MASTER

The development of an integrated operating working capital model

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The development of an integrated operating working capital model

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Abstract

Manufacturing firms, consisting of multiple business units, often set their company’s Operating Working Capital (OWC) targets top-down, based on incremental changes versus the past. This report describes two new models to define the minimum required OWC level of a business unit, such that the company, as a business group, can bottom-up set the OWC targets per business unit. The first model is an analytical model in which the minimum required OWC is implicitly calculated in terms of the independent variables, i.e. based on the dependent variables as outcome of OWC management. The second model is an OWC simulation model in which the total OWC is explicitly simulated as result of the independent variables that drive the OWC of a firm, i.e. based on the input to OWC management, defined by the business principles. Changes in OWC, as results of independent variable adjustments, can be quantified using the latter mentioned model. We show with regard to OWC for two real supply chain case studies, belonging to the same business group, how they score on operational efficiency, how they differ as result of the business principles, and where they can be improved best. Finally, we show that simulation models based on historical demand data can be enhanced by making use of empirical demand distributions, and we invent a new method to transform such an empirical distribution.
Management summary

The manufacturing company (anonymous) in this thesis, like many manufacturers, has stringent targets on their OWC. The target setting for each business unit (BU) in recent years was built on incremental changes versus last years. While the company is getting tighter and tighter on OWC management, the BUs have highlighted a need for a different approach. In this report we present the results of a master thesis relating to the company’s global project to improve the OWC target settings, and to find what (and how) business principles drive the company’s OWC.

Throughout this thesis we make use of two different supply chain case studies for the OWC targeting. These case studies are based on real supply chain structures within the company and are chosen to be the ‘pilot cases’ to apply methods and models developed in this thesis. In the remainder of the management summary the two supply chain case studies are called SC1 and SC2, respectively. Both SCs belong to the same business group (BG).

**The minimum required level of OWC**

We define two different models that can be used to calculate the minimum required level of OWC: (1) the bottom-up model, and (2) the integrated OWC model. The first model explains an analytical and separate approach in which the minimum required OWC levels for each of the OWC elements (i.e. inventories, account receivables, and accounts payables) is implicitly calculated in terms of the independent variables, i.e. based on the dependent variables as outcome of OWC management. Thereupon, the OWC elements can be summed up to find the total (bottom-up) required OWC level. The integrated OWC model explains a simulation model in which the total OWC is explicitly simulated as result of the independent variables that drive the OWC of a firm, i.e. based on the input to OWC management, defined by the business principles. The integrated OWC model is successfully validated based on statistical hypothesis testing. In addition, it is verified and approved by the company.

SC1 denotes a total modified %OWC referent of 31.2%\(^1\), or 32.4%\(^2\), in year 2014. For SC1 we find a bottom-up total %OWC equal to 24.9%. Furthermore, as result of the integrated OWC model, we find an end-of-month average %OWC based on year 2014 of 25.4%\(^2\). When the integrated OWC model uses empirical distributions for the demand (integrated OWC model+), assuming 2014’s mean demand and variance of demand, then we find an average %OWC of 25.0%. This implies a calculated gap in operational efficiency of 6.6%, and a simulated gap in operational efficiency of 7.0%\(^1\).

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\(^1\) Actual OWC referents are subject to modifications applied and explained in this thesis.

\(^2\) Actual OWC referents for the integrated OWC model are subject to additional modifications due to the assumptions of the integrated OWC model.
and 7.4%, respectively. These gaps are approximately for 75%-85% caused by an efficiency gap in AR management (half of the AR gap is due to the bankruptcy of two major customers; other half due to overdue payments).

SC2 shows total modified %OWC referent of 13.5%\(^1\), or 15.1%\(^2\), in year 2014. For SC2 we find a bottom-up total %OWC level equal to 13.5%. This implies a that SC case study 2’s performance in 2014 is equal to the bottom-up calculations. The second case study is only analyzed according to historical master data and not according to empirical demand distributions. By using the integrated OWC model, we find an end-of-month average %OWC based on year 2014 of 14.3%. This means a simulated gap in operational efficiency of 0.8%.

Both approaches show that SC2 performs better in terms of operational efficiency than SC1, based on year 2014. Furthermore, SC2 requires a significantly lower %OWC level, due to the tactical and strategic decisions of the firm. This strategic benefit is mainly caused by inventory management, and should be taken into consideration for future OWC target settings.

**The impact of OWC main driver changes**

The table below summarizes the effect of OWC main drivers on the %OWC of the company. The definitions of the symbols used are as follows: ++ = strong positive related; + = weak positive related; –– = strong negative related; –= weak negative related; o= no significant relation. In addition, the star mark (*) indicates that the two variables are linear related. All other cases which are not linear related have either a well-behaved compounding or diminishing effect, as can be seen in the graphs in this thesis.

<table>
<thead>
<tr>
<th>OWC driver</th>
<th>Reorder points</th>
<th>Minimal lot sizes</th>
<th>Production wheel length</th>
<th>Percentage third party sales</th>
<th>Days in payment run cycle</th>
<th>Mean of demand distribution</th>
<th>Variance of demand distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>%OWC</td>
<td>++*</td>
<td>++</td>
<td>o</td>
<td>––</td>
<td>–*</td>
<td>--</td>
<td>+</td>
</tr>
</tbody>
</table>

**Piecewise empirical demand distributions**

The integrated OWC model is developed to simulate the OWC performance based on historical demand data, since there cannot be found a significant fit of the demand observed with a theoretical distribution. Though, we develop a method to create a piecewise empirical demand distribution and use it to create numerous demand samples. Furthermore, we show how to transform the empirical demand distribution, such that either the mean demand is changed whilst the volatility of demand is preserved, or the volatility of demand is changed whilst the mean demand is preserved. This enhances
the applicability of the integrated OWC model to perform more general analyses (based on a number of samples), and to find the impact of changing demand parameters (as shown in the table above).

Our recommendations

Based on the two supply chain case studies, we conclude this management summary with our recommendations for the company.

Our recommendations to improve the current OWC performance of the selected business scope:

- **Improve the AR management of SC1**: Get rid of the outstanding sales order payments of bankrupt customers, and reduce overdue payments; A reduction of approximately more than 5% in the total %OWC of SC1 can be achieved if SC1’ AR management is completely efficient.
- **Improve the minimal lot sizes of SC1**: Minimal lot sizes have a high impact on the total OWC; significantly lower lot sizes are proven to work for SC2, therefore, knowledge sharing could help in this respect; For instance, if the company would realize a 20% or 40% reduction of the minimal lot size in SC1, then it would reduce its total %OWC by approximately 2% and 4%, respectively.
- **On the long-term, check feasibility to bring the internal BG sales from SC1 to SC2**: Theoretically this would reduce the overall %OWC of the BG, assuming unconditional transition possibilities; If all internal customer sales orders are unconditionally transited from SC1 to SC2, then SC1 would reduce its %OWC level by 18% and SC2 would expectedly increase its %OWC level by 9%. This results in a combined reduction in %OWC of approximately 4% (weighted average of external sales).
- **Emphasize the importance of less variance in demand to the Sales department**: This fosters the supply chains’ efficiencies, i.e. providing the customers with a higher service level whilst operating with lower levels of OWC.

Our recommendations for future OWC management to the company:

- **Scale-up the two models developed in this thesis for the future OWC target settings**
  - Use the bottom-up OWC model for business scopes that cannot comply with the integrated OWC model’s assumptions;
  - Apply the integrated OWC model to improve OWC target settings; to give input to OWC optimization projects;
- **Use piecewise empirical demand distributions to cope with problems due to the integrated OWC model’s historical demand data assumption**;
- **Appoint a team responsible for the use of the integrated OWC model with key users for each selected business scope**.
Preface

Eindhoven, July 2015

This thesis concludes my graduation project at my graduate company (anonymous). The company is a wonderful company and I would like to thank everyone I’ve met during this graduation period; especially my first and second company supervisors (anonymous). First company supervisor, you have an inspirational drive to improve supply chains and to enable people, and I would like to thank you for the opportunity to work with you in the supply chain team. Second company supervisor, you have a very valuable experience in project management and executions for both academic and practical project, and I would like to thank you for sharing this with me and guiding me through this project.

Next, I would like to thank my university supervisors prof. dr. M.J. (Matthew) Reindorp and prof. dr. A. (Arun) Chockalingam. Matthew, I’m very thankful for learning about your great knowledge in finance, operations, and accounting sciences, and I highly appreciate that you’ve spent time for the last year to provide me with useful feedback, on a weekly basis. Arun, I appreciated your knowledge in simulations and helpful feedback.

This thesis also concludes my student life, during which I’ve lived in Eindhoven, Barcelona and Bogotá. I will always remember these three places and the great people I’ve met there. Hope to see you soon!

Specially, my year in Barcelona has been extraordinary, since I had the pleasure to meet Patricia Giménez Sanchez, who is now my beloved girlfriend. Patricia, I’m very thankful for your support and I look forward to sharing our future.

Finally, I would also like to thank my friends and family for their support during this project; I appreciated it a lot. I’m proud to say I’m the brother, and friend, of Teun, Thijs, Janouk Kelderman, and Cailin van Loon. With you, I hope to enjoy many more great moments in life. A special thanks goes to my parents Bob and Thea, who are always there when I need them. Without you, I would not have been able to succeed in my education and in this graduation project!

Bram van de Meerendonk
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# List of abbreviations

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<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>%OWC</td>
<td>Total operating working capital over third party sales (see Formula 1.1 in sub-Section 2.1.3.)</td>
</tr>
<tr>
<td>AP</td>
<td>Accounts payable</td>
</tr>
<tr>
<td>AR</td>
<td>Accounts receivable</td>
</tr>
<tr>
<td>BG</td>
<td>Business group</td>
</tr>
<tr>
<td>BS</td>
<td>Bucket size (a.k.a. production wheel length in days)</td>
</tr>
<tr>
<td>BU</td>
<td>Business unit</td>
</tr>
<tr>
<td>CCC</td>
<td>Cash conversion cycle</td>
</tr>
<tr>
<td>cdf</td>
<td>Cumulative distribution function</td>
</tr>
<tr>
<td>CO</td>
<td>Change over time</td>
</tr>
<tr>
<td>DIO</td>
<td>Days inventory outstanding</td>
</tr>
<tr>
<td>DPO</td>
<td>Days payables outstanding</td>
</tr>
<tr>
<td>DSO</td>
<td>Days sales outstanding</td>
</tr>
<tr>
<td>EOQ</td>
<td>Economic order quantity</td>
</tr>
<tr>
<td>FP</td>
<td>Frozen period</td>
</tr>
<tr>
<td>GRPT</td>
<td>Goods received process time</td>
</tr>
<tr>
<td>EPQ</td>
<td>Economic production quantity</td>
</tr>
<tr>
<td>INV</td>
<td>Inventories</td>
</tr>
<tr>
<td>JIT</td>
<td>Just-in-time</td>
</tr>
<tr>
<td>kt</td>
<td>Kilo tonnes</td>
</tr>
<tr>
<td>MLS</td>
<td>Minimal lot size</td>
</tr>
<tr>
<td>OEE</td>
<td>Overall equipment effectiveness</td>
</tr>
<tr>
<td>OWC</td>
<td>Operating working capital</td>
</tr>
<tr>
<td>pmf</td>
<td>Probability mass function</td>
</tr>
<tr>
<td>PRC</td>
<td>Payment run cycle</td>
</tr>
<tr>
<td>SC</td>
<td>Supply chain</td>
</tr>
<tr>
<td>ROP</td>
<td>Reorder point</td>
</tr>
<tr>
<td>SKU</td>
<td>Stock keeping unit</td>
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</table>
In this report we present the results of a master thesis relating to a multinational's global project aimed at improving the Operating Working Capital (OWC) management. The company consists of the three Business Units (BU) each mainly focused on its own region. This particular research project is carried out in Europe, but all regions are covered. By selected supply chain case studies, we aim to provide insights to the OWC management for a smaller scope, which ultimately can be used for the global scale-up.

