of this substantial cost proportion comes from the difficulties of incorporating a non-linear cost function that moreover depends on shipment mode utilization and, therewith, even on item characteristics. Within this chapter, a logic for this unhandy problem shall be developed. The expected output of the EOQ logic is a proposed order quantity on item level as per the time when the proposal is run.

5.2 Basic approach

To solve this EOQ calculation in optimal manner, it would be required to solve the entire problem as a whole. Due to the number of dependencies and linkages in conjunction with non-linear cost factors and constraints such as transport costs, discounts, and MOQ requirements, this is quasi unfeasible and especially not compatible with the stipulation of simplicity and transparency. Therefore, the problem shall be split into smaller sub problems that are somehow solvable. To avoid circular dependencies, a linear two-step approach that only considers transportation cost in the first period after the replenishment time shall be applied, refer figure 5.1.

	…	W17	W18	W19	W20	W21	W22	W23	W24	…	
Item A	Frozen period	100	100	100	100	100	100	100	100	…	End of horizon
Item B		150	160	170	180	190	200	210	220	…	
Item C		220	200	180	160	220	200	180	160	…	
Item D		80	90	100	110	500	130	140	150	…	
Item E			100	80	120	80	100	80	120	…	
Joined transport			JT1	JT2	JT3	JT4	JT5	JT6	JT7		

Fig. 5.1: Schematic of two step approach to avoid circular references

In a first step, individual product schedule optimizations that are completely independent from each other shall be performed. Thereby, packcodes, minimum order quantities and discounts shall be considered.

In a second step, a joint transportation cost optimization for the first period of the free interval shall be performed. The impact on transport costs in other periods is thereby ignored.

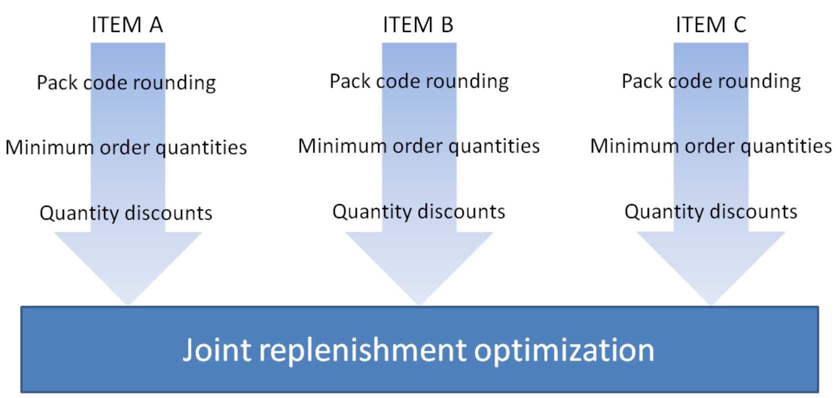


Fig. 5.2: Top-level optimization flow

5.3 Initial consideration

5.3.1 Starting point for optimization

The demand forecasting function as described in chapter 4 delivers a JIT inbound schedule. This means that all shipments arrive as late as possible, which means in turn that what is expected to be consumed in a certain week arrives in the same week. Doing so represents the most cost efficient setup with regards to inventory cost but at the same time the most inefficient setup in regards to ordering cost and presumably also in regards to discounts, as figure 5.3 illustrates.

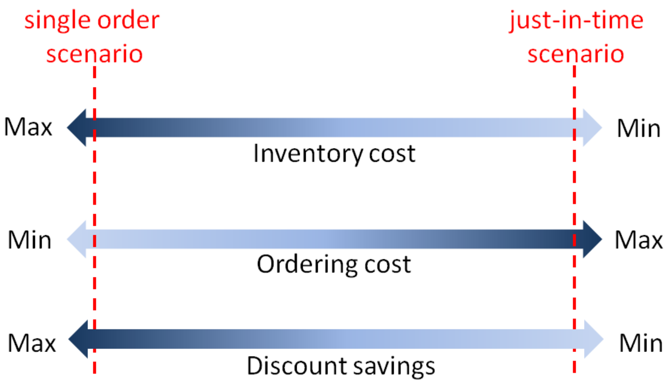


Fig. 5.3: Visualization of the starting point for the improvement process

Even though JIT is highly unlikely to be the most efficient setup in regards to total cost in the given context, it is a good starting point for the improvement process because there is only one possible direction towards achieving improvements. As the just-in-time inbound schedule marks the latest point in time when goods are allowed to arrive, shipments can always only be preponed to an earlier point of time but never be postponed to later since they would otherwise arrive too late to satisfy the demand.

For all optimization that are done within this chapter applies that whatever is added/deducted from a shipment must be deducted/added to another shipment. The overall sum remains the same.

5.3.2 Cost impact of shipment preponement

In a single item scenario, the impact of rescheduling a shipment is easy to grasp. The basic EOQ calculation of Harris is based on the assumption that combining two shipments reduces ordering cost but increases inventory costs.
Yet, in a multi-item scenario this is not necessarily the case. Preponing a shipment or part of it to an earlier point in time does still cause inventory cost. The ordering cost, though, is not necessarily reduced. In table 5.2, the shipments of item A in week 20 and 21 have been preponed to week 19. However, since other products still need to be shipped in week 20 and 21, the ordering cost does not decrease.

	…	W17	W18	W19	W20	W21	W22	W23	W24	…	
Item A	Frozen period	100	100	300	0	0	100	100	100	…	End of horizon
Item B		150	160	170	180	190	200	210	220	…	
Item C		220	200	180	160	220	200	180	160	…	
Item D		80	90	100	110	500	130	140	150	…	
Item E			100	80	120	80	100	80	120	…	

Table 5.2: Example for dependency of joint ordering cost

Therefore, in the first step – the individual product optimization – ordering costs are completely omitted. In the second stage of transport cost optimization they will then be integrated.

Since reductions in order cost are not obtainable, potential discounts and MOQ requirements are the only reasons for preponements during the individual item optimization.

5.3.3 Expected outcome

The expected outcome of the EOQ is fundamentally the list of items and quantities that are supposed to be ordered right now. Potential savings through improvements of container utilization or through claims of discounts are hence securable at present.
On the contrary, identified savings in future periods are only good prospects, as they are still unrealized and depend on schedule stability.

5.3.4 Schedule stability

During the review of existing ways to calculate the EOQ, the urgency of schedule stability was identified. Stability means that in the course of inventory reviews, shipments do not permanently get rescheduled (Narayanan and Robinson, 2010). In an extreme case of instability, a new shipment has to be brought in every week unexpectedly. Such a case was demonstrated in the analysis of chapter 3. However, instability can also occur in a properly operated inventory control, as the following example will demonstrate.

5.3.4.1 Example – JIT scenario

An item shall be considered to have a constant demand forecast of 100 pieces per week, which is not impacted by demand variations (e.g. by using exponential smoothing with of alpha = 0). Based on this, shipments of 100 pieces per week have been scheduled until the end of the frozen interval of 3 months. The free interval is also 3 periods long, so that the total horizon equals two times the lead time. The required safety stock has been determined as 10 units, which is at the same time the opening stock for week 7, as no overstock is carried. The current focus lies on Week 3, where it is necessary to plan the shipments for the free interval in weeks 7 to 9. The question marks in table 5.3 mark those values that are under questions, whereby only the inbound values can be chosen.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6	T+7
Phase	History			Frozen interval			Free interval				
Actual demand	100	100	100	-	-	-	-	-	-	-	-
Forecast	-	-	-	100	100	100	100	100	100	-	-
Opening stock	10	10	10	10	10	10	10	**?**	**?**	-	-
Inbound	100	100	100	100	100	100	**?**	**?**	**?**	-	-
Closing stock	10	10	10	10	10	10	**?**	**?**	**?**	-	-

Table 5.3: Initial situation for just-in-time scenario – week 3

Apparently, all shipments should be planned as just-in-time shipments so that no inventory has to be carried apart from the safety stock. Thereby, only for W7 a fixed order is placed to remain maximum flexibility. Table 5.4 visualizes the example.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6	T+7
Phase	History			Frozen interval			Free interval				
Actual demand	100	100	100	-	-	-	-	-	-	-	-
Forecast	-	-	-	100	100	100	100	100	100	-	-
Opening stock	10	10	10	10	10	10	10	**10**	**10**	-	-
Inbound	100	100	100	100	100	100	**100**	**100**	**100**	-	-
Closing stock	10	10	10	10	10	10	**10**	**10**	**10**	-	-

Table 5.4: Scheduled shipments for just-in-time scenario – week 3

Against the expectation, the demand in week 4 increased by 5 pieces, which reduced the safety stock by 5 pieces. Therefore, re-planning as per table 5.5 is required.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-4	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6
Phase	History				Frozen interval			Free interval			
Actual demand	100	100	100	105	-	-	-	-	-	-	-
Forecast	-	-	-	-	100	100	100	100	100	100	-
Opening stock	10	10	10	10	5	5	5	5	**?**	**?**	-
Inbound	100	100	100	100	100	100	100	**?**	**?**	**?**	-
Closing stock	10	10	10	5	5	5	5	**?**	**?**	**?**	-

Table 5.5: Changed situation for just-in-time scenario – week 4

The current inventory position is the sum of stock on hand and outstanding orders, which is 5 + 300 = 305.

The reorder point has to be calculated as the sum of required safety stock and the normal consumption during lead time plus review periodicity because a periodic review system is applied. The reorder point is 10 + 400 = 410.

Obviously, the inventory position falls short of the reorder point and hence a reorder is triggered. Within an EOQ calculation the just-in-time version delivers again the lowest cost, which is why 105 pieces are ordered to satisfy the normal consumption and the safety stock requirement.

The according result of the planning is illustrated in table 5.6.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-4	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6
Phase	History				Frozen interval			Free interval			
Actual demand	100	100	100	105	-	-	-	-	-	-	-
Forecast	-	-	-	-	100	100	100	100	100	100	-
Opening stock	10	10	10	10	5	5	5	5	**10**	**10**	-
Inbound	100	100	100	100	100	100	100	**105**	**100**	**100**	-
Closing stock	10	10	10	5	5	5	5	**10**	**10**	**10**	-

Table 5.6: Scheduled shipments for just-in-time scenario – week 4

In weeks 5, 6, and 7, the demand remains at 105 pieces, so that each week 105 pieces have been ordered. To summarize this, one order was placed every week and the overstock has been permanently 0, which is in line with the expectation for a just-in-time schedule.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Demand	100	100	100	105	105	105	105	105	105	105	105
Inbound	100	100	100	100	100	100	100	105	105	105	105
Order count	1	1	1	1	1	1	1	1	1	1	1
Overstock	0	0	0	0	0	0	0	0	0	0	0

Table 5.7: Order count and overstock for just-in-time scenario

5.3.4.2 Example – Combined shipment of two weeks

Fundamentally, the frame conditions remain the same – the only difference is that this time the EOQ calculation finds the combination of two week's demand into one shipment to be the most cost efficient setup. Hence, this time shipments are scheduled for every second week, as table 5.8 illustrates.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6	T+7
Phase	History			Frozen interval			Free interval				
Actual demand	100	100	100	-	-	-	-	-	-	-	-
Forecast	-	-	-	100	100	100	100	100	100	-	-
Opening stock	10	110	10	110	10	110	10	**110**	**10**	-	-
Inbound	200	0	200	0	200	0	**200**	**0**	**200**	-	-
Closing stock	110	10	110	10	110	10	**110**	**10**	**110**	-	-

Table 5.8: Scheduled shipments for two-week scenario – week 3

Again, the demand in week 4 exceeded the expectation, as table 5.9 shows.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-4	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6
Phase	History				Frozen interval			Free interval			
Actual demand	100	100	100	105	-	-	-	-	-	-	-
Forecast	-	-	-	-	100	100	100	100	100	100	-
Opening stock	10	110	10	110	5	105	5	105	**?**	**?**	-
Inbound	200	0	200	0	200	0	200	**?**	**?**	**?**	-
Closing stock	110	10	110	5	105	5	105	**?**	**?**	**?**	-

Table 5.9: Changed situation for two-week scenario – week 4

The reorder point remains the same at 410 pieces. The inventory position is 5 + 400 = 405 and falls, therewith, just short of the reorder point, which triggers an order to arrive in W8. The EOQ calculation again finds the combination of two week's demand into one shipment to be most cost efficient, which is why in total 205 pieces are ordered. The schedule in table 5.10 was accordingly adjusted.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-4	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6
Phase	History				Frozen interval			Free interval			
Actual demand	100	100	100	105	-	-	-	-	-	-	-
Forecast	-	-	-	-	100	100	100	100	100	100	-
Opening stock	10	110	10	110	5	105	5	105	**210**	**110**	-
Inbound	200	0	200	0	200	0	200	**205**	**0**	**0**	-
Closing stock	110	10	110	5	105	5	105	**210**	**110**	**10**	-

Table 5.10: Rescheduled shipments for two-week scenario – week 4

Based on the output of EOQ, the replenishment that was scheduled for week W9 has been preponed. Apparently, ordering again after only one week was not the original plan, which factually means that the additional cycle stock of 100 pieces that arrived in W7 was hold for nothing. The shipment that is now scheduled to arrive in week 8 together with the current stock is supposed to cover three weeks of demand. However, if the demand in one of the next two weeks exceeds 100 pieces, then again the reorder point will be under cut and a new purchase order is triggered. The order count and overstock evaluation in table 5.11 shows that every week unnecessary overstock of 100 pieces is hold in the given example.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Demand	100	100	100	105	105	100	100	100	100	100	100
Inbound	200	0	200	0	200	0	200	105	105	105	105
Order count	1		1		1		1	1	0	1	0
Overstock	100	0	100	0	100	0	100	200	100	200	100

Table 5.11: Order count and overstock for two-week scenario

5.3.4.3 Summary of findings

The examples have shown that minor positive demand deviations (demand higher than forecast) can put the stability of a schedule at risk – no matter how good the forecast is. If reorders are triggered earlier, the total number shipments but also the unnecessarily hold inventory increase – which ultimately results in additional costs. The higher the count of periods (n) that are combined in a single shipment, the lower the frequency of the occurrences, as usually only the n^{th} period is affected by the instability. If a reorder was triggered earlier than expected, the unnecessary inventory was basically held for n-1 periods.

5.3.4.4 Provisions for stability

It has been, shown that even a small deviation of 1 piece can trigger additional orders, if the reorder point is under cut. In face of the fluctuations that the organization sees, the probability that no rescheduling is necessary for a longer horizon is low. Therefore, orders should be placed as late as possible to allow for maximal flexibility. However, for the optimization of logistic costs, low stability is still a huge obstacle.

The higher the number of shipments that are merged together, the higher the probability that the plan can be followed, as the deviations of several shipments tend to outbalance each other (agglomeration effect). With this in mind, the smoothed absolute sum error (SASE) was chosen within the forecasting.

The schedule deviation does also decrease with the number of merged shipments, as in most cases only the last period is impacted. Therefore, higher agglomeration is positive for schedule stability. However, the degree of agglomeration is fluctuating dependent on the economic order quantity calculation and hence not definable. To increase schedule stability the following alternative measures could be taken:

- Underrating inventory costs leads to a higher tendency of agglomeration, whilst the accuracy of the cost optimization is reduced
- Increasing the length of review periods does implicitly lead to demand smoothing – a similar principle as the reduction of sum errors. Yet, the automatic email alert in case that the reorder point is undercut prevents the practical applicability. Additionally, safety stock levels would need to be increased what is also costly.
- Ignoring the entire reorder point system and instead placing the next order when due as per schedule is a third option that is, though, dangerous, as the purpose of safety stock is undermined.
- Adding additional "safety" stock that is only considered during the JIT schedule creation but ignored during the reorder point check appears to be a viable and comparably cheap option. This means that the target safety stock level during the ordering process is higher than required for the purpose of service level adherence. This additional stock is excluded from the reorder point calculation, which allows the difference between both stock levels to act as a buffer against slight demand variations that endanger schedule stability. The service level during ordering might be set to 98%, whilst the reorder point only validates for 96%, the resulting difference in safety stock is then able to outbalance smaller demand variations without triggering a reorder.

From the enumerated options, adding additional "safety" stock is clearly preferred. The level of this additional stock can be adjusted to a niveau that provides adequate schedule stability.

The same example as before shall be used for illustration.

- The reorder point safety stock remains 10 pieces.
- The safety stock for ordering is set to 20 pieces.

The order policy is changed in week 3 so that the target stock level for ordering is now 20 pieces. Therefore, 210 pieces arrive in week 7.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6	T+7
Phase	History			Frozen interval			Free interval				
Actual demand	100	100	100	-	-	-	-	-	-	-	-
Forecast	-	-	-	100	100	100	100	100	100	-	-
Opening stock	10	110	10	110	10	110	10	**120**	**20**	-	-
Inbound	200	0	200	0	200	0	**210**	**0**	**200**	-	-
Closing stock	110	10	110	10	110	10	**120**	**20**	**110**	-	-

Table 5.12: Example – additional safety stock for stability – week 3

Again, the actual demand has increase by 5 pieces in week 4. The safety stock for the reorder point has not been changed, which is why the reorder point remains the same at 410 pieces. The inventory position is 5 + 410 = 415 and does hence not fall below the reorder point – no order is triggered.

Week	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11
Relative period	T-4	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5	T+6
Phase	History				Frozen interval			Free interval			
Actual demand	100	100	100	105	-	-	-	-	-	-	-
Forecast	-	-	-	-	100	100	100	100	100	100	-
Opening stock	10	110	10	110	5	105	5	115	**15**	**120**	-
Inbound	200	0	200	0	200	0	210	**0**	**205**	**0**	-
Closing stock	110	10	110	5	105	5	115	**15**	**120**	**20**	-

Table 5.13: Example – additional safety stock for stability – week 4

For a certain degree of fluctuation, this buffer can obviously ensure schedule stability. This increase stability comes along with additional inventory costs, which can be expected to be bearable though. Based on experience, the size of the additional buffer can be adapted to serve the needs.

As a way to increase schedule stability was identified, the actual design of the EOQ logic can be conducted with the underlying assumption that the schedule is rather stable.

5.4 Step 1: Item specific optimization

Before looking at joint transport cost optimization, the optimization of individual item schedules is discussed within this section. Thereby, packcodes, minimum order quantity requirements, and discounts will be considered.

5.4.1 Packcode rounding

5.4.1.1 Reasoning, implications and prerequisites

With regards to efficiency, ordering full pallets is advantageous since the handling of goods is more efficient and the utilization of storage space is better compared to broken pallets. Therefore, it shall be stipulated that only multiples of full pallet quantities are considered for ordering within the functionality of EOQ calculation. Admittedly, this is a limitation for products with very sporadic demand where the demanded quantity is low compared to the pallet quantity and that would hence incur additional inventory costs whenever a full pallet is ordered. However, in the forecasting discussion it was suggested that products with highly sporadic demand should, nevertheless, be treated differently by setting a fixed reorder and max level, as forecasting and safety stock calculations are likely to fail. For SKUs with higher volumes the implications are comparably small, because the ratio of additional ordered quantity versus overall consumption is low. Slightly higher stock levels can also be of advantage for schedule stability, as it was just found in the previous section.

In conclusion, the negative effects of the packcode rounding are limited, whilst the imposed limitation to the degrees of freedom is simplifying the problem significantly. The prerequisite for packcode rounding is that the packcode quantity is known – how many pieces are stored on one pallet. This is given for most of the items but needs to be obtained for some items – especially for new items. The pallet quantity might be either obtained from the supplier directly, from previous shipments or by calculation (pallet stuffing software). To enable the EOQ functionality proper packcodes must then be created in the ERP system for all items.

5.4.1.2 Application

The JIT shipping quantities are directly dependent on the demand forecasting and can hence include whatever number without compliance to the MOQ and regardless of standard box quantities (packcodes). The rounding to full pallet packcodes shall be performed as a first step. Due to the fact that pallet packcode rounding has been stipulated to be mandatory, the cost impact of it can be neglected. The procedure of packcode round shall be explained at the following example for better understanding,

Example

An item with a pallet quantity of 500 pieces and minimum order quantity of 1000 pieces has a replenishment time of 120 days (17 weeks). The just-in-time inbound schedule suggests an inbound quantity of 498 pieces for week 17, as shown in table 5.14.

	W...	W16	W17	W18	W19	W20	W21	W22	W23	W24	W25
JIT Inbound	0	0	498	465	520	531	505	531	463	421	513

Table 5.14: Sample JIT inbound schedule

In a first step, week 17 shall be rounded to the next higher pack code. This means two pieces have to be added, which get deducted from the subsequent shipment in week 18. The resulting JIT shipment quantity for week 18 is 463 (465-2) pieces and hence 37 pieces short of the pallet packcode quantity. Therefore, 37 pieces are preponed from week 19 to week 18. This procedure is continued until week 35 (end of the 8 months forecasting horizon).

In remembrance of the postulation that shipments cannot be postponed: even if only small quantities are left, they must be filled up to the full packcode quantity. Due to the limited horizon, the last shipment might require special treatment, as no further shipments are available for preponement. In this case the last shipment shall just be set to the next multiple of the packcode quantity.

Table 5.15 illustrates the entire series of preponements that had to be performed for the packcode rounding of the sample schedule.

	W...	W16	W17	W18	W19	W20	W21	W22	W23	W24	W25
JIT Inbound schedule	0	0	498	465	520	531	505	531	463	421	513
Deducted quantity	0	0	0	-2	-37	-17	-486	-481	-450	-421	-66
JIT after deduction	0	0	0	463	483	514	19	50	13	0	447
Next bigger pack code	0	0	500	500	500	1000	500	500	500	0	500
Preponed quantity	0	0	+2	+37	+17	+486	+481	+450	+487	0	+53
Output	0	0	500	500	500	1000	500	500	500	0	500

Table 5.15: Output of the pack code rounding function

5.4.2 MOQ and quantity discounts

5.4.2.1 Adaption of the least-unit-cost heuristic

Hu and Munson (2002) summarized that the least-unit-cost heuristic was found to be the method of choice in a number of comparisons concerning the inclusion of quantity discounts. Minimum order quantities are fundamentally not considered in this approach. However, to incorporate the MOQ in the least-unit-cost heuristic, the base purchasing price shall be considered as quasi infinite. A quantity discount break is added for the MOQ, whereby the purchase price is set to the standard price when the MOQ threshold is exceeded.

- If q < MOQ then purchase price is 999,999 (infinity)
- If MOQ >= q < discount threshold 1 then purchase price is standard price
- If MOQ >= discount threshold 1 < discount threshold 2 then purchase price is discounted price 1
- …

To consider Hu, Munson and Silver's (2004) finding that the relative high purchase costs falsify results, only the delta in purchase price versus the standard price is considered. Other than in the typical application of the least-unit-cost heuristic, ordering costs must be denied due to the dependency on the joint replenishment.

5.4.2.2 Test samples for the least-unit-cost heuristic

In this section the behaviour of the least-unit-cost heuristic shall be evaluated with the help of sample schedules. In the examples the pallet quantity is 100 pieces, the minimum order quantity is 200 pieces, and all-unit discounts of $1.5 from the original price of $10 are granted if order quantities reach 500 pieces. Inventory costs are estimated at $1 per unit per period.

<u>Case 1</u>

The schedule for the first test case is given in table 5.16.

Period	P0	P1	P2	P3	P4
Pack code rounded schedule	200	100	400	300	0

Table 5.16: Test case 1 for the least-unit-cost heuristic - input

With the least-unit-cost heuristic the cost effect per piece for the combination of shipments is evaluated. It shall be noted that the investigation cannot be aborted after the first increase in per piece cost due to the existence of multiple discount breaks. Therefore, search must be aborted when the first increase in per piece cost after reaching the highest discount threshold occurs.

P0 only: Delta purchase cost is 0.
Inventory costs are 0.
Total cost effect per piece: $0

P0 + P1: Delta purchase cost is 0.
Inventory costs are $100.
Total cost effect per piece: $100 / 300 = $0.3333

P0 + P1 + P2: Delta purchase cost is -$1.5 * 700 pieces = -$1050
(> discount qty) Inventory costs are $100 + 2 * $400 = $900
Total cost effect per piece: -$150 / 700 = **-$0.214**

P0 + P1 + P2 + P3: Delta purchase cost is -$1.5 * 1000 pieces = -$1500
(> discount qty) Inventory costs are $100 + 2 * $400 + 3 * $300 = $1800
Total cost effect per piece: $300 / 1000 = $0.3

Based on the result, the shipments of periods P0, P1 and P2 are combined. Since no further shipments can be combined with the shipment in P3, the quantity in P3 remains at 300 pieces.

Period	P0	P1	P2	P3	P4
Least-unit-cost optimized schedule	700	0	0	300	0

Table 5.17: Test case 1 for the least-unit-cost heuristic – solution

The total purchase cost for the schedule is $8.5 * 700 +$10 * 300 = $8950. The inventory cost is $100 + 2 * $400 = $900. The total schedule cost is $9850.

However, the perfect schedule would have planned two shipments of 500 pieces each in period P0 and P1.

Period	P0	P1	P2	P3	P4
Perfect schedule	500	0	500	0	0

Table 5.18: Test case 1 for the least-unit-cost heuristic – optimal solution

The total purchase cost for the schedule is $8.5 * 500 + $8.5 * 500 = $8500. The inventory cost is, thereby, only $100 + 2 * $200 + $300 = $800. The total schedule cost in the optimal case is only $9300 and hence 5.5% lower.

Apparently it would have been advantageous not to prepone the entire shipment of period P2 but rather only part of it that is sufficient to achieve the discount threshold.

P0 + P1 + P2 (200pc): Delta purchase cost is -$1.5 * 500 pieces = -$750
Inventory costs are $100 + 2 * $200 = $500
Total cost effect per piece: -$250 / 500 = **-$0.5**

The logic should, therefore, be extended to check whether partial preponements lead to better results.

Case 2

A different schedule is given in table 5.19 to which the adapted procedure is applied.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	200	100	0	300	200	0	0	0	300

Table 5.19: Test case 2 for the least-unit-cost heuristic – input

P0 only: Delta purchase cost is 0.
Inventory costs are 0.
Total cost effect per piece: $0

P0 + P1: Delta purchase cost is 0.
Inventory costs are $100.
Total cost effect per piece: $100 / 300 = $0.3333

P0 + P1 + P3 (100pc): Delta purchase cost is 0
Inventory costs are $100 + 3 * $100 = $400
Total cost effect per piece: $400 / 400 = $1

P0 + P1 + P3 (200pc): Delta purchase cost is -$1.5 * 500 pieces = -$750
Inventory costs are $100 + 3 * $200 = $700
Total cost effect per piece: -$50 / 500 = **-$0.1**

P0 + P1 + P3 (300pc): Delta purchase cost is -$1.5 * 600 pieces = -$900
Inventory costs are $100 + 3 * $300 = $1000
Total cost effect per piece: $100 / 600 = $0.1667

In the first step, the shipments of P0 + P1 and 200 pc of P3 are combined. The intermediate solution is depicted in table 5.20.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Solution after focussing P0	500	0	0	100	200	0	0	0	300

Table 5.20: Test case 2 for the least-unit-cost heuristic – step 1

P3 only: Delta purchase cost is $999,999 (infinity).
Inventory costs are 0.
Total cost effect per piece: $999,999 (infinity).

P3 + P4 (100pc): Delta purchase cost is 0.
Inventory costs are $100.
Total cost effect per piece: $100 / 200 = **$0.5**

P3 + P4 (200pc) Delta purchase cost is 0.
Inventory costs are $200.
Total cost effect per piece: $200 / 200 = $1

P3 + P4 + P8 (100pc): Delta purchase cost is 0.
Inventory costs are $200 + 5 * $100 = $700
Total cost effect per piece: $700 / 500 = $1.4

P3 + P4 + P8 (200pc): Delta purchase cost is -$1.5*500 = -$750
Inventory costs are $200 + 5 * $200 = $1200
Total cost effect per piece: $450 / 500 = $0.9

In order to comply with the MOQ requirement, the shipment of P3 and partially P4 are combined. To comply with the MOQ in P4, 100 pieces must then be preponed from P8.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Final schedule	500	0	0	200	200	0	0	0	200

Table 5.21: Test case 2 for the least-unit-cost heuristic – solution

The total purchase cost for the schedule is $8.5 * 500 + 3 * $10 * 200 = $10250. The inventory cost is $100 + 3 * $200 + $100 + 4 * $100 = $1200. The total schedule cost is $11450.

Apparently, the partial preponement of P3 in the first step to reach the discount threshold in P0 has led to a series of preponements in subsequent weeks that are kind of unpredictable without solving the entire horizon exactly. Preponing the entire shipment of period P3 would have led to higher unit costs in the direct comparison but to overall lower costs. The according schedule is shown in table 5.22.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Alternative A	600	0	0	0	200	0	0	0	300

Table 5.22: Test case 2 for the least-unit-cost heuristic – alternative solution

The total purchase cost for this schedule is $8.5 * 600 + $10 * 200 + $10 * 300 = $10100. The inventory cost is $100 + 3 * $300 = $1000. The total schedule cost for the alternative schedule is $11100.

However, moving only part of the shipment and leaving a leftover was not necessarily bad. If in the second step the entire shipment of P4 would have been preponed to P3, there would have been no need for further preponements. The outcome is displayed in table 5.23.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Alternative B	500	0	0	300	0	0	0	0	300

Table 5.23: Test case 2 for the least-unit-cost heuristic – optimal solution

The total purchase cost for the schedule is $8.5 * 500 + 2* $10 * 300 = $10250. The inventory cost is $100 + 3 * $200 + $100 = $800. Thus, the total schedule cost for alternative B is $11050, and therewith slightly lower than for the alternative A in table 5.22.

Due to the inherent uncertainty of leftover quantities smaller than the MOQ with regards to further preponements, it shall be stipulated that it is not allowable to leave leftovers that are less than the MOQ.

Case 3

Table 5.24 illustrates another problematic case that shall be analysed.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	200	100	100	100	100	100	100	100	200

Table 5.24: Test case 3 for the least-unit-cost heuristic – input

P0 only:	Delta purchase cost is 0. Inventory costs are 0. Total cost effect per piece: $0
P0 + P1:	Delta purchase cost is approx. -$999,999 (infinity) * 100. Inventory costs are $100. Approx. cost effect per piece: -infinity*100/300=-infinity*1/3
P0 + P1 + P2:	Delta purchase cost is approx. -$999,999 (infinity) * 200 Inventory costs are $100 + $200 = $300 Approx. cost effect per piece: -infinity*200/400=-infinity*2/4
P0 + P1 + P2 + P3:	Delta purchase cost is approx. -$999,999 (infinity) * 300 Inventory costs are $100 + $200 + $300 = $600 Approx. cost effect per piece: -infinity*300/500=-**infinity*3/5**

…

Due to the virtually huge cost saving of not violating the MOQ, all shipments that are less than the MOQ will be preponed to the first period.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Proposed by least-unit-cost heuristic	900	0	0	0	0	0	0	0	200

Table 5.25: Test case 3 for the least-unit-cost heuristic – proposed solution

Instead of preponing all MOQ-violating shipments, it would have been advantageous to combine some shipments at a later point of time to avoid the high MOQ cost, e.g. as shown in table 5.26.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Alternative schedule	600	0	0	0	0	500	0	0	0

Table 5.26: Test case 3 for the least-unit-cost heuristic – improved solution

In case of low sellers where every periods demand falls below the MOQ unlimited preponements will occur, which needs to be prevented.