This chapter is organized as follows. First of all, the problems addressed in this thesis are described briefly in Section 1.1. Then, to obtain insight into all aspects of OWC management, a short literature review on relevant topics is presented in Section 1.2. Based on the general problem statement and results of the literature review, the research questions are formulated, and presented in Section 1.3. The methodology used to answer these research questions is discussed in Section 1.4. Finally, an outline of the remainder of this report finalizes this chapter.

1.1. Problem statement
We make use of the cause and effect diagram developed in the article by Ishikawa [1990] to find the main problem and its root causes. To solve the main problem, the root cause(s) must be tackled. The relevant findings of applying the techniques by Ishikawa [1990] are presented in this section.

The main problem is a high OWC level, and inherently linked to this, are the high OWC costs. In order to improve the OWC levels, the firm as business group (BG) sets targets for its business units (BU). There exist two main root causes of the problem: (1) the non-existence of the appropriate bottom-up OWC computation methodology, and (2) the lack of knowledge in the main OWC drivers and their impact. These two root causes are be tackled in this thesis, such that in the end we help the firm’s higher management in making better OWC target settings and better decisions on where to improve. In the next section a short literature review on relevant topics is presented. The cause and effect diagram is not added to the thesis due to confidentiality reasons.

1.2. Literature review
In this literature review we aim to give the relevant theoretical background for a working capital project. Working capital is often expressed and understood differently, but the meaning typically referred to is the company’s current assets (inventories and accounts receivables) minus its current liabilities (accounts payables). It indicates the firm capability to pay-off creditors in short-term. [Schilling, 1996]

*Inverted U-shaped relation between working capital and the firm’s performance.*

Based on the disadvantages and advantages of working capital, the literature strongly supports the existence of ‘an inverted U-shaped relation’ between investment in working capital and the firm’s performance. It is shown that there exist an optimal working capital level given a business, i.e. a working
level for which the advantages and disadvantages are balanced and increasing or decreasing leads to a lower shareholder value of the firm. [Caballero, Teruel, & Solano, 2014]

**Incentives to offer trade credit.**

Trade credit has shown to be relevant for corporate finance. The party that offers trade credit builds up an accounts receivable position and the trade credit receivers builds up an accounts payable position. Firms may find many benefits to offer trade credit to their buyers, which often boil down to increased company-customer relations and the possibility to discriminate the price [Bougheas, Mateut, & Mizen, 2009; Gupta & Wang, 2009]. A relatively new concept within trade credit management is reversed factoring. Reversed factoring the phenomenon in which the seller borrows the money from a bank, and simultaneously lends it to the buyer so that the buyer can make use of the seller’s potentially more beneficial credit rating. [Jain, 2001; Vliet, Reindorp, & Fransoo, 2015]

**Inventory management: the order-up-to (s,S)-policy is optimal in the infinite horizon situation; the dynamic safety stock is superior to the static safety stock.**

Besides accounts payable and accounts receivable, working capital also exists in inventories. There exists elaborate research in the field of multi-period inventory models. Researcher have proven that an order-up-to policy (s,S-policy) is optimal in the infinite-horizon situation [Muckstadt & Sapra, 2010]. Furthermore, it is shown that the dynamic safety stock is superior to the static safety stock. For a dynamic safety stock, a planner takes both demand and production uncertainties into account, and modifies the safety stock accordingly. [Inderfurth & Vogelgesang, 2013]

**Importance to coordinate and integrate inventory and trade credit management.**

Several researchers have shown that it is very important to coordinate and integrate inventory and trade credit management, because inventory management has an incentive to offer trade credit. Namely, it can avoid holding costly inventories by extending trade credit to its customers. However, trade credit is itself costly as the firm foregoes cash which is needed to repay its own creditors. In sum, it is shown that an integrated working capital approach becomes highly recommendable in order to optimize the shareholder value of the firm as result working capital decisions. [Bougheas, Mateut, & Mizen, 2009; Crum, Klingman, & Tavis, 1983; Schiff & Lieber, 1974]

**Non-existence of integrated working capital models.**

Despite the importance of coordinating and integrating inventory- and trade credit management, researchers have not yet been able to concretely model the firm performance as a function of the total working capital. The inventory-AR and inventory-AP relations have been indicated and proven to exist, but not yet been made concrete and applicable. The integrated working capital models that exist in this respect are fairly abstract. There have not yet been developed bottom-up integrated working capital models that incorporate the main aspects of working capital management as indicated in this literature review. Science remains incomplete for this area within the field of working capital management. Notwithstanding, simulations can help in a time and money efficient way to build-up an integrated working capital model. [Bougheas, Mateut, & Mizen, 2009; Crum, Klingman, & Tavis, 1983; Schiff & Lieber, 1974; Nagy, Burca, Butaci, & Bologa, 2013; Binder & Heermann, 2010]
1.3. Assignment formulation

The main problems and findings of the literature review have been defined in Section 1.1. and Section 1.2. Based on the insight we gained from those two sections, we define 5 research questions. In this chapter, the research questions are presented in sub-Section 1.3.1. Thereupon, the underlined concepts in this chapter are explained in more detail in sub-Section 1.3.2, such that misunderstandings are prevented.

1.3.1. Research questions

In order to solve the main problem as stated in Section 1.1., the overall objective of this graduation project can be formulated as follows:

Development and analysis of an integrated OWC model to improve the OWC target setting

This main objective can be split up into the following research questions:

1. Which model can be used to calculate the minimum required level of OWC?
   1.1 What is the supply chain structure?
   1.2 What are the OWC drivers?
   1.3 What are the key performance indicators?
   1.4 Which are the decision variables?
   1.5 Which are the dependent variables?

2. What is the current OWC performance on BU level?

3. What is the minimum required OWC level given the tactical and strategic boundaries?
   3.1 What is the bottom-up minimum required OWC in inventory, AR, and AP?
   3.2 What is the integrated minimum required OWC level?

4. What is the impact of OWC driver changes on the OWC level?

5. How to scale-up the models and methods to a larger scope?

The first research question focuses on how to build up a model to define the minimal required OWC level for a business. To answer this question, we evaluate the supply chain case studies selected in this thesis. The results of this analysis indicate the key aspects for the input and output of such a OWC model.

Furthermore, the current OWC performance of the company on a Business Unit (BU) level is defined. Thereupon, the differences between BUs are analyzed.

The third research question focuses on the core of this thesis, i.e. the computation of the minimum required OWC level needed to run a business setup. This research question is answered by two approaches: (1) separate approach (i.e. calculating each element of OWC individually), and (2) an integrated approach. First of all, in the separate approach, the minimum required values for each OWC element (i.e. inventory, AR, and AP) is computed according to a bottom-up OWC model. Throughout the process of computing the minimum required (bottom-up) values for inventory, AR, and AP, it is highly
important to find the key business rules (principles), such as, the decision to aim for a safety stock of 15 DDI (Demand Days of Inventory). Secondly, in the integrated approach it is chosen to develop an OWC simulation model (called integrated OWC model) based on these key business rules. The integrated OWC model aims to simulate the firm’s OWC in an integrated manner. Hence, it also takes linkages between inventory, AP, and AR into account. Then, the simulation model is validated with the results from the bottom-up model and the real OWC figures. Finally, both the separate approach and the integrated approach is used to find the operational efficiency gap.

In order to answer the fourth research question the integrated OWC model can be used to analyze the input parameters (i.e. the OWC drivers) on sensitivity and impact. This serves to make the split in OWC levels between BUs more transparent and understandable. Finally, the last research question focuses on the scale-up of this bottom-up model to a larger scope.

1.3.2. Concepts
In the previous section there are words underlined. This section aims to give the exact meaning of these underlined concepts, such that misconceptions are prevented.

- **Integrated OWC model** (= OWC simulation model). The integrated OWC model comprehensively simulates the businesses within scope to find the minimum required OWC to run the business according to the business rules. This implies that linkages between inventories, AR, and AP are taken into account.

- **OWC target setting**. The company sets its targets every year with regard the OWC. The BUs strive to meet these targets. This is currently done top-down, i.e. every year the targets are gradually modified. However, this project aims to support the zero base OWC target setting.

- **Minimum required**. The minimum required is often seen as the optimum when all parameters are changeable. In this project the minimum required OWC level can also exist within certain boundaries due to the business setup. Often it is referred to as operational minimum.

- **OWC Driver**. Any factor that influences Accounts Receivable, Accounts Payable, and Inventories, and thus, influences the OWC.

- **Bottom-up OWC model** (separate approach). Bottom-up OWC modeling (a.k.a. ‘zero base’ modeling) means that without looking at the history of OWC target settings, the minimum OWC required to operate within the strategic and tactical boundaries is determined.

- **Operational efficiency gap**. As mentioned three bullet point earlier, a company has a minimum required OWC level given the strategic and tactical boundaries. If in reality the actual OWC level is higher or lower, then this difference represents the operational efficiency gap.

- **Split**. Given certain strategic and tactical decisions it is very likely that the minimum OWC levels differ between the regions (BUs). This difference is indicated as the split between BUs.

1.4. Methodology
To answer the research questions, we follow the regulative cycle as defined by Van Strien [1997] (see Figure 1). The first step of the regulative cycle by Van Strien [1997], defining the problem, is discussed in Section 1.1. The problem definition is the result of the problem mess, indicated by the cause and effect diagram [Ishikawa, 1990].
The second and third steps of the regulative cycle are focused on in the remainder of this project. According to the model of Kempen and Keizer [2000] these two steps can be best described as the ‘analysis’ and ‘design’ phases of the project, respectively. The ‘analysis’ phase is focused on the investigation of the selected supply chain cases. This includes a clear overview of the entire goods flow and processes, current decisions and policies, data analysis, the scope for the OWC drivers that are analyzed on their impacts, and finally the requirements of the solutions. The research questions belonging to the Analysis & Diagnosis phase are research questions 1 until 3.1. Subsequently, the ‘design’ phase is focused on meeting the overall objective of this project. This is done by modeling an integrated OWC (simulation) model, such that the minimum required OWC level given a business setup is shown and the impact of the main drivers can be analyzed. The research questions belonging to this phase are research question 3.2 until 5.

The last two steps of the regulative cycle are not executed due to time limitations. These steps are the actual intervention and the evaluation of the results. Though, it has always been the intention to actually get an improved global OWC target setting, and thus, the solutions and recommendations are supportive and used as input for the intervention to be done by the firm.

![Regulative cycle Van Strien [1997]](image)

Figure 1: Regulative cycle Van Strien [1997]

1.5. Thesis outline

In this thesis first the bottom-up working capital modeling methodology (for the bottom-up OWC model) is shown in Chapter 2. Thereafter, in Chapter 3, we present the two case studies as part of existing supply chain structures within the company, including results from the methods defined in Chapter 2. The development of the integrated OWC model (simulation) that supports OWC decision making is formulated in Chapter 4. This integrated OWC model is validated and verified for the two case studies in Chapter 5, based on the actual performances and bottom-up values from Chapter 3. The impact of input parameters changes (OWC main drivers changes) on the total OWC performance is presented in Chapter 6. In addition, Chapter 7 is dedicated to sensitivity analysis of changing demand input parameters. Finally, the thesis is finalized by presenting conclusions and recommendations in Chapter 8.
Bottom-up Operating Working Capital modeling

Bottom-up OWC modeling means that we aim to define the minimum required OWC level to run a business setup given the strategic and tactical boundaries. This implies modeling, and eventually target setting, without looking at the history of OWC levels and OWC targets. This chapter focuses on all theoretical aspects of such an approach. We present an introduction to OWC in Section 2.1. Thereafter, a comprehensive overview of OWC main drivers is shown in Section 2.2. Finally, in Section 2.3, we develop the bottom-up model to define the bottom-up value for OWC.

2.1. Operating Working Capital

This section focuses on the introduction of OWC. Firstly, the theoretical background of operating and cash conversion cycles are presented in sub-Section 2.1.1. Thereafter, we describe the role of OWC in supply chain management in sub-Section 2.1.2. Lastly, the OWC key performance indicators that are used throughout this thesis are introduced in sub-Section 2.1.3.

2.1.1. Operating and Cash Conversion Cycles

Brealey et al. [2013] define a simple cycle of operations, as illustrated in Figure 2. It depicts the process of a typical business that buys raw materials, processes them into finished goods, and then sells these goods on credit. Furthermore, Brealey et al. [2013] state that the delay between the initial investment in inventories and the final sales date is called inventory period, also known as Days Inventory Outstanding (DIO). The delay between the time that goods are sold and the time these goods are actually paid is called accounts receivable period, also known as Days Sales Outstanding (DSO). The total length of time from purchase of raw materials until the final payment is termed the operating cycle, see Figure 3. However, the firm is not out of cash the entire length of the operating cycle, because they might have purchased raw materials, but it does not generally pay for them immediately. This accounts payable period, a.k.a. Days Payable Outstanding (DPO), reduces the amount of the time that firm is out of cash. The time between the payment of raw materials and cash collected from the customers for the goods sold is termed as the firm’s Cash Conversion Cycle (CCC). A firm needs to employ capital to finance the ‘out of cash’ period. In this study, we define this type of capital as the Operating Working Capital (OWC).
Finally, we define the first to third element of OWC as OWC in inventories, OWC in accounts receivables, and OWC in accounts payable, respectively. The role of OWC in supply chain management is described below.

### 2.1.2. Operating working capital's role in the supply chain management

We define a supply chain management triangle to illustrate the prominent role of OWC in supply chain management, see Figure 4. OWC is inherently linked to customer satisfaction and cost of financing the supply chain. With customer satisfaction we often refer to the customer service levels, which is the percentage of orders delivered within the promised customer lead time [Schiff & Lieber, 1974]. However, there are more ways to increase customer satisfaction, such as the allowance of a higher customer payment delay on the customer sales order [Wilner, 2000]. Increasing customer satisfaction is positively related with OWC in both directions, as higher service levels require more capital employed in OWC, and higher OWC levels enhance the services levels. Finally, OWC is positively related to supply chain costs, because more OWC leads to an increased cost of capital employed, which can be seen as supply chain costs [Faulkender & Wang, 2006]. The triangle below shows the relations between the three main aspects in supply chain management.

![Figure 4: Supply chain management triangle](image)

#### 2.1.3. OWC Key Performance Indicator

As OWC Key Performance Indicator (KPI) for this report we use the commonly used KPI by the company. This KPI is calculated as follows:

\[
\frac{\text{OWC}}{\text{SALES}^{3rd}} \times \% = \frac{\text{INV} + \text{AR}^{3rd} - \text{AP}^{3rd}}{4 \times \text{SALES}^{3rd} \text{lthree months}}
\]  \[1.1\]

This KPI is also be referred to as %OWC. It is usually calculated by the end of the month. In this formula the OWC (numerator) is expressed as the inventory position at the last day of the month, plus the AR position on that day for all outstanding sales to external party (3rd), minus the AP position on all third party purchases outstanding. Then, %OWC is calculated by dividing this OWC position on the last day of the month by last 3 months of sales to third parties multiplied by 4 (denominator).

The KPI of third party Sales, AR, and AP (generally, there is no payment term on internal sales) is taken such that on a Business Group (BG) level (Global) the internal sales are filtered out, because internal sales do not increase the company’s income as BG. Though, for the BUs it might seem unfair because when a BU has higher internal sales, it would have a higher OWC% since the BU would need to hold inventories for the internal sales (the numerator increases, and the denominator doesn’t). This thesis also analyzes this impact of internal sales in sub-Section 6.1.4. Finally, the company takes as denominator of the KPI four times the last three months of Sales^{3rd} as representative of the yearly sales.
to emphasize effects of seasonality and strong growth. By taking three months, the company avoids that these effects are averaged out over a year’s time.

Finally, in sub-Section 2.1.2. the role of OWC in supply chain management is described. For any firm, its working capital position should be seen in respect to its customer service performance level, because without this we might get an idea of how much working capital is employed, but not what performance is obtained due to this working capital. As customer service KPI for this report we apply the commonly used On Time in Full (OTIF) KPI by the company. The OTIF formula is as follows:

\[
OTIF [\%] = \frac{\text{Goods issued on time in full}}{\text{Total amount goods issued}} \quad [1.2]
\]

The OTIF tells the firm the percentage of on-time goods issues, without missing articles. If goods are issued on time in full, then related sales orders left the plant before the customer promised goods issue dates. This neglects the transportation time after the goods issues.

2.2. Main drivers of OWC

This section presents a comprehensive overview of the main drivers of OWC in inventories, accounts receivable, and accounts payable. In the sub-Section 2.2.1. the main drivers of OWC in inventories are presented. Thereafter, sub-Section 2.2.2. shows the main drivers of OWC in accounts receivables. Lastly, in sub-Section 2.1.3. the main drivers of accounts payables are presented. Several of these OWC main drivers are tested on their sensitivity in Chapter 6 and 7.

2.2.1. Main drivers of OWC in inventories

Based on interviews with the supply chain managers and the demand chain planners of the company there are defined different types of stock examples that mostly apply to any manufacturing firm: Consignment stock, Strategic stock, Safety stock, Cycle stock, WIP, Quality (QC) stock, In-Transit stock, and Excess stock. The main drivers of each of these stocks can be found in Figure 30, Appendix A. The different examples of types of stock and their main drivers are described below.

Consignment stock. Consignment stock is stock owned by the firm but stored at the customer premises. Consumption is invoiced. Consignment stock is determined by the firm’s strategic decisions and hand made deals. Strategic decisions could be to apply or not apply this consignment stock to certain customers groups. The amount and conditions are defined through tailored deals per customer.

Strategic stock. Strategic stock (a.k.a. anticipation stock) serves to anticipate for expected events that have a medium impact, or for foreseen large upswings in demand. Typically a firm’s strategic stock arises because of planned production stops.

Safety stock. Safety stock is used to cover demand and supply uncertainty. More uncertainty between demand and supply requires a higher safety stock. Sometimes firms also aim to hold certain level of safety stock for unexpected events (contingency events). It serves as an insurance against stock outs. The three main drivers of safety stock are the demand distribution, the desired customer service level, and the lead time between the replenishment request and renewed availability. A service level
often taken is the percentage of customer orders delivered within time, called the P1-service level [Muckstadt & Sapra, 2010]. Increasing the customer service level demands for higher safety stocks to fulfil this service level. Furthermore, the lead time is relevant, since safety stock serves to meet the demand during the replenishment lead time of a firm. A higher replenishment lead time implies a higher safety stock level.

**Cycle stock.** Cycle stock results from a batch process and is the unbalance in supply (quantities & timing) and consumption/demand. Cycle stock drives the saw blade pattern of inventory. The main driver of cycle stock for a firm is the production batch size (produced good) or the order quantity (purchased good). The best production batch size, or order quantity, depends on the firm’s production wheel (sequence of producing SKUs in a production batch), inventory holding cost, time-based definitions, the planning review period, and minimal lot sizes.

**Work in Process (WIP).** The WIP stock can be seen as pipeline stock. It is inventory that is being processed in a specific moment in time. It is mainly driven by the production lead time and the throughput (amount of items flowing through the production process per time period). The firm’s throughput is defined by the bottleneck, as the capacity of the production step with the lowest capacity determines the capacity of the entire system.

**Quality Control stock (QC stock).** Quality stock is needed to cover the time needed for quality inspection. It can be calculated by throughput and quality inspection lead time.

**Good in Transit stock (GIT).** GIT stock is stock as result of in transit movements between plants, warehouses, and customers. It can be calculated by defining all main in-transit flows, the size of the flows and the transportation lead time.

**Excess stock.** There can exist many more different types of small stock that might need to be included into the total stock level determination. The firm under study sums these types of stock up into excess stock.

Figure 30 in Appendix A summarizes the OWC in inventory breakdown into its main drivers. Each type of stock can be seen as a driver of total OWC, and the factors on the right-hand side of the figure indicate the business principles that drive the OWC in inventories. The product portfolio indicates the values of each SKU. Most stocks are defined and calculated in this study, whereas the product portfolio is taken as given based on cost price data per SKU.

### 2.2.2. Main drivers of OWC in accounts receivable

Based on interviews with the company’s Customer Service and Sales Controllers, we define the main drivers of AR illustrated in Figure 31 in Appendix A. The AR position is the sum of all outstanding sales order values. On average this is the number of Days Sales Outstanding (DSO) times the total credit sales per day. The main drivers of the total credit sales (greyed out in Figure 31 in Appendix A) are considered out of scope in this study, because it mainly boils down to finding the best marketing mix in order to positively drive sales. Notwithstanding, the main drivers of DSO are taken into the scope.
AR has a key main driver, which is the payment term negotiated per customer order. The payment term should be a result of overall industry benchmark studies and the appropriate discount vs. interest optimization, because a firm can offer discounts on early payment such that it alleviates interest costs on OWC tied up in AR. Furthermore, overdue payments, which are late payments, lead to increased AR positions. Therefore, a firm typically tries to find the lowest possible payment term and closely manages customers to prevent overdue payments. Cross-departmental cooperation, good relations with the customers, and responsibility and awareness help in this respect. Finally, the internal/external sales proportion of a firm impacts the AR position, because a firm has usually no (or a lower) payment term on internal company sales.