5.4.2.3 Fundamental of new heuristic

In the previous assessment it has been found that in difference to the least-unit-cost heuristic partial preponements shall be allowed for the obtainment of discounts. Thereby, no leftover quantity shall be lower than the MOQ. It has also been identified that the least-unit-cost heuristic tends to combine unnecessarily many shipments in case of high discount savings. This does occur especially frequent due to the inclusion of the MOQ as a discount break.

Apparently, the application of a function that merely corrects the MOQ violations prior to the application of the discount heuristic would help to prevent the unnecessary combination of shipments. Therefore, a two-step approach will be proposed.

All cost comparisons between schedules throughout the heuristic are based on total schedule cost as it was calculated in the various cases of 5.4.2.2. The total schedule cost considers purchase costs and inventory costs that are based on the schedule's overstock in comparison to the packcode rounded schedule.

5.4.2.4 Planning options for MOQ rounding

In case the minimum order quantity is not achieved in a certain period, there are three possible options to correct this.

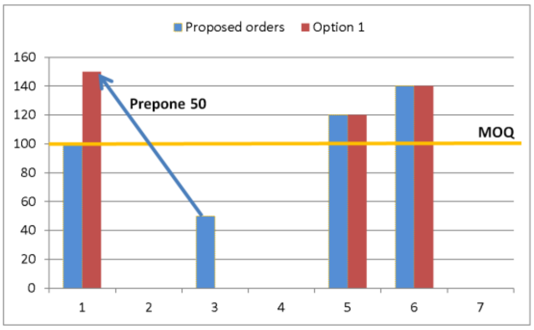


Fig. 5.4: MOQ option 1

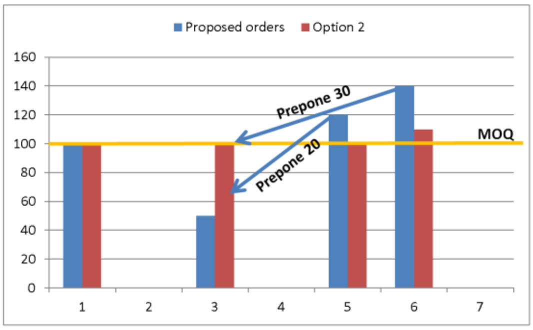


Fig. 5.5: MOQ option 2 – case a

The first option is to preopone the shipment that violates the MOQ requirement itself. In the example in figure 5.4 where the MOQ is 100 pieces, additional inventory costs for two month arise due to the preponement. At the same time the preponement reduces the need for an order in period three, which has no impact on cost due to the joint-replenishment dependency. For the application of option 1 it must be validated that the prior shipment is not yet frozen.

The second option is to fill up the shipment that violates the MOQ by deducting quantities from subsequent shipments. Thereby, the integrity of subsequnet shipments with regerads to the MOQ is considered. In option 2 – case a (figure 5.5), the subsequent shipment exceeds the MOQ, whereby only the exceeding of the MOQ quantity is preponed. The difference in cost is solely based on additional occuring inventory costs.

In option 2 – case b (figure 5.6), the subsequent shipment itself falls short of the MOQ. In this case the entire shipment is preponed in line with the postulation in section 5.4.2.3. The remaining shortage quantity if any is then deducted from a later shipment under consideration of MOQ integrity for these shipments.

In case of very sporadic shipments, it might be cheaper to to preopone a subsequent shipment entirely even though it satisfies the MOQ (figure 5.7). In this third option, the quantity of the shipment to be preponed excess the MOQ only by a quantity that is less than the shortage quantity of the shipment to be filled – otherwise 2a would apply

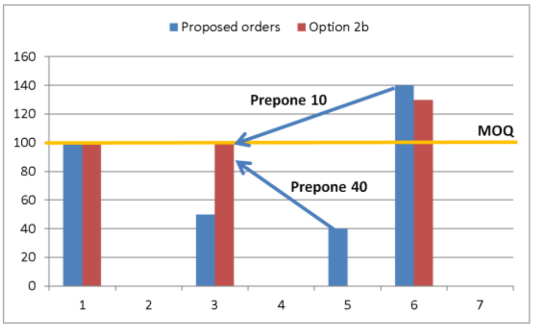


Fig. 5.6: MOQ option 2 – case b

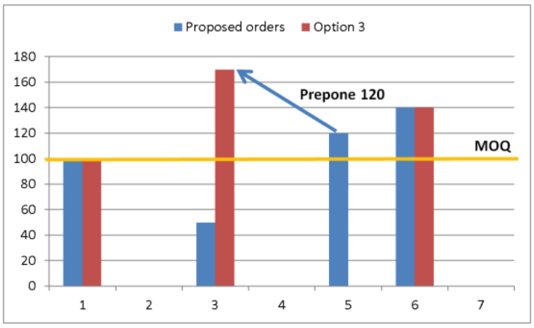


Fig. 5.7: MOQ option 3

Fundamentally, the decision for one or the other option is entirely cost driven. Even though this is theoretically sound at first glance, initial tests have revealed that option 2 can under circumstance lead to sub-optimal results.

One example for the sub-optimality is illustrated in table 5.27.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	100	200	200	200	100	100	200	200	200

Table 5.27: Scenario for sub-optimality of option 2b

Applying option 2 to the example would prepone the shipment of period P4 to P0 during the MOQ rounding since the effect of purchase cost reduction overrules the other cost factors. For this reason the cheaper option 3 of combining P0 and P1 as well as P4 and P5 is overlooked. Since this has been a rather frequent observation during initial testing, option 2 shall be neglected. In case that option 1 and option 3 result in the same cost impact, option 1 shall be preferred since this guarantees to reduce the number of shipments for this item and hence may ultimately have a positive effect on ordering cost even though this is not considered at this stage.

5.4.2.5 Quantity discounts

In a next step quantity discounts shall be considered. A quantity discount shall be realized, if the savings in purchase costs are higher than the additional arising inventory costs that are caused by the necessary preponement. Within this thesis, the all-quantity discount shall be focussed, as this is the by far most relevant type of discount for the organization's business.

The all-quantity discount provides a cheaper price for the shipped quantity, if a certain discount threshold is reached. The MOQ rounded schedule is the output of the MOQ rounding that was discussed in the previous section and, therewith, the input for the discount function.

The all-unit discount is most cost efficiently claimed when the discount threshold is just reached. This is illustrated by table 5.28 and 5.29.
In the first discounted schedule the same quantity is subjected to discounts as in the second discount schedule, whilst significantly lower inventory costs are incurred.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Discounted schedule 1	500	0	0	500	0	0	500	0	0

Table 5.28: Inventory cost efficient claim of quantity discount

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Discount schedule 2	1500	0	0	0	0	0	0	0	0

Table 5.29: Inventory cost inefficient claim of quantity discount

In case that inventory costs are comparably low to the discount saving, the cost comparison would opt for combining many shipments, as total schedule costs or unit costs still decrease with each preponed shipment. Eventually, this is the same issue that has been faced for the MOQ with regards to option 2.

Based on the general approach of most heuristics to work the schedule off from the first to the last period, the foresight that discounts could be claimed at a later period for less inventory cost is not given. Therefore, another alteration shall be proposed. Instead of combining shipments as long as the total schedule cost decreases, the discount function shall be applied in two runs. The procedure shall be illustrated at the sample schedule in table 5.30. Other conditions remain same as in previous examples.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	200	200	200	200	200	200	0	300	400

Table 5.30: Sample schedule for discount explanation – input

First run

During the first run, the target is to investigate whether just achieving the discount in a period brings cost advantages. Once the discount threshold is exceeded due to the preponement of a shipment, the search is aborted and the schedule impact calculated.

With regards to the sample schedule, the combination of P0 and P1 does not exceed the discount threshold of 500. Therefore, the combination of P0, P1, and P2 is tested. Fundamentally, the most cost efficient way is to just prepone 100 pieces from period P2. Since leaving 100 pieces (less than the MOQ) in P2 might have negative cost implications for subsequent periods, the entire quantity of P2 is moved as per previous postulation. The result is shown in schedule 5.3.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	600	0	0	200	200	200	0	300	400

Table 5.31: Sample schedule for discount explanation – after P0

A number of corrections for the potential sub-optimality of the preponement of the entire shipment in P2 have been evaluated. On average the corrections did though deliver inferior results, which is why the rule of not leaving MOQ violating quantities is accepted.

The outcome of the complete first discount run is shown in table 5.32.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	600	0	0	600	0	0	0	500	200

Table 5.32: Sample schedule for discount explanation – after first run

Second run

In the second run the discount functionality is now applied as normal and follows the premise: “combine shipments as long as the cost impact is positive”. Since this check is very similar to the application of the previously discussed least-unit-cost heuristic, it shall not be examined again at this stage. The output of the second run for the previous example is given in table 5.33.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	600	0	0	600	0	0	0	700	0

Table 5.33: Sample schedule for discount explanation – after second run

5.4.2.6 Qualitative review

Within the description of MOQ rounding and discount evaluation it has been addressed that with a heuristic approach it is rather unpredictable what effect a certain decision will have on future periods. In an effort to limit the risk of severe cost impacts, some “safer” decisions that might prevent an optimal solution have been taken, e.g. the requirement not to leave MOQ violating leftovers.

The decision for one or the other option in case of cost impact equality is a further potential source of sub-optimality. However, it must be noted that some kind of deviations to the optimal solution must be accepted whenever a heuristic approach is applied.

5.4.3 The proceeding in brief

The individual schedule optimization starts with a just-in-time schedule, where in general the incoming shipment of a period equals the demand of that period and hence no stock other than the safety stock is carried over.

All cost comparisons are based on total schedule cost, which considers the sum of purchase cost and the sum of inventory costs. Inventory costs are thereby calculated by evaluating the preponements in relation to the pack code rounded schedule.

1. Packcode rounding
    - All shipment quantities must represent a multiple of the packcode quantity.
    - The difference between the JIT quantity of a period and the next bigger full packcode quantity must be preponed from later periods.

2. MOQ rounding
    - Evaluate the cost of preponing the MOQ violating shipment itself
    - Evaluate the cost of preponing the shortage quantity from the first shipment after the MOQ violating shipment. If the remaining quantity is lower than the MOQ, the entire shipment must be preponed.
    - Perform the option that has the better impact on schedule cost.
    - If cost impacts are equal chose the prepone the violating shipment itself.

3. Quantity discount – first round
    - Evaluate the cost impact of combining as many shipments or partial shipments as necessary to <u>just</u> achieve the threshold that is necessary to receive the discount (overachievement does most times not pay off for the all quantity discount).
    - If the remaining quantity of the partial shipment is lower than the MOQ, the entire quantity of this shipment shall be preponed.
    - If the cost impact is positive, perform the combination

4. Quantity discount – second round
    - Combine as many shipments as it makes economic sense.

5.5 Step 2 – Joint replenishment

With the inclusion of quantity discounts, the optimization on individual product level is completed. So far transportation cost has not been considered, which shall be done with in this section. As Narayanan and Robinson (2010) pointed out, the potential of transport cost saving forms the joint between otherwise individual products. The need to consider transportation cost within economic order considerations is frequently discussed within the literature. However, the way of including the transport cost is usually rather undifferentiated right up to superficial. Often transport cost is considered as a fixed sum within the ordering cost. In practice though, transport cost is subjected to significant economies of scale. It was moreover, presented that transport costs are not linear and that certain quantities are local optima, whilst others are local maxima – refer figure 5.8.

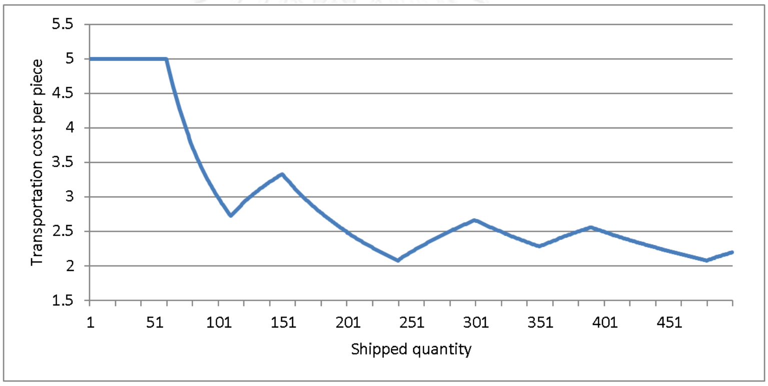


Fig. 5.8: Transportation cost in dependence of quantity shipped

The optima represent optimal degrees of container utilization. In case a container is not fully utilized it is expedient to evaluate whether it is economic to ship a higher quantity of the same item or even to add a different item of the same supplier to the shipment. To assess the container utilization, the exact loading has to be planned, which is in a multi-item scenario a rather complex problem which shall be processed subsequently.

Once the individual product schedules have run through packcode rounding, MOQ rounding, and discounting, the minimal shipping setup that can accommodate the goods must be determined.

As a first step, a “minimum shipping list” which lists all items that shall be shipped as per the individual product optimization schedules, shall be compiled. In a second step the cost optimal shipping mix (combination of i * 40FT container, j * 20FT container, and k weight measures of LCL) shall be determined for the minimum shipping list. How to arrive at the optimal shipping mix will be discussed in sections 5.5.1 and 5.5.2. As final step, it shall then be evaluated in section 5.5.3 whether adding additional items/quantities to the shipping list yields cost savings.

5.5.1 Containerization

5.5.1.1 Introduction and constraints

In a single item scenario the quantity that a container type can accommodate is static (how many pallets of this item fit into the container). In a multi-item scenario, this is though a dynamic problem since the loading relation between two different items is complicated. Theoretically, the required container volume follows equation 5.1.

$$Required\ volume = volume\ item\ A\ \cdot qty\ of\ A + volume\ item\ B\ \cdot qty\ of\ B + \cdots$$

Equation 5.1: Total volume requirement

However, in practice goods are not deformable like that and dimensions have to be considered. For this purpose several calculators for container stuffing are available that not only consider dimensions but also weight, e.g. Searates.com, n.d.). Beyond that is palletisation possible, which limits the possibilities to rotate the goods and hence decreases the degrees of freedom. Fig. 5.9 illustrates the output of such a tool.

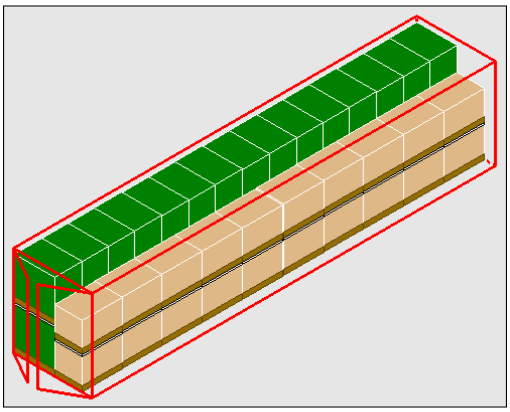


Fig. 5.9: Output of container stuffing calculation (Searates.com, n.d.)

For the practical applicability of such a container stuffing calculation, the stackability of goods should be considered in order not to damage the goods. For the envisioned implementation into the ERP system the following side constraints shall be considered:

- The maximum stackable weight of a pallet is limited
- All goods are palletized on Euro pallet (Hafele standard)
- The maximal total container weight is not exceeded
- At this point maximum internal container height shall be set to 2200 mm, which excludes high cube containers. These can be added at a later stage

In order to solve this problem a heuristic approach was implemented that shall be described subsequently.

5.5.1.2 Partial problem 1 - Creating pallet stacks

For reasons of handling and storability, the use of Euro pallets for all goods was stipulated and is also contractually agreed with suppliers. With regards to this, the individual product schedules have previously all been rounded to a quantity that is a multiple of the according pallet quantity. For a certain week, a list of all pallets that need to be shipped shall be created in order to systematically assign them to a container, which is a multi-staged approach.

The following situation shall be imagined: The individual item optimization has brought about a crowd of pallets that must be shipped in a certain week. It shall now be checked whether this crowd of pallets fits into a 20FT container that offers eleven ground floor pallet spaces.

Each of these ground floor spaces can in turn accommodate a stack of pallets (multi-layer), as it is factually represents a cube that is 1200mm long, 800mm wide, and 2200mm high. To optimize the overall container utilization, the utilization of the 11 individual cubes must be maximized by an algorithm, which means the stacks of pallets must be as close to 2200 mm as possible. Thereby, the maximum stackability of individual pallets must be abided by the algorithm. The stackability of a pallet shall be measured by the maximum weight that can be stacked on top of the pallet ("stackable weight").

The heuristic algorithm that was implemented to assemble efficient pallet stacks works as follows:

1. Identify all pallets that have a maximum stackable weight of zero. These pallets have to be placed on top of the pallet stack ("column" and "pallet stack" are used as synonyms). The count of the pallets that cannot carry any weight prescribes the minimum number of pallet stacks ("mandatory columns"). For instance if 14 pallets have a maximum stackable weight of zero then at least 14 pallet stacks are required – a 20FT container will not be able to accommodate them.

For the next steps, recursive programming was used.

2. Sequentially, all identified mandatory columns are now filled up from top down. The list of unused pallets is sorted by maximum stackable weight ascending. The algorithm is then running through this list seeking the first pallet that is able to support the weight of the top level pallet (mandatory pallet).

3. If the sum height does not exceed the maximum height of 2200 mm, the pallet is added to the bottom of the stack. The search for a pallet that can carry the current stack is repeated.

4. If no further pallet can be found that can be added to the stack, either because of weight or volume restrictions, the combination of pallets is saved as current maximum in case it is higher than the previously found maximum. To find the best solution each pallet is exchanged by the 2nd, 3rd, …, nth best one in terms of stackable weight by means of the recursive programming.

5. Yet, for high numbers of pallets this combination can be rather time consuming, which is why a threshold of 1900mm was set. If a pallet stack exceeds the height of 1900mm it is accepted and further searches are aborted. If this is not achieved, the stack is discarded for the moment. However, if no combination with better total height was found, it can still be used.

6. This procedure is repeated for all mandatory columns. If all mandatory columns are completely stacked and still pallets are left, the procedure is started with the pallets with the lowest stackable weight out of the remaining pallets.

Example

The heuristic shall be explained at the following example to add clarity. Table 5.34 shows the pallets that have to be loaded. The table is already sorted by maximum stackable weight.

Pallet Type	Height in mm	Weight in kg	Max stackable weight in kg
P1	900	400	0
P2	850	150	200
P3	1000	200	200
P4	650	350	350
P5	800	300	500
P6	1300	650	800

Table 5.34: Example – pallets to be stacked – round 1

P1 forms a mandatory pallet column since nothing can be stacked on top of P1 due to its maximum stackable weight of 0. In the first step the column consists of only P1 and has hence a weight of 400 kg and is 900 mm high. In several iterations the pallet stack which is initiated by P1 shall be filled up. The closer the stack comes to the maximum height of 2200mm the better the utilization.

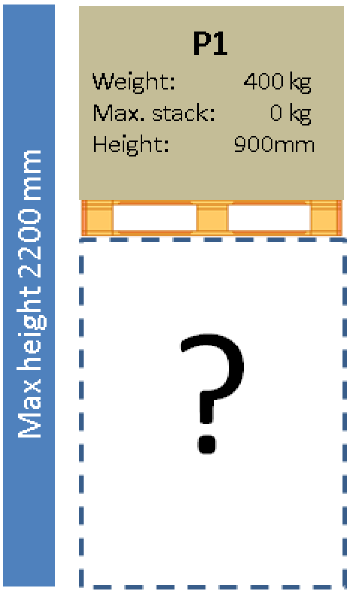


Fig. 5.10: Stack 1 during first iteration

First iteration

The search for a pallet that complete the column is started:

- The total height of P2 and P1 is 1750mm (900 + 850), which is less than the maximum of 2200mm. However, P2 is not able to carry the weight of P1. As a result P2 is skipped.
- The total height of the potential stack of P3 and P1 with 1900mm (900+1000) is suitable. Yet, P3 is again not strong enough.
- P4 is also skipped because of the weight issue.
- P5 and P1 are 1700mm high and P5 is able to carry the weight of P1. Therefore, P5 is added to the stack.

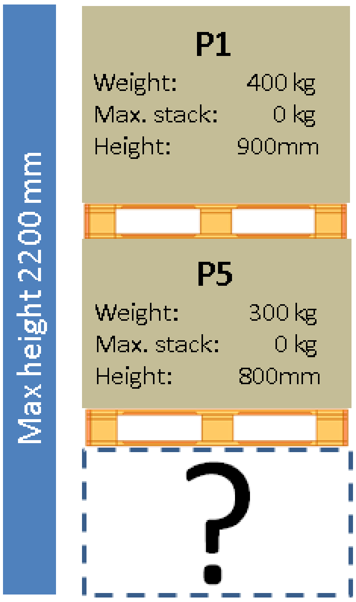


Fig. 5.11: Stack 1 during second iteration

Second iteration

The total weight of the current stack is now 700 kg and the total height is 1700 mm. The search for another pallet to complete the stack is started.

- P2 to P4 do not need to be evaluated again, since the stackable weight was already not sufficient enough to carry P1 alone.[3]
- P5 is already used and hence exempted from the list
- P6 is able to carry the weight but too high to fit.
- As there are no further pallets, the search is aborted.

→ The current maximum is 1700 mm high with the iteration path “P1>> P2”

[3] If these pallets would have been skipped because of the dimension check, not because of the weight check, then they would also fail now since the stack is even higher.

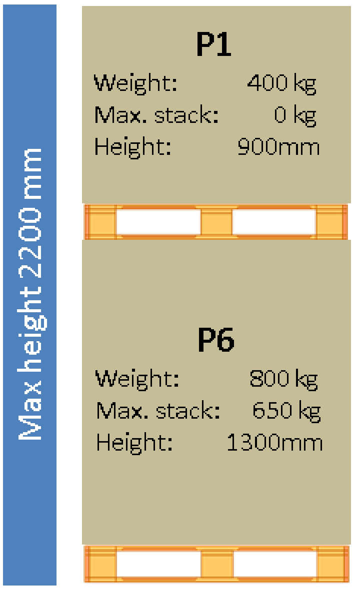


Fig. 5.12: Stack 1 solution

First iteration

Because of recursive programming, the search jumps back into the first iteration and continues seeking through the list of pallets to find a better solution for P1. The next pallet in the list is P6, which is able to carry the weight of P1. The total height of 2200mm (900+1300) is just within the maximum. P6 is added. Since the total height of 2200mm does not allow for improvement, the second iteration is not started. The height of this stack is higher than the previous maximum of 1700 mm and hence the new maximum. As a result the first column is composed by P1 and P6.

Both pallets, P1 and P6, are removed from the pending list, see table 5.35.

Pallet Type	Height in mm	Weight in kg	Max stackable weight in kg
~~P1~~	~~900~~	~~400~~	~~0~~
P2	850	150	200
P3	1000	200	200
P4	650	350	350
P5	800	300	500
~~P6~~	~~1300~~	~~650~~	~~800~~

Table 5.35: Example – pallets to be stacked – round 2

As there are no further mandatory columns, the composing continues with the pallet with the lowest stackable weight since this pallet should be logically placed on top of a stack. P2 and P3 have the same stackable weight. In this case the pallet with the greater height is served first since smaller pallets are always easier to accommodate. The search function is called again with the first iteration starting with P2.

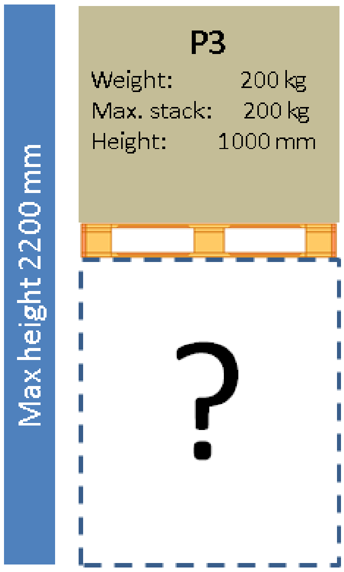


Fig. 5.13: Stack 2 during first iteration

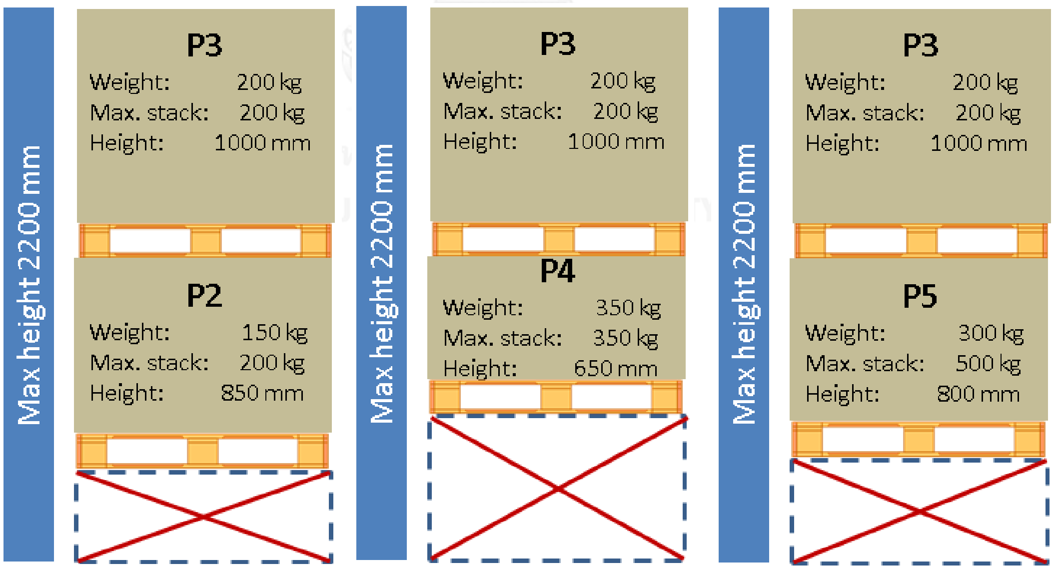
First iteration

P2 is able to carry the weight and does not exceed the maximum height, as the combined height is 1850 mm.

Second iteration(s)

Since the difference between this value and the maximum height of 2200 mm is only 350 mm and, therewith, smaller than the smallest pallet in the entire list (650 mm), there is no point in searching for another pallet that could join this stack in order to improve height utilization. The search gets aborted.

For the further search, 1850 mm is the maximum value that has to be beaten. Yet, also in second iteration the stacks of P3 and P4 as well as of P3 and P5 are not able to point against the 1850mm of P3 and P2, which is why the second column is composed of P3 and P2.



(aborted in second iteration) (aborted in second iteration) (aborted in second iteration)

Fig. 5.14: The different options for stack 2 in during second iteration

In the continuation of this process P4 and P5 are logically found to form the last column. In total three columns have been formed: column 1 consists of P1 and P6, column 2 consists of P3 and P2, column 3 consists of P4 and P5

5.5.1.3 Partial problem 2 - Containerization of pallet stacks

The previously presented function delivers a list of rather optimized pallet stacks that now need to be loaded into containers or that should get assigned to LCL, whichever is the most cost efficient setup.

Whenever a container is used, it should be utilized as much as possible in order to achieve the lowest transport cost per weight measure. Utilization shall, thereby, summarize both – weight utilization and volume utilization (in this case pallet space utilization). In this respect, container capacity is wasted when:

- not all pallet spaces can be occupied because otherwise the maximum payload of the container would be exceeded
- all pallet spaces are occupied with light goods and heavy goods are left over for LCL

That means it shall be ensured that all container spaces are occupied whilst the combined weight is pushed to the maximum.

Given is a pool of pallet stacks and a certain container, either 20FT or 40FT. The count of pallet spaces for a 20FT container shall be set as 11, whilst the maximum net weight is defined as 28,200 kg. For the 40FT container the number of pallet spaces is set to 24 and the maximum net weight to 26,600 kg.

A function shall be implemented that selects several pallet stacks from the pool of unassigned stacks, which would optimally utilize the container in terms of weight and volume.

In order to arrive at a solution, all columns are sorted by weight in descending order. Looking at a 40FT container, the first 24 columns are covered by a "window". If the total weight of the 24 columns within the window exceeds the maximum weight, the window is moved down by one column. Implicitly, the heaviest pallet column is replaced by the next lighter one. If the total weight still exceeds the maximum, the window is further moved downward until the total weight just falls below the maximum permissible weight. The identified columns are removed from the list of pending columns. The count of columns that have been loaded is returned by the function. In case of overweight or too few pending columns, the number of loaded columns could fall short of the number of pallet spaces. Table 5.36 illustrates this heuristic approach.

Column	Weight	Possible combination in 40FT container (24 columns)											
C1	2000	37,500 kg (overweight)											
C2	2000		36,480 kg (overweight)										
C3	2000			35,280 kg (overweight)									
C4	1900				34,080 kg (overweight)								
C5	1900					32,980 kg (overweight)							
C6	1850						31,880 kg (overweight)						
C7	1850							30,780 kg (overweight)					
C8	1800								29,680 kg (overweight)				
C9	1800									28,630 kg (overweight)			
C10	1780										27,580 kg (overweight)		
C11	1700											**26,550 kg**	
C12	1600												25,530 kg (underutilization)
C13	1600												
C14	1500												
C15	1500												
C16	1450												
C17	1375												
C18	1315												
C19	1250												
C20	1150												
C21	1100												
C22	1050												
C23	1050												
C24	980												
C25	980												
C26	800												
C27	800												
C28	800												
C29	800												
C30	750												
C31	750												
C32	750												
C33	750												
C34	680												
C35	630												
C36	500												
C37	500												
C38	350												
C39	350												
C40	350												

Table 5.36:Application of containerization window

5.5.2 Currently optimal shipment mix

The result of partial problem 1 is a list of pallet stacks that are waiting for being loaded to a container. Partial problem 2 has demonstrated a heuristic for selecting pallets that can be loaded into a certain container.