2.2.3. Main drivers of OWC in accounts payables
Based on interviews with the company’s Procurement Manager, Procurement employees, and the AP controllers, we define the main drivers of AP illustrated in Figure 32 in Appendix A. The AP position is the sum of all outstanding purchase orders at a specific point in time. On average this is the average Days Payable Outstanding (DPO) times total cost of sales per day. Similarly to AR, the total cost of sales’ main drivers (greyed out in Figure 32 in Appendix A) are considered out of scope in this study, but the main drivers of DPO are taken in the scope.

Again, the key main drivers is the payment term negotiated per purchase order. Typically in procurement the purchasing party has less bargaining power than the selling party. In AP management the payment processes, which include the payment run cycle and overdue cancelation cycle, are influential because they determine the cyclic nature of the OWC in AP (e.g. all payments on last day of the week). Furthermore, the bank transaction time is one of the AP main drivers because if the selling party requires its money on a specific due date, then the payment due date of the buying firm is equal to the due date minus the bank transaction time. Finally, a firm might have made tailored agreements with their supplier, such as consignment stocks, and global confirming agreements, i.e. the phenomenon in which the seller borrows the money from a bank, and simultaneously lends it to the buyer. This phenomenon nowadays is also known as reserved factoring. Factoring is reserved when the factor, normally a financial institution, effectively lends money to the buyer, but indirectly funds to the seller. Hence, it is a service to the buyer rather than for the seller. [Vliet, Reindorp, & Fransoo, 2015]

2.3. Bottom-up values OWC elements
In sub-Section 2.1.1. we indicate that there exist three element in OWC (inventories, AR, and AP). In this section we present a methodology to calculate the bottom-up values for each of these OWC elements. The results of using this methodology are shown for each case study in Chapter 3.

2.3.1. List of parameters
The list of parameters below shows all parameters defined for the bottom-up OWC calculation for each of the individual elements.

**Inventory parameters**

- \( CP_i \) = Cost price SKU \( i \) [€/kg]
- \( CS_i \) = Cycle stock of SKU \( i \) [kg]
- \( F_i \) = All transit flows for SKU \( i \) \([0,1,...]\)
\[ f_i = \text{Transit flow of SKU } i \ [1,...,F_i] \]
\[ GIT_i = \text{Goods in Transit stock for SKU } i \ [\text{kg}] \]
\[ i = \text{Stock Keeping Unit (SKU) } i \ [1,...,N] \]
\[ J = \text{All types of stocks } j \ (\text{e.g. safety stock, cycle stock, etc.}) \ \text{of the firm} \ [1,2,...] \]
\[ j = \text{Type of stock} \ [1,...,J] \]
\[ L = \text{All stock keeping locations} \ l \ \text{of the firm} \ [1,2,...] \]
\[ l = \text{Stock keeping location} \ [1,...,L] \]
\[ LT_i = \text{Production lead time of SKU } i \ [\text{days}] \]
\[ N = \text{Total number of SKUs} \ [0,1,2,...] \]
\[ OWC_{INV} = \text{Operating Working Capital value in inventories} \ [\text{€}] \]
\[ Q_{ij} = \text{Quantity of SKU } i \ \text{in stock type} \ j \ \text{at stock keeping location} \ l \ [\text{kg}] \]
\[ QLT_{ij} = \text{Quality inspection lead time for SKU } i \ [\text{days}] \]
\[ QS_i = \text{Quality stock of SKU } i \ [\text{kg}] \]
\[ QTP_i = \text{Throughput of SKU } i \ \text{in quality inspection} \ [\text{kg/day}] \]
\[ RQ_i = \text{Replenishment quantity of SKU } i \ [\text{kg}] \]
\[ SALES_{3rd \ last \ three \ months} = \text{Total sales to third party customers in the last three months} \ [\text{€}] \]
\[ TLT_{if} = \text{Transportation lead time of SKU } i \ \text{in transit flow} \ f \ [\text{days}] \]
\[ TP_i = \text{Total throughput of SKU } i \ [\text{kg/day}] \]
\[ TTP_i = \text{Throughput of SKU } i \ \text{in transit} \ [\text{kg/day}] \]
\[ WIP_i = \text{Work in process of SKU } i \ [\text{kg}] \]

**Accounts receivable parameters**

\[ AR(t) = \text{Accounts receivable position at time} \ t \ [\text{€}] \]
\[ S = \text{All customer sales orders} \ [1,2,...] \]
\[ s = \text{Customer sales order } s \ [1,2,...,S] \]
\[ ID_s = \text{Invoice date of sales order } s \ [\text{date}] \]
\[ PT_s = \text{Baseline (or bottom-up) reference payment term for sales order } s \ [\text{days}] \]
\[ SALES_{3rd \ last \ three \ months} = \text{Total sales to third party customers in the last three months} \ [\text{€}] \]
\[ SalesOrder_s = \text{Value of customer sales order } s \ \text{in euros} \ [\text{€}] \]
\[ t = \text{Time} \ [\text{date}] \]
\[ Z_t = \text{Set of customer sales orders } s \ \text{outstanding at time} \ t \ [0,1,...] \]

**Accounts payable parameters**

\[ AP(t) = \text{Accounts payable position at time} \ t \ [\text{€}] \]
\[ iD_j = \text{Invoice date of purchase order } j \ [\text{date}] \]
\[ j = \text{Purchase order } j \]
\[ PT_j = \text{Baseline (or bottom-up) reference payment term for purchase order } j \ [\text{days}] \]
\[ PurchaseOrder_j = \text{Purchase order value in euros} \ [\text{€}] \]
\[ SALES_{3rd \ last \ three \ months} = \text{Total sales to third party customers in the last three months} \ [\text{€}] \]
\[ t = \text{Time} \ [\text{date}] \]
\[ Y_t = \text{Set of purchase orders } j \ \text{outstanding at time} \ t \ [0,1,...] \]

### 2.3.2. Bottom-up inventory target setting

As shown in sub-Section 2.2.1. OWC in inventories arises from different types of stock. The money tied up in inventories is determined by the company’s total stock level multiplied by the product portfolio. This product portfolio indicates the value of the products stored per SKU. In this thesis, the value of a
SKU is based on the cost price of the SKU, and taken as given. The company’s total stock level is split up into different types of stock. These stock volume are from a bottom-up perspective the result of production management and could be considered independent of time. This would result in one specific bottom-up inventory value given the input to the formulas. We define the generic formula for the firm’s bottom-up OWC in inventories is as follows:

\[
OWC_{INV} = \sum_{i=1}^{L} \sum_{i=1}^{N} \sum_{j=1}^{J} CP_i Q_{ijl} \quad [2.1]
\]

\[
%OWC_{INV} = \frac{OWC_{INV}}{4 \times SALES^{3rd \ last \ 3 \ months}} \quad [2.2]
\]

Hence, we take the sum of all quantities \(Q_{ijl}\) in all types of stock \(j\), for all SKUs \(i\), for all stock keeping locations \(l\). And this is multiplied by the cost price \((CP_i)\) of SKU \(i\) (Formula 2.1). Finally, the \%OWC INV (Formula 2.2) is the OWC in inventory part of the total \%OWC, defined in Formula 1.1 (sub-Section 2.1.3.).

Some of the stock types are static by nature and purely based on decisions made by strategic management, such as consignment stock, strategic stock, and safety stock. In a bottom-up OWC target setting they should merely be taken as given. Though, it might be arguable to evaluate actual stock levels versus what is agreed upon with the customer (consignment stock) or with higher management (strategic stock and safety stock).

Other stock types fluctuate more by nature and can be expressed in mathematical manners. Below we define a set of examples and formulas per type of stock \(j\) that can be used for the bottom-up calculation of each type of stock \((Q_{ij})\). These are also used in Chapter 3 to compute the bottom-up values for each of the OWC elements for the case studies.

**Examples of OWC in different types of stock \(j\) [Muckstadt & Sapra, 2010]**

**Cycle Stock (CS) formula.** The average cycle stock of a firm is half the replenishment quantities \((RQ_i)\) per SKU \(i\). The replenishment quantities can be set in many different ways, such as the well-known Economic Order Quantity (EOQ) and Economic Production Quantity (EPQ). The expected volume in cycle stock is as follows:

\[
E[CS_i] = \frac{RQ_i}{2} \quad [3.1]
\]

**Work In Process (WIP) formula.** A firm’s WIP is the sum of all products that are in a specific moment in time in the system. Expectedly, this is equal to the throughput \((TP_i)\) times the production lead time \((LT_i)\).

\[
E[WIP_i] = TP_i \times LT_i \quad [3.2]
\]
**Quality inspection Stock (QS) formula.** The QS volume is the sum of volumes of products that are in quality inspection. Expectedly, this equals the quality inspection throughput ($QT_{Pi}$) times the quality inspection lead time ($QLT_i$).

$$E[QS_i] = QT_{Pi} \times QLT_i \quad [3.3]$$

**Goods In Transit (GIT) formula.** The GIT volume is the sum of volumes of products that are in transit. The expected volume of stock in GIT is the in-transit throughput ($TTP_{if}$) times the in-transit lead time ($TLT_{if}$), for all $f \in F_i$.

$$E[GIT_i] = \sum_{f=1}^{F_i} TTP_{if} \times TLT_{if} \quad [3.4]$$

### 2.3.3. Bottom-up accounts receivable target setting

In sub-Section 2.2.2, we illustrate that accounts receivable positions per day are determined by the credit sales per day per product (SKU) and the corresponding DSO. For the bottom-up inventory target setting (previous section) we define formulas to find expected values, independent of the time index. However, the bottom-up AR position of a firm is directly related to the sales orders at time $t$. Therefore, we introduce the time index $t$, and we define the bottom-up AR position of a firm dependent of time $t$. The formulas to find the AR position at time $t$ can be defined as follows:

$$AR(t) = \sum_{s \in Z_t} SalesOrder_s \quad [4.1]$$

$$Z_t = \{ s \mid ID_s < t < ID_s + PT_s \} \quad [4.2]$$

$$\%OWC\ AR\ (t) = \frac{OWC\ AR\ (t)}{4 \cdot SALES^{3rd\ last\ 3\ months}} \quad [4.3]$$

Hence, the AR position at time $t$ is the sum of all sales orders $s$ for which the date $t$ is in-between the invoice date ($ID_s$) and the payment date ($ID_s + PT_s$) based on which baseline reference payment term ($PT_s$) is taken. We use in this report the negotiated payment terms with third parties ($PT_s =$ the actual payment term negotiated with the customer for sales order $s$) for the two supply chain case studies in Chapter 3. Results are shown in Chapter 3.

The $\%OWC\ AR$ at time $t$ (Formula 4.3) is the OWC in accounts receivable part of the total $\%OWC$, defined in Formula 1.1, sub-Section 2.1.3.

### 2.3.4. Bottom-up accounts payable target setting

In sub-Section 2.2.3, it can be seen that accounts payable positions per day are determined by the total cost per purchased item and the corresponding DPO. Similarly to AR, the bottom-up AP position of a firm is directly related to the purchase orders at time $t$. Therefore, we introduce the time index $t$, and we define the bottom-up AP position of a firm dependent of time $t$. We define the AP position at time $t$ with the following formulas:
\[ AP(t) = \sum_{j \in Y_t} PurchaseOrder_j \]  
\[ Y_t = \{ j \mid ID_j < t < ID_j + PT_j \} \]

\[
\%OWC\ AP\ (t) = \frac{OWC\ AP\ (t)}{4 \times SALES^{3rd}\ last\ 3\ months}
\]

Similarly to the AR formula, the AP position at time \( t \) is the sum of all purchase orders \( j \) for which the date \( t \) is in-between the invoice date (\( ID_j \)) and the payment date (\( ID_j + PT_j \)) based on which baseline reference payment term (\( PT_j \)) is taken. In this report the payment term baseline reference is the actual negotiated payment term with the supplier. Results are shown in Chapter 3.

The \%OWC AP at time \( t \) (Formula 5.3) is the OWC in accounts payable part of the total \%OWC, defined in Formula 1.1, sub-Section 2.1.3.
In this chapter, we present the two different supply chain (SC) case studies for the bottom-up OWC targeting. These case studies are based on real supply chain structures within the company and are chosen to be the ‘pilot cases’ to apply methods and models developed in this thesis. For each SC case study, we shortly discuss the SC structure, the goods flow overview, and the general information relevant for an OWC targeting study. Furthermore, we present results of the bottom-up calculations of each of the OWC element, by following the bottom-up methodology developed in Section 2.3.

Based on interviews with the relevant stakeholders, we created two supply chain case studies for the bottom-up OWC calculations. The first SC case study is described in Section 3.1. Thereupon, the second SC case study is elaborated upon in Section 3.2.

### 3.1. Supply Chain Case Study 1

#### 3.1.1. Overview supply chain case study 1

The goods flow overview of this supply chain study case is shown in Figure 5. This SC case study is a two-steps production process following process steps 1 through 2, or 1 through 3. There exist three stocking keeping points A, B, and C to store respectively raw materials (RM), Intermediate Products (IP), and End Products (EP).

The supply chain is supplied with raw materials from external suppliers on which the firm has accounts payables. RM also include packaging materials. Sales exist on both IP and EP to both internal and external parties. Internal company sales are sales that go to business units owned by the same company. Account receivables only arise from external party sales, because there do not exist payment terms on internal company sales. The percentage external sales in SC case study 1 in 2014 was about 80%.

The first production step converts the RM into a few intermediate product SKUs, for which the majority is used for the conversion into end product SKUs. The majority of these are converted into end-product SKUs in process 2, and one of the intermediate product SKUs is converted into end-product SKUs via process 3. Demand exists on each SKU.

Finally, the SC case study operates according to a ‘full load’ principle, which implies that production step 1 runs 24/7 ‘pushing’ the intermediate products into the supply chain. This first production step is fairly stable with an Overall Equipment Effectiveness (OEE) above 90%. Production step 2 or 3 can be triggered by Make to Order (MTO) production order (pull) or a Make to Stock (MTS) production order (push), in which the latter production order is based on a forecast. Based on historical data the proportion MTO/MTS is approximately 40/60.
3.1.2. Results bottom-up methods supply chain case study 1

Bottom-up computation methods developed in Section 2.3. are applied to this supply chain case study to find the bottom-up values for each of the three OWC elements. Methods are applied to multiple periods in time based on historical data. Thereupon, results are validated by the responsible project team member. The results of year 2014 are added to Appendix B.

**OWC in inventories**

The OWC in inventory for this supply chain case study exists in intermediate & end products, raw materials (incl. packaging materials), and engineering materials (Maintenance, Repair, and Operation items & spare parts). The contribution to the total OWC in inventories is approximately 70%, 23%, and 7%, respectively. According to actual figures the %OWC INV denotes 18.2%, whilst bottom-up we computed a %OWC INV of 16.7%. This leads to an operational efficiency gap of 1.6% (\( \Delta = \) actual %OWC INV – bottom up %OWC INV).

The bottom-up %OWC INV of 16.7% can be split up into all the different types of stock. For the intermediate & end products these types of stock are as follows:

1. Continuous intermediate products (%OWC INV = 1.1%): As result of ‘full load’ production step 1 it is assumed that all intermediate SKUs’ bottom-up inventory levels are equal to the actual stock levels, since the actual stock level is the results of the strategic decision.
2. Safety stock (%OWC INV = 4.8%): Explained in sub-Section 2.3.2.
3. Cycle stock (%OWC INV = 2.9%): Idem.
4. Quality stock (%OWC INV = 1.0%): Idem.
5. Consignment stock (%OWC INV = 4.8%): Idem.
7. Goods in Transit stock (%OWC INV = 0.0%): Idem.
8. Correction (%OWC INV = 0.1%): The actual stock levels added to the ‘correction stock’ for those SKUs for which no stock type information is available.

Based on the same rationale, we defined the following types of stock for raw materials:

1. Safety stock (%OWC INV = 1.7%): Explained in sub-Section 2.3.2.
2. Cycle stock (%OWC INV = 0.3%): Idem.
3. Work in Process (%OWC INV = 1.2%): Idem.
4. Quality stock (%OWC INV = 0.2%): Idem.
5. Blocked stock (%OWC INV = 0.0%): Result of blocked stock report 2014.
6. Additional replenishment stock (%OWC INV = 0.5%): Result of buildup stock to cover up the weekend (no replenishment during the weekends, whilst production is 24/7).
7. Unexplained stock (%OWC INV = 0.1%): The actual stock levels added to the unexplained stock for those RM for which no stock type information is available.

Furthermore, there exists a 1.3% OWC in engineering materials, which include maintenance repair & operation (MRO) parts and spare parts. Applying Formula 2.1 leads to a total sum of 16.7% OWC INV, based on the cost price per SKU in 2014.

**OWC in accounts receivable**

The OWC in accounts receivable for this SC case study denotes an average of 15.1% in monthly reports of 2014. The baseline reference payment term used is the actual negotiated payment terms with the customers. We find with use of Formula 4.1, 4.2, and 4.3 a bottom-up %OWC AR of 10.2%. This implies an operational efficiency gap of 4.9%.

**OWC in accounts payable**

Purchases are divided into direct and indirect purchases, in which direct purchases are purchases directly linked to the production of end products, such as raw materials and packaging materials, and indirect purchases are not directly linked to production, such as for example office accessories. This study only focuses on the direct purchases for both the analysis of actual financial figures and the bottom-up calculations. The OWC in accounts payable for direct purchases in this SC case study showed an average of 2.1% in the monthly financial reports in 2014. The baseline reference payment term for the bottom-up AP calculation has been the actual negotiated payment terms with the suppliers. We find a bottom-up OWC AP of 2.0% by applying Formulas 5.1 to 5.3. This implies that this SC case study performed better in 2014 than the baseline standard, which corresponded to an operational efficiency gap of 0.05%. The operational efficiency gap in this case is beneficial for the firm.

**Total OWC**

The total %OWC position of this SC case study was 31.5% in 2014, after modifications. Summing up the bottom-up values for all three elements of OWC we find a bottom-up total %OWC equal to 24.9%. This implies a gap in operational efficiency of 6.6%. This gap is for approximately 75% caused by the efficiency gap in AR management.

3.2. Supply Chain Case Study 2

3.2.1. Overview supply chain case study 2
The goods flow overview of this supply chain study case is shown in Figure 6. The second SC case study sells the same products as SC case study 1, but is focused on a different geographical region. Therefore, besides a slightly different supply chain structure, the SC case study is also characterized by different business dynamics, terminology, culture, and many more business aspects.
The second supply chain is a two-step production process (1 and 2) with three stocking points (A, B, and C). Stocking points A, B, and C store respectively raw materials (RM), intermediate products (IP), and end products (EP).

Raw materials are ordered from external suppliers on which the firm has accounts payables. RM also include packaging materials. Sales exist only on EP to mostly external parties. Account receivables arise from these external party sales, and not from internal company sales, because internal company sales are always due immediately. The first production step convert the RM into several intermediate product SKUs, which all are used for the conversion into end-product SKUs via production step 2. Demand exists on each SKU.

The first production process step is characterized as push, as it continuously pushes intermediate products to stocking point B, 7 days a week, 24 hours a day. The second process step is characterized as pull and can only be triggered by a ‘Make to Order (MTO)’ order. The second process step always has sufficient capacity to process all orders, because of a backup machine that can be used in case of under capacity.

Finally, important to mention is that sales and production are very well outlined. Not only is produced what needs to be sold, but the managers of this SC case study also emphasize the importance of making sure that they sell what is produced. For example, in case of a stock out, account managers often sell products with slightly other specifications than specified in the initial order. This leads to high order fulfillments, and lower average stock levels.

![Supply chain structure SC case study 2](image)

**Figure 6: Supply chain structure SC case study 2**

### 3.2.2. Results bottom-up methods supply chain case study 2
Similar to SC case study 1, bottom-up computation methods developed in Section 2.3. are applied to this supply chain case study to find the bottom-up values for each of the three OWC elements. The results of all time periods are validated by the responsible project team member for this region. The results of SC case study 2 for year 2014 are added to Appendix C.

**OWC in inventories**

The contribution to the total OWC in inventories is approximately 53%, 33%, and 14%, respectively for intermediate & end products, raw materials (incl. packaging materials), and engineering materials (Maintenance, Repair, and Operation items & spare parts). According to actual figures the %OWC INV denotes 5.4%, whilst bottom-up we compute a %OWC INV of 5.3%. This leads to an operational efficiency gap of 0.1%.
The bottom-up %OWC INV of 5.3% can be split up into all the different types of stock. For the intermediate & end products these types of stock are as follows:

1. Safety stock (%OWC INV = 0.0%): Explained in sub-Section 2.3.2.
2. Cycle stock (%OWC INV = 1.4%): Idem.
3. Quality stock (%OWC INV = 0.4%): Idem.
4. Consignment stock (%OWC INV = 0.0%): Idem.
5. Blocked stock (%OWC INV = 0.2%): Result of blocked stock report 2014.
6. Goods in Transit stock (%OWC INV = 0.8%): Idem.
7. Correction (%OWC INV = 0.0%): No correction applied.

We defined the following types of stock for raw materials:

1. Safety stock (%OWC INV = 0.7%): Explained in sub-Section 2.3.2.
2. Cycle stock (%OWC INV = 0.1%): Idem.
3. Work in Process (%OWC INV = 0.8%): Idem.
4. Quality stock (%OWC INV = 0.2%): Idem.
5. Blocked stock (%OWC INV = 0.0%): Result of blocked stock report 2014.
6. Additional replenishment stock (%OWC INV = 0.0%): no buildup stock to cover up the weekend (replenishment during weekends as well).

Furthermore, there exist a 0.8% OWC in engineering materials, which include maintenance repair & operation (MRO) parts and spare parts. Applying Formula 2.1 leads to a total sum of 5.4% OWC INV, based on the cost price per SKU in 2014.