Yet, it is still to be decided which containers to use. The term “shipping mix” shall denote the compilation of a certain number of 40FT and 20FT containers, but also of a certain count of weight measure that is assigned to LCL. The optimal shipping mix is that combination that brings about the lowest transport costs. The approach to solve this problem was realized by recursive programming that calls the containerization function described as partial problem 2.

At first, the containerization function is deployed on the pool of pallet stacks with regards to a 40FT container. The normal expectation is that a full 40FT container is the cheapest option to ship, which is why it should be used as a first choice. If this container is fully utilized (loaded column = number of pallet spaces) a second 40FT container is added and so on. If a 40 FT container is not fully utilized, a 20FT container is tried instead. If a 20FT container is not fully utilized, LCL is tried out. Figure 5.16 illustrated the decision tree

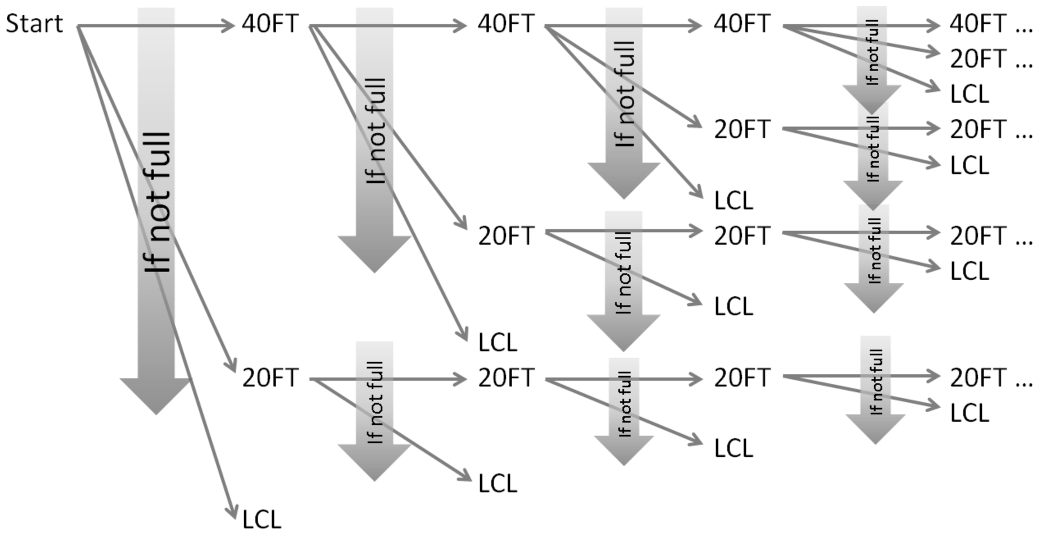


Fig. 5.15: Option tree for shipment mix

Table 5.37 illustrates the output of the containerization function for the different shipment mixes at an example of 40 columns. The costs that are involved in the different options are compared. The shipment mix with the lowest cost is finally selected.

Column	Option A		Option B			Option C			Option D		Option E				Option F			
	40FT	40FT	40FT	20FT	20FT	40FT	20FT	LCL	40FT	LCL	20FT	20FT	20FT	20FT	20FT	20FT	20FT	LCL
C1																		
C2																		
C3																		
C4																		
C5																		
C6																		
C7																		
C8																		
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C40																		

Table 5.37: Output of containerization function for the different shipment mixes

5.5.3 Joint transport cost optimization

5.5.3.1 Concept and review of underlying cost struture

Based on the individual item schedules a shipping list for the focus period had been generated. In the previous section, the cost optimal shipping mix – the combination of 40 FT and 20FT containers as well as LCL – has been determined.

The retrieved shipping mix is, though, only the cost optimal transport option for the shipping list, which is not necessarily a local optimum on the transport cost curve. Figure 5.16 illustrates this circumstance.

Fig. 5.16: Sub-optimality of potential as-is position on transport cost curve

A 20 FT container has been found to deliver the lowest cost for the “as is” shipping list. Apparently, shipping a higher quantity would deliver lower transportation costs per piece respectively per weight measure.[4]

Yet, whenever additional goods are added to the shipment, variations are made to the previously optimized individual product schedules, as the added goods are eventually preponed from future periods. In general, these variations can be expected to increase individual schedule costs.

Logically, goods should only be added to the shipment if the savings in transportation costs exceed the increases in individual schedule costs. In the following sections, both factors shall be examined in greater depth.

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[4] Since a per piece basis is only expedient in a single item scenario, per weight measure (w/m) shall be used onwards to standardize the measure for multiple items.

5.5.3.2 Transport cost degression

The aim of the addition of pallets and hence weight measures (w/m) is to increase the utilization rate of a shipping mix and hence to achieve a transport cost degression. This cost degression implies a reduction in shipping costs per w/m for the original crowd of pallets that is supposed to be shipped in the focus period. The cost impact on the shipping costs for the preponed goods is hardly predictable and hence rather vague.

The absolute transport cost saving shall be defined as the product of the saving in shipping cost and the original count of weight measures, equation 5.2. The cost saving is therewith deliberately not considering the impact on the shipping cost of the preponed w/m.

$$Transport\ cost\ saving = \Delta shipping\ cost\ per\ {}^{w}/_{m} \cdot shipped\ {}^{w}/m_{before}$$

Equation 5.2: Transport cost saving

The delta in shipping cost per w/m is calculated as the simple difference between the “before” and “after” shipping costs per w/m, equation 5.3.

$$\Delta shipping\ cost\ per\ {}^{w}/_{m} = shipping\ cost\ per\ {}^{w}/m_{before} - shipping\ cost\ per\ {}^{w}/m_{after}$$

Equation 5.3: Delta in shipping cost per w/m

The shipping cost per weight measure in turn is calculated by dividing the total shipping cost by the count of shipped w/m. For the “before” cost per w/m, the total transport cost of the optimal shipping mix is divided by the count of w/m of the original pallet crowd, equation 5.4.

$$shipping\ cost\ per\ {}^{w}/m_{before} = \frac{total\ shipping\ cost\ of\ optimal\ shipping\ mix}{shipped\ {}^{w}/m_{before}}$$

Equation 5.4: Shipping cost per w/m$_{before}$

The shipping cost per w/m after the addition is calculated as the total shipping cost of the optimal shipping mix for the “after” shipping list divided with the total count of w/m of the “after” shipping list.

$$shipping\ cost\ per\ {}^{w}/m_{after} = \frac{total\ shipping\ cost\ of\ prospect\ shipping\ mix}{shipped\ {}^{w}/m_{after}}$$

Equation 5.5: Shipping cost per w/m$_{after}$

The total shipping costs of a shipment mix are calculated as:

	Fixed FCL shipment cost (if m + n > 0)
+	m * variable 20FT container charge
+	n * variable 40FT container charge
+	Fixed LCL shipment cost (if k > 0)
+	k * variable LCL charge per w/m
=	Total shipping cost

Equation 5.6: Total shipping cost

Example

The impact shall be illustrated at an example where the original shipping list contains a total of 40 w/m. Obviously, increasing the count of shipped weight measures delivers significant transport cost savings, whereby fully utilized containers logically deliver the highest saving. Adding slightly more goods than the container can accommodate reduces the savings again since fixed costs for LCL apply.

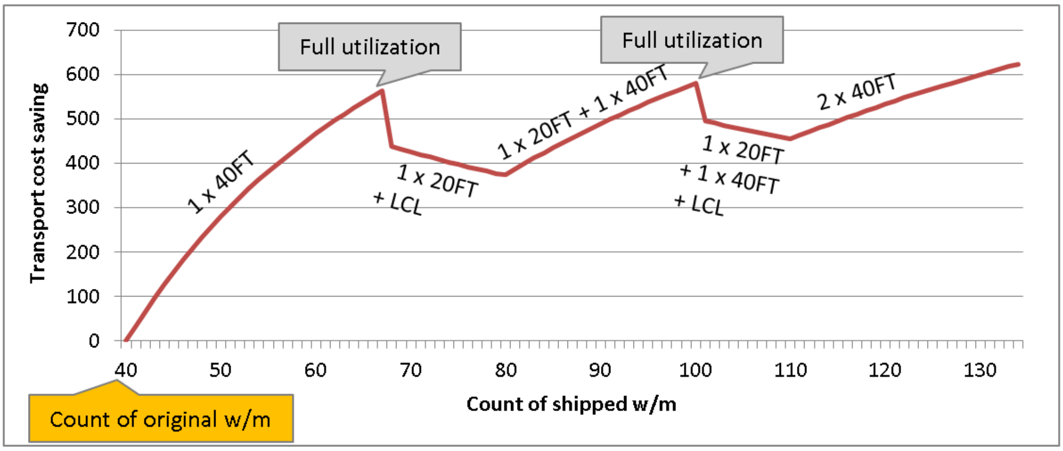

Fig. 5.17: Transport cost savings in dependence of shipped w/m

5.5.3.3 Determination of unutilized space

The count of weight measures and, therewith, the position on the transportation cost curve can be easily determined. However, this knowledge does not allow drawing inferences about how many additional pallets can be added to the shipping mix without overshooting the full utilization cap.

Therefore, a function was implemented that determines the unused space (unoccupied pallet spaces) in any (m,n) shipping mix for a given pallet crowd. The function is very simple, as it deploys the 20FT containerization window n times and afterwards the 40FT containerization window m times. The number of allocated pallet stacks is counted and contrasted with the total number of available pallet spaces (m times the pallet spaces in a 40FT container plus n times the pallet spaces in a 20FT container).

- If pallet spaces are empty, the number of empty pallet spaces is returned.
- If not all pallet stacks can be loaded due to too little space or weight capacity then the return value is -1.
- If no pallet spaces are empty and at the same time all pallet stacks are occupied, the function returns 0. Yet, this means that half a pallet space could be empty.

5.5.3.4 Prospect shipping mixes

In a first run, the function to determine the empty spaces is applied to the combination of original shipping list and optimal shipping mix. Based on the result it is now possible to define the prospect shipping mixes. These are those shipping mixes that offer slightly more space than the optimal shipping mix, consist of FCL only, and hence have potential to yield cost savings. They are generically defined as per below:

- If the space utilization check returns a value that is greater or equal to 0, then an optimization with the shipping mix (m,n) shall be run. This means that the optimal mix is not fully utilized and hence attempts to achieve better utilization shall be undertaken.

- In case that the optimal shipping mix contains LCL, the next attempt is done with the shipping mix (m, n+1), which means one 20FT container is added to replace LCL. This is also desired when the shipment mix contains already a 20FT container. That is because even though two 20FT containers lead to higher costs than one 40FT container, the higher maximum allowable net weight can yield overall savings.
- In case that the optimal shipping mix contains LCL, another attempt is to add a 40FT container to replace LCL. The resulting shipment mix is (m+1,n).
- If the optimal shipping mix contains 20FT containers, the last attempt is done with the shipping mix (m+k, n-k). This means that 40FT containers are used to replace 20FT containers.

Under normal circumstances this means that further investigations either aim at filling up the optimal shipping mix, at adding one 20FT container, or at adding one 40FT container. Ultimately, the decision for one of these shipment mixes will be entirely driven by its impact on total cost.

With the help of the function presented in 5.5.3.3, the number of empty pallet spaces can be retrieved for a particular prospect shipping mix in relation to the original shipping list. Hence the question of which item to prepone arises.

Logically, the item that sees the lowest increase in individual schedule cost when being preponed should be added to the container. It must, thereby, be noted that the increase in schedule cost does actually depend on the quantity that is preponed. Ex ante it is practically impossible to predict for which item the addition of pallets to the shipment crowd causes the lowest difference in schedule cost.

Therefore, each item shall be actually tested towards its preponement cost impact. In order to be able to compare the increase in schedule cost of different items, the increase cost shall be calculated on per-preponed-w/m basis. To start with, it shall be determined for each item how many pallets could be added to the container physically – “space filling problem”.

5.5.3.5 Space filling problem

The space utilization function delivered the count of empty pallets spaces with regards to the prospect shipping mix. To translate this into a number of pallets of a specific item, a function was implemented that calculates how many pallets of an item can be stored in one pallet space in compliance with height and stackability constraints. The maximum number of pallets for this item that fit into the container is retrieved by multiplying the number of empty pallet spaces with the pallet count per stack for this item. Thereby, it must also be validated that the unutilized container net load allows the loading of these pallets. If this is not given, the maximum pallet count shall be accordingly reduced.

It must be noted that the retrieved maximum number of pallets might have been underestimated since the addition of a pallet might entail the possibility that overall more efficient pallet stacks can be build and hence even more pallets can be fitted. To refine the result, the same calculation procedure shall be repeated after the goods have been added to the shipping list.

After the maximum number of addable pallets has been found for each item, the implied costs per preponed w/m shall be calculated.

5.5.3.6 Impact of preponement on schedule costs

The application of slight changes to a schedule can have significant impact on total schedule cost. The quantity that is added to shipment has to be deducted from some of the adjacent periods and changes, therewith, the entire schedule.

Individual schedule costs

To evaluate the overall cost impact of a schedule change on subsequent periods, the total schedule cost before the change shall be compared with the total schedule cost after the change.

$$\Delta schedule\ cost = schedule\ cost_{after} - schedule\ cost_{before}$$

Equation 5.7: Delta in schedule cost

Thereby, the total schedule cost shall be defined as:

$$total\ schedule\ cost \stackrel{\text{def}}{=} \sum purchase\ cost + \sum inventory\ cost$$

Equation 5.8: Definition of total schedule cost

Apparently, this is the same definition and, therewith, the same function that has been applied during the individual schedule optimization. The procedure shall be explained at the following example.

Example

All cost factors remain the same as in the individual item schedule optimization examples. Inventory costs are $1 per piece/per period. The MOQ is 200 pieces and the discount threshold is 500 pieces. The discounted price is $1.5 less than the original price of $10.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	400	0	0	300	0	0	0	300	0
Before schedule	500	0	0	200	0	0	0	300	0

Table 5.38: Example schedule for preponement cost calculation

The total schedule cost before the addition of goods is calculated by adding purchase costs and inventory costs in relation to the packcode rounded schedule:

Purchasing costs: 500 * $8.5 + 200 * $10 + 300 * $10 = $9250

Inventory costs: 100 * 3 * $1 = $300

Before schedule cost = $9250 + $300 = $9550

The basis for the schedule change is the packcode rounded schedule. The quantity that shall be added to the container is added to P0 and deducted from the next shipment. The received schedule must then be optimized with the previously described MOQ rounding and discount optimization functions. Thereby, the first period is exempted since this quantity is fixed by the available space.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Pack code rounded schedule	400	0	0	300	0	0	0	300	0
Unrounded after schedule	600	0	0	100	0	0	0	300	0
Optimized after schedule	600	0	0	200	0	0	0	200	0

Table 5.39: Preparation of after schedule

In the next step the total costs for the optimized "after" schedule are calculated.

Purchasing costs: 600 * $8.5 + 200 * $10 + 200 * $10 = $9100

Inventory costs: 200 * 3 * $1 + 100 * 4 * $1 = $1000

After schedule cost = $9250 + $300 = $10100

The delta in individual item schedule cost is hence $10100 - $9550 = **$550**.

The process is summarized in figure 5.18.

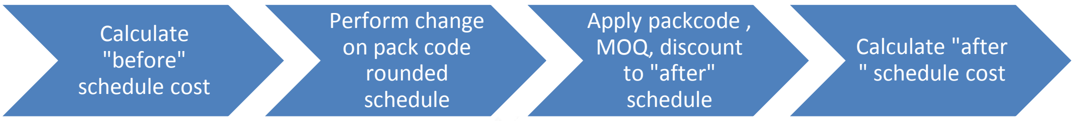

Fig. 5.18: Changing cost for individual schedule

Ordering costs

So far ordering costs have not been considered because the dependencies have been complicated. At this stage now, ordering cost can be considered in a fairly easy way. The ordering cost is due whenever at least one item is shipped in a certain period. The total ordering costs for the schedule are hence retrieved by counting the periods for which an order is placed and multiplying it with the ordering cost. This counting is performed before the preponement and after. The difference between before and after is the saving.

$$\Delta ordering\ cost = total\ ordering\ cost_{after} - total\ ordering\ cost_{before}$$

Equation 5.9: Delta in ordering cost

Combined

The sum of both differences gives the absolute cost impact caused by the preponement. Since the moveable quantity can differ between different items, standardization is required to allow for comparison. Therefore, the delta in absolute cost shall be divided by the number of weight measures that are added to the container.

$$schedule\ impact\ per\ {}^{w}/_{m} = \frac{\Delta ordering\ cost + \Delta schedule\ cost}{added\ w/m}$$

Equation 5.10: Schedule impact per w/m

5.5.3.7 Addition in face of discontinuities in cost increase function

From the calculation of the schedule impact per w/m it can be concluded that adding a high number of pallets of the same item to the container will bring about a disproportional increase in schedule cost compare to the addition of a lower number. The dependency of the schedule impact per w/m from the count of preponed pallets is a result of discontinuities in the cost increase function.

Example

It shall be imagined that the space filling problem has brought about that 6 more pallets (600 pieces) of item A would fit into the container that is supposed to arrive in P0. One pallet of item A equals 1.6 w/m. Alternatively, 8 pallets of item B would fit into the container, whereby one pallet of B equals 1.2 w/m.

All cost factors remain again the same as in the individual item schedule optimization examples. Inventory costs are $1 per piece/per period. The MOQ is 200 pieces and the discount threshold is 500 pieces. The discounted price is $1.5 less than the original price of $10.

The individual item schedules for item A and B are shown in table 5.40. For the consideration of discontinuities the before and after schedule shall be compared directly, as the visibility in regards to the packcode rounded schedule is low.

Period	P0	P1	P2	P3	P4	P5	P6	P7	P8
Before schedule of item A	0	200	500	0	300	0	0	700	0
Before schedule of item B	0	400	0	0	300	0	300	0	300

Table 5.40: Sample schedule for discount explanation – after second run

To add 600 pieces of item A to the container, 200 pieces from P1 and 400 pieces from P2 would need to be preponed. This would leave 100 pieces in P2, which is per stipulated policy “not to leave a remaining quantity less than the MOQ” already not allowed. Since 700 pieces would not fit into the container, only 300 pieces from P2 could be preponed, which means 500 pieces in total.

The move of 500 pieces of item A would not affect the purchase cost since the preponed quantity of P1 will receive now a discount, whilst the remaining 200 pieces in P3 lose their discount. Inventory costs can be calculated as (200 * 1 + 300 * 2) * $1 = $800. The cost impact per w/m is hence $800/(1.6*5)= $100.

For adding 800 pieces of item B to the container, 400 pieces from P1, 300 pieces from P4, and 100 pieces of P6 must be preponed. Since the combined shipment is now exceeding the discount threshold, a purchase cost saving of -$1.5 * 800 = -$1200 can be claimed. Therefore, inventory costs of (400 * 1 + 300 * 4 + 100 * 6) * $1 = $2200 incur. The cost per w/m is $1000 / (1.2*8) = $104.2.

It would hence be the cheaper option to add item A to the container. In case that the transport cost saving would be $75 per w/m, the savings in transport costs would not rectify the increases in schedule costs. However, there is no need to fill the container entirely. If the preponement of a smaller quantity delivers an overall saving this is still advantageous, which is why it shall be investigated to load the container in incremental steps up to the maximum. The size of the incremental steps is, thereby, defined by the discontinuities of the cost increase function.

Step 1

For item A, at least 200 pieces have to be preponed in order not to violate the MOQ rule. The according inventory costs are $200 for 3.2 w/m, which leads to an impact per w/m of $62.5. For item B either 100, 200 or 400 pieces could be moved at the same cost. The preponement of 100 pieces is, though, not possible since this would undercut the MOQ in the first period. The according impact per w/m is $200/2.4 = $83.3. Due to the lower schedule impact 200 pieces of item A are preponed. The remaining container space allows for 4 more pallets of item A or 5 pallets of item B.

Step 2

Another preponement of item A would cause a loss of the discount in P2 since only 400 pieces can be preponed due to the space constraint. With regards to the MOQ requirement only 300 pieces can be preponed. The impact is $125 per w/m. The impact of a preponement for item B remains the same at $83.3 per w/m. Therefore, 400 pieces of item B are preponed even though this cost is higher than the generated saving in transport cost. The remaining space allows for one more pallet of A or one more pallet of B.

Step 3

The impact of A remains the same at $125 per w/m. For B one pallet could be preponed from P4, which at the same time would bring about a discount saving in P0. The impact is hence -$350 per w/m, which is actually a saving. Hence one pallet of B is preponed.

Result

Since there are no empty pallet spaces left, the search is concluded. Fundamentally, the same procedure would have now been applied to the next bigger prospect shipping mix, which shall though be skipped in this example.

As shown in table 5.41, all steps have brought about an absolute cost saving. Since step 3 delivered by far the highest cost saving, the according shipping list (200 A and 500 B) is proposed for order.

Step	Accumulated delta schedule cost	Accumulated delta transport cost	Total delta
1	$62.5 * 2 = $125	-$85 * 2 = -$170	-$45
2	$62.5 * 2 + $83.3 * 4 = $458.2	-$85 * 6= -$510	-$51.8
3	$62.5 * 2 + $83.3 * 4 + -$350 * 1 = $108.2	-$85 * 7 = -$595	-$486.8

Table 5.41: Final cost effect comparison for discontinuity example

The example has shown that the step-wise approach has brought about a much better solution than filling up the entire container with pallets of the same item. The rules with regards to the treatment of the discontinuity shall be summarized and generalized in the following.

Generic formulation

Several thresholds can be identified that represent discontinuities in the cost function with regards to preponements of goods. These thresholds delimit separate quantity blocks within the total quantity, as depicted in figure 5.19

Fig. 5.19: Discontinuity thresholds

- The quantity of block 1 is that quantity which exceeds the discount threshold. Preponing this quantity leads to additional inventory cost and the loss of discount savings on the moved quantity.
- The movement of block 2 would likewise cause additional inventory cost. The loss of discount saving does, though, not only impact the moved quantity but also the remaining quantity. The impact is hence more severe than moving a partial quantity of block 1.
- If a quantity is preponed that leaves the remaining shipment with a quantity less than the MOQ, preponement from future weeks would be required. To avoid this, block 3 has to be moved entirely if touched, which is in line with the previous stipulations. Moving the block entirely does not negatively impact discount saving. Merely inventory costs apply.

Apparently, the discount threshold and the MOQ are points of unsteadiness for the cost increase function, which leads to a dependency of cost per moved pallet on the count of moved pallets. Yet, the MOQ and discount threshold do not only play a role for the shipment to be preponed, but also for the shipment in the focus period itself.

The following factors are of importance for the decision.

- Shipment quantity of the item in the focus period [SHIP1]
- Shipment quantity of the item in the period to prepone from [SHIP2]
- Minimum order quantity [MOQ]
- Discount threshold [DIS]
- Maximal count of moveable quantity by space constraint [SPACE]

The target variable is the quantity to move [MOVE]. The calculation of [MOVE] is a bit complex, which is why the principle shall be explained at this place. A sample source code that can deliver the envisioned results can be found in appendix A.1.

The basic rules of this function are:

- If the space allows for moving the entire shipment, the entire shipment is moved since this will take along potential discounts.

- The minimum move quantity is that quantity which is required to achieve the MOQ in the focus period. If the space is smaller than the minimum quantity, no preponement will be performed.

- The recommended move quantity is the lower quantity of the quantity that is needed to fill the first shipment up to the discount threshold and of the quantity that the second shipment exceeds the discount threshold. The aim of this is to obtain the discount in both periods.

- If the previous rule does not apply, the maximum quantity is moved. The maximum quantity is either limited by the space in the container or by the size of the shipment which shall be preponed (in line with first rule). If the space in the container does not allow moving the entire shipment but a quantity that would leave a leftover less than the MOQ in P1, then the maximum quantity is set so that the MOQ is not touched.

Example

The rules shall be illustrated at examples where the MOQ is again 200 pieces, and the discount threshold 500 pieces. For the different scenarios the reason is given for the decision of moved quantity.

[SHIP1]	[SHIP2]	[SPACE]	[MOVE]	Reason
0	300	100	0	MOQ in P0 cannot be reached
0	300	200	0	Leftover in P1 would be less than MOQ
0	300	300	300	Moving all
0	400	400	400	Moving all
0	500	400	300	MOQ cannot be touched in P2
0	500	500	500	Moving all
0	500	600	500	Moving all
100	200	500	200	Rectify MOQ for both periods
100	300	500	300	Consistent cost impact of moving all
100	700	400	200	Discount in P2 shall be kept
100	700	800	700	Moving all
200	700	400	200	Keep discount in P2
300	700	400	200	Get discount in both periods
400	700	400	100	Obtain discount in P1
500	500	300	300	Consistent cost impact of moving all
700	700	600	200	Keep discount in P2

Table 5.42: Examples for preponement quantity calculation in face of discontinuities

5.6 Complete example for EOQ calculation

To clarify the process flow, an example that illustrates the entire flow of the EOQ calculation is demonstrated within this section. Some simplifications have been undertaken to keep the example comprehensible and to reduce the number of calculations and iterations.

5.6.1 Input data

A supplier delivers four items A, B, C, and D. For reasons of comprehensibility all of these items have the same pallet quantity and are non-stackable. This allows conducting the simulation without the containerization functions, which in itself is rather clear but unhandy to illustrate.

Item	Schedule type	P1	P2	P3	P4	P5
A	JIT-inbound schedule	140	160	280	200	170
B	JIT-inbound schedule	50	300	300	200	0
C	JIT-inbound schedule	70	520	160	180	60
D	JIT-inbound schedule	0	200	100	0	200

Table 5.43: Just-in-time inbound schedules for complete example

- Inventory costs are $1 per piece per period.
- Ordering costs are $100 per order.
- Normal purchase price is $10 per piece and equal for all 4 items. In case of purchases of at least 500 pieces, the entire quantity is discounted to $8.5 per piece.
- The minimum order quantity is 200 pieces.
- The pallet quantity is 100 pieces. One pallet equals 1 w/m.
- The shipping costs for FCL shipments are:

  Fixed costs: $200

  Per 40FT container, which can accommodate 15 pallets: $2000

  Per 20Ft container, which can accommodate 7 pallets: $1200
- The shipping costs for LCL shipments are:

  Fixed costs: $100

  Variable cost: $250 per w/m

5.6.2 Individual item schedule optimization

Item A

In a first step the packcode rounding is applied, whereby missing quantities are preponed from future weeks. In a second step the MOQ rounding is performed. To achieve a discount in P1 the shipments in period P2 and P3 have to be preponed. Thereby, the shipment of P3 is entirely preponed, as it would otherwise fall below the MOQ.

Discount savings: 600 pcs * ($10/pcs - $8.5/pcs) = $900

Additional inventory cost: 300 * 2 wk * $1/pcs/wk = $600

Total improvement: $900 - $600 = $300

Item	Schedule type	P1	P2	P3	P4	P5
A	JIT-inbound schedule	140	160	280	200	170
A	Packcode rounded	200	100	300	200	200
A	MOQ rounded	300	0	300	200	200
A	Discounted schedule	600	0	0	200	200

Table 5.44: Individual schedule optimization for item A

In this case the stipulation of not leaving a leftover that is less than the MOQ leads to a sub-optimal result. That is because leaving 100 pieces in P3 would have allowed for obtaining another discount in P3. The relative increase in schedule cost is 2%, which can be at least partially declared as end-of-horizon effect.

Item B

The packcode rounding is also the first step for item B, which is followed by the MOQ rounding. Afterwards the first round discount function and the second round discount function are applied as per the explanation in section 5.4.2.5. For reasons of readability, units are neglected in subsequent formulas.

First round discount function (focus at just achieving the discount threshold)

Discount saving: 500 * 1 * 1.5 = 750

Additional inventory cost: 200 * 1 * 1 + 100 * 2 * 1 = 400

Total improvement: **350**

Second round discount function (focus at combining as per economic sense)

Discount saving: 200 * 1 * 1.5 = 300

Additional inventory cost: 200 * 2 * 1 = 400

Total improvement: -100

Since the preponement 200 pieces for P3 delivers no improvement, this option is neglected. Hence only the result of the first round discount function is applied.

Item	Schedule type	P1	P2	P3	P4	P5
B	JIT-inbound schedule	50	300	300	200	0
B	Packcode rounded	100	300	300	200	0
B	MOQ rounded	200	200	300	200	0
B	Discounted schedule	500	0	200	200	0

Table 5.45: Individual schedule optimization for item B

Item C

For item C the MOQ rounding leads to the preponement of 100 pieces from P2 to P1. The discount function in first round does then prepone the remaining 300 pieces from P2 to P1 in order to obtain the discount and to comply with the no leftover below the MOQ stipulation.

Discount saving: 600 * 1 * 1.5 = 900

Additional inventory cost: 400 * 1 * 1 = 400

Total improvement: 500

The second round of discount opts for no further change.

Item	Schedule type	P1	P2	P3	P4	P5
C	JIT-inbound schedule	70	520	160	180	60
C	Packcode rounded	100	500	200	200	0
C	MOQ rounded	200	400	200	200	0
C	Discounted schedule	600	0	200	200	0

Table 5.46: Individual schedule optimization for item C

Item D

For item D the first shipment is scheduled for P2. The MOQ violating shipment of P3 is preponed to P2. Afterwards, the discount evaluation is performed for P2.

Discount saving: 500 * 1.5 = 750

Additional inventory cost: 200 * 3 * 1 = 600

Total improvement: 150

Item	Schedule type	P1	P2	P3	P4	P5
D	JIT-inbound schedule	0	200	100	0	200
D	Packcode rounded	0	200	100	0	200
D	MOQ rounded	0	300	0	0	200
D	Discounted schedule	0	500	0	0	0

Table 5.47: Individual schedule optimization for item D

5.6.3 Optimal shipping mix and prospect shipping mix

5.6.3.1 Optimal shipping mix

The result of the individual product optimizations for the four products is displayed in table 5.48.

Item	Schedule type	P1	P2	P3	P4	P5
A	Discounted schedule	600	0	0	200	200
B	Discounted schedule	500	0	200	200	0
C	Discounted schedule	600	0	200	200	0
D	Discounted schedule	0	500	0	0	0

Table 5.48: Summary of discounted schedules for the items

For the shipment of P1 the crowd of pallets is listed, see table 5.49.

Item	Pallet count
A	6
B	5
C	6

Table 5.49: Pallet crowd in period P1 after individual schedule optimization

For this crowd of pallets, the optimal shipment mix is calculated by trial and error. This is permissible since the number of options is limited. In the example, Option 3 – a shipment mix of one 40FT container and 2 w/m of LCL has delivered the lowest cost.