**OWC in accounts receivable**

The OWC in accounts receivable for this SC case study denotes an average of 10.8% in monthly reports of 2014. The baseline reference payment terms used is the actual negotiated payment terms with the customer. We find with use of Formula 4.1, 4.2, and 4.3 a bottom-up %OWC AR of 11.3%. This implies an operational efficiency gap of 0.5%. This operational efficiency gap is beneficial for the firm.

**OWC in accounts payable**

The OWC in accounts payable for direct purchases in this SC case study shows an average of 2.7% in the monthly financial reports in 2014. The baseline reference payment term for the bottom-up AP calculation has been the actual negotiated payment terms with the suppliers. By applying Formulas 5.1 to 5.3 we find a 3.1% OWC AP. This implies that this SC case study performed worse in 2014 than the baseline standard, which corresponded to an operational efficiency gap of 0.4%.

**Total OWC**

The total %OWC position of SC case study 2 was 13.5% in 2014, after modifications. Summing up the bottom-up values for the three elements of OWC we find a total %OWC level equal to 13.5% as well. This implies that SC case study 2’s performance in 2014 is equal to the bottom-up calculations.
Appropriate supply chain management is fundamental to any firm producing and/or selling goods. This chapter shows how OWC is built up from dependent and independent events in a system, and presents an approach to model OWC from an integrated perspective. We make use of the flowchart conceptual modeling method presented in the book Simulation Modeling & Analysis by Law [2007].

Figure 7 gives a general overview of the modeling approach. Section 4.1. focusses on what part of the supply chain events are captured by the existing production simulation model of the company, called the ARENA model (anonymous). Thereupon, in Section 4.2. we develop additional features to the existing production model to extent it to an integrated OWC model that finds the OWC performance given a set of additional input parameters.

In the integrated OWC model the AR and AP positions are the result of inventory and production management. By doing so, we ensure that the integrated model complies with effects that inventory management might have on AR and AP management. Hence, the integrated OWC model hypothetically includes all relevant linkages in OWC management. This is analyzed in more detail in the next chapter.

4.1. Existing production simulation model in Arena

In this section we present the ARENA model developed by the company’s specialized modeling (anonymous) department. Over the last five years, simulation modelers of this department have created this discrete event simulation model in Arena® Simulation Software. Arena® is a discrete event simulation software developed by Rockwell Automation. The ARENA model uses ’Meta Modeling’ which means that the model’s functionality describes a general workflow, that case specifics are defined in the input data, and that it handles widely differing cases without model customization. By manipulating the product portfolio, Bill of Material (BOM), machine allocation and resource network, different settings like a warehouse, a plant, a site, or even a whole supply network can be modelled. The company has applied this ARENA model successfully to two of its production lines with the objective to analyze the overall inventory level of the SKUs within scope. The ARENA model is merely described in conceptual terms, due to confidentiality matters. Notwithstanding, the conceptual description provides all information needed to fully understand the modeling approach towards an integrated OWC model.
Firstly, the relevant business processes are described in sub-Section 4.1.1. Thereafter, in sub-Section 4.1.2, we show the input and output of the model that would make the model applicable to be part of the integrated OWC model. Finally, the main assumptions are presented in 4.1.3.

4.1.1. ARENA model: business processes
The description of the business processes of the existing ARENA model and Figure 8 were available for your use, but omitted for confidentiality reasons.

Figure 8: Flowchart ARENA model
(This figure is omitted for confidentiality reasons)

4.1.2. ARENA model: input vs. output
The ARENA model is successfully validated by the company before, and is validated again in the next chapter. However, the ARENA should be made suitable for the integrated OWC model. This can be done by selecting the right input parameters and input data for the system. The input data are:

- Sales orders: including quantities, request date, and due date;
- Forecasted volumes: including quantities, and due date.

The input parameters for the system are:

- Stock keeping locations: $L$ in the list of inventory parameters in sub-Section 2.3.1.;
- Supply chain network: including the external supply per SKU $i$ at stock keeping location $l$, the internal production of a SKU $i$ at location $l$, the external sales per SKU $i$ at $l$, and the internal in-transit flow $f_i$ of SKU $i$ between all $L$;
- Bill of Materials (BOM): the BOMs of all SKUs including the proportion of raw materials and packaging materials;
- Strategic decisions
  - Reorder points per SKU (ROP$_i$)
  - Minimal lot sizes SKU (MLS$_i$)
  - Frozen period per SKU (FP$_i$)
  - Planning bucket size (production wheel) per SKU (BS$_i$)
  - Resource allocation per SKU
  - Capacities per resource (CAP$_r$)
  - Goods Received Process time per SKU (GRPT$_i$)
  - Changeover time per SKU (CO$_i$)

According to these settings the ARENA model generates an output report. This output report can be described as an event track record of each simulation run. It shows the inventory movements based on the events, orders moving through the system at specific moments in time, raw material consumption at specific moments in time, etc. The output that complies with the input needed for the integrated OWC model can be specified as follows:

- Inventory levels on SKU levels: date of inventory movements, and quantity of change;
- Customer Service Level: On Time In Full (OTIF) per customer order;
- Goods issued dates;
- Precursor material consumption: date of inventory movements, date of precursor material orders, and quantities in precursor material orders.

### 4.1.3. ARENA model: main assumptions

The ARENA model is based on several assumptions of a production and inventory system. We indicate below the main assumptions of the ARENA model that should be incorporated in the integrated OWC model.

- **Just in time principle**: The ARENA model plans production and goods issues according to the JIT principle, implying that the system tries to plan actions at the latest time possible.
- **Convergence in the system**: Precursor materials can arrive from multiple sources, but a precursor material can only flow to one subsequent step. E.g., A and B can be the precursor materials of items C and D, then A can only be converted to C or to D, B can only be converted to C or to D, and items C and D can be the result of a conversion of A, B, or A and B.
- **Customer sales orders are historical based**.
- **Production capacity is deterministic and constant**.
- **All orders that are not issued in time are backordered**.
- **Customer service levels are based on goods issue dates from the plant**: this means that transport inaccuracies are not taken into account.
- **After the goods issue the stored goods belong to the customers**: Inventory in transport belongs to the customer.
4.2. Integrated OWC model Extension

In this section we present the extension of the ARENA simulation model towards and integrated OWC model. The integrated OWC model takes the ARENA simulation model’s output as input, and is written in Excel’s Visual Basic. It can be loaded in the ARENA output folder and automatically retrieves all relevant data. In addition, it is necessary to specify other input parameters to the simulation. Each of these input parameters are shown in this chapter.

To realize the extension, we define three additional modules: the OWC in Accounts Payable Module, the OWC in Accounts Receivable Module, and the OWC in Inventories Module. Each of the modules are conceptually described in the sub-Sections 4.2.1., 4.2.2., and 4.2.3., respectively. Each subsection describes the business processes, the list of variables and input parameters, the list of main assumptions of the base model relevant to the company, and the formulas applied in the integrated model to keep track of the OWC performance, and OWC positions over the simulated time.

4.2.1. OWC in Accounts Payable Module

4.2.1.1. Business processes

In this module we model the Accounts Payable position of the firm over the simulated time. Figure 9 illustrates the flowchart of this module. The ARENA simulation model can trigger this module with two events: (1) raw material received from the supplier, and (2) replenishment order quantity (end-products) received from the supplier. If the corresponding purchase order is supplied by an internal supplier, then the system does nothing, because there do not exist payment terms on internal suppliers. If the purchase orders arrives from an external supplier, then it is processed by the system. Each purchase order is characterized by a specific payment term belong to the SKU type purchased.

For each purchase order it could have an option to realize an early payment against a suggested discount. A common example within the company is the option to pay 30 days earlier against an 1% discount on the total purchase value. If this early payment option is available, then it is the company’s choice to make use of the early payment option or not. If the company chooses to pay earlier, then the discounted purchase value needs to be added up to the AP position. If the early payment option is not available or the company chooses not to use the early payment option, then the regular purchase order value is added up to the AP position.

Typically firms do not pay every day, but rather once in a specified number of days. We define this number of days at the company as the payment run cycle (PRC). Hence, the company pays it suppliers every end of the PRC. A firm may choose to structurally pay its suppliers in the PRC that contains the payment due date, or to structurally pay them in one PRC earlier. The first decision would lead to mostly late payments to the supplier, and the latter decision would ensure that the purchasing firm always pays it suppliers in time. Notwithstanding, the first decision leads to lower OWC employed on yearly basis.

Finally, when the firm has decided to allocate a purchase order to the right PRC, then we may deduct the AP position with the regular or discounted purchase order value once the payment date in that PRC is expired.
4.2.1.2. **List of variables and input parameters for the AP module**

For the AP module we define additional main variables and input parameters (star mark) to the ones defined for the bottom-up calculations in sub-Section 2.3.1. These are as follows:

**Parameters from bottom-up section 2.3.1.**

- \( AP(t) \) = Account payable position at time \( t \) [€]
- \( i \) = SKU number \( i \) of the firm \([i,...,N]\)
- \( j \) = Purchase order \( j \) \([1,2,3,...,J]\)
- \( J \) = Total number of purchase order \([0,1,...]\)
- \( N \) = Total number of SKU of the firm \([0,1,...]\)
- \( PT_j^* \) = Due-in-days (payment term) for purchase order \( j \) [days]
- \( t \) = Time [days]
- \( Y_t \) = Set of purchase orders \( j \) outstanding at time \( t \) \([0,1,...]\)
Additional parameters for integrated OWC model

\[ C_i^* = \text{Cost price of SKU i at time t [€/kg]} \]
\[ DC_j^* = \text{Discount payment choice identifier for purchase order j [0,1]} \]
\[ d_j = \text{Discount rate offered to the firm for purchase order j [%]} \]
\[ e = \text{Percentage of external suppliers [%]} \]
\[ EP_j^* = \text{Early payment option identifier for purchase order j [0,1]} \]
\[ EXT_j = \text{External supplier identifier for purchase order j [0,1]} \]
\[ ID_j = \text{Invoice date of purchase order j} \]
\[ p_j^* = \text{Payment-in-days for purchase order j [days]} \]
\[ PO_j = \text{Amount purchased of purchase order j [kg]} \]
\[ prc^* = \text{Payment run cycle [days]} \]
\[ rc = \text{Payment run cycle number [0,1,...]} \]
\[ rci^* = \text{Payment run cycle identifier [0,1]} \]
\[ RM^* = \text{Set of SKUs belonging the raw materials [{}]} \]
\[ V_j = \text{Value of purchase order j [€]} \]

4.2.1.3. List of main assumptions for the AP module

Based on interviews with employees of the procurement department we make the following assumptions for the base model:

a. The system pays its suppliers in the payment run cycle that contains the due date (\(rc=\text{ROUNDUP}(PT_j/prc)\)), or in one payment run cycle earlier (\(rc=\text{ROUNDUP}((PT_j/prc)-1)\));

b. The payment term (\(p_j\)) and percentage of external supplier (\(e\)) are deterministic and calculated based on data;

c. The early payment option is deterministic and calculated based on data;

d. The firm’s choice to make use of the early payment option is deterministic and calculated based on data.

4.2.1.4. Main formulas for the AP module

To find the discounted or regular purchase order value of each raw material SKU i we define Formula 7.1:

\[ V_{ijt} = \begin{cases} 
  C_{it} * d_j * PO_{ij} : EP_j = DC_j = 1 \\
  C_{it} * PO_{ij} : EP_j = 0 or DC_j = 0 
\end{cases} \quad [7.1] \]

Where, \(EP_j\) and \(DC_j\) are the indicators of the early payment option available and the business choice to accept this early payment option, respectively. Furthermore, to plan the payment-in-days (\(p_j\)) of purchase order j we define formula 7.2:

\[ p_j = \begin{cases} 
  prc * \text{ROUNDUP} \left( \frac{PT_j}{prc} \right) : EXT_j = 1 and rci = 1 \\
  prc * \text{ROUNDUP} \left( \frac{PT_j}{prc} - 1 \right) : EXT_j = 1 and rci = 0 \\
  0 : EXT_j = 0 
\end{cases} \quad [7.2] \]
Where, rci indicates in which payment run cycle the firm plans to pay and \(\text{EXT}_j\) indicates if purchase order \(j\) is ordered from an external supplier or an internal supplier. \(\text{EXT}_j\) is binominal distributed with its probability distribution as follows:

\[
\Pr(\text{EXT}_j = 1) = e \quad [7.3]
\]

Finally, based on the bottom-up AP formulas from sub-Section 2.3.4 we model the AP position of the firm as follows:

\[
AP(t) = \sum_{i \in \text{ERM}} \sum_{j \in Y_t} V_{ijt} \quad [7.4]
\]

\[
Y_t = \{ j \mid ID_j < t < ID_j + p_j \} \quad [7.5]
\]

### 4.2.2. OWC in Accounts Receivable Module

#### 4.2.2.1. Business processes

In this module we model the Accounts Receivable position of the firm over the simulated time. Figure 10 shows the flowchart belonging to this module. The ARENA simulation model can trigger this module based on the only event ‘goods issued’. The key difference of this module versus the AP module defined in 4.2.1. is that in this module the system dependents on the customer payment, whereas in the AP module the system can plan the payment itself. However, similarly to the AP module is that if the corresponding sales order is ordered by an internal client, then the system does nothing, because there do not exist payment terms for internal customers. If the sales orders belong to an external customer, then it is processed by the system.

For each sales order the company could decide to offer a discount against a suggested reduction of the payment term. A common example within the company is the discount offer to the customer in which he pays 30 days earlier against an 1% discount on the total sales value. In this way, the selling firm reduces its AR position. If this early payment option is available, then it is the customer’s choice to make use of the early payment option or not. If the company offers the discount offer and the customer accepts it, then the discounted sales value needs to be added up to the AR position. If the early payment option is not offered by the company or the customer chooses not to use the early payment option, then the regular purchase order value is added up to the AP position.

Finally, when the firm has received the payment from the customer, then the AR position is reduced by the regular or discounted sales order value.
4.2.2.2. List of variables and input parameters for the AR module

We define the main variables and input parameters (marked with a star) of this AP module as follows:

Parameters from bottom-up section 2.3.1.

- **AR(t)** = Account receivable position at time t [€]
- **i** = SKU number i of the firm [1,...,N]
- **ID_s** = Invoice date of customer sales order s [date]
- **N** = Total number of SKU of the firm [1,2,...]
- **PT_s** = Payment-in-days (payment term) for sales order s [days]
- **s** = Customer sales order s [1,2,3,..., S]
- **S** = Total number of customer sales orders s [1,2,...]
- **t** = Time [days]
- **Z_t** = Set of sales orders s outstanding at time t [0,1,..]
Additional parameters for integrated OWC model

\[ DC_s^* \] = Discount payment choice identifier for customer sales order \( s \) [0,1]

\[ d_s^* \] = Discount rate offered to the firm for customer sales order \( s \) [%]

\[ EP_s^* \] = Early payment option identifier for customer sales order \( s \) [0,1]

\[ EXT_s \] = External customer identifier for sales order \( s \) [0,1]

\[ PI^* \] = Payment term setting type \([1,2,3]\)

\[ SV_{0is} \] = Initial sales value of SKU \( i \) of sales order \( s \) [€]

\[ SV_{is} \] = Sales value of SKU \( i \) of sales order \( s \) [€]

For the payment term setting type (\( PI^* \)) we define two different types of how payment terms requested to the customer can be set in the system. Type 1 corresponds to the setting in which the system sets payment terms according to historical negotiated payment terms. Type 2 corresponds to the setting in which the system sets the payment term according to manual input.

**4.2.2.3. List of main assumptions for the AR module**

Based on interviews with employees of the customer service department and supply chain management we made the following assumptions for the base model:

a. The payment term (PT) per sales order is deterministic and according to the historical data;

b. The date of sales order payment received in the system equals to the invoice date of the sales order plus the payment-in-days (PT) of the sales order. Hence, there doesn’t exist overdue on customer payments (this could be simulated by manipulating the PT);

c. The early payment option offered by the system is deterministic and according to the historical data per customer sales order;

d. The customer’s choice to make use of the early payment option is deterministic and according to the historical data per customer sales order.

**4.2.2.4. Main formulas for the AR module**

To find the discounted or regular customer sales order value of SKU \( i \) we define Formula 8.1:

\[
SV_{is} = \begin{cases} 
  d_s \cdot SV_{0is} & : EP_s = DC_s = 1 \\
  SV_{0is} & : EP_s = 0 \text{ or } DC_s = 0
\end{cases} \quad [8.1]
\]

Where, \( EP_s \) and \( DC_s \) are the indicators of the early payment option offered by the system and the customer’s choice to accept this early payment option, respectively. Furthermore, to plan the payment-in-days (PT) in the system of customer sales order \( s \) we define formula 8.2:

\[
PT_s = \begin{cases} 
  PT_{s-1} & : EXT_s = 1 \text{ and } PI = 1 \\
  PT_{s-2} & : EXT_s = 1 \text{ and } PI = 2 \\
  0 & : EXT_s = 0
\end{cases} \quad [8.2]
\]

Where, \( PI^* \) indicates payment term setting type the firm desired and \( EXT_s \) indicates if sales order \( s \) is ordered from an external customer \([1 = \text{yes}, 0 = \text{no}]\). Finally, based on the bottom-up AR formulas from sub-Section 2.3.3. we model the AR position of the firm as follows:
\[ AR(t) = \sum_{i \in N} \sum_{s \in Z_t} SV_{ist} \quad [8.3] \]

\[ Z_t = \{ s \mid ID_s < t < ID_s + PT_s \} \quad [8.4] \]

### 4.2.3. OWC in Inventories Module

The inventory module needs relatively little attention in this report, because this is modeled by the ARENA model. Section 4.1. has given an elaborate description of the inventory position modeled over the simulated time in the ARENA model. This inventory position \((QINV_i(t))\) simulated by the ARENA model is in terms of quantities (kg). Though, in order to make it applicable for the integrated OWC model, it is necessary to model the inventory value (€) position over the simulated time.

To model the inventory value position \((€INV_i(t))\) over the simulated time we use the same cost price information per SKU \(i\) at time \(t\) \((C_i)\) as defined as input parameter in the AP module. Then to keep track of the inventory value position over time we define Formula 9:

\[ €INV(t) = \sum_{i \in N} QINV_i(t) \ast C_{it} \quad [9] \]
Before we may use the integrated OWC model for the analysis of the OWC performance, and eventually as simulation model that supports the future OWC target setting, the integrated OWC model needs to be validated given a certain tolerance, and verified by the company. As shown in assumption a. of Section 4.1.3., the ARENA model is driven by historical customer orders. This implies that if we take the same input parameters as in the real situation for the integrated OWC model and we run it for the historical demand data, then we should be able to accurately simulate the real situation. We define this ‘as is’ setup for the integrated OWC model as the ‘base model’.

In this chapter we aim to validate and verify the input-output transformation of the integrated OWC model. The validation tests consist of comparing the output from the real situation to the outputs from the model for the same set of input parameters. Data recorded while observing the system is made available to perform these tests. [Sargent, 2011]

For this chapter we follow the validation (i.e. validity check of the model), verification (feasibility check of the model), and accreditation (i.e. summary management decision; relevant considerations) processes, defined by Pace [2004]. In Section 5.1, we start-off by defining three main hypotheses with regard to the base models. In Section 5.2. we present for SC case study 1 (defined in Chapter 3) the input parameters and key assumptions for the base model, and the results of applying the integrated OWC model to the base model. The results include an analysis of means, and an analysis of variance. Thereupon, in Section 5.3 this is done for SC case study 2. Lastly, in Section 5.4. we draw conclusions with regard to the validation, verification, and accreditation of the integrated OWC model. The validation sub-section (5.4.1.) in the last section is based on statistically hypothesis testing of the results found in Sections 5.2. and 5.3. This chapter focuses on the approval or rejection of the three main hypotheses.

### 5.1. Hypotheses base models

We hypothesize that the base models simulate an overall OWC position that is lower than the actual historical OWC levels, because the simulation model would maximize operational efficiency, whereas in reality we expect to find operational inefficiencies. In other words, the simulation model should stick to its policies in all circumstances, whilst in real situations planners can make mistakes or consciously deviate from policies due to unforeseen events.[Singh, 2009]

**Hypothesis 1.1:** The base models based on historical demand data simulate an overall OWC position that is statistically lower than the actual historical OWC levels. Due to correlation between the two variables (see Section 5.2. and 5.3.) we test the difference between the two variables.

\[
\begin{align*}
H_{1:0}: \text{the actual measure of OWC} &- \text{the integrated OWC model measure of OWC} > 0 \\
H_{1:1}: \text{the actual measure of OWC} &- \text{the integrated OWC model measure of OWC} <= 0
\end{align*}
\]
In Section 2.3, we have defined a bottom-up OWC methodology to determine the zero base minimal OWC values for each of the OWC elements (Inventories, AR, and AP). The results of these methods are shown in the descriptions of the SC case studies in Chapter 3. We expect that the integrated OWC model gives different results at specific moments in time due to different OWC variances and patterns. However, in the long run these effects would average out and it is expected to give similar results. Hence, we further hypothesize that the base models simulate an overall OWC position that are statistically indistinguishable from the sum of all bottom-up values for each of the OWC elements.

**Hypothesis 1.2:** The base models based on historical demand data simulate an overall OWC position that is statistically indistinguishable from the sum of all bottom-up values for each of the OWC elements.

\[ H_{2:0}: \text{the integrated OWC model measure of OWC} = \text{the sum of all bottom-up OWC values}; \]
\[ H_{2:1}: \text{the integrated OWC model measure of OWC} \neq \text{the sum of all bottom-up OWC values}. \]

Finally, we hypothesize that the OTIF performances of the base models based on historical demand data are statistically indistinguishable from the real historical OTIF performances of the businesses within scope, because the integrated OWC model aims to simulate this accurately.