	Option 1	Option 2	Option 3	Option 4	Option 5	Option 6	Option 7
40FT	2	1	1	0	0	0	0
20FT	0	1	0	3	2	1	0
LCL	0	0	2 w/m	0	3 w/m	10 w/m	17 w/m
Cost	4200	3400	2800	3800	3450	4000	4350

Table 5.50: Shipping mix options

5.6.3.2 Prospect shipping mixes

Apparently, a smaller part of the shipment is supposed to be sent via LCL, which can be considered to be very cost inefficient. Prospect shipment mixes are:

- Prospect 1: One 40FT container and one 20FT container
- Prospect 2: Two 40FT containers

5.6.4 Joint optimization

Within the section the evaluation for the prospect shipping mix 1 shall be discussed in great detail. The following joint optimization steps are repeated until there are no unused pallet spaces left for the prospect shipping mix. Then the entire process is repeated for the second prospect shipping mix.

5.6.4.1 Unused pallet spaces

For prospect 1, the empty pallet space function returns that 5 pallet spaces are unoccupied, which is calculated as one 40FT container with 15 pallet spaces and one 20FT container with 7 pallet spaces minus the 17 pallets that are already part of the crowd.

For prospect 2, the empty pallet space function returns that 13 pallet spaces are unoccupied, which is calculated as two 40FT container with 15 pallet spaces minus the 17 pallets that are already part of the crowd.

5.6.4.2 Item-wise preponement evaluation – round 1

As a first step, the before ordering cost is calculated, which is still item independent. For each period where at least on item is shipped the ordering costs of $100 apply. In the initial scenario shipments are planned for each period so that ordering costs of $500 apply, see table 5.51.

Item	Schedule type	P1	P2	P3	P4	P5
A	Discounted schedule	600	0	0	200	200
B	Discounted schedule	500	0	200	200	0
C	Discounted schedule	600	0	200	200	0
D	Discounted schedule	0	500	0	0	0
"Before" ordering cost		100	100	100	100	100
						500

Table 5.51: "Before" ordering cost – round 1

The item-wise evaluation with regards to preponements is done for each individual item.

Item A

Currently, the schedule that is planned for item A equals the discounted schedule from the individual schedule optimization. The before schedule cost is $9,800. It shall be noted that the inventory costs are calculated versus the packcode rounded schedule. Hence inventory costs are accounted for the preponement of 100 pieces from P2 and 300 pieces from P3.

Item	Schedule type	P1	P2	P3	P4	P5
A	Discounted schedule	600	0	0	200	200
Purchase cost		5100	0	0	2000	2000
Inventory cost		400	300	0	0	0
Total per month		5500	300	0	2000	2000
"Before" schedule cost						9800

Table 5.52: Total "before" schedule cost item A – round 1

The next shipment that could be preponed is scheduled in period 4. Even though 13 pallet spaces are still available in the shipping mix, the discontinuity constraint allows for only moving two pallets, which equals the entire shipment of P4. Table 5.53 illustrates the optimized schedule after the preponement.

Item	Schedule type	P1	P2	P3	P4	P5
A	"After schedule"	800	0	0	0	200
A	Packcode rounded	800	0	0	0	200
A	MOQ rounded	800	0	0	0	200
A	Discounted "after" schedule	800	0	0	0	200

Table 5.53: "After" schedule rounding item A – round 1

The preponement caused inventory costs over 3 months for 200 pieces from P4 to P1. At the same time discount savings have been achieved so that the total "after" schedule cost rose only to $10,100.

Item	Schedule type	P1	P2	P3	P4	P5
A	Discounted "after" schedule	800	0	0	0	200
Purchase cost		6800	0	0	0	2000
Inventory cost		600	500	200	0	0
Total per month		7400	500	200	0	2000
"After" schedule cost						10100

Table 5.54: Total "after" schedule cost item A – round 1

The total ordering cost has not changed as still one shipment is sent every week, see table 5.55.

Item	Schedule type	P1	P2	P3	P4	P5
A	"After" schedule	800	0	0	0	200
B	Discount optimized	500	0	200	200	0
C	Discount optimized	600	0	200	200	0
D	Discount optimized	0	500	0	0	0
"After" ordering cost		100	100	100	100	100
						500

Table 5.55: "After" ordering cost item A – round 1

Contrasting "before" and "after" costs delivers a delta of $300, which means $150 per w/m. This prorating is necessary for reasons of comparison.

"Before" schedule cost	9800
"Before" ordering cost	500
"After" schedule cost	10100
"After" ordering cost	500
Delta cost	+300
Moved w/m	2
Cost per moved w/m	+150

Table 5.56: Cost per w/m for item A – round 1

Item B, C, and D

The changes for item A are rolled back and the same principle is applied for items B, C, and D. The according tables can be found in the appendix A3.

Comparison of round 1

For the decision of which item to prepone the cost per moved w/m for the different items is contrasted. In case that two items exhibit the same cost, the item with the higher moveable quantity as per discontinuity constraint shall be moved. In the example two pallets could be moved of either item B or C. In this case the preponement decision should be taken by other criteria, e.g. the item's ranking by revenue.

Item	Cost per moved w/m
A	150
B	50
C	50
D	80

Table 5.57: Comparison of cost per moved w/m for round 1

In the example 2 pallets of item B shall be preponed, which leaves 11 empty pallet spaces.

5.6.4.3 Item-wise preponement evaluation – round 2

The same calculations that have been conducted in round 1 are repeated. First, the "before" ordering cost is calculated. As per table 5.58, the "before" ordering costs are still $500.

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
B	Round 1	700	0	0	200	0
C	Discount optimized	600	0	200	200	0
D	Discount optimized	0	500	0	0	0
"Before" ordering cost		100	100	100	100	100
						500

Table 5.58: "Before" ordering cost – round 2

Item A

The analysis for item A can be found in appendix A.4.

Item B

Item B has been selected in the first round for preponement. Hence the starting schedule is no longer the discount optimized schedule but the output schedule of round 1.

Item	Schedule type	P1	P2	P3	P4	P5
B	Round 1	700	0	0	200	0
Purchase cost		5950	0	0	2000	0
Inventory cost		600	300	0	2000	0
Total per month		6550	300	0	2000	0
"Before" schedule cost						8850

Table 5.59: Total "before" schedule cost item B – round 2

For item B the next shipment takes place in period 4. The maximal moveable quantity by discontinuity constraint is 200 pieces. The other tables for the calculation of the w/m impact of preponing B can be found in appendix A.4.

Item C

The preponement of item C leaves period P3 with no remaining shipment as table 6.10 shows.

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
B	Round 1	700	0	0	200	0
C	“After” schedule	800	0	0	200	0
D	Discount optimized	0	500	0	0	0
“After” ordering cost		100	100	0	100	100
						400

Table 5.60: “After” ordering cost item C – round 2

At this time the reductions in ordering costs are considered, which has a positive impact one the w/m cost impact for item C, see table 5.61. The remaining tables can be found in appendix A.4.

“Before” schedule cost	9600
“Before” ordering cost	500
“After” schedule cost	9700
“After” ordering cost	400
Delta cost	0
Moved w/m	2
Cost per moved w/m	0

Table 5.61: Cost per w/m for item C – round 2

Item D

The preponement of item D would reduce the ordering costs in period P2. This is illustrated in appendix A.4.

Comparison of round 2

Due to the positive discount effect for item C and the reduction in ordering cost, the preponement of item C causes the lowest cost per moved w/m. 9 pallet spaces remain unoccupied.

Item	Cost per moved w/m
A	150
B	150
C	0
D	80

Table 5.62: Comparison of cost per moved w/m for round 2

5.6.4.4 Final decision

The process that has been demonstrated in the previous sections is repeated until all pallet spaces of the container are filled. Then the same process is repeated for the other prospect shipping mixes that have been identified.

The transport cost saving for each option is calculated by dividing the absolute transport cost of the applied shipping mix by the count of loaded w/m and multiplying the result with the w/m of the original shipping list. The saving is then received by contrasting the obtained result with the absolute transport cost of the original shipping list. The lowest logistic cost is achieved by applying that option that exhibits the highest total change. Table 5.63 shows the cost impact of the various incremental proponent steps for both prospect shipping mixes.

	Shipping mix	Absolute transport cost	Loaded w/m	Transport cost per w/m	Transport cost saving	Additional schedule costs	Total change
Optimal	1*40FT + 2 w/m LCL	2800	17	164.71	0	0	0
Mix 1 Round 1	1*40FT + 1*20FT	3400	19	178.95	-242.08	2*50 =100	-343.08
Mix 1 Round 2	1*40FT + 1*20FT	3400	21	161.90	+47.77	2*50+2*0 =100	-52.23
Mix 1 Round 3	1*40FT + 1*20FT	3400	22	154.55	+172.72	2*50+2*0+1 *150 =250	-77.28
Mix 2 Round 1	2*40FT	4200	19	221.05	-957.82	2*50 =100	-1057.82
Mix 2 Round 2	2*40FT	4200	21	200	-599.93	2*50+2*0 =100	-699.93
Mix 2 Round 3	2*40FT	4200	26	161.54	+53.89	2*50+2*0+5 *80 =500	-446.11
Mix 2 Round 4	2*40FT	4200	28	150	+250.07	2*50+2*0+5 *80 +2*150=800	-549.93
Mix 2 Round 5	2*40FT	4200	30	140	+420.07	2*50+2*0+ 5*80+2*150 +2*150 =1100	-679.93

Table 5.63: Listing of the identified options for both prospect shipping mixes

As per table 5.63, the original shipping list was found to be still the best option since preponing has led to absolute higher costs.

Sensitivity evaluation

Table 5.64 shows the result for the example for LCL costs that have been increased from $250 per w/m to $300 per w/m. In this case a small saving can be generated by preponing 200 pieces of item B and 200 pieces of item C from period P3.

	Shipping mix	Absolute transport cost	Loaded w/m	Transport cost per w/m	Transport cost saving	Additional schedule costs	Total change
Optimal	1*40FT + 2 w/m LCL	2900	17	170.59	0	0	0
Mix 1 Round 1	1*40FT + 1*20FT	3400	19	178.95	-142.12	2*50 =100	-242.12
Mix 1 Round 2	1*40FT + 1*20FT	3400	21	161.90	147.73	2*50+2*0 =100	+47.73
Mix 1 Round 3	1*40FT + 1*20FT	3400	22	154.55	272.68	2*50+2*0+ 1*150 =250	22.68

Table 5.64: Listing of the identified options for $300 per w/m

Table 5.65 shows that the transport cost optimization could yield a saving $147.96 in case of LCL costs of $350 per w/m.

	Shipping mix	Absolute transport cost	Loaded w/m	Transport cost per w/m	Transport cost saving	Additional schedule costs	Total change
Optimal	1*40FT + 2 w/m LCL	3000	17	176.47	0	0	0
Mix 1 Round 1	1*40FT + 1*20FT	3400	19	178.95	-42.11	2*50 =100	-142.11
Mix 1 Round 2	1*40FT + 1*20FT	3400	21	161.90	247.96	2*50+2*0 =100	147.96
Mix 1 Round 3	1*40FT + 1*20FT	3400	22	154.55	372.73	2*50+2*0+ 1*150 =250	122.73

Table 5.65: Listing of the identified options for $350 per w/m

From the findings illustrated in table 5.64 and 5.65 it can be concluded that the advantage of transport cost optimization is strongly dependent on the cost factors. It has been demonstrated that in some cases significant savings can be achieved whilst in other scenarios the preponement does not yield any savings.

5.6.4.5 Alternative option of postponement

The original example ($250 per w/m) brought about that following the optimized individual schedules delivers the lower shipping costs. Yet, in the example, a fully utilized 40FT container is only exceeded by 2 w/m, which eventually leads to a significant cost increase. The shipping costs have been determined as $2800 for 17 w/m, whilst a full 40FT container would have cost $2200 for 15 w/m. Prorating the shipping costs reveal that unloading 2 w/m would deliver a cost advantage of $270.59. Hence it should be investigated whether the unloading of 2 w/m is possible, which means that these goods are not mandatory to meet the demand. This means that only those quantities that have been preponed to claim discounts can be postponed. The according discount savings that would be lost in case of postponement shall be contrasted with the transport cost saving.

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
B	Discount optimized	500	0	200	200	0
C	Discount optimized	600	0	200	200	0
D	Discount optimized	0	500	0	0	0

Table 5.66: Discount optimized schedules

Comparing the MOQ rounded and the discount optimized schedules in table 5.66 and 5.67, it becomes obvious that parts of the shipment quantities in P1 for items A, B, and C are not mandatory.

Item	Schedule type	P1	P2	P3	P4	P5
A	MOQ rounded	300	0	300	200	200
B	MOQ rounded	200	200	300	200	0
C	MOQ rounded	200	400	200	200	0
D	MOQ rounded	0	300	0	0	200

Table 5.67: MOQ rounded schedules

It must hence be evaluate whether unloading some goods from the shipment can provide an overall cost saving. Thereby, it appears expedient to consider the discontinuity points that have been defined for the addition of goods.

Item A

For item A this is the difference between the planned value 600 and the discount threshold of 500. The moveable 100 pieces should now be postponed as long as possible in order to save on inventory costs. This opts for a postponement to P3.

Item	Schedule type	P1	P2	P3	P4	P5
A	MOQ rounded	300	0	300	200	200
A	Discount optimized	600	0	0	200	200
A	Postponed	500	0	100	200	200
A	Postponed MOQ rounded	500	0	300	0	200
A	Postponed discounted	500	0	500	0	0

Table 5.68: Postponement analysis for item A

Inventory costs have been saved for 100 pieces over 2 periods, whereby at the same time inventory costs for 200 pieces over 2 periods from P4 to P3 have incurred to comply with the MOQ requirement. However, applying the discounting function brings about that a discount can be achieved in P3 with the rather low effort of preponing 200 pieces from P5 to P3. Therewith, the optimal schedule has ultimately been found, which reduces the total schedule costs from $9800 to $9600. This equals a saving of $150 per w/m.

Item B

For item B, the discount threshold is just reached, which means whatever will be moved will cause a loss of discount for all 500 pieces. Since 2 w/m shall be removed from the shipment, 200 pieces shall be considered for postponement. The inventory cost saving is $200, whilst the increase in product cost is $750. This leads to a total change of $550 prior to MOQ and discount application. The discount function brings about that preponing the shipments of P3 and P4 allows for obtaining a discount in P2, which leads to a saving of $300. The total impact is hence $250, which equals $125 per w/m.

Item	Schedule type	P1	P2	P3	P4	P5
B	MOQ rounded	200	200	300	200	0
B	Discount optimized	500	0	200	200	0
B	Postponed	300	200	200	200	0
B	Postponed MOQ rounded	300	200	200	200	0
B	Postponed discounted	300	600	0	0	0

Table 5.69: Postponement analysis for item B

Item C

For item C, 100 pieces are suitable for postponement by reasons of discontinuities. This does ultimately cause additional inventory costs of $100 and discount losses of $150. In this case another discount is envisioned in P2, which ultimately delivers a total cost advantage of $100 per w/m.

Item	Schedule type	P1	P2	P3	P4	P5
C	MOQ rounded	200	400	200	200	0
C	Discount optimized	600	0	200	200	0
C	Postponed	500	100	200	200	0
C	Postponed MOQ rounded	500	300	0	200	0
C	Postponed discounted	500	500	0	0	0

Table 5.70: Postponement analysis for item C

Comparison of postponement round 1 and 2

In the first round, item A is postponed as it even provides a high saving per w/m. Yet, as the discontinuity criteria does only allow for the postponement of 1 w/m, a second round for another 1 w/m has to be started. In the second round, item C has the lowest postponement costs.

Item	Cost per moved w/m in 1st round	Cost per moved w/m in 2nd round
A	**-150**	400
B	125	0
C	-100	**-100**
D	No goods to prepone	No goods to prepone

Table 5.71: Postponement costs per w/m

Results

It has been found that the preponement of 1 w/m of A and 1 w/m of C would bring about a cost saving of -$250 whilst an additional prorated transport cost saving of only $270.59 can be captured. Therewith, a total saving of $520.59 can be achieved by the transport cost optimization, which can be partially attributed to the sub-optimal individual item optimization that is partially caused by the end-of-horizon effect.

Item	Initial shipping list	After transport cost optimization
A	6	5
B	5	5
C	6	5

Table 5.72: Pallet count before and after transport cost optimization

5.7 Costing

The economic order quantity calculation that was just described requires the contrasting of inventory cost, ordering cost, and transport cost. Within the literature research, these basic cost factors have been briefly outlined. The application to practice is very specific to the organization and its products and hence not universally applicable. Therefore, this chapter shall not go to deep into specifics but rather explain, which factors should be considered, and advice on how to prorate costs.

5.7.1 Inventory cost

The literature research – e.g. Lee and Billington (1992) – has shown that the practical application of inventory costing is difficult for several reasons. First, the matters of expenses associated with holding inventory are varied. Second, most of the inventory costs are shared common expenses and, therefore, have to be realistically attributed.

5.7.1.1 Capital cost

The capital cost as one of the major portions of inventory cost depends very much on the organizations bank lending rate, and should hence be provided by the finance department. Risks shall be considered under inventory risks and must hence not be considered within the capital cost.

5.7.1.2 Storage cost

For the purpose of inventory holding, a distribution center that is situated on the eastern outskirts of the Bangkok metropolitan area is operated by the company. The building has an area of 10,000 sqm, a height of 17 m, and hosts around 21,000 pallet positions as well as a bulk area with a volume of 3,800 cubic meters (equal to 56 40-FT containers). Without inventory, there would be no need for providing racking to store the inventory. Hence the racking depreciation can be fully attributed to storage. The cost of one pallet space is independent of the product that is stored inside and hence the same for all products. The cost of one pallet space shall be calculated as total racking depreciation divided by the number of pallet positions.

The area of the building where the racking is placed can also be solely attributed to storage. However, prorating the total building depreciation based on square meters appears unfair since office spaces and special areas – like the dock area with all its dock levellers – have caused a proportionately higher share of the total building cost. A comparison of the square meter rental prices of nearby warehouses, of which some provide very good facilities and others only plain storage spaces suggest that the cost relation should be factored in with 0.6.

$$Storage\ space\ cost = \frac{Racking\ cost + 0.6\ \cdot \frac{Building\ cost}{Total\ sqm} \cdot Storage\ sqm}{Number\ of\ pallet\ positions}$$

Equation 5.11: Storage space cost

Racking cost and building cost do, thereby, include depreciation and maintenance. Maintenance for the storage space can be expected to be proportionately less than 0.6 of overall building maintenance cost. Yet, it shall be accepted as a share of operating cost.

5.7.1.3 Inventory service cost

Inventory service cost summarizes cost for stock transfers, cycle counting and the like. For both activities forklifts and people are needed. With regards to warehouse operation, the depreciation of forklifts and the maintenance are major cost proportions. At the same time, forklifts also account for most of the energy consumption. Yet, also incoming goods and despatch uses forklifts, which is why the cost needs to be shared.

In 2014, on average 3400 pallet transfers, 22500 picks, and 7000 put-away have been performed within a month. One pallet transfer includes a pick of a full pallet and the put-away in a different position. The overall effort shall be considered to be 1.5 times the effort of an incoming goods' put-away. As multiple order picks can be performed during one forklift ride, five picks shall be considered equal to one put-away.

The cost from forklift operation (depreciation, maintenance, and electric) shall hence be shared as: 42% for incoming put-away, 31% for inventory service and 27% for despatch. Thereby, the total electric cost shall be considered to arise from forklift usage, as the usage for light and IT is comparably very small.

Within the warehouse, a dedicated team that takes care of cycle counting and a separate team that takes care of replenishment are existent. The annual cost of these two teams divided by the number of pallet positions delivers the cost of servicing one pallet position for one year. This figure can then be prorated to the length of the stay.

$$Inventory\ service\ cost = \frac{0.31 \cdot (forklift + energy\ cost) + team\ cost}{Number\ of\ pallet\ positions}$$

Equation 5.12: Inventory service cost

5.7.1.4 Inventory risks

The risks involved in the holding of inventory can be clustered as:

Shrinkage and damage of products do normally lead to stock adjustments in the ERP system. The yearly total of the stock adjustment for a SKU shall be divided by the average annual stock level. This delivers the average adjustment cost for an item that is hold for one year. It must be ensured, though, that the stock adjustments which are considered for the total only relate to the storage or inventory service. Damages that occurred during put-away or picking must not be included.

$$Shrinkage\ and\ damage\ cost = \frac{Total\ stock\ adjustment\ (storage\ related)}{Average\ stock\ quantity}$$

Equation 5.13: Shrinkage and damage cost on item level

Obsolescence risk is very difficult to estimate, as it differs for every product and can be hardly foreseen before the product is obsolete. It shall hence be recommended to account for obsolescence risk by simply applying a percentage of product cost that relates to the x, y, z rating or a more in depth ranking of the item.

5.7.2 Ordering cost

5.7.2.1 Purchasing cost

The purchasing cost results from the administration of orders. It appears logically to divide the total annual staff cost of the purchasing department by the annual number of purchase orders that have been issued. Thereby, those staffs that are taking care of indirect purchasing, e.g. office supplies, shall be exempted.

5.7.2.2 Warehouse receiving cost

At first glance, the scope and the cost involved in the receiving of goods appear extensive. However, most of the costs are incurred independently of the number of orders into which an annual quantity is split. As pointed out in chapter 2, the unloading, the physical preparation, and the actual put-away have to be performed on per pallet basis and are hence independent of the number of shipments. Merely, the document handling and the ERP processing effort increase. The annual payroll of warehouse admins that take care of the inbound processing shall be divided by the number of shipments to account for the effort. The packcode rounding, which ensures full pallet shipments, actually provides the advantage of quantity independent ordering cost due to standardization.

5.7.3 Transport cost

Transport costs are commonly split between supplier and Hafele. Yet, the agreed incoterm and therewith the exact split of cost is different from supplier to supplier.
If a supplier takes over part of the costs – e.g. FOB – his portion of transport cost will under normal circumstances be reflected in the purchase price. With regards to EOQ consideration, the supplier usually employs quantity discounts that balance the average transportation cost. In one or the other way, the organization has to pay for the transport cost and must hence look into the reduction of this cost factor.
Transport costs are subjected to economies of scale, as certain cost factors like document fees and usually also customs clearance are charged on shipment basis, which means that this remains same no matter if one or ten containers are shipped.

Other costs such as the freight rate itself have to be paid for each container. Based on a review of actual freight invoices, various cost factors have been marked in table 5.73 as on shipment basis or as on container basis.

Cost factor	Per shipment	Per container
Pick-up charge		X
Customs clearance, export license, …	X	
Terminal handling charge at origin		X
Sea freight charge		X
Emergency bunker charge		X
Container imbalancing charge		X
Terminal handling charge at destination		X
Customer clearance import	X	
Delivery order fee	X	
Handling charge		X
Transport charge at destination		X

Table 5.73: Transport cost factor basis for FCL shipments (review of actual invoices)

Out of these factors, the actual freight cost, the bunker charge, and also the local transportation are the biggest cost portions, which are all on container basis. However, the costs of customs clearance must not be underestimated. The cost relation between a 20FT and a 40FT container is around 6:10. This does, however, very much depend on the route and is hence only an estimated value. Yet, it can be concluded that in most cases sending a 40FT container is cheaper than sending two 20FT containers

For LCL shipments, the majority of cost arises on shipment level, as shown in table 5.74. The actual freight charges are comparably low.

Cost factor	Per shipment	Per w/m
Pick-up charge	X	
Customs clearance, export license, …	X	
Terminal handling charge at origin		X
Sea freight charge		X
Terminal handling charge at destination		X
Customs clearance import	X	
Delivery order fee	X	
Handling charge	X	
Transport charge at destination		X

Table 5.74: Transport cost factor basis for LCL shipments (review of actual invoices)

It must be noted that LCL shipments and FCL shipments cannot be combined under one bill of lading, which is why they are considered as entirely individual shipments.

5.8 Chapter summary

Within this chapter, the methodology for the economic order quantity calculation has been developed. In preparation, therefore, the issue of schedule stability has been discussed. It has been identified that inaccurate forecasts as they must be expected in regards to the historically recorded data, are a massive obstacle to schedule stability and hence putting the relevancy of the EOQ at risk. As a result it has been suggested to add an additional level of safety stock that solely hedges against schedule instability. To function as intended, this additional safety stock must not be considered by the reorder point formula, but though within the determination of the inventory position and within the creation of the JIT inbound schedule.

For the EOQ calculation itself, it has been identified that solving the entire problem in one go would be very complex and in no way compatible with the stipulation of simplicity and transparency. Therefore, the problem has been split into an individual item optimization and a joint transport optimization.

The individual item optimization starts with rounding quantities to the next full pallet quantity, which was stipulated to simplify the problem but which makes also sense with regards to handling and storage efficiency and, thereby, standardizes ordering and inventory costs. In a second step, minimum order quantities and discounts have been considered. Therefore, a heuristic has been proposed that comes along with higher foresight than standard heuristics like the least-unit-cost heuristic, whilst not increasing the calculation effort massively. In this context a total schedule cost evaluation function has been developed, which allows the inclusion of other heuristics on the run since it ultimately chooses the schedule with lowest overall cost.

Based on the optimized item schedules, the most cost efficient shipping mix (composure of 20FT, 40FT containers and LCL) must be calculated which requires the consideration of the actual container loading. For this purpose, a combination of three functions has been proposed that make use of the static count of pallets respectively stacks of pallets that a certain container can accommodate on ground level. The first function assembles pallet stacks that are optimized towards height utilization under consideration of stackability. The second function assigns those pallet stacks to a container whilst considering the number of ground floor pallet spaces and the maximum net load of the container. The third function recursively applies the second function to identify shipment mixes that can accommodate the pallet stacks. Ultimately, the cheapest option in terms of transportation cost is chosen, which does not automatically mean that high utilization is achieved.

To evaluate the cost effect of filling up the container by preponing shipments or partial shipments from future periods, another heuristic has been proposed. This heuristic does basically compare the savings in terms of transportation cost with the increase in individual schedule cost. Logically, those items that would experience the lowest increase in individual schedule cost are preponed. Additionally, it is also evaluated which total cost impact the postponement of pallets has, whereby only those pallets that have been preponed to generate discount savings can be postponed.

The option with the lowest total cost is selected, which in turn determines the item quantities that are proposed for purchasing. The overall flow is depicted in figure 5.20.

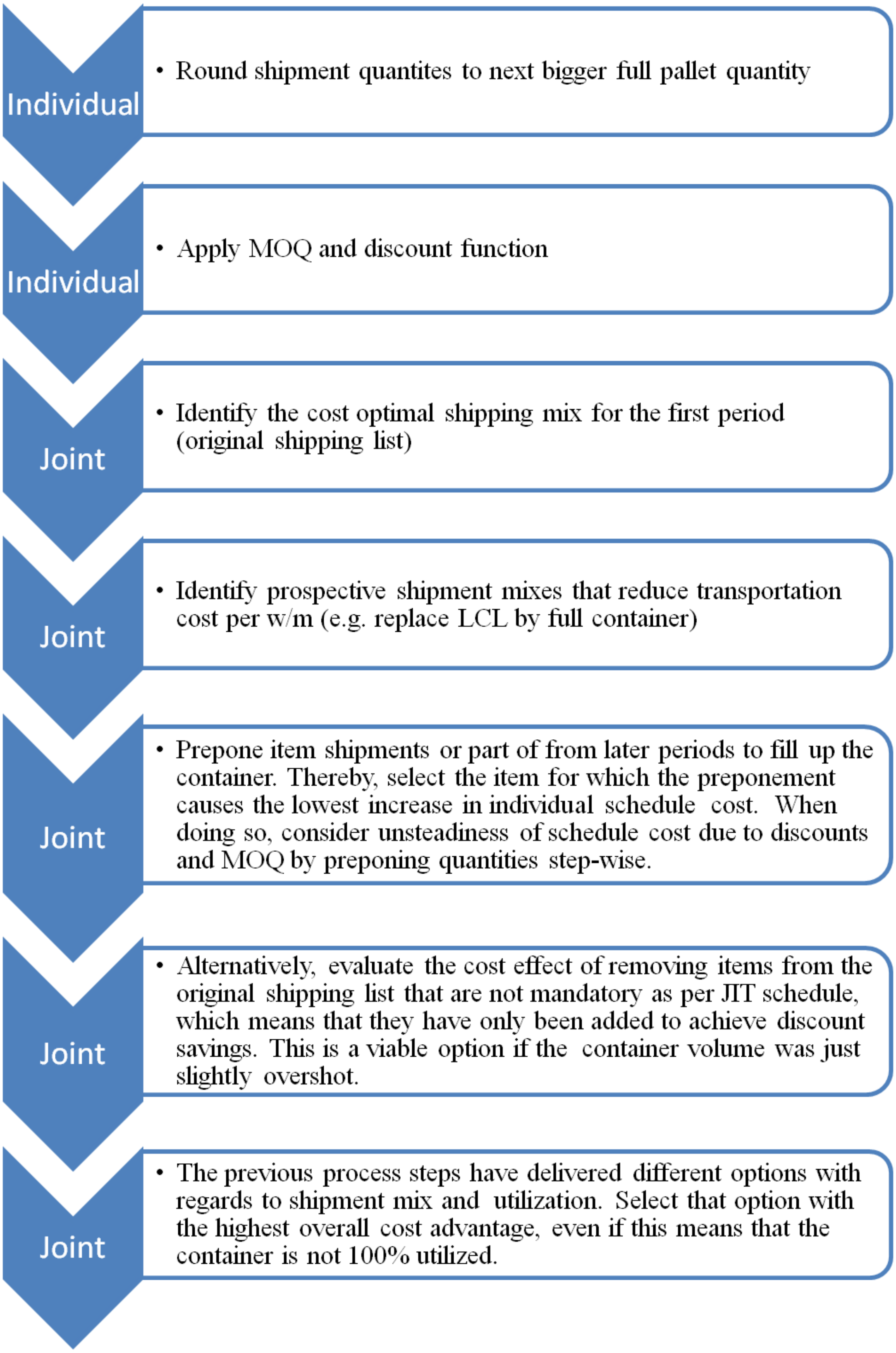

Fig. 5.20: Top level flow of economic order quantity calculation

6 RESULTS

The forecasting function and the EOQ methodology have – as the scope of the thesis outlined – not yet been implemented in the ERP system. Therefore, the ultimate impact on average inventory levels and the realization of savings cannot be proven with actual data.

Hence the functionality of the suggested solutions shall be demonstrated by means of simulations. Thereby, the quality of demand forecasting and EOQ calculation can be independently assessed, as merely the JIT inbound schedules are handed over.

6.1 Assessment of demand forecasting

As outlined in the literature research, the robustness of a forecast is maybe the most important criteria for the practical applicability. This is especially true when considering that the inventory review – that produces the business alert, which urges the purchase to run the purchase proposal – works in the background and has hence to work fully reliable, as presumably no one would notice that the alert fails to appear before the stock-out occurs. On that account, the first part of the testing will focus on the general ability to detect patterns and its robustness. The evaluation will be based on qualitative assessments with regards to the shape of the forecasted curve in comparison to the input values.

The second part of the testing will focus on the accuracy of the forecast. Thereby, a quantitative comparison with the currently implemented 6-month weighted moving average will be performed. The basis for the comparison is the actual pick data of 600 items that has been extracted from the organization’s ERP system.

It shall be mentioned that during all adjacent simulations a smoothing factor of 0.2 has been used for the smoothed absolute sum error (SASE), which was selected based on trial runs.

6.1.1 Detection of pure standard patterns

First of all, the ability of the automatic pattern recognition to detect and adequately continue standard patterns shall be evaluated. Therefore, the input data for the simulator was accordingly prepared. The visualization function of the implemented simulator gives a good indication with regards to the plausibility of the forecast. In all the displayed graphs, the solid line represents the available demand history, whilst the dotted line depicts the forecast.

Linear patterns

The figures 6.1 until 6.4 demonstrate the forecasting methodology's ability to detect linear trend pattern. The linear incline, decline and the combination of all three basic linear patterns uses the double exponential smoothing. The forecast of the combination deviates slightly due to the history that is carried on with exponential smoothing.

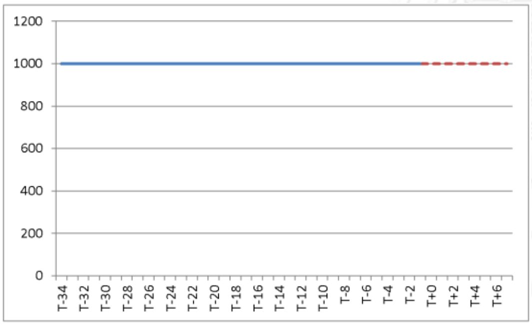

Fig. 6.1: Constant pattern

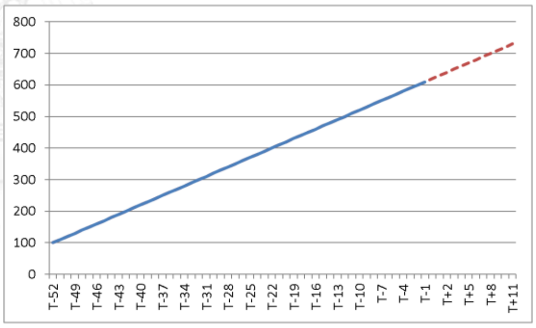

Fig. 6.2: Linear incline pattern

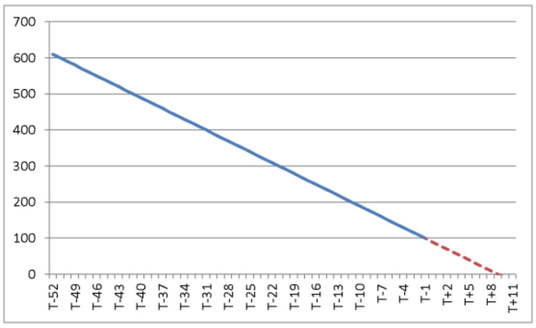

Fig. 6.3: Linear decline pattern

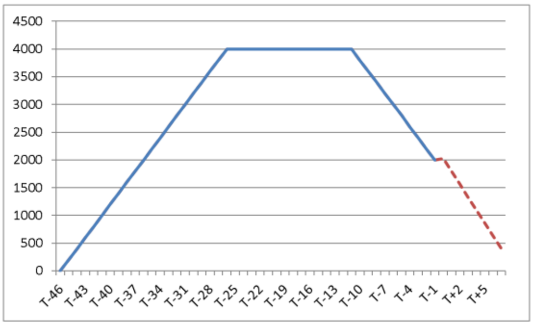

Fig. 6.4: Combined pattern

Non-linear patterns

To simulate non-linear patterns a polynomial of 2nd degree, a logarithmic function, an inverted root function and a polynomial of 3rd degree have been tested. Practically, it must not be expected that the demand follows more exciting patterns, as all types of curves within the life cycle are captured.

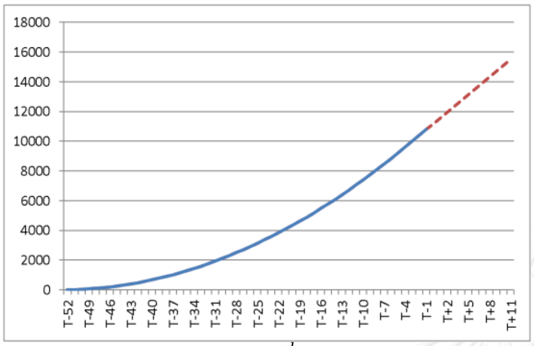

Fig. 6.5: Polynomial of 2nd degree (introduction)

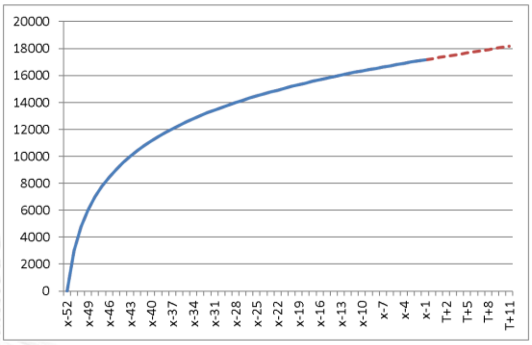

Fig. 6.6: Logarithmic function (maturity)

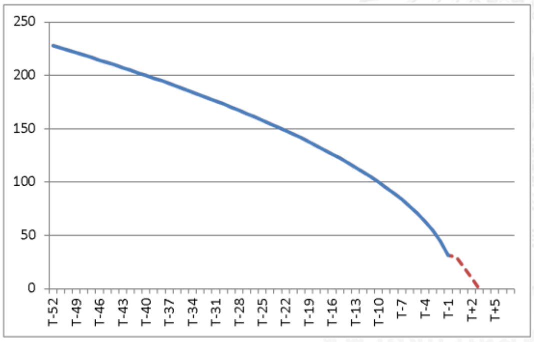

Fig. 6.7: Inverted root function (decline)

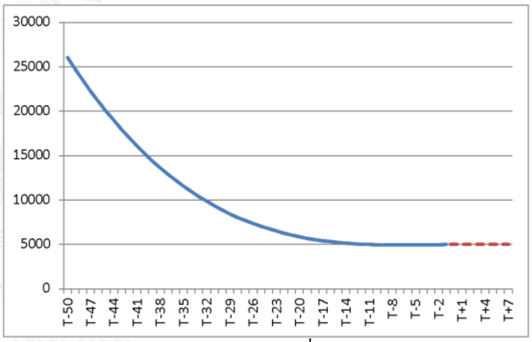

Fig. 6.8: Polynomial of 3rd degree (phase out)

Seasonal patterns

To validate the functionality of the seasonal pattern function, pure seasonality and seasonality with an underlying incline have been simulated. The results are illustrated in figure 6.9 and figure 6.10.

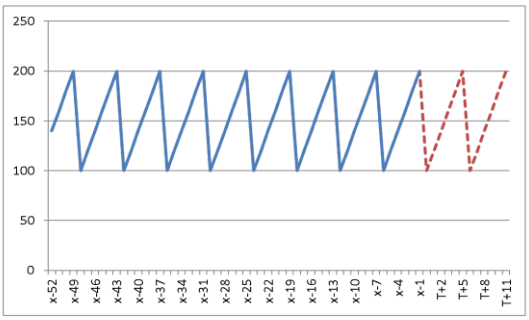

Fig. 6.9: Recurring pattern

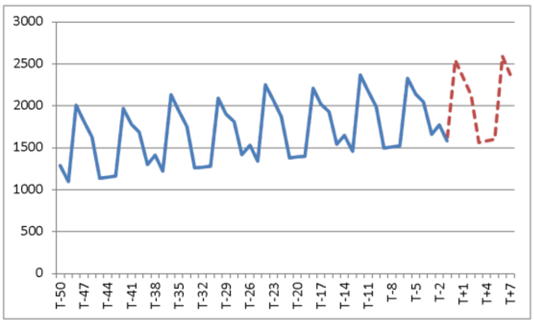

Fig. 6.10: Incline pattern with recurring pattern

6.1.2 Detection of standard patterns contaminated with noise

In practice, the demand history is at least contaminated with noise. Therefore, the recognition of standard patterns was tested whilst a random noise was added to the previous demand data. The main expectation with regards to the forecast is again the robustness.

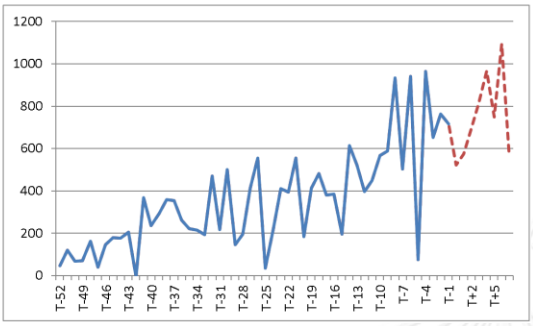

Fig. 6.11: Incline with standard deviation = 40% of underlying value

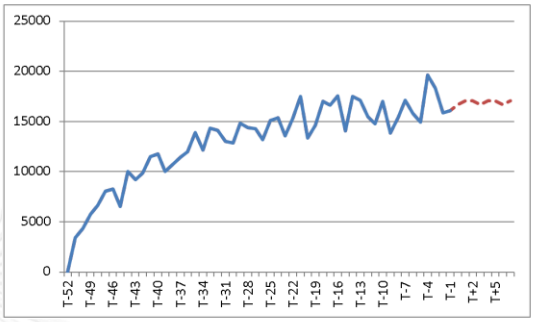

Fig. 6.12: Logarithmic function with standard deviation =10% of underlying value

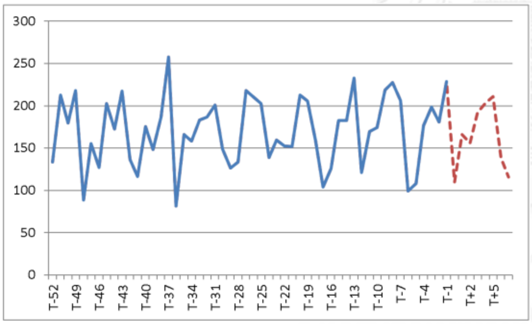

Fig. 6.13: Seasonal pattern with standard deviation = 30% of underlying value

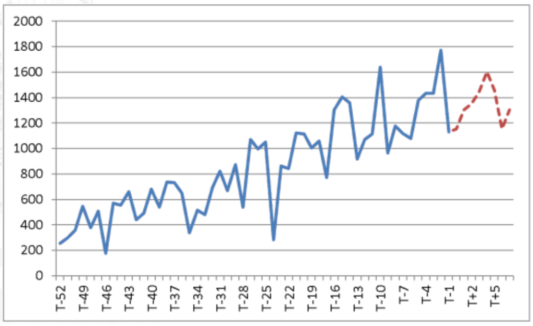

Fig. 6.14: Ramp combined with recurring pattern and noise with stdev = 20% of underlying value

Apparently, the implemented forecasting functionality is robust enough to handle severe fluctuations. The implementation of a linear regression via least square can be expected to deliver slightly more robust output, which is though not as significant as it would outweigh the disadvantages with regards to denying medium term trends.

6.1.3 Handling of zero values

The previous section has shown that the forecast is rather robust against random errors. In this section the ability to digest stock-outs shall be demonstrated. Figure 6.15 depicts the forecast of double exponential smoothing with disabled stock-out correction. Obviously, the graph drifts of significantly as a consequence of the zero values. The activation of the zero values correction as displayed in figure 6.16, leads to a proper forecast. Yet, it was previously discussed that identifying stock-outs based on the inventory ledger (inventory quantity of almost 0 at the end of a day) is advantageous, as the mere ignorance of zero values can lead to problems when the demand is really zero (phase-out).

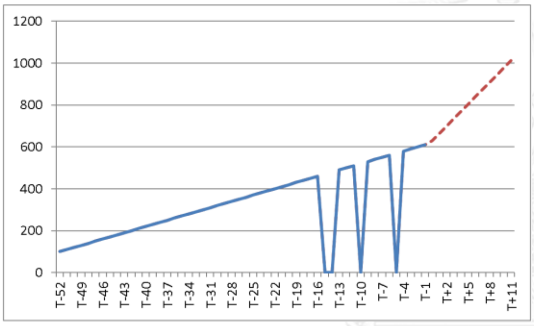

Fig. 6.15: Double exponential smoothing without stock-out correction

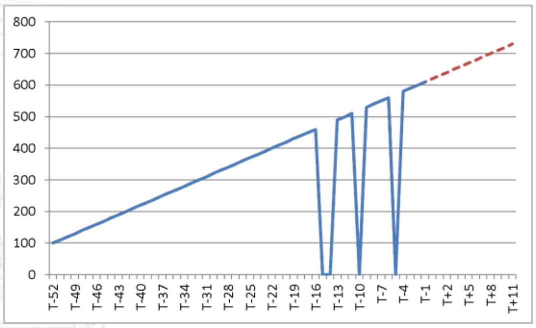

Fig. 6.16: Double exponential smoothing with stock-out correction

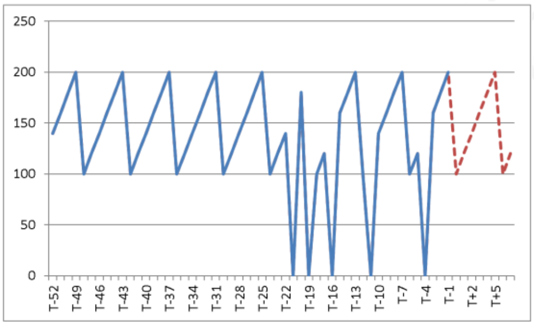

Fig. 6.17: Seasonal pattern distorted by stock-outs

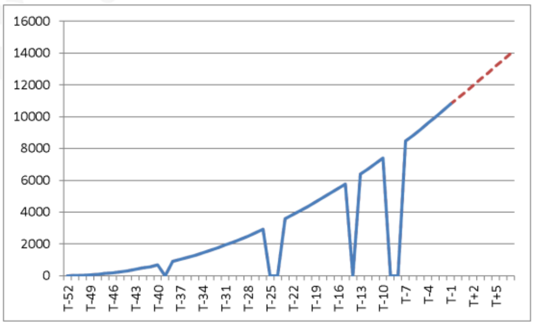

Fig. 6.18: Polynomial pattern distorted by stock-outs

Seasonal pattern and polynomial pattern are also detected despite frequent stock-outs. Therefore, it is important that the seasonal factor calculation itself ignores stock-out values.

6.1.4 Combination

For most severe testing, all of the distorting elements have been combined. The pattern recognition found a seasonal pattern in the data of figure 6.19, which was not contained in the original data. However, considering the degree of distortion that the historic data exhibits in this example the results can be considered as adequate. The example depicted in figure 6.20, exhibits additionally spikes that have been added next to stock-outs and the anyhow very severe fluctuations. The forecasting result in this case can be considered as very good for the circumstances.

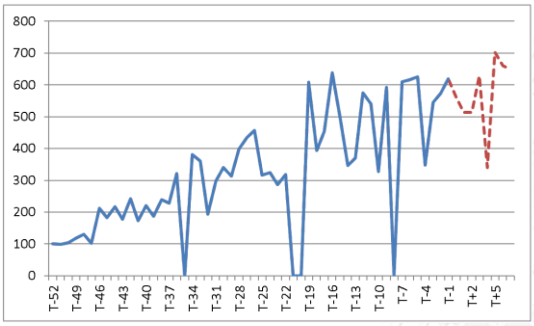

Fig. 6.19: Incline pattern with severe noise and stock-out

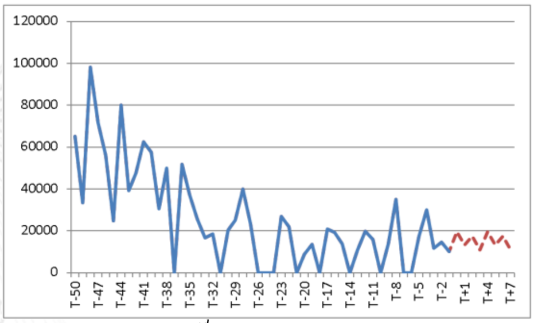

Fig. 6.20: 3rd degree polynomial with seasonality, stock-outs, spikes, and noise with stdev = 50%of underlying value

6.1.5 Qualitative testing on actual historic data

The theoretical ability of the forecasting methodology to identify patterns and to calculate the standard deviation has been demonstrated in the previous sections. Onwards, its ability to cope with real product history shall be evaluated. Besides two key items, two randomly selected products have been tested with the forecasting simulator.

The monthly demand history from 2010 to 2013 was used to predict the first eight months of 2014. The eight months forecast was then split into weeks by the described technique. The safety stock was calculated for a service level of 95%

6.1.5.1 Product A

The first product to evaluate is the knob-lock set that is the leader in terms of revenue generation.

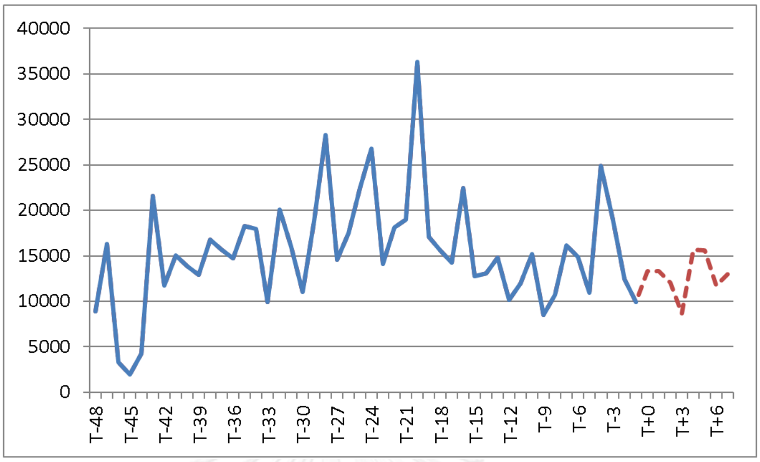

Fig. 6.21: Demand forecasting applied to knob-lock set

When contrasting the historic curve with the demand curve, it appears that the forecast is underestimated. The standard deviation over the history with regards to the mean is 6193.23, which leads to a calculated safety stock of 26,166 pieces. In figure 6.22 the actual value and the forecasted value are contrasted. Apparently, the actual value curve contains some significant spikes, which is though captured by safety stock, which was set according to the recommendation by the simulator.

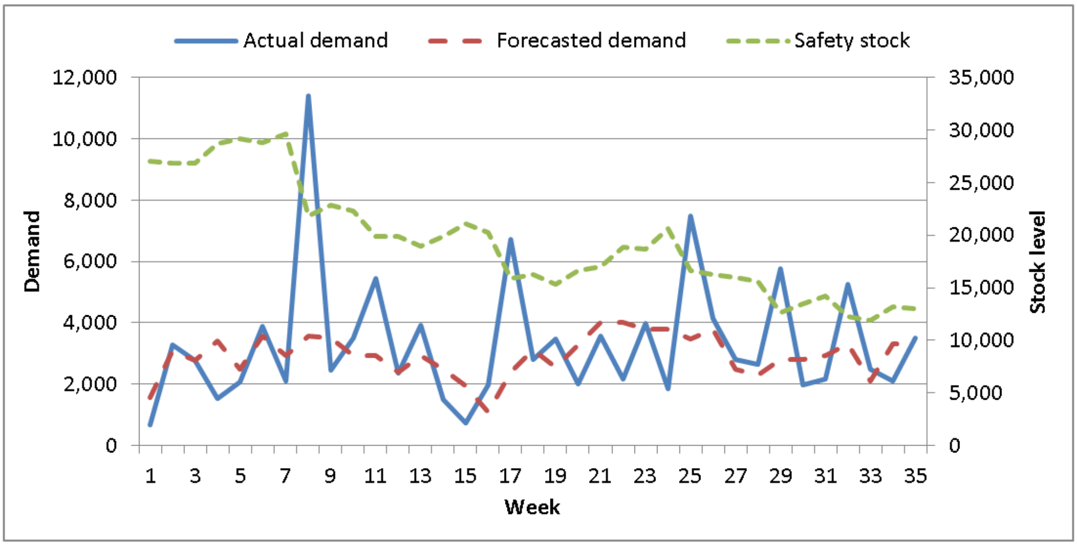

Fig. 6.22: Forecast vs. actual for knob-lock set

6.1.5.2 Product B

The second product is the most picked screw that is part in a huge number of bundling items. The demand forecasting delivers a stable forecast that is based on exponential smoothing with alpha = 0.4.

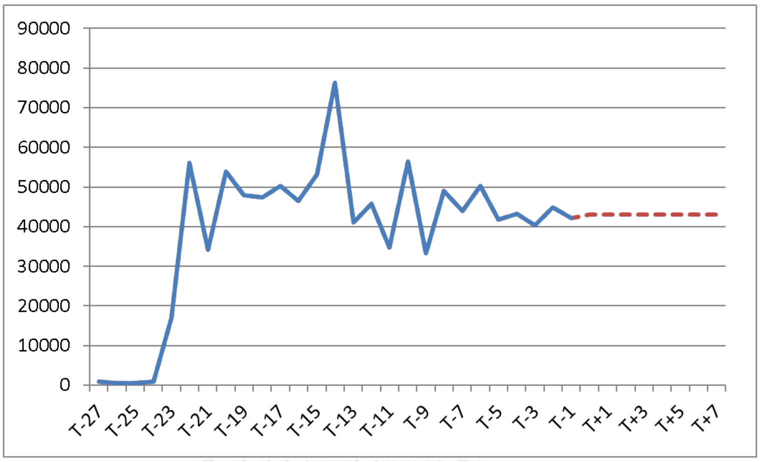

Fig. 6.23: Demand forecasting applied to knob-lock set

The standard deviation towards the mean is 9266.70 when excluding the first five months. The safety stock is calculated to be 75,665 pieces. Figure 6.24 shows that the forecast is more or less capturing the demand. The difference is again buffered by the safety stock.

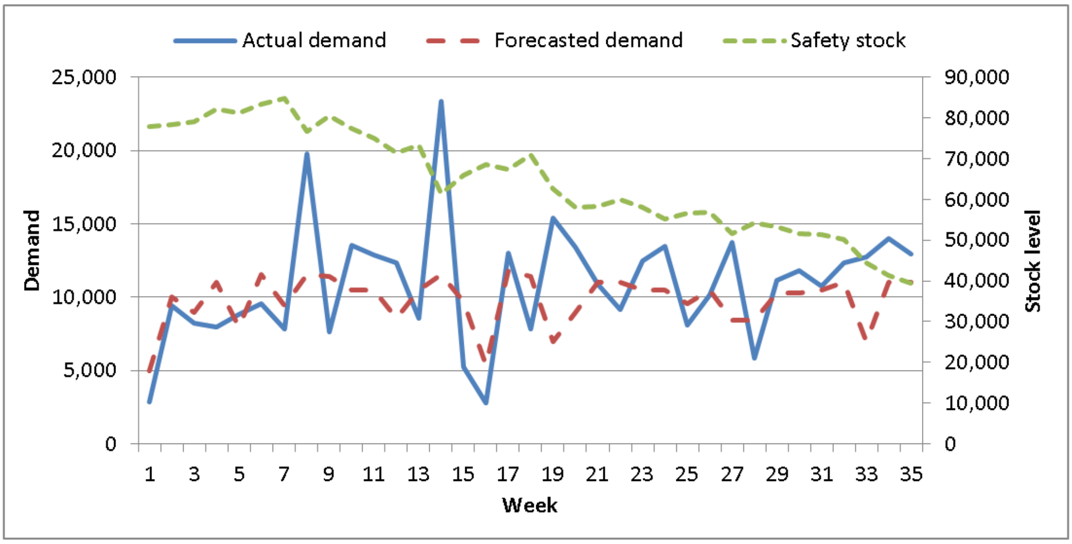

Fig. 6.24: Forecast vs. actual for screw

6.1.5.3 *Product C*

Product C is a kitchen sink that was randomly selected. The demand for this item is comparably small. On the contrary, the target safety stock is with 457 pieces very high, which is a result of the massive fluctuations that this product experiences.

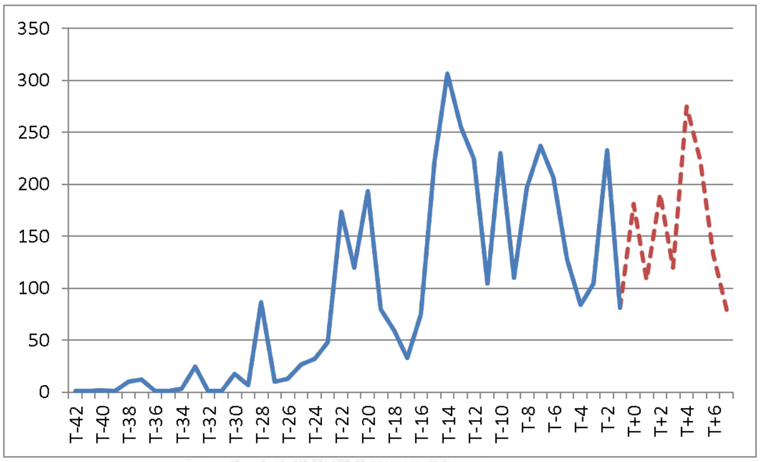

Fig. 6.25: Demand forecasting applied to sink

Comparing the forecasted values with the actual values reveals that the demand was overestimated. Hence overstock accumulates.

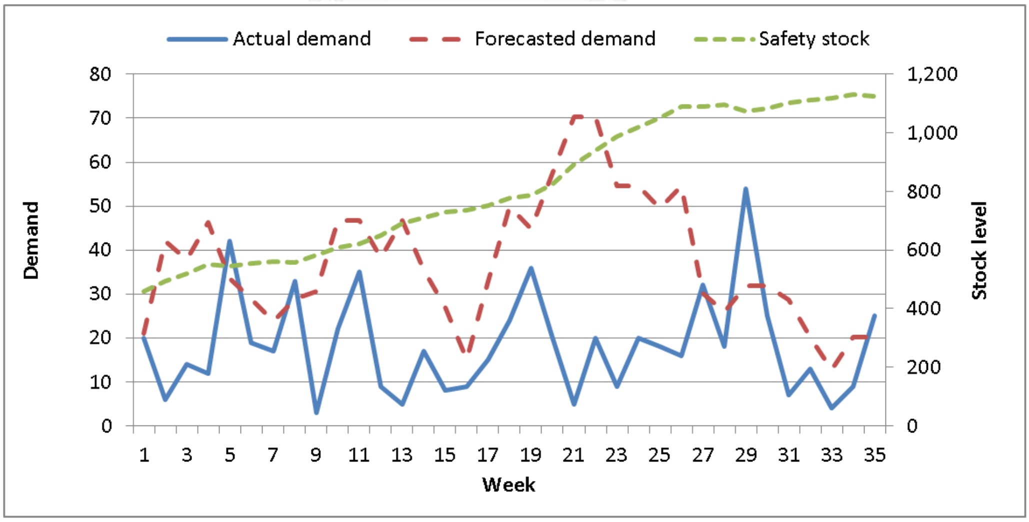

Fig. 6.26: Forecast vs. actual for sink

However, what is much more interesting is the product introduction of this item and how the simulation deals with it. Therefore, the focus has been set back for several periods to the first spike that has not yet reached 100 pieces.

The demand history at this point of time is with fifteen periods rather short. As required during the discussion of seasonality, the inclusion of a seasonal pattern shall be disabled for demand histories that are shorter than two times the season cycle.

Figure 6.27 and 6.28 illustrate the different behaviour. In figure 6.27 it becomes obvious that merely the pattern from one season cycle back is copied. In figure 6.28, seasonality has been disabled and hence trend pattern was applied, which represented the actual pattern more appropriately.

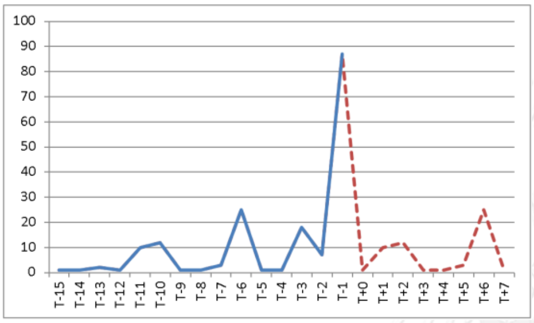

Fig. 6.27: Seasonality enabled

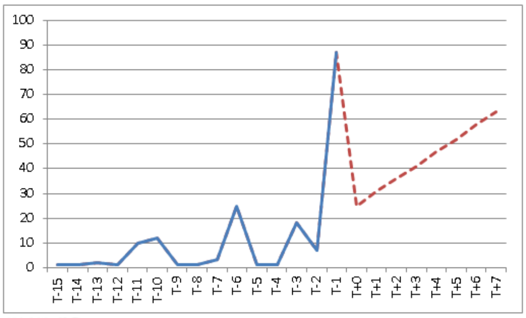

Fig. 6.28: Seasonality disabled

To investigate how the simulation behaves when the threshold for seasonality enabling is passed, the cursor was set to the 24th period, which is right the first period for which seasonality is auto enabled. Figure 6.29 illustrates how the simulation struggled due to the application of seasonality.

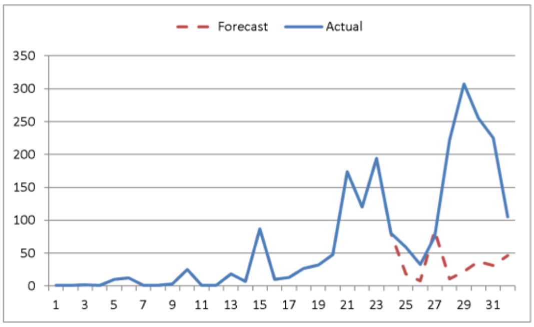

Fig. 6.29: Seasonality auto-enabled

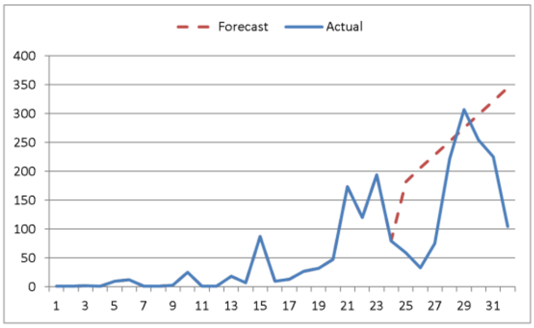

Fig. 6.30: Seasonal safe guarded applied

The malfunctioning results from the flatness of the first periods that do not have significant weightage compared to the most recent periods. Table 6.1 illustrates how pronounced some of the seasonal factors are.

0.262	0.110	1.23	0.152	0.318	0.539	0.456	0.677	2.444	2.002	2.693	1.119

Table 6.1: Applied seasonal factors in the 24th period

It transpires that highly imbalanced seasonal factors are indicating a misinterpretation. It must be noted that this is only true for the business of Hafele, for the sales of Easter eggs or the like, extreme differences between seasonal factors are reasonable. In order to safe guard against misinterpretation caused by the seasonality pattern, a validation was integrated that disables the seasonality if one of the factors is lower than 0.5 or higher than 2.0. Figure 6.30 illustrates how the result is improved by the seasonality safeguard.

6.1.5.4 Product D

A randomly selected flush handle with the historic demand as per figure 6.31 was tested. Obviously the product sees a heavily distorted demand. The standard deviation with regards to the mean is 740.25.

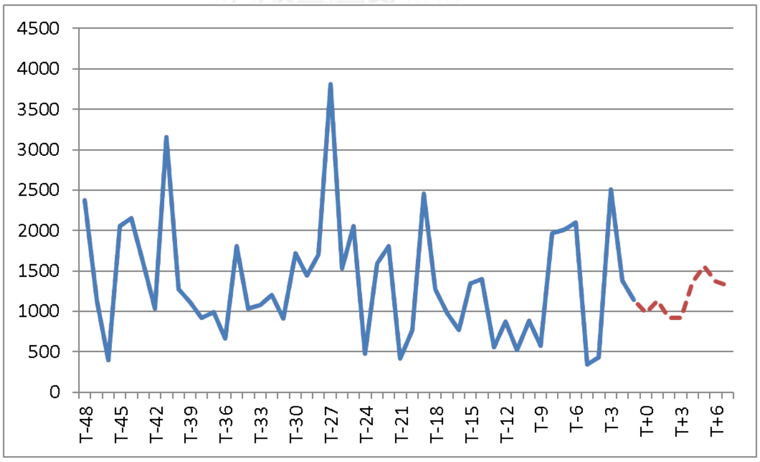

Fig. 6.31: Demand forecasting applied to flush handle

The forecasting simulator applied exponential smoothing with alpha=0.1, learning time=5 periods, and seasonality cycle = 12. The STDEV for 95% service level and 120 days replenishment time has been calculated as 616.27 resulting in a safety stock of 4,197. Figure 6.32 shows that the demand was again slightly underestimated so that the safety stock had to safeguard.

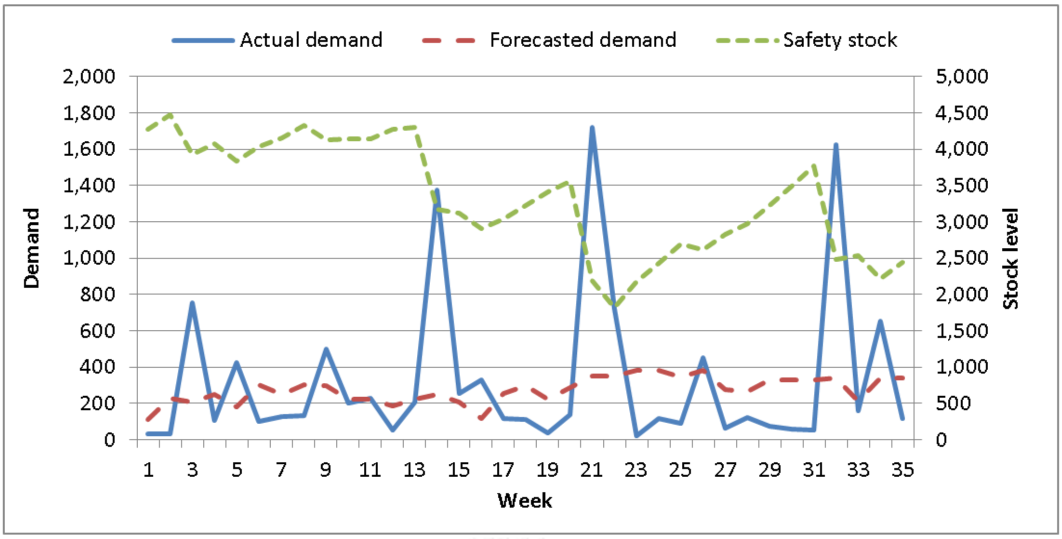

Fig. 6.32: Forecast vs. actual for flush handle

6.1.5.5 Evaluation

Overall, the forecasting results can be considered as adequate for the quality of the input data. Stock-outs have not been observed whilst the safety stock levels for the frequently ordered items knob-lock (A) and screw (B) are significantly lower than the current target stock level of 3 month of the normal consumption. For item (C) and (D) the calculated target safety stock levels are, though, higher than 3 months of the normal consumption.

Running a number of simulations reveals that the sum of forecasted values tends to be lower than the actual sum, whilst the forecasted value itself exceeds the actual value in most months. At the same time it can be observed that the safety stock is comparably high. The cause for this must be seen in the positive skewness of the demand distribution, which was briefly discussed in the forecasting chapter (refer figure 6.33).

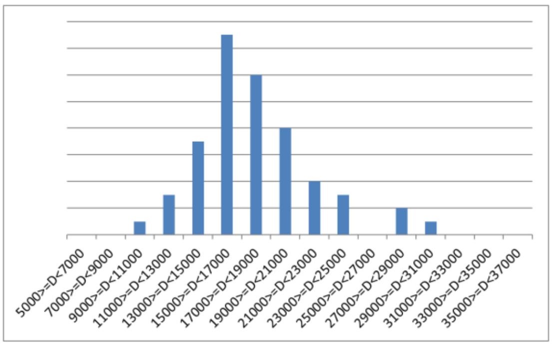

Fig. 6.33: Positive skewness of monthly demand frequency distribution

The standard deviation function delivers significantly higher values for skewed errors when compared to non-skewed errors, which is why a comparably high safety stock level can be observed. As in most cases exponentially smoothing is applied, the few high values are relatively lower pronounced, which is especially true for very low values of alpha but also common for high values of alpha in case that the last peak lies already a few periods in the past. In result, the expected value has a bias towards lower values.

With regards to the service level both effects are kind of outbalancing each other so that the service level can still be maintained.

6.1.6 Comparison with current implementation

To evaluate the performance of the automatic pattern matching in comparison with the currently implemented 6-month weighted (2,2,2,1,1,1) average, 600 x-items have been tested. The range of products reaches from absolute best sellers with long demand history to comparably low sellers that have just recently been launched.

6.1.6.1 Test procedure and performance measure

To compare the performance of the 6- month weighted moving average and of the automatically selected forecasting method in regards to actual values, the absolute sum error over the replenishment time is selected as the primary performance indicator since this was identified to be most important for schedule stability. This has also been the reason why the absolute sum error was also chosen as the measure upon which the automatic pattern matching selects the forecasting method. For the replenishment time an average value of 120 days equal to 4 months is assumed.

In order to retain sufficient data for comparison, the most recent 4 months of the demand history are kept out from the automatic pattern matching. With the remaining historic data, the automatic pattern matching was applied as per the presented design. Figure 6.34 depicts the procedure of the comparison.

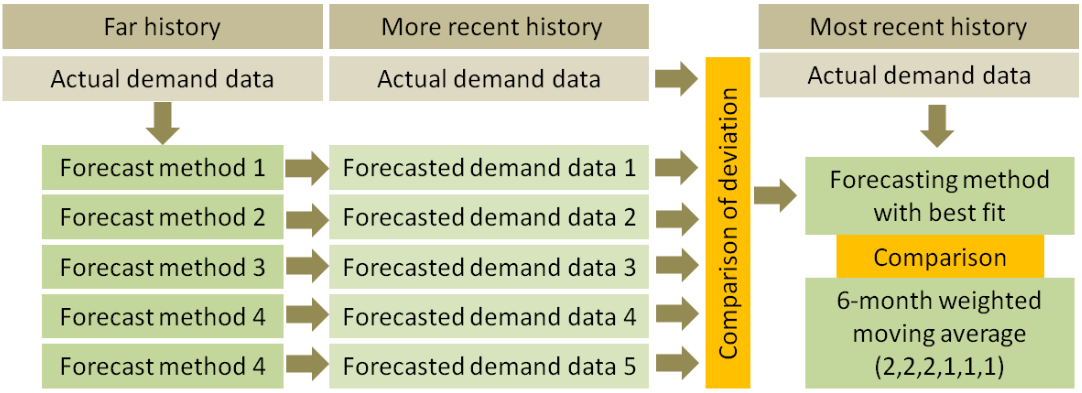

Fig. 6.34: Schematic of comparison

With regards to the far history data, minor corrections have been undertaken to prepare the data that was obtained from the organization's Qlikview. The download of historic data was limited to three years because the significance of older values is comparably low, whilst their inclusion would increase calculation times significantly. The historic data before the first occurrence of a non-zero value (product introduction) was cut off since such non-information containing data has negative impact on the performance of exponential smoothing functions.

6.1.6.2 Scoring method

The absolute sum error over the replenishment time was selected as the measure for the performance of the forecasting technique. The technique that achieves the lower error for a particular sample item scores a point.

In the literature research and during the design it was pointed out that robustness is of significant importance in order to achieve results that are reasonable and hence reliable – even if they may not be hundred percent accurate. Since the final score does not allow for conclusions about the robustness of either contestant, the actual error must be considered. Yet, a high forecasting error does not automatically mean that the forecast is bad, as the actual values can contain zero values that are caused by stock-outs. This obstructs the application of standard error measures like the MAPE. Therefore, the sum error should be evaluated in relation to the sum error of the second contestant. To allow for more fair weighting, the average of both forecast errors is taken to relativize the sum error of a contestant. Equation 6.1 and 6.2 show the constructed measure.

$$Error\ relation\ 1 = \frac{1}{600} \cdot \sum_{n=1}^{600} \frac{sum\ error\ of\ forecast\ 1}{\frac{1}{2} \cdot (sum\ error\ of\ forecast\ 1 + sum\ error\ of\ forecast\ 2)}$$

Equation 6.1: Error relation between forecasting methods for contestant 1

$$Error\ relation\ 2 = \frac{1}{600} \cdot \sum_{n=1}^{600} \frac{sum\ error\ of\ forecast\ 2}{\frac{1}{2} \cdot (sum\ error\ of\ forecast\ 1 + sum\ error\ of\ forecast\ 2)}$$

Equation 6.2: Error relation between forecasting methods for contestant 2

Due to the construction of the measure, error relation 1 and error relation 2 are symmetric towards 1, e.g. 0.95/1.05. For the example, the error relation must be interpreted that contestant 1 delivered an error that is 10% lower on average compared to contestant 2. The conversion between error relation factor and actual error relation are shown in table 6.2.

Error relation factors	Actual error relation
0.18/1.82	Error 1 = 0.10 * Error 2
0.40/1.60	Error 1 = 0.25 * Error 2
0.67/1.33	Error 1 = 0.50 * Error 2
0.86/1.14	Error 1 = 0.75 * Error 2
0.95/1.05	Error 1 = 0.90 * Error 2
1.00/1.00	Error 1 = Error 2

Table 6.2: Error conversion factors

6.1.6.3 Forecasting methods and parameter combinations

The forecasting methods and their parameter combinations that have been subjected to testing by the automatic pattern recognition are displayed in table 6.3. Each of those method-parameter combinations has been tested with and without the inclusion of multiplicative seasonal factors. The functionality of learning time for exponential and double exponential smoothing has not been used, as the number of functions is with 78 functions nevertheless already high.

Method	Periods	Weighing factors	Alpha	Beta
Moving average	1 month			
Moving average	2 months			
Moving average	3 months			
Moving average	4 months			
Moving average	5 months			
Moving average	6 months			
Moving average	12months			
Moving average	50 months			
Weighted moving average	3 months	3;2;1		
Weighted moving average	5 months	5;4;3;2;1		
Weighted moving average	6 months	2;2;2;1;1;1		
Weighted moving average	10 months	3;3;3;3;2;2;2;1;1;1		
Weighted moving average	12 months	2;2;2;2;2;2;1;1;1;1;1;1		
Weighted moving average	12 months	4;4;4;3;3;3;2;2;2;1;1;1;		
Moving median	3			
Moving median	6			
Moving median	9			
Moving median	12			
Moving median	50			
Exponential smoothing			0.1	
Exponential smoothing			0.2	
Exponential smoothing			0.3	
Exponential smoothing			0.4	
Double exponential smoothing			0.1	0.1
Double exponential smoothing			0.1	0.2
Double exponential smoothing			0.1	0.3
Double exponential smoothing			0.1	0.4
Double exponential smoothing			0.2	0.1
Double exponential smoothing			0.2	0.2
Double exponential smoothing			0.2	0.3
Double exponential smoothing			0.2	0.4
Double exponential smoothing			0.3	0.1
Double exponential smoothing			0.3	0.2
Double exponential smoothing			0.3	0.3
Double exponential smoothing			0.3	0.4
Double exponential smoothing			0.4	0.1
Double exponential smoothing			0.4	0.2
Double exponential smoothing			0.4	0.3
Double exponential smoothing			0.4	0.4

Table 6.3: Utilized methods-parameter combinations in automatic pattern recognition

6.1.6.4 Test results

The 6-month weighted moving average and automatic pattern recognition with all methods listed in table 6.3 have been deployed on the 600 sample histories. The results are shown in table 6.4.

Total samples	Total score of the 6-month weighted moving average	Total score of automatic pattern recognition	Draws	Error relation
600	304 (50.7%)	285 (47.5%)	11 (1.8%)	0.998/1.002

Table 6.4: Results of base comparison

Within the test, the weighted 6-month weighted moving average achieved a slightly higher score, whilst the automatic pattern recognition achieved slightly better results for the average error. Declaredly, the results fall short of the expectations, which shall be further analysed. For this purpose, the success ratio by forecasting model is displayed in table 5. In table A.5.1 the appendix A.5, a more detailed split by model and parameter combination can be found.

Method	Applied	Lost	Won	Draw	Error relation	
No seasonality	344	178	156	10	1.005	0.995
Seasonality	256	126	129	1	0.989	1.011
Double Exponential smoothening	79	43	35	1	1.031	0.969
Exponential smoothening	45	26	19	0	1.022	0.978
Moving average	218	100	115	3	0.977	1.023
Weighted moving average	57	29	23	5	1.010	0.990
Moving median	201	106	93	2	0.999	1.001
Total	600	304	285	11	0.998	1.002

Table 6.5: Results by model – initial test run

Obviously, neither of the forecasting models performs significantly good or bad. The breakdown by model-parameter combination reveals though that methods with more special parameters tend to deliver inferior results on average. These are either methods that take too short history – for instance exponential or double-exponential smoothing with high smoothing factors – or too long history into account. This is in line with the findings of the literature research, which stated that a higher degree of speciality increases model and parameter risks. To validate this, a second test run was performed, where these methods have been exempted. Results are shown in table 6.6, and in appendix table A.5.2 on detailed level.

Method	Applied	Lost	Won	Draw	Error relation	
No seasonality	350	167	171	12	0.984	1.016
Seasonality	250	117	132	1	0.979	1.021
Double Exponential smoothening	63	30	32	1	0.976	1.024
Exponential smoothening	35	13	21	1	0.909	1.091
Moving average	282	136	143	3	0.990	1.010
Weighted moving average	28	10	12	6	0.948	1.052
Moving median	192	95	95	2	0.991	1.009
Total	600	284	303	13	0.982	1.018

Table 6.6: Results by model – second test run

With the exclusion of some methods (greyed out in appendix table A.5.2) the automatic pattern recognition delivers slightly superior results. However, since also the application of demand filters of 4 MAD respectively 3 MAD are not able to change tack, the application of automatic pattern recognition does not appear to pay off.

6.1.6.5 Proposed solution to forecasting

The previous testing on actual data has shown that the automatic pattern recognition is not able to outperform the 6-month weighted moving average in a way that would justify the efforts of implementation and of longer calculation times during application.

Apparently, the available demand history is either too contaminated by one-time orders and external events, or the notion that historic patterns will continue in the future is wrong.

Anyway, the implementation of automatic pattern recognition cannot be recommended at this time. The implementation of manual sales forecasting, the fixed reorder point/target for low sellers, and the zero value correction based on the inventory ledger is on the contrary recommended.

If these measures are able to improve historic data quality as expected, the roll-out of automatic pattern recognition might yield in future, which is why the performed tests shall be repeated in regular intervals starting approximately six months after implementation of the counter measures.

Meanwhile, a static and robust forecasting model with static parameters shall be utilized for forecasting. To select the best forecasting method, the performance of each individual model/parameter combination was tested. The results can be found in appendix A.5 table A.5.3. The findings confirm the previous statement that neither short nor long spanning models are delivering good results. Especially, the double exponential smoothing shows problems with regards to robustness due to its trend component.

The exponential smoothing with non-updating for zero values as a very robust measure receives best results in the comparison. The smoothing factor of 0.25 has been found to deliver best results and an approximately 5.3% lower average error compared to the 6-month weighted moving average. Hence the utilization of the exponential smoothing with alpha = 0.25 is recommended at least on an interims basis.

Total samples	Total score of the 6-month weighted moving average	Total score of exponential smoothing with alpha = 0.25	Draws	Error relation
600	243 (40.5%)	345 (57.5%)	12 (2.0%)	0.973/1.027

Table 6.7: Performance of exponential smoothing with alpha = 0.25

6.2 Evaluation of the economic order calculation

6.2.1 Performance test of individual schedule optimization

Within this section the performance of the heuristic for the individual schedule optimization shall be reviewed. The current implementation of the purchase proposal does not involve any kind of economic order quantity consideration. It is, therefore, not possible to contrast its results with the results produced by the proposed solution. The historic course of the stock level of the previously cited knob-lock set that is illustrated in figure 6.35 clearly indicates that there is a need for economic ordering considerations.

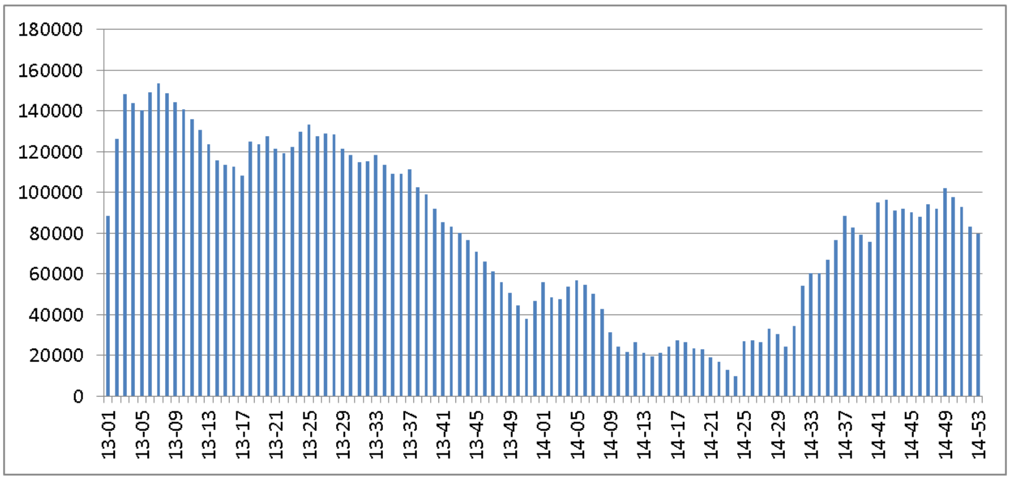

Fig. 6.35: Stock level of knob-lock set by week

Previously it was described that the absence of EOQ calculations leaves the purchaser with the decision on the quantity to be ordered. This is not only inefficient but apparently also prone to suboptimal solutions in terms of cost.

For the purpose of performance evaluation of the proposed heuristic, it is also difficult to consult the optimal solution since it is unknown and the calculation difficult. By the time the optimal solution can be easily obtained, there would be no need for a heuristic. Therefore, the only viable option to evaluate the performance of the proposed heuristic is to compare its results with the results of other heuristics.

6.2.1.1 Contestants

Hu and Munson (2002) summarized that the least-unit-cost heuristic was found to be the method of choice in a number of previous comparisons in the literature. Therefore, the output of the proposed solution shall be compared with that of the least-unit-cost heuristic. To incorporate the MOQ in the least-unit-cost heuristic, it needs to be adapted as discussed in chapter 5. The base purchasing price shall be considered as infinite. A quantity discount break is added for the MOQ, whereby the purchase price is set to the normal price when the MOQ threshold is exceeded. The actual discount forms a second break in the purchase price function. To consider the finding of Hu, Munson and Silver (2004), only the delta in purchase price towards the normal price is considered. The second contestant is the proposed staged-heuristic as it was developed in chapter 5.

6.2.1.2 Test setup

In a setup with a packcode quantity of 100 pieces, a minimum order quantity of 200 pieces, and a discount threshold of 500 pieces, the performance of the least-unit-cost heuristic and of the proposed heuristic have been tested for different horizon lengths (5, 10, 15, 20, 25 periods). Each test was conducted with 100 sample JIT schedules. Thereby, the JIT values of each period have been randomly generated with equal probability for all values ("randbetween" function of MS Excel).

Three series of tests have been conducted.

- In the first series the random values have been generated between 0 and 1000. "RANDBETWEEN(0,1000)"
- To increase the difficulty, a second series has been tested, whereby the values have been randomized between 0 and 499 and, therewith, lie below the discount threshold. The probability of a zero values has been set to 25%. The probabilities for all other values are equally distributed. "IF(RANDBETWEEN(1,4)=1,0,RANDBETWEEN(1,499))"
- In a third series, values have been randomized between 0 and 199 and hence below the MOQ. The probability of zero values is 10%. The probabilities for all other values are again equally distributed. "IF(RANDBETWEEN(1,10)=1,0,RANDBETWEEN(1,199))"

6.2.1.3 Test results

To compare both contestants, the total schedule cost is compared. It is calculated as the sum of inventory costs for overstocks and of the total purchasing cost. The comparison uses the same function that is used to compare various options within the heuristics. In the following result tables a score is given to either heuristic if it delivered lower total schedule costs. In case of equal total schedule costs, a draw is recorded.

Series 1

RANDBETWEEN(0,1000)					
Horizon lengths	5	10	15	20	25
Simulation count	100	100	100	100	100
Lower total schedule cost by least-unit-cost heuristic	5	0	4	2	0
Lower total schedule cost by proposed heuristic	74	93	95	98	100
Draw	21	7	1	0	0

Table 6.8: Results for different horizon lengths – test series 1

The test data shows that the proposed heuristic delivers better results than the least-unit-cost heuristic. For short periods the comparison brings a high number of draws about, whereas the results for longer periods are even more distinct.

Series 2

IF(RANDBETWEEN(1,4)=1,0,RANDBETWEEN(1,499))					
Horizon lengths	5	10	15	20	25
Simulation count	100	100	100	100	100
Lower total schedule cost by least-unit-cost heuristic	10	10	12	11	9
Lower total schedule cost by proposed heuristic	50	76	82	87	91
Draw	40	14	6	2	0

Table 6.9: Results for different horizon lengths – test series 2

In the second test series, the least-unit-cost heuristic performs slightly better than in the first series. Yet, the proposed heuristics still outperforms the least-unit-cost heuristic significantly.

Series 3

IF(RANDBETWEEN(1,10)=1,0,RANDBETWEEN(1,199))					
Horizon lengths	5	10	15	20	25
Simulation count	100	100	100	100	100
Lower total schedule cost by least-unit-cost heuristic	0	13	15	21	23
Lower total schedule cost by proposed heuristic	38	53	55	55	64
Draw	62	34	30	24	13

Table 6.10: Results for different horizon lengths – test series 3

In the third series, which can be considered as a rather unrealistically tough test environment, the differences between both contestants are reduced for longer horizons. The cause for this shall be analysed at one of the schedule where the least-unit-cost delivered better results, refer table 6.11.

Period	0	1	2	3	4	5	6	7	8
JIT schedule	104	0	159	196	152	54	146	160	188
Packcode rounded	200	0	100	200	200	0	200	100	200
Least-unit-cost	200	0	500	0	0	0	500	0	0
Proposed heuristic	500	0	0	0	500	0	0	0	200

Table 6.11: Selected sample schedule for investigation

Apparently, the proposed heuristic captured a discount in the first period, whereas the least-unit-cost heuristic opted for the discount in the third period. The total schedule cost for the example in 6.11 for the least-unit-cost heuristic was $11600 whilst the proposed heuristic incurred schedule costs of $12000, which equals an increase of 3.4%. The MOQ functionality can be identified to be the cause of this sub-optimality. That is because the MOQ rounding prepones the MOQ violating quantity of period 2 to period 0 as a first step without considering the cost impact. When the discount optimization is applied afterwards, it is only necessary to prepone 200 pieces by 3 periods from P3 to P0 to reach the discount threshold. The discount saving of $750 is outweighing the increase in inventory costs of $600, which is why the preponement is performed. It can be concluded that the MOQ rounding can lead in some cases to sub-optimal results when compared to the least-unit-cost heuristic.

At this point it must be emphasized that the total schedule cost evaluation - that is also performed for the evaluation within the testing - can actually be used to choose the best heuristic with regards to total schedule cost. It is hence possible to initially apply both - the proposed heuristic and the least-unit-cost heuristic. The decision for one or the other heuristic is then solely based on the total schedule cost evaluation. This allows for the application of even more heuristics, which increases the chances to match the optimal solution. Applying several heuristics with significantly different intra-evaluation measures increases the likelihood to identify the optimal solution under difficult circumstances. The combination of least-unit-cost heuristic and proposed heuristic is already building a strong base that can be expected to deliver consistently sufficient results in face of uncertainty with regards to schedule stability.

6.2.2 Evaluation of joint replenishment optimization

With regards to the joint replenishment optimization neither the optimal solution nor solutions by other heuristics are known. Hence it is not possible to quantitatively compare the results, which is why a rather qualitative evaluation must be performed.

6.2.2.1 Qualitative assessment of pallet stack creation

The procedure on how to arrive at a solution has been described and demonstrated in chapter 5. The solution is obtained by recursive programming, which can be expected to deliver good results since a very high number of combinations are tried out.

A potential reason for sub-optimality is the sequential processing of pallet stacks and, thereby, the negligence of future impact on other pallet stacks. This means that if a certain pallet is chosen to join a pallet stack, it is not evaluated whether this pallet would have more perfectly fit into another stack that is assembled afterwards.

The approach to start the procedure with the highest pallets first – pallets that are more difficult to accommodate – and the preference for those pallets with lower stackable weight, are counter measures that limit the number of occurrence to seldom cases. Under certain constellations of pallets with different weights and different stackable weights, the solution can be suboptimal. An example is depicted in tables 6.12 and 6.13.

Pallet Type	Height	Weight	Max stack weight	Pallet count
P1	1400	200	0	1
P2	600	600	800	1
P3	400	300	300	1
P4	500	400	0	1

Table 6.12: Sample shipping list for pallet-stack creation

Column ID	Total height	Total weight	Volume	W/M	Container	Pallet 1 (top)	Pallet 2 (bottom)
C1	2000	800	1.92	1.92	LCL (1)	P1	P2
C2	500	400	0.48	0.48	LCL (1)	P4	
C3	400	300	0.384	0.384	LCL (1)	P3	

Table 6.13: Proposed solution for pallet-stack creation example

The optimal solution for this example is shown in table 6.14. A reduction from three to two pallet stacks would have been possible. Since in this case only three stacks have to be shipped, LCL would still have been the most cost efficient solution, which is why there is no negative impact in terms of cost. A cost impact would only observed in case that a full container load is shipped, which though means that the shipping list contains more pallets, which in turn increases the allocation efficiency, as more combinations are possible and as potential leftover spaces can be filled up with other pallets. The percentage error in relation to the overall container is low.

Column ID	Total height	Total weight	Volume	W/M	Container	Pallet 1 (top)	Pallet 2 (bottom)
C1	1800	1000	1.728	1.92	LCL (1)	P1	P3
C2	1100	500	1.056	0.48	LCL (1)	P4	P2

Table 6.14: Optimal solution for pallet-stack creation example

A second potential source of sub-optimality is the stack height acceptance threshold of 2000mm that was set to improve calculation times. This decreased calculation times significantly, whilst leading to minimal deviating results in some of the test cases. The deviations are, though, not necessarily negative, as a lower threshold in the previous example might have prevented the sub-optimality.

6.2.2.2 Further samples for pallet stack creation

With two further examples it shall be illustrated that for a higher count of pallets and different pallets the space utilization that is achieved by the proposed functionality is satisfactory.

Example 1

In this example the pallet heights still range from 300mm to 1400mm, whilst weight and maximum stackable weight have been randomized. Also the pallet count has been randomized.

Pallet Type	Height	Weight	Max stack weight	Pallet count
P1	300	270	680	3
P2	400	460	370	1
P3	500	290	710	2
P4	600	335	620	4
P5	700	395	430	2
P6	800	460	570	1
P7	900	465	580	5
P8	1000	485	380	6
P9	1100	285	470	5
P10	1200	305	610	4
P11	1300	340	560	1
P12	1400	335	690	3

Table 6.15: Shipping list as input for containerization function – example 1

In the solution in table 6.16, the height of the proposed pallet stacks is consistently high without significant waste of volume. Stacks that do not reach the target height of at least 2000mm are limited due to the weight restrictions.

Column ID	Total height	Total weight	Volume	W/M	Container	Pallet 1	Pallet 2	Pallet 3
C6	1900	950	1.824	1.824	40F (1)	P8	P7	
C7	1900	950	1.824	1.824	40F (1)	P8	P7	
C8	2100	950	2.016	2.016	40F (1)	P5	P9	P1
C9	2100	950	2.016	2.016	40F (1)	P5	P9	P1
C14	1800	930	1.728	1.728	40F (1)	P7	P7	
C10	2000	890	1.92	1.92	40F (1)	P9	P1	P4
C11	2100	865	2.016	2.016	40F (1)	P9	P3	P3
C13	2100	800	2.016	2.016	40F (1)	P11	P6	
C1	1800	795	1.728	1.728	40F (1)	P2	P12	
C2	2200	790	2.112	2.112	40F (1)	P8	P10	
C3	2200	790	2.112	2.112	40F (1)	P8	P10	
C4	2200	790	2.112	2.112	40F (1)	P8	P10	
C5	2200	790	2.112	2.112	40F (1)	P8	P10	
C12	2000	750	1.92	1.92	40F (1)	P9	P7	
C15	2000	670	1.92	1.92	40F (1)	P4	P12	
C16	2000	670	1.92	1.92	40F (1)	P4	P12	
C17	600	335	0.576	0.576	40F (1)	P4		

Table 6.16: Proposed solution of containerization function – example 1

Example 2

Table 6.17 and 6.18 show another example of twelve different pallet types, of which two pallets each have to be loaded. The pallet heights range from 300mm to 1400mm, weight and stackable weight are equal.

Pallet Type	Height	Weight	Max stack weight	Pallet count
P1	300	300	1800	2
P2	400	300	1800	2
P3	500	300	1800	2
P4	600	300	1800	2
P5	700	300	1800	2
P6	800	300	1800	2
P7	900	300	1800	2
P8	1000	300	1800	2
P9	1100	300	1800	2
P10	1200	300	1800	2
P11	1300	300	1800	2
P12	1400	300	1800	2

Table 6.17: Shipping list as input for containerization function – example 2

In the solution all columns except the last one exceed 2000mm. The solution makes hence adequate use of the container height.

Column ID	Total height	Total weight	Volume	W/M	Container	Pallet 1	Pallet 2	Pallet 3
C1	2000	900	1.92	1.92	20F (1)	P12	P1	P1
C2	2200	900	2.112	2.112	20F (1)	P12	P2	P2
C5	2200	900	2.112	2.112	20F (1)	P10	P3	P3
C9	2200	900	2.112	2.112	20F (1)	P8	P4	P4
C3	2000	600	1.92	1.92	20F (1)	P11	P5	
C4	2000	600	1.92	1.92	20F (1)	P11	P5	
C6	2000	600	1.92	1.92	20F (1)	P10	P6	
C7	2000	600	1.92	1.92	20F (1)	P9	P7	
C8	2000	600	1.92	1.92	20F (1)	P9	P7	
C10	1800	600	1.728	1.738	20F (1)	P8	P6	

Table 6.18: Proposed solution of containerization function – example 2

6.2.2.3 Qualitative assessment of container assignment

The assignment of pallet stacks to a certain container has been realized by a window that is moved through the list of pallet stacks sorted by weight descending, e.g. the list in table 6.16 that is already sorted in that way. The basic principle is that the heaviest pallet of the container window was exchanged with that pallet right below the window. In case that the maximum container weight is just exceeded by "one gram", the maximum difference from the optimal solution occurs.

$$Max\ wasted\ weight = Weight\ of\ 1st\ pallet - weight\ of\ replacement\ pallet$$

Equation 6.3: Maximum of wasted container weight capacity

This error may be reduced by not exchanging the heaviest pallet but rather the lightest pallet. The procedure would be to move the window just above the first slightly underweight window and then to move down the last pallet stack until the total weight is just lower than the maximum weight. This procedure is depicted in table 6.19. In the example this overall more accurate method does though not yield a better result, as the steps between two pallet stacks are very small.

Considering that the maximum weight of the container is usually not a limitation to the shipments of the organization the originally presented methods appears sufficient. Yet, implementing the add-on is a very simple extension that could be implemented with a few lines of source code.

Column	Weight	Possible combination in 40FT container (24 columns)											
C1	2000	37,500 kg (overweight)											
C2	2000		36,480 kg (overweight)										
C3	2000			35,280 kg (overweight)									
C4	1900				34,080 kg (overweight)								
C5	1900					32,980 kg (overweight)							
C6	1850						31,880 kg (overweight)						
C7	1850							30,780 kg (overweight)					
C8	1800								29,680 kg (overweight)				
C9	1800									28,630 kg (overweight)			
C10	1780										27,580 kg (overweight)	**27,460 kg**	
C11	1700												**26,550 kg (slight underweight)**
C12	1600												
C13	1600												
C14	1500												
C15	1500												
C16	1450												
C17	1375												
C18	1315												
C19	1250												
C20	1150												
C21	1100												
C22	1050												
C23	1050												
C24	980												
C25	980												
C26	800												
C27	800												
C28	800												
C29	800												
C30	750												
C31	750												
C32	750												
C33	750												
C34	680												
C35	630											X	
C36	500												
C37	500												
C38	350												
C39	350												
C40	350												

Table 6.19: Slightly more accurate method for containerization

6.2.2.4 Assessment of optimal shipping mix determination

The shipment mix determination itself is an optimal calculation, as long as the 40FT container is really the cheaper option compared to a 20FT container. If this is not the case the recursive programing that was employed can easily be changed to evaluate the entire tree of options and not only to evaluate lower options in case of not full utilization – the “if not full” check is removed.

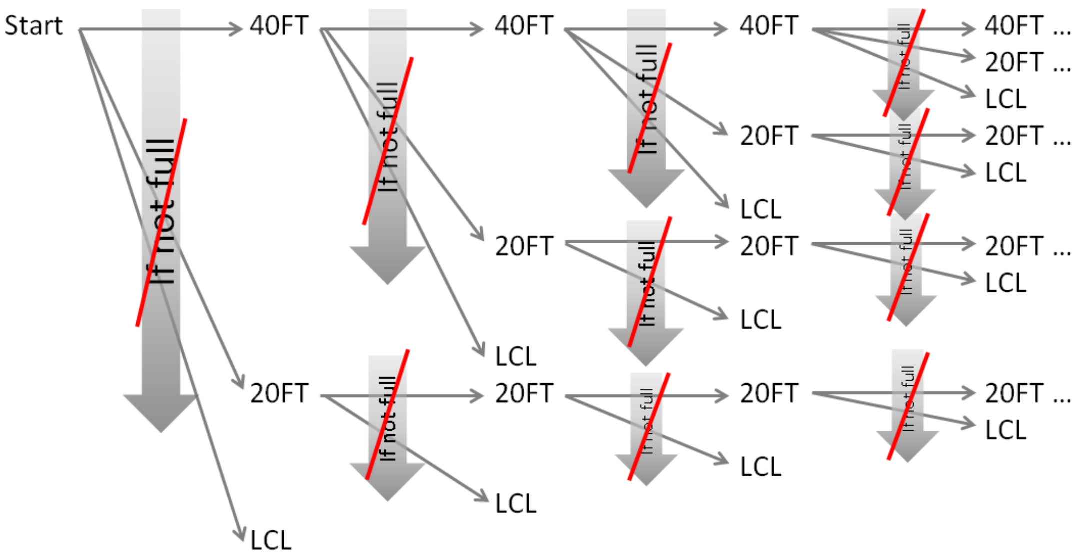

Fig. 6.36: Decision tree for shipment mix with disabled “if full” check

Assessing the entire tree increases calculation times for the optimal shipping mix. Yet, also the count of prospect shipping mixes increases, which implies a further increase in calculation time. Since the 40FT container will usually be the cheapest option in most cases, the activation/ deactivation of the “if not full” check shall be based on the comparison of the 40FT and 20FT transportation cost for the respective supplier.

Even though this calculation itself is an accurate calculation since all possibilities are calculated and compared, the optimality of the result depends on the container assignment, which itself can be expected to be rather close to the optimum, refer 6.2.2.3

6.2.2.5 Assessment of transport cost optimization

Ultimately, the proposed heuristic for the preponement decision making in face of transport cost savings shall be qualitatively assessed. The decision for or against a preponement of partial or entire quantities is made upon the assessment of the absolute cost impact. The absolute cost impact is calculated by contrasting the exact transport cost saving for the focussed period with the impact on individual item schedule cost. The individual item schedule cost impact is determined by contrasting the total schedule cost of the discount optimized schedule before the preponement and of the discount optimized schedule after the preponement. It has previously been shown that the individual item optimization achieves good results, whilst allowing for further fine tuning by adding additional heuristics into the comparison.
The transport costs in future periods have been neglected during the entire optimization, which seems reasonable in face of schedule instability, as it is unlikely that the exact shipping list can be maintained over a number of periods. Savings in the focus period can on the contrary be directly secured.

With regards to the selection of particular items and quantities to fill up a shipping mix, the unsteadiness of cost increase functions requires a step-wise approach, which under circumstances can overlook the absolute cost advantage of moving a bigger lot when a relative disadvantage is seen versus a smaller lot of another item.

Example

The previously used frame conditions shall be used to illustrate this scenario: Packcode quantity is 100 pieces; MOQ is 200 pieces; discount of $1.5 is granted above 500 pieces. The leftover space in the container allows for 5 pallets. The saving of filling up the container by five pallets shall be assumed to be $220 per pallet. The inventory costs of item 1 are $1 per period for item 1 and $0.75 for item 2.

Period	P0	P+1	P+2	P+3	P+4	P+5	P+6
Item 1	200	200	0	0	0	0	300
Item 2	200	0	0	500	0	0	0

Table 6.20: Sample for the assessment of the preponement decision

For item 1 the next shipment takes place in P+1, the schedule cost impact for one pallet is the inventory cost that incurs for one week ($100).
For item 2 the next shipment takes place in P+3, the preponement of the entire shipment is feasible as the space constraints allows for it. The schedule impact is constituted by the increase in inventory cost and the discount saving for the 200 pieces in P0. It can be calculated to be (200*-$1.5+0.75*500*3)/5pallets = $825/5pallets = $165 per pallet.

At this stage the preponement of item 1 is chosen as the cost increase per pallet is lower. To fill up the remaining three spaces the calculation is performed again.
For item 1 the preponement cost from period P+6 to P0 is $600 per pallet. For item 2 it is unfortunately no longer possible to prepone 500 pieces and, therewith, to profit from positive discount effects. In face of the space constraint, the preponement of 300 pieces leads to a loss of discount for 200 pieces in P+3 whilst additional discount for 200 pieces is gained in P+0. The cost impact is hence solely constituted by the inventory cost increase – $225 per pallet.

The options are:

- No preponement – no transport cost saving but also no schedule cost impact
- Preponement of 200 pieces of item 1 from period P+1
  The transport cost impact is $440.
  The schedule cost impact is $200.
  Total saving: $240
- Preponement of 200 pieces of item 1 from period P+1 and 300 pieces of items 2 from P+3
  The transport cost impact is $1100.
  The schedule cost impact is $875
  Total saving: $225

From these options, the second option of preponing only 200 pieces of item 1 would have been selected since it delivers the higher absolute cost saving, which is $240.

However, actually the preponement of 500 pieces of item 2 from P+3 would have brought about a negative schedule impact of $825 but reduced transportation cost by $1100. The overall saving would have been $275 and hence $35 higher than the proposed solution.

Even though, the optimal solution can apparently not be guaranteed, the degree of deviation and the probability can be considered as not severe. Changing input cost factors in above example slightly brings about the optimal solution. For instance if the transport saving would have been $205 instead of $220 per pallet, the preponement of only 200 pieces of item 1 would have been the best solution. Nevertheless, the difference in cost saving between optimal and proposed solution is comparably small to the overall saving.

6.3 Chapter summary

Within this chapter, the proposed solutions that have been developed in chapters 4 and 5 have been reviewed with regards to theoretical and where applicable with regards to existing solutions.

The automatic pattern recognition that was developed as a solution to the forecasting problem of a high number of diverse SKU has at first been tested for its ability to adequately identify and continue standard patterns. Thereby, the results have been throughout positive, which is why noise, zero values and outliers have been added to qualitatively assess the robustness of the method. In this context slight corrections have been proposed to increase the robustness, for instance a reasonability check for seasonality factors. In a next step the complete functionality of forecasting, safety stock calculation, and JIT inbound schedule creating has been deployed to real product data.
Thereby, forecasted values have been contrasted with actual values whilst the impact on safety stock levels has been observed. It has become apparent that the forecast in many cases slightly underestimates the demand whilst the standard deviation and hence the safety stock are determined on a rather high level. Skewness of the random

error has been identified as main cause for this observation, which is though not a deal breaker, as both effects kind of outbalance each other so that the service level can still be achieved. In a final test on the data of 600 items, the forecasting error of the automatic pattern recognition has been contrasted with the error of the currently implemented 6-month weighted moving average. Thereby, it has been found that the proposed pattern recognition only outperforms the existing method slightly, which at this time would not rectify the effort of implementation. Since the low quality of input data is the most probable reason for this finding, the impact of the previously proposed measures to improve data quality shall be bided before taking a final decision for or against the implementation. Meanwhile exponential smoothing with a smoothing factor of 0.25 is proposed to replace the 6-month weighted moving average since it delivered better results in 58% of test cases.

For the economic order quantity calculation, the first stage of individual product schedule optimization was contrasted with an adapted least-unit-cost heuristic that has been proposed within the literature. It has, thereby, been found that the proposed heuristic outperformed the least-unit-cost heuristic for 1,111 out of 1,500 sample schedules – in 254 cases a draw has been achieved. Yet, by means of the total schedule cost evaluation function, it is possible to integrate the least-unit-cost heuristic into the assessment so that it is possible to profit from the advantages of both functions.

For the second stage – the joint transport cost optimization – there is no alternative solution available that considers the transportation costs in equivalent detail and hence allows for comparison. For this reason, a qualitative assessment has been conducted. Due to the absolute calculation of costs, the veracity of the calculated cost saving is guaranteed as long as schedule stability is given. With regards to the optimality, a qualitative assessment has been conducted that has adjudged good chances to find the optimal result, whilst deviations in case of non-optimal results can be expected to be comparably low.

7 CONCLUSION AND RECOMMENDATION

7.1 Review of the intentions behind the thesis

In the introductory chapter it has been pointed out that holding products in stock is the basis for the key competitive advantage of the organization. That is because inventory allows for next-day delivery and indirectly for the remittal of minimum order quantities, which forms the core of the organization's customer value proposition. In an effort to pursue further growth in increasingly saturated markets, the organization consistently expands its product and hence stock range. Since the proliferation of stock items comes along with increasing complexity for the supply chain, not only revenues but also costs have significantly increased in recent years. Having acknowledged the need for cost reduction, efficient purchasing has been identified as a source for significant savings, which is why this thesis focusses on enabling the purchasing department to take logistic cost efficient purchasing decisions.

7.2 Solution for research problem

The precise objective of the thesis has been set to provide the purchasing with a purchase proposal function, which supports the purchasing decision making by suggesting meaningful and cost-wise optimized order quantities.
Meaningfulness is only given if the demand forecast as basis for all planning is accurate and robust. Therefore, a sub-problem has been defined to the review and if possible to improve the forecasting functionality.
A second sub-problem has then been set to the design of the logic that recommends actual purchasing quantities that are logistic cost optimized, whilst ensuring the ability to satisfy the forecasted demand.
Fundamentally, both sub-problems are strongly interconnected since the output of the demand forecast defines the input for the so called economic order quantity calculation (EOQ) as figure 7.1 depicts. However, implementation-wise both sub-problems can be kept rather independent as technically only a list of values if handed over. This allows for taking the decision for or against the implementation of the

functions independently, which is why both sub-problems will be discussed sequentially within this conclusion. In case that manual manipulation of the demand plan is desired, the EOQ functionality must also be independently trigger-able for recalculating the proposed quantities.

Fig. 7.1: Data flow through purchase proposal functionality

7.2.1 Sub-problem 1

Detailed summaries of the findings specific to each chapter have been given at the end of the relevant chapter and shall hence not be repeated at this time. However, a brief recapitulation shall be given at this stage to remind the reader.

7.2.1.1 Recapitulation

The sub-problem 1 was formulated as "Suggest on how to improve the current demand forecasting – factually the basis for an adjacent economic order calculation – with regards to forecast accuracy and robustness"

According to previous research, a one-method-fits-all approach is not able to cope with the variety of demand patterns that can be observed for products in different life cycle stages, with different product characteristics, or with different customer groups. The fundamental assumption is hence that the currently implemented 6-month weighted moving average is unlikely to deliver good results for all items.

Based on this assumption, an automatic pattern recognition functionality has been implemented, which tests various forecasting model/parameter combinations on previous data under the expectation that patterns which have been observed in the past will continue in the future. For the assessment of fit, the smoothed absolute sum error over the replenishment period ("frozen" horizon) has been selected. That is because the minimization of the sum error is important to get the inventory position right, which in turn is decisive for any ordering decision. Even though the implemented functionality has delivered very good results during testing on standard patterns and on heavily contaminated standard patterns, it has not been able to outperform the 6-month weighted moving average significantly when applied to actual product data. The main cause of failure has been identified to be the low quality of the available historic data, which is contaminated with outliers, zero-values, severe random error, skewness and influenced by external events. Since a correction of these violations against the basic preconditions of quantitative-intrinsic forecasting has not been possible by means of data filters, the comparably robust 6-month weighted moving average has been able to deliver almost equally good results on average.

To improve the quality of historic data in the long term, the implementation of a manual forecasting function that allows for additional qualitative forecasting has been proposed. Such function can be expected to have positive effects on fulfilment rate but also helps to prevent the transition of one-time orders into demand history, which reduces distorting spikes in the data. To correct observed zero-demand due to stock-outs, the consideration of the inventory ledger has been suggested. Thereby, a day's demand value shall be replaced by the average daily demand of the month, whenever the closing-stock falls short of a threshold, e.g. 2 days demand. In this case it can be assumed that demand has been lost due to the insufficiency of stock to satisfy all demand. For items with highly sporadic demand, the chances of good results for pattern recognition are low, which is why a fixed reorder point policy has been recommended in first place.

Since the automatic pattern recognition was not able to convince, other statically applied forecasting methods have been tested against the 6-month moving average. Thereby, exponential smoothing with alpha = 0.25 has delivered better results in 58% of cases, whilst providing a 5% lower average deviation.

7.2.1.2 Suggested solution and recommended further actions

Forecasting technique

Based on the finding that automatic pattern recognition does currently not yield significantly better results than the currently implemented 6-months weighted moving average, its implementation is not recommended at present time.

Instead the suggested measures to improve the quality of data history shall be implanted. This is on one hand the manual forecasting function, which allows for qualitative products on item-customer level and that is expected to prevent the transition of huge one-time orders into the demand history statistics. On the other hand, the proposed stock-out correction based on a period's closing stock is recommended for implementation. Both can be expected to improve the data history overtime, as long as the manual forecasting screen is actually used. To ensure this, the sales management must develop incentive systems that encourage proper usage.

Once these measures are in operation for some time (approximately 6 to 8 months) the performance of the automatic pattern recognition shall be tested again.

Meanwhile it is suggested to replace the 6-month weighted moving average with exponential smoothing with alpha = 0.25 since this method achieved better results on average whilst implementation effort is comparably low.

Safety stock

With regards to safety stock, it is recommended to move away from the current safety time that is fixed based on x,y,z classification. Instead it is recommended to calculate the historic standard deviation between actual values and the forecasted values by the exponential smoothing. Based on this standard deviation and the service level that is applicable for the item, the safety stock requirement shall be calculated. The service level for each item or cluster of items must be defined by the organization.

Visibility

With regards to the purchase proposal screen, it is furthermore recommended to illustrate the demand forecast in a same manner as the developed simulator, where the curve of forecasted demand continues the curve of previous demand, see figure 7.2. This allows for easy verification whether the forecast is trustworthy or not.

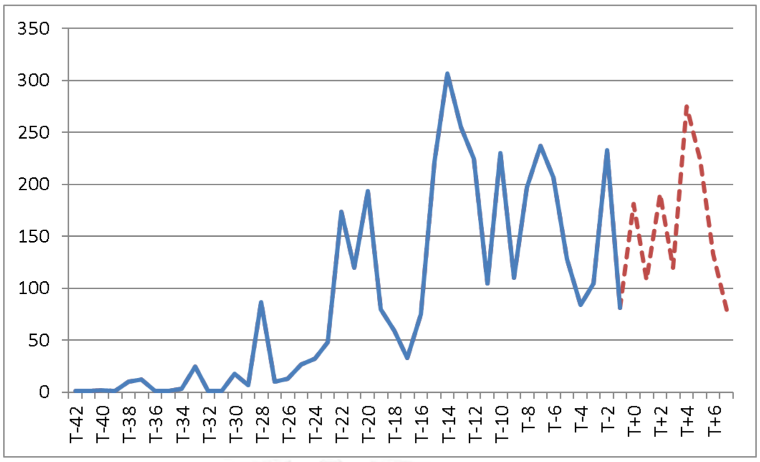

Fig. 7.2: Recommended visualisation of forecasting results

A visibility improvement with regards to safety stock will be suggested in the review of sub-problem 2.

7.2.1.3 Suggestion for further academic research

No further academic research is suggested.

7.2.2 Sub-problem 2

7.2.2.1 Recapitulation

The second sub-problem was defined as to “Design a purchase proposal logic that outweighs the various cost factors involved in the provision of stock and hence supports cost efficient purchasing decisions”. Therewith, the scope of the envisioned logic is to translate the demand plan that is handed over by the forecasting module into a cost efficient ordering recommendation. In order to arrive at a cost efficient recommendation inventory costs, ordering costs, and transportation costs have to be considered adequately for practical deployment. In this context “adequately” means that the way of including cost factors must reflect the actual structure of the cost

factor. With regards to transportation cost this means that the relevant economies and diseconomies of scale are reflected within the logic, which implies that the approach must be as detailed as to consider even the container stuffing.
In the introduction it was furthermore addressed that most of the organization's suppliers deliver several up to a few hundred SKUs. This promotes the inclusion of transport and ordering costs to a so called joint-replenishment problem. Further complexity is added by the need to incorporate minimum order quantities and discounts.

Within the literature research no methods that consider costs and dependencies in such great detail have been found, which is why a new logic has been proposed. The proposed logic does fundamentally consist of two stages – an individual item schedule processing and a joint transportation optimization.

The individual item schedule processing starts with packcode rounding that follows the stipulation to only order full pallet quantities. Ordering full pallets allows for higher handling and storage efficiency and does, thereby, ensure constant ordering and inventory costs. Moreover, does the insistence on full pallets reduce the complexity of the transportation cost calculation. Based on identified short comings of the least-unit-cost heuristic, an alternative has been developed that considers MOQ and discounts subsequently to the packcode rounding in a 3 step procedure. This heuristic outperformed the least-unit-cost heuristic in 1,111 out of 1,500 test cases, whilst achieving additional 154 draws.

Afterwards the second stage of joint-transport optimization is applied. For this purpose a set of functions has been developed, which calculates the container utilization in terms of weight and volume under consideration of pallet stackability. With the help of this function is it is possible to determine the most cost efficient shipping setup (40" FCL, 20" FCL, LCL, or a combination thereof) and the unutilized space within this setup in terms of pallets per item. This knowledge enables the evaluation whether the preponement of future item shipments endows a cost advantage through transportation cost savings that exceeds the increase in individual item schedule cost.

To complete the subject matter of economic order quantity, guidance on how to determine the different cost factors (inventory cost, ordering cost, transportation cost) and there structure has been given.

7.2.2.2 Suggested solution and recommended further actions

EOQ functionality

With regards to the quantitative tests that have confirmed superior performance compared to the least-unit-cost and with regards to the qualitative assessment of the joint-transportation cost optimization, the implementation of the proposed functionality is fully recommended.

Required preparations

To enable the EOQ calculation, actual values for the three involved cost factors have to be calculated from the organizations accounting data.

- Inventory costs have to be determined for each item on per piece/per period basis.
- Ordering costs have to be calculated as lump sum.
- Transportation costs have to be split into a fixed amount per shipment and variable costs for the different container types. Since costs vary depending on the location of the supplier, the transportation costs must be determined on supplier basis.

It might also be necessary to conduct supplier negotiations for the establishment of a consistent pricing structure and consistent incoterms among all suppliers. If each supplier applies his own discount and cost setup, e.g. to include freight cost completely in the purchase cost, the applicability of the EOQ calculation is limited.

At last, proper pallet packcodes with correct pallet quantities, dimensions, weight and stackability must be created in the ERP system to enable the container stuffing functionality.

Visibility

With regards to transparency and, therewith, implicitly to the creation of trust it is recommended to provide maximal visibility. In the context a process log for visualizing the solution finding shall be implemented. The kind of visualization can be orientated towards the example which has been given in chapter 5.

Another graphic visualization that allows for quick verification that the planned schedule is sufficient to satisfy the demand is recommended. The chart that is proposed in figure 7.3 illustrates the accumulated received quantity versus the accumulated demand and the accumulated demand plus required safety stock.

In case that the accumulated received quantity (frozen schedule and proposed schedule) undercuts the “demand + safety stock” curve, a safety stock violation is projected. In case that the “demand” curve is undercut, a stock-out is projected. On the other side if the accumulated received quantity exhibits a significant gap to the “demand + safety stock” curve, overstock is indicated.

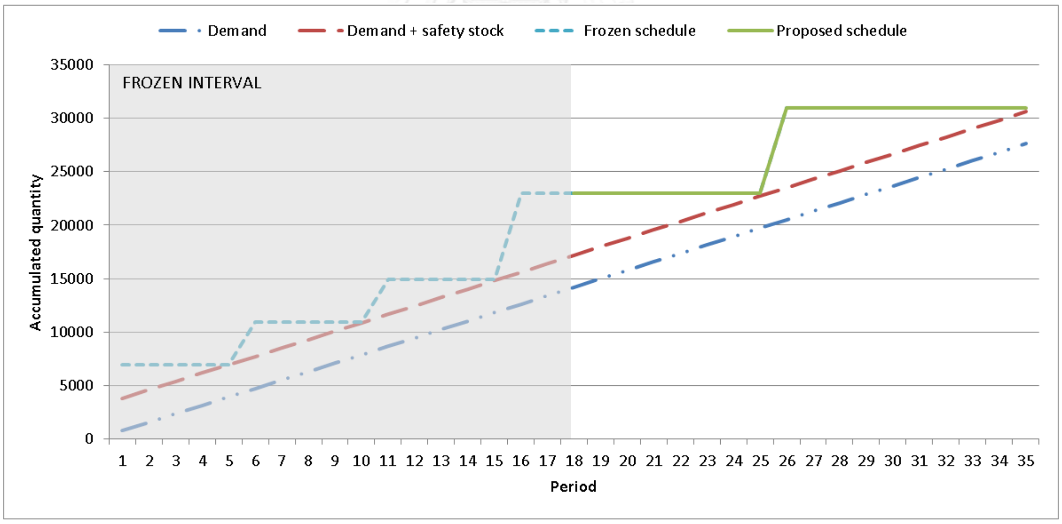

Fig. 7.3: Visualization of proposed schedule on item level

On a more detailed level this method of visualization can help to convey the idea of the economic order quantity and to visualize the reasonability and impact of the different calculation steps, see figure 7.4.

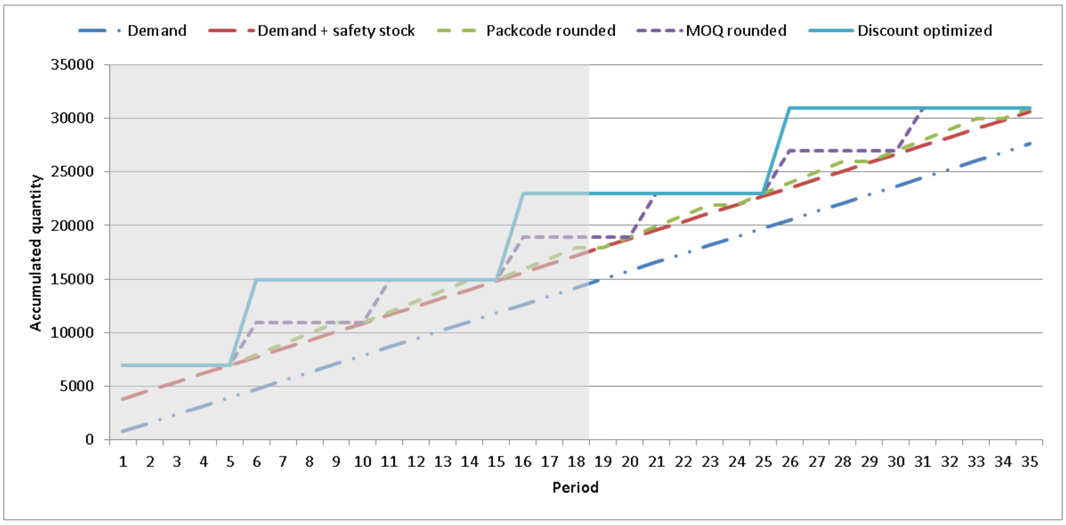

Fig. 7.4: Visualization of economic order quantity calculation steps on item level

To ensure trust that the shipping setup can actually accommodate the goods and quantities which are proposed for shipment, the container allocation should be visualized in detail. This information should even be attached to the purchase order to advise the supplier on how to stuff the container, which might ultimately help to reduce in-transit damages. Graphical visualization as shown in figure 7.5 would deliver the highest transparency, which might though be difficult to achieve with the functionality of the ERP system. Further considerations of how to illustrate the allocation in a simple but transparent way shall be undertaken.

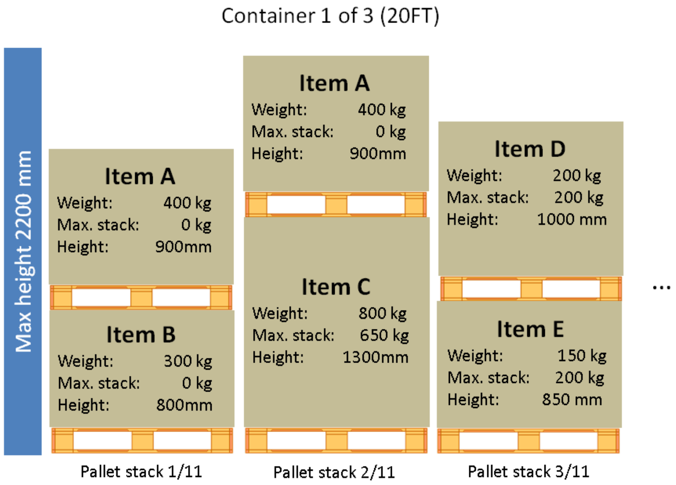

Fig. 7.5: Visualization of container allocation

7.2.2.3 Suggestions for further academic research

Within the EOQ functionality the stipulation of pallet quantities is the most vigorous restriction, which is though reasonable for the application at Hafele.
A change from the defined standard of Euro-pallets to other pallet formats can be simply done by adjusting the maximum number of pallet spaces for each container. Also the maximum container height can be adjusted easily.

Further research is recommended with regards to the ability of handling loose quantities and, therewith, to the removal of the pallet quantity restriction. This will then require the incorporation of 3-dimensional stuffing, which can though be expected to face issues in regards to the consideration of stackability.

Additional research might be performed to include different types of discount, as the implementation has been limited to the all-unit discount, which is by far most relevant to the organization.

7.3 Review with regards to stated objectives

7.3.1 Confrontation with deliverables and postulated principles

The deliverable of this thesis has been defined as to deliver a step-by-step description on how to arrive at the economic order quantity, which shall be used as a blue print for a subsequent IT development.

The principles of both – forecasting and economic order quantity calculation – have been described as they have been implemented in Visual Basic. The actual programming (source code) heavily depends on the format of underlying data (e.g. Excel tables, Oracle databases), which is why the focus has been set to convey the idea behind the functions. The fact that functions have been implemented and tested confirms the functionality, which is why a successful implementation in the ERP system can be expected.

To ease the implementation, simplicity has been postulated as guiding principle throughout the development. Even though the solution appears rather complex at first glance, the individual functions are fairly simple, which is especially true when compared with other heuristics that can be found in the literature.

Especially the determination of the container fill rate requires several steps that include recursive programming. However, since the functionality was broken down in several smaller functions, clarity and replicability are increased, which can be in turn expected to have a positive impact on implementation time and the number of encountered problems. Smaller functions with straight information flow and simple interface are also of advantageous for quality checks upon implementation.

The number of options, e.g. with regards to the number of quantity discount options, is limited, which is in line with the effort to reduce unnecessary pluralism and hence complexity and error-proneness. It shall be noted that the function must work reliably especially in the initial stage to gain trust among the purchasing staff. Trust is mandatory for user acceptance and hence for the achievement of the business objectives.

7.3.2 Confrontation with business objectives

The business objective of providing a basis for cost conscious decision making in the area has been achieved by the inclusion of all cost factors that are impacted by the purchasing decision.

The objective of workload reduction can be achieved when the purchase proposal is implemented, accepted, and working with low manual interventions. The economic order quantity component can be trusted to require comparably low manual intervention. With regards to the forecasting, it has to be observed how much the proposed methods to increase data quality can accomplish. It must be kept in mind that the forecast accuracy is a main determinant for the yield of the overall package. Overall, it can be concluded that the logic that was developed within this thesis fully achieved the business objective within the limits of the available data.

7.4 Personal review

Personally, the processing of this thesis has given me a deep insight into the subject matter of forecasting and EOQ calculation. Maybe even more valuable was, though, the practice of formulating and optimizing heuristics to solve business problems, which I will be able to apply numerous times with in my future career independently of the subject area.

Even though, the automatic pattern recognition has not been identified as advantageous at present time, the failure to do so was a good lesson that perfect performance on test cases and performance during application are two different pair of shoes.

At last I would like to point out that a strive for simplicity will accompany me a whole lifetime since it has been demonstrated that simple approaches can still deliver very good results that fit the purpose.

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APPENDIX

Appendix A.1: Source code for discontinuity function

```
FUNCTION MOVE(SHIP1, SHIP2, SPACE) AS INTEGER
IF SPACE > 0 THEN

'MAX MOVEABLE
IF SPACE >= SHIP2 THEN MAXMOVE = SHIP2
IF SPACE >= SHIP2 - MOQ AND SPACE < SHIP2 THEN MAXMOVE = SHIP2 - MOQ
IF SPACE < SHIP2 - MOQ THEN MAXMOVE = SPACE

'MIN MOVEABLE
IF SHIP1 < MOQ THEN MINMOVE = MOQ - SHIP1

R = MAXMOVE
RECOMMEND = MAXMOVE
IF SHIP1 < DIS THEN R = DIS - SHIP1
IF R < RECOMMEND THEN RECOMMEND = R

IF SHIP2 > DIS THEN R = SHIP2 - DIS
IF R < RECOMMEND THEN RECOMMEND = R

IF RECOMMEND < MINMOVE THEN MOVE = MINMOVE ELSE MOVE= RECOMMEND

IF SHIP1 + SHIP2 < 2 * MOQ THEN
   IF SPACE >= SHIP2 THEN
      MOVE = SHIP2
   ELSE
      MOVE = 0
   END IF
END IF

IF SHIP2 - MOVE < MOQ THEN MOVE = SHIP2
IF SPACE < MOVE THEN MOVE = 0
IF SPACE >= SHIP2 THEN MOVE = SHIP2
END IF
END FUNCTION
```

Appendix A.2: Flowchart for EOQ calculation

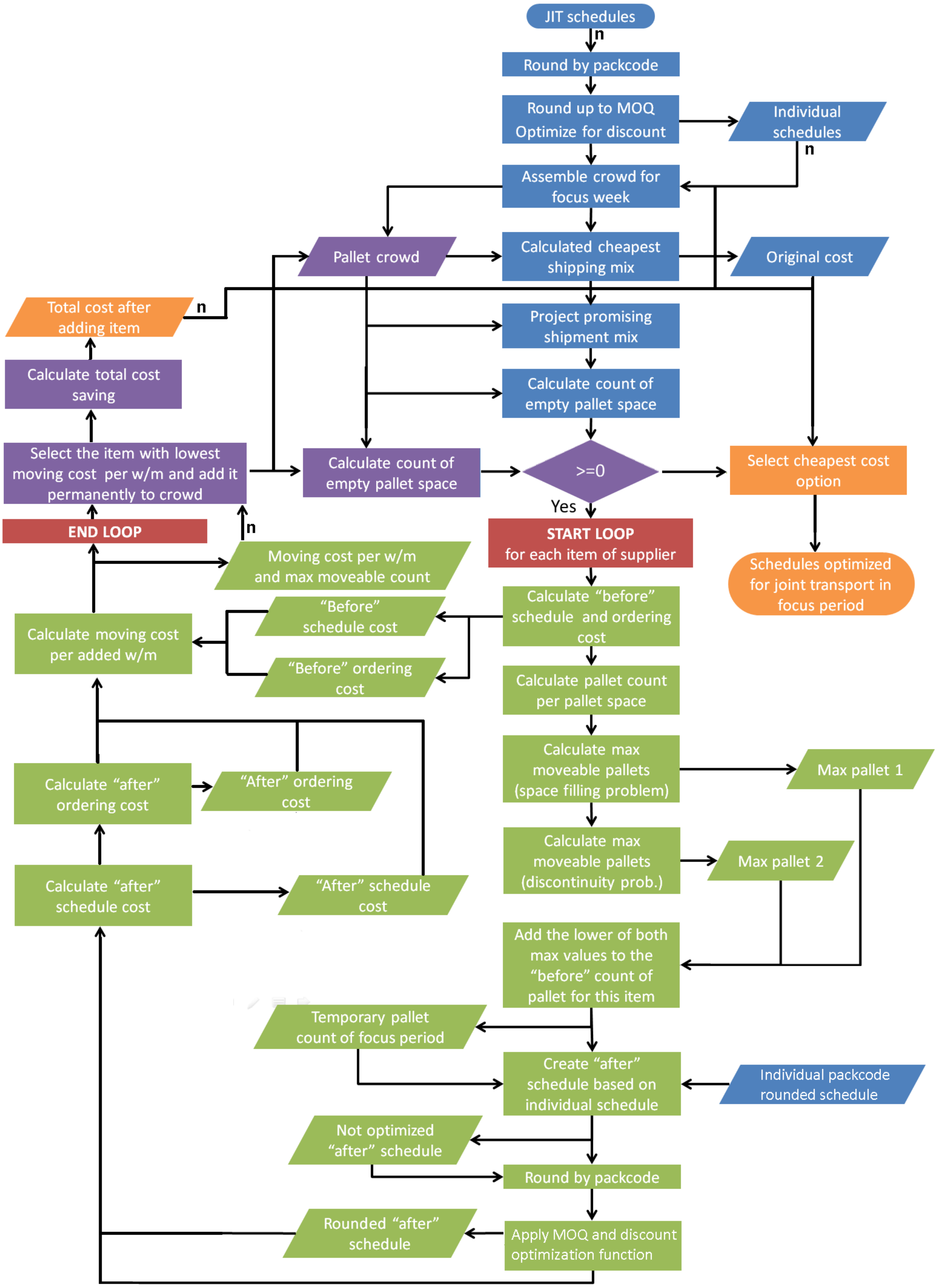

Figure A.2.1: Complete flow chart of EOQ methodology

Appendix A.3: EOQ functionality example – round 1

ITEM B

Item	Schedule type	P1	P2	P3	P4	P5
B	Discount optimized	500	0	200	200	0
Purchase cost		4250	0	2000	2000	0
Inventory cost		400	100	0	0	0
Total per month		4650	100	2000	2000	0
"Before" schedule cost						8750

Table A.3.1: Total "before" schedule cost item B – round 1

Maximum move by space constraint: 13

Next shipment in P3; Maximum move by discontinuity constraint: 200

Item	Schedule type	P1	P2	P3	P4	P5
B	"After schedule"	700	0	0	200	0
B	Packcode rounded	700	0	0	200	0
B	MOQ rounded	700	0	0	200	0
B	Discount optimized	700	0	0	200	0
B	Optimized "after" schedule	700	0	0	200	0

Table A.3.2: "After" schedule rounding item B – round 1

Item	Schedule type	P1	P2	P3	P4	P5
B	Optimized "after" schedule	700	0	0	200	0
Purchase cost		5950	0	0	2000	0
Inventory cost		600	300	0	0	0
Total per month		6550	300	0	2000	0
"After" schedule cost						8850

Table A.3.3: Total "after" schedule cost item B – round 1

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
B	"After" schedule	700	0	0	200	0
C	Discount optimized	600	0	200	200	0
D	Discount optimized	0	500	0	0	0
"After" ordering cost		100	100	100	100	100
						500

Table A.3.4: "After" ordering cost item B – round 1

"Before" schedule cost	8750
"Before" ordering cost	500
"After" schedule cost	8850
"After" ordering cost	500
Delta cost	+100
Moved w/m	2
Cost per moved w/m	+50

Table A.3.5: Cost per w/m for item B – round 1

ITEM C

Item	Schedule type	P1	P2	P3	P4	P5
C	Discount optimized	600	0	200	200	0
Purchase cost		5100	0	2000	2000	0
Inventory cost		500	0	0	0	0
Total per month		5600	0	2000	2000	0
“Before” schedule cost						9600

Table A.3.6: Total “before” schedule cost item C – round 1

Maximum move by space constraint: 13

Next shipment in P3; Maximum move by discontinuity constraint: 200

Item	Schedule type	P1	P2	P3	P4	P5
C	“After schedule”	800	0	0	200	0
C	Packcode rounded	800	0	0	200	0
C	MOQ rounded	800	0	0	200	0
C	Discount optimized	800	0	0	200	0
C	Optimized “after” schedule	800	0	0	200	0

Table A.3.7: “After” schedule rounding item C – round 1

Item	Schedule type	P1	P2	P3	P4	P5
C	Optimized “after” schedule	800	0	0	200	0
Purchase cost		6800	0	0	2000	0
Inventory cost		700	200	0	0	0
Total per month		7500	200	0	2000	0
“After” schedule cost						9700

Table A.3.8: Total “after” schedule cost item C – round 1

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
B	Discount optimized	500	0	200	200	0
C	“After” schedule	800	0	0	200	0
D	Discount optimized	0	500	0	0	0
“After” ordering cost		100	100	100	100	100
						500

Table A.3.9: “After” ordering cost item C – round 1

“Before” schedule cost	8600
“Before” ordering cost	500
“After” schedule cost	9700
“After” ordering cost	500
Delta cost	+100
Moved w/m	2
Cost per moved w/m	+50

Table A.3.10: Cost per w/m for item C – round 1

ITEM D

Item	Schedule type	P1	P2	P3	P4	P5
D	Discount optimized	0	500	0	0	0
Purchase cost		0	4250	0	0	0
Inventory cost		0	300	200	200	0
Total per month		0	4550	200	200	0
"Before" schedule cost						4950

Table A.3.11: Total "before" schedule cost item D – round 1

Maximum move by space constraint: 13

Next shipment in P2; Maximum move by discontinuity constraint: 300

Item	Schedule type	P1	P2	P3	P4	P5
D	"After schedule"	500	0	0	0	0
D	Packcode rounded	500	0	0	0	0
D	MOQ rounded	500	0	0	0	0
D	Discount optimized	500	0	0	0	0
D	Optimized "after" schedule	500	0	0	0	0

Table A.3.12: "After" schedule rounding item D – round 1

Item	Schedule type	P1	P2	P3	P4	P5
D	Optimized "after" schedule	500	0	0	0	0
Purchase cost		4250	0	0	0	0
Inventory cost		500	300	200	200	0
Total per month		4750	300	200	200	0
"After" schedule cost						5450

Table A.3.13: Total "after" schedule cost item D – round 1

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	100
B	Discount optimized	500	0	200	200	100
C	Discount optimized	600	0	200	200	0
D	"After" schedule	500	0	0	0	0
"After" ordering cost		100	0	100	100	100
						400

Table A.3.14: "After" ordering cost item D – round 1

"Before" schedule cost	4950
"Before" ordering cost	500
"After" schedule cost	5450
"After" ordering cost	400
Delta cost	+400
Moved w/m	5
Cost per moved w/m	+80

Table A.3.15: Cost per w/m for item D – round 1

Appendix A.4: EOQ functionality example – round 2

ITEM A

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
Purchase cost		5100	0	0	2000	2000
Inventory cost		400	300	0	0	0
Total per month		5500	300	0	2000	2000
"Before" schedule cost						9800

Table A.4.1: Total "before" schedule cost item A – round 2

Maximum move by space constraint: 11

Next shipment in P4; Maximum move by discontinuity constraint: 200

Item	Schedule type	P1	P2	P3	P4	P5
A	"After schedule"	800	0	0	0	200
A	Packcode rounded	800	0	0	0	200
A	MOQ rounded	800	0	0	0	200
A	Discount optimized	800	0	0	0	200
A	Optimized "after" schedule	800	0	0	0	200

Table A.4.2: "After" schedule rounding item A – round 2

Item	Schedule type	P1	P2	P3	P4	P5
A	Optimized "after" schedule	800	0	0	0	200
Purchase cost		6800	0	0	0	2000
Inventory cost		600	500	200	0	0
Total per month		7400	500	200	0	2000
"After" schedule cost						10100

Table A.4.3: Total "after" schedule cost item A – round 2

Item	Schedule type	P1	P2	P3	P4	P5
A	"After" schedule	800	0	0	0	200
B	Round 1	700	0	0	200	0
C	Discount optimized	600	0	200	200	0
D	Discount optimized	0	500	0	0	0
"After" ordering cost		100	100	100	100	100
						500

Table A.4.4: "After" ordering cost item A – round 2

"Before" schedule cost	9800
"Before" ordering cost	500
"After" schedule cost	10100
"After" ordering cost	500
Delta cost	+300
Moved w/m	2
Cost per moved w/m	+150

Table A.4.5: Cost per w/m for item A – round 2

ITEM B

Item	Schedule type	P1	P2	P3	P4	P5
B	Round 1	700	0	0	200	0
Purchase cost		5950	0	0	2000	0
Inventory cost		600	300	0	2000	0
Total per month		5550	300	0	2000	0
“Before” schedule cost						8850

Table A.4.6: Total “before” schedule cost item B – round 2

Maximum move by space constraint: 11

Next shipment in P4; Maximum move by discontinuity constraint: 200

Item	Schedule type	P1	P2	P3	P4	P5
B	“After schedule”	900	0	0	0	0
B	Packcode rounded	900	0	0	0	0
B	MOQ rounded	900	0	0	0	0
B	Discount optimized	900	0	0	0	0
B	Optimized “after” schedule	900	0	0	0	0

Table A.4.7: “After” schedule rounding item B – round 2

Item	Schedule type	P1	P2	P3	P4	P5
B	Optimized “after” schedule	900	0	0	0	0
Purchase cost		7650	0	0	0	0
Inventory cost		800	500	200	0	0
Total per month		8450	500	200	0	0
“After” schedule cost						9150

Table A.4.8: Total “after” schedule cost item B – round 2

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
B	“After” schedule	900	0	0	0	0
C	Discount optimized	600	0	200	200	0
D	Discount optimized	0	500	0	0	0
“After” ordering cost		100	100	100	100	100
						500

Table A.4.9: “After” ordering cost item B – round 2

“Before” schedule cost	8850
“Before” ordering cost	500
“After” schedule cost	9150
“After” ordering cost	500
Delta cost	+300
Moved w/m	2
Cost per moved w/m	+150

Table A.4.10: Cost per w/m for item B – round 2

ITEM C

Item	Schedule type	P1	P2	P3	P4	P5
C	Discount optimized	600	0	200	200	0
Purchase cost		5100	0	2000	2000	0
Inventory cost		500	0	0	0	0
Total per month		5600	0	2000	2000	0
"Before" schedule cost						9600

Table A.4.11: Total "before" schedule cost item C – round 2

Maximum move by space constraint: 11

Next shipment in P3; Maximum move by discontinuity constraint: 200

Item	Schedule type	P1	P2	P3	P4	P5
C	"After schedule"	800	0	0	200	0
C	Packcode rounded	800	0	0	200	0
C	MOQ rounded	800	0	0	200	0
C	Discount optimized	800	0	0	200	0
C	Optimized "after" schedule	800	0	0	200	0

Table A.4.12: "After" schedule rounding item C – round 2

Item	Schedule type	P1	P2	P3	P4	P5
C	Optimized "after" schedule	800	0	0	200	0
Purchase cost		6800	0	0	2000	0
Inventory cost		700	200	0	0	0
Total per month		7500	200	0	2000	0
"After" schedule cost						9700

Table A.4.13: Total "after" schedule cost item C – round 2

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
B	Round 1	700	0	0	200	0
C	"After" schedule	800	0	0	200	0
D	Discount optimized	0	500	0	0	0
"After" ordering cost		100	100	0	100	100
						400

Table A.4.14: "After" ordering cost item C – round 2

"Before" schedule cost	9600
"Before" ordering cost	500
"After" schedule cost	9700
"After" ordering cost	400
Delta cost	0
Moved w/m	2
Cost per moved w/m	0

Table A.4.15: Cost per w/m for item C – round 2

ITEM D

Item	Schedule type	P1	P2	P3	P4	P5
D	Discount optimized	0	500	0	0	0
Purchase cost		0	4250	0	0	0
Inventory cost		0	300	200	200	0
Total per month		0	4550	200	200	0
"Before" schedule cost						4950

Table A.4.16: Total "before" schedule cost item D – round 2

Maximum move by space constraint: 11

Next shipment in P2; Maximum move by discontinuity constraint: 300

Item	Schedule type	P1	P2	P3	P4	P5
D	"After schedule"	500	0	0	0	0
D	Packcode rounded	500	0	0	0	0
D	MOQ rounded	500	0	0	0	0
D	Discount optimized	500	0	0	0	0
D	Optimized "after" schedule	500	0	0	0	0

Table A.4.17: "After" schedule rounding item D – round 2

Item	Schedule type	P1	P2	P3	P4	P5
D	Optimized "after" schedule	500	0	0	0	0
Purchase cost		4250	0	0	0	0
Inventory cost		500	300	200	200	0
Total per month		4750	300	200	200	0
"After" schedule cost						5450

Table A.4.18: Total "after" schedule cost item D – round 2

Item	Schedule type	P1	P2	P3	P4	P5
A	Discount optimized	600	0	0	200	200
B	Round 1	700	0	0	200	0
C	Discount optimized	600	0	200	200	0
D	"After" schedule	500	0	0	0	0
"After" ordering cost		100	0	100	100	100
						400

Table A.4.19: "After" ordering cost item D – round 2

"Before" schedule cost	4950
"Before" ordering cost	500
"After" schedule cost	5450
"After" ordering cost	400
Delta cost	+400
Moved w/m	5
Cost per moved w/m	+80

Table A.4.20: Cost per w/m for item D – round 2

Appendix A.5: Result by model-parameter combination

	Without seasonality						With seasonality					
Parameters	Applied	Lost	Won	Draw	Error relation		Applied	Lost	Won	Draw	Error relation	
Moving average												
1m	5	4	1	0	1.09	0.91	4	0	4	0	0.67	1.33
2m	6	2	4	0	0.96	1.04	5	1	4	0	0.72	1.28
3m	7	3	4	0	0.99	1.01	12	6	6	0	0.92	1.08
4m	10	4	6	0	0.83	1.17	5	2	3	0	0.72	1.28
5m	15	6	7	2	1.02	0.98	9	7	2	0	1.40	0.60
6m	8	5	3	0	0.99	1.01	12	4	8	0	0.96	1.04
12m	17	7	9	1	0.99	1.01	2	1	1	0	0.88	1.12
50m	57	23	34	0	0.96	1.04	44	25	19	0	1.02	0.98
Weighted moving average												
3 m/3;2;1	3	1	2	0	1.09	0.91	3	1	2	0	0.72	1.28
5m/5;4;3;2;1	1	1	0	0	1.10	0.90	3	1	2	0	0.78	1.22
6m/2;2;2;1;1;1	5	0	0	5	1.00	1.00	6	3	3	0	0.97	1.03
10m/3;3;3;3;2;2;2;1;1;1	9	4	5	0	1.01	0.99	12	7	5	0	1.15	0.85
12m/2;2;2;2;2;2;1;1;1;1;1;1	7	5	2	0	0.93	1.07	1	0	1	0	0.65	1.35
12m/4;4;4;3;3;3;2;2;2;1;1;1;	3	3	0	0	1.07	0.93	4	3	1	0	1.14	0.86
Exponential smoothing												
0.1	15	10	5	0	1.06	0.94	9	5	4	0	1.07	0.93
0.2	4	2	2	0	0.83	1.17	4	2	2	0	0.91	1.09
0.3	6	2	4	0	0.95	1.05	0	0	0	0		
0.4	3	3	0	0	1.34	0.66	4	2	2	0	0.94	1.06
Double exponential smoothing												
0.1/0.1	11	4	7	0	0.92	1.08	2	0	1	1	0.70	1.30
0.1/0.2	5	3	2	0	1.10	0.90	7	2	5	0	0.93	1.07
0.1/0.3	9	7	2	0	1.18	0.82	3	3	0	0	1.36	0.64
0.1/0.4	2	1	1	0	0.94	1.06	6	3	3	0	1.09	0.91
0.2/0.1	0	0	0	0			1	0	1	0	0.32	1.68
0.2/0.2	4	3	1	0	1.04	0.96	3	2	1	0	0.94	1.06
0.2/0.3	2	1	1	0	0.92	1.08	1	1	0	0	1.21	0.79
0.2/0.4	5	4	1	0	1.17	0.83	4	1	3	0	0.74	1.26
0.3/0.1	0	0	0	0			1	1	0	0	1.35	0.65
0.3/0.2	0	0	0	0			1	0	1	0	0.86	1.14
0.3/0.3	1	0	1	0	0.65	1.35	2	1	1	0	1.11	0.89
0.3/0.4	3	3	0	0	1.24	0.76	1	0	1	0	0.82	1.18
0.4/0.1	0	0	0	0			0	0	0	0		
0.4/0.2	0	0	0	0			0	0	0	0		
0.4/0.3	1	0	1	0	0.64	1.36	0	0	0	0		
0.4/0.4	4	3	1	0	1.33	0.67	0	0	0	0		
Moving median												
3m	9	7	1	1	1.26	0.74	14	7	7	0	0.82	1.18
6m	12	5	6	1	0.86	1.14	24	9	15	0	0.86	1.14
9m	18	13	5	0	1.11	0.89	14	9	5	0	1.13	0.87
12m	19	9	10	0	0.99	1.01	7	5	2	0	1.23	0.77
50m	58	30	28	0	0.97	1.03	26	12	14	0	1.06	0.94

Table A.5.1: Result by model-parameter combination of first test run

	Without seasonality						With seasonality					
Parameters	Applied	Lost	Won	Draw	Error relation		Applied	Lost	Won	Draw	Error relation	
Moving average												
1m	9	6	3	0	0.97	1.03	5	1	4	0	0.86	1.14
2m	10	4	6	0	0.94	1.06	7	2	5	0	0.81	1.19
3m	9	4	5	0	0.98	1.02	16	7	9	0	0.86	1.14
4m	12	6	6	0	0.88	1.12	7	3	4	0	0.86	1.14
5m	17	7	8	2	1.01	0.99	9	7	2	0	1.40	0.60
6m	14	9	5	0	1.01	0.99	20	8	12	0	0.98	1.02
12m	28	14	13	1	1.01	0.99	9	7	2	0	1.37	0.63
50m	62	26	36	0	0.97	1.03	48	25	23	0	0.99	1.01
Weighted moving average												
3 m/3;2;1	4	1	3	0	1.05	0.95	5	1	4	0	0.55	1.45
5m/5;4;3;2;1	1	1	0	0	1.10	0.90	4	2	2	0	0.87	1.13
6m/2;2;2;1;1;1	6	0	0	6	1.00	1.00	8	5	3	0	1.12	0.88
10m/3;3;3;3;2;2;2;1;1;1	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
12m/2;2;2;2;2;2;1;1;1;1;1;1	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
12m/4;4;4;3;3;3;2;2;2;1;1;1;	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
Exponential smoothing												
0.1	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
0.2	13	4	8	1	0.89	1.11	8	3	5	0	0.82	1.18
0.3	10	5	5	0	1.02	0.98	4	1	3	0	0.89	1.11
0.4	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
Double exponential smoothing												
0.1/0.1	11	4	7	0	0.92	1.08	2	0	1	1	0.70	1.30
0.1/0.2	9	5	4	0	1.11	0.89	7	2	5	0	0.93	1.07
0.1/0.3	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
0.1/0.4	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
0.2/0.1	0	0	0	0			1	0	1	0	0.32	1.68
0.2/0.2	8	7	1	0	1.21	0.79	4	2	2	0	0.95	1.05
0.2/0.3	3	1	2	0	0.88	1.12	6	2	4	0	0.85	1.15
0.2/0.4	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
0.3/0.1	0	0	0	0			2	2	0	0	1.37	0.63
0.3/0.2	0	0	0	0			2	1	1	0	0.98	1.02
0.3/0.3	3	2	1	0	1.04	0.96	3	1	2	0	0.83	1.17
0.3/0.4	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
0.4/0.1	0	0	0	0			0	0	0	0		
0.4/0.2	2	1	1	0	0.81	1.19	0	0	0	0		
0.4/0.3	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
0.4/0.4	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
Moving median												
3m	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
6m	23	13	9	1	0.99	1.01	30	13	17	0	0.93	1.07
9m	~~0~~	~~0~~	~~0~~	~~0~~			~~0~~	~~0~~	~~0~~	~~0~~		
12m	26	12	14	0	1.01	0.99	14	9	5	0	1.14	0.86
50m	70	35	34	1	0.97	1.03	29	13	16	0	1.02	0.98

Table A.5.2: Result by model-parameter combination of second test run

Parameters	Applied	Lost	Won	Draw	Error relation	
Moving average						
1m	600	368	231	1	1.092	0.908
2m	600	321	277	2	1.023	0.977
3m	600	343	249	8	1.032	0.968
4m	600	313	276	11	1.000	1.000
5m	600	288	297	15	0.987	1.013
6m	600	296	286	18	1.009	0.991
12m	600	278	312	10	0.962	1.038
50m	600	296	303	1	1.001	0.999
Weighted moving average						
3 m/3;2;1	600	319	276	5	1.001	0.999
5m/5;4;3;2;1	600	284	302	14	0.986	1.014
6m/2;2;2;1;1;1	600	0	0	600	1.00	1.00
10m/3;3;3;3;2;2;2;1;1;1	600	265	321	14	0.997	1.003
12m/2;2;2;2;2;2;1;1;1;1;1;1	600	267	324	9	0.973	1.027
12m/4;4;4;3;3;3;2;2;2;1;1;1;	600	263	324	13	0.972	1.028
Exponential smoothing						
0.1	600	280	315	5	0.977	1.023
0.2	600	247	338	15	0.977	1.023
0.3	600	237	349	14	0.977	1.023
0.4	600	278	310	12	0.989	1.011
Double exponential smoothing						
0.1/0.1	600	392	205	3	1.202	0.798
0.1/0.2	600	464	134	2	1.366	0.634
0.1/0.3	600	459	141	0	1.302	0.698
0.1/0.4	600	396	203	1	1.147	0.853
0.2/0.1	600	311	287	2	1.025	0.975
0.2/0.2	600	396	200	4	1.088	0.912
0.2/0.3	600	391	207	2	1.122	0.878
0.2/0.4	600	426	173	1	1.146	0.854
0.3/0.1	600	364	234	2	1.045	0.955
0.3/0.2	600	383	214	3	1.097	0.903
0.3/0.3	600	403	196	1	1.136	0.864
0.3/0.4	600	415	183	2	1.160	0.840
0.4/0.1	600	349	250	1	1.070	0.930
0.4/0.2	600	388	212	0	1.107	0.893
0.4/0.3	600	406	194	0	1.132	0.868
0.4/0.4	600	406	193	1	1.157	0.843
Moving median						
3m	600	345	248	7	1.033	0.967
6m	600	289	298	13	0.995	1.005
9m	600	305	291	4	0.989	1.011
12m	600	286	310	4	0.963	1.037
50m	600	319	279	2	0.997	1.003

Table A.5.3: Results of one-on-one testing against weighted 6-month moving average

GLOSSARY

20FT	20 foot container
40FT	40 foot container
CDM	Customer demand planning
COGS	Cost of goods sold
DC	Distribution centre
DIY	Do-it-yourself
DES	Double exponential smoothening
EOQ	Economic order quantity
ERP	Enterprise resource planning software
FCL	Full container load
LCL	Less than container load
LT	Lead time
MAD	Mean absolute deviation
MAPE	Mean absolute percentage error
MOQ	Minimum order quantity
PR	Purchase requisition
QA	Quality assurance
QTY	Quantity
RT	Replenishment time
SAPSE	Smoothed absolute percentage sum error
SASE	Smoothed absolute sum error
SKU	Stock keeping unit

VITA

Ralf Donner was born in Neuruppin, Germany. After completion of the high school he took up studies in electrical engineering in a joint program of the University of Cooperative Education Mannheim and ABB. After completion Ralf started his full-time professional carrier in an engineering position in Vienna, where he shortly after took on additional Bachelor studies of business administration at the Vienna University of Economics and Business majoring in logistics/supply chain management and finance. As part of the studies, Ralf spent an exchange semester at the National Chengchi University in Taipei and an internship in Bangkok. After completion of the Bachelor studies Mr. Donner took on a position at major 3rd party logistics provider in Bangkok and joined the part-time Dual-Master programme of the Chulalongkorn University and the University of Warwick with the target of obtaining Master degrees in engineering management and supply chain management. During the course of studies Ralf accepted his current position at Hafele Thailand, which is also the focal company of this Master thesis.