**Hypothesis 1.3:** The OTIF performances of the base models based on historical demand data is similar to the real historical OTIF performances.

\[ H_{3:0}: \text{the integrated OWC model measure of OTIF} = \text{the actual measure of OTIF}; \]
\[ H_{3:1}: \text{the integrated OWC model measure of OTIF} \neq \text{the actual measure of OTIF}. \]

In next two sections we aim to describe the base scenarios (base models) for the two supply chain case studies shown in Chapter 3. Thereafter, in Section 5.4.1. the first two hypotheses are statistically tested by using t-tests. The last hypothesis is tested by making use of face validity techniques.

### 5.2. Base scenario supply chain case study 1

SC case study 1 (see Section 3.1.) is the two-step production process following processes 1 through 2 or 1 through 3, with three stocking points A, B, and C. Moreover, it is characterized by a proportion MTS/MTO of roughly 60/40.

**5.2.1. Key assumptions and input parameters of the base model**

This section focuses on showing that the base model scenario for SC case study 1 is appropriate and realistic. This sub-section shows the key assumptions made and the input parameters set, in order to create the baseline simulation.
For SC case study 1 we make the following key assumptions:

a. All customer orders are deterministic and based on historical data, including all SKUs within this supply chain scope except specialty products (+/- 20% of all SKUs) for a time period of two years and two months (01.2012 – 03.2015).

b. All forecasts per SKU are deterministic and based on historical data.

c. Production step 1, see Figure 5 in Section 3.1.1., continuously produces intermediate products resulting in a deterministic flow from stocking point A to B in kilograms per day.

d. The percentage internal orders are deterministic and based on the historical data.

e. The cost price per SKU is deterministic and based on the historical data.

f. All end product SKUs are produced through either production step 2 or production step 3. There are no replenishments on end products done by external parties.

g. There is one raw material SKU that is the precursor material of the intermediate products. The BOM for each intermediate product consist of solely this raw material in the proportion 1:1.

h. All options to pay early in the AP module are deterministic and set to 0 \( (EP_j = 0 \text{ for all } j \mid j \in J) \)

i. Payment terms to external suppliers and customer are deterministic.

j. Payment terms to internal suppliers and customers are zero.

Moreover, the main input parameters for SC case study 1 are set as shown below in Table 1. For parameter definitions of the AP module see Section 4.2.1., of the inventory module see Section 4.1.2., and of the AR module see Section 4.2.2. In the inventory module the input parameter ROP is the total sum of all SKUs, and the input parameters MLS, FP, BS, GRPT, CO are averages of all SKUs.

Table 1: Input parameters baseline integrated OWC model SC case study 1

(This table is omitted for confidential reasons)

5.2.2. Results Integrated OWC model supply chain case study 1

Before showing the results, the right representative time should be chosen for the validation of the results. Figure 11 shows the total values of the inventory position, the AR position, and the AP position over the simulated time for SC case study 1. It can be seen that the system is stable around day number 423 (date: 1-3-2014) until day 760 (date: 31-01-2015). Therefore, we define a warm-up period of 423 days and a number or representative days of 337 days. When simulating the %OWC over the representative time we find the results presented in Figure 12.
The next two sub-sections show the mean results and variance results. In Section 5.4. these finding are interpreted and the three main hypotheses are statistically tested based on these results.

5.2.2.1. Mean results supply chain case study 1

The results of the simulation run of the integrated OWC model with the baseline input parameters are presented in Table 2. This table shows that the average %OWC over the representative time for this base model is equal to 25.8% if measured daily, and is equal to 25.4% if only measured at the end of each month belonging to the representative time period. The %OWC KPI, which is the OWC as percentage of 3rd party Sales, is defined in formula 1.1 in Section 2.1.3. On daily basis, the 25.8% consists of -1.2% OWC AP, 18.5% OWC INV, and 8.4% OWC AR. On end-of-month basis, 25.4% consists of -1.2% OWC AP, 18.1% OWC INV, and 8.6% OWC AR.

For the bottom-up values for each of the elements we use the bottom-up calculations, and for the real figures we use actual data from year 2014. This corresponds to the representative time except for January 2014. Table 2 shows the results of the bottom-up values for each of the OWC elements as result of the methodology applied in Chapter 3. These values correspond to the figures in Appendix B. The real figures also correspond with values in Appendix B. For the real inventory level of 2014 it can be seen in Figure 37 (Appendix B) that without the specialty products (campaign products) the %OWC INV was equal to 17.8% (= 18.2% - 0.4%), and according to the bottom-up model we find a %OWC INV of 16.5% (= 16.7% - 0.2%). This is the result of assumption a., Section 5.2.1. Furthermore, Figure 38 in Appendix B shows that the %OWC AR for the real figures in 2014 was %15.1, and the bottom-up %OWC AR for 2014 is 10.2%. Finally, the %OWC AP requires some modifications as result of assumption g.,
Section 5.2.1. This is due to the fact that only one raw material is considered in the system, and this is mostly bought from an internal supplier (anonymous). There don't exist AP positions on internal supplies, as payment terms are set to zero. Though, in case of an out-of-stock situation at the internal supplier, then the company decides to buy the raw material from a ‘back-up’ external supplier. In 2014 this has happened for roughly 13% of the company’s raw material supplies. This has resulted in a %OWC AP on the raw material supplies of -0.51%. This -0.51% is also taken as substitute of the bottom-up %OWC AP value.

Hence, taking all results together, we find that for SC case study 1 the real figures based on the end-of-month positions showed 7.0% higher average %OWC than the results of the integrated OWC model. This corresponds to a relative difference of -21.6% of the simulation results versus the real figures. Further, we find that the sum of the bottom-up values of each of the OWC elements shows a daily average of 0.4% higher than the daily average of results of the integrated OWC model. This corresponds to a relative difference of -1.6% of the integrated OWC model results versus the bottom-up calculations.

Table 2: OWC validation report supply chain case study 1

<table>
<thead>
<tr>
<th>%OWC AP (%)</th>
<th>Integrated OWC model</th>
<th>Real Figures</th>
<th>Bottom-up</th>
<th>Dev. from Real Figures</th>
<th>Dev. from Bottom-up</th>
<th>Difference [%]</th>
<th>Difference [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Avg [%]</td>
<td>-1.2%</td>
<td>-1.2%</td>
<td>-0.5%</td>
<td>-0.5%</td>
<td>0.7%</td>
<td>0.7%</td>
<td>1.377</td>
</tr>
<tr>
<td>EOMonth Avg [%]</td>
<td>18.5%</td>
<td>18.1%</td>
<td>17.8%</td>
<td>16.5%</td>
<td>-0.2%</td>
<td>-2.0%</td>
<td>0.013</td>
</tr>
<tr>
<td>%OWC INV [%]</td>
<td>8.4%</td>
<td>8.6%</td>
<td>15.1%</td>
<td>10.2%</td>
<td>6.5%</td>
<td>1.8%</td>
<td>-0.433</td>
</tr>
<tr>
<td>%OWC AR [%]</td>
<td>25.8%</td>
<td>25.4%</td>
<td>32.4%</td>
<td>26.2%</td>
<td>7.0%</td>
<td>0.4%</td>
<td>-0.216</td>
</tr>
<tr>
<td>%OWC [%]</td>
<td>25.8%</td>
<td>25.4%</td>
<td>32.4%</td>
<td>26.2%</td>
<td>7.0%</td>
<td>0.4%</td>
<td>-0.216</td>
</tr>
</tbody>
</table>

Finally, we find an On Time in Full (OTIF) percentage in our integrated OWC model of 89.2%, whilst the OTIF in the time period 1-3-2014 through 31-01-2015 has been on average 92.7% (Table 3). This implies that the integrated OWC model showed a difference of -3.8% versus the real figures. For the OTIF formula, see sub-Section 2.1.3.

Table 3: OTIF validation report supply chain case study 1

<table>
<thead>
<tr>
<th>Integrated OWC model</th>
<th>Real figures</th>
<th>Deviation</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>OTIF</td>
<td>89.2%</td>
<td>92.7%</td>
<td>-3.5%</td>
</tr>
</tbody>
</table>

5.2.2.2. Variance results supply chain case study 1

To support the statistically hypothesis testing of hypothesis 1.1 we construct the variance report shown in Table 4. The simulated %OWC per end-of-month is tested against the actual end-of-month %OWC of the company. Between these two variables, it is expected to find high correlations. This correlation is
Therefore, we created the variance report for the difference between the simulated %OWC per end-of-month and the actual end-of-month %OWC of the company. A 95%-confidence interval is presented around this difference in %OWC. The [a,b] interval is constructed as presented in the article by Sargent [2014]:

\[ a = \mu - t_{\alpha/2,n-1} \frac{\sigma}{\sqrt{n}} \quad \text{and} \quad b = \mu + t_{\alpha/2,n-1} \frac{\sigma}{\sqrt{n}} \]  \[10\]

Where, \( n \) is the number of end-of-months, \( \mu \) is the simulated mean difference per end-of-month, \( \sigma \) is the simulated standard deviation of the difference per end-of-month, and \( t_{\alpha/2,n-1} \) is the critical value from the t-distribution for the given level of significance and \( n-1 \) degrees of freedom. It is shown that the 95%-confidence interval around the mean difference is [11.04%, 13.57%].

![Figure 13: %OWC simulated and actual %OWC per end-of-month](image)

**Table 4: Variance report of the difference in %OWC simulated vs. actual figures based on end-of-month figures**

<table>
<thead>
<tr>
<th>n</th>
<th>( \mu )</th>
<th>( \sigma )</th>
<th>Confidence coefficient</th>
<th>Margin</th>
<th>Lower bound (a)</th>
<th>Upper bound (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>12.31%</td>
<td>2.14%</td>
<td>1.96</td>
<td>1.27%</td>
<td>11.04%</td>
<td>13.57%</td>
</tr>
</tbody>
</table>

Furthermore, to support the statistically hypothesis testing of hypothesis 1.2 we construct the variance report presented in Table 5. The simulated %OWC mean is tested against the fixed bottom-up %OWC value. The number of simulations is one (n=1) due to the fact that integrated OWC model is historical demand data driven. This implies that the simulation of the base model always simulates the same %OWC. Therefore, a 95%-confidence interval is presented around the simulated mean %OWC per day. The [a,b] interval is constructed according to Formula 10. Table 5 indicates that the 95%-confidence interval around the simulated mean %OWC is [22.47%,29.09%].

<table>
<thead>
<tr>
<th>n</th>
<th>( \mu )</th>
<th>( \sigma )</th>
<th>Confidence coefficient</th>
<th>Margin</th>
<th>Lower bound (a)</th>
<th>Upper bound (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25.78%</td>
<td>1.69%</td>
<td>1.96</td>
<td>3.31%</td>
<td>22.47%</td>
<td>29.09%</td>
</tr>
</tbody>
</table>

![Table 5: Variance report of %OWC measured daily](image)
Finally, it is impossible to compute the variance of the OTIF, since the simulation gives the same OTIF performance for each simulation run. Though, we test hypothesis 1.3 by face validity, and given a certain tolerance level. This is presented in sub-Section 5.4.1.

5.3. Base scenario supply chain case study 2
SC case study 2 is the two-step production process following processes 1-2, with three stocking points A, B, and C (see Section 3.2.). Moreover, it is characterized by a sole MTO structure.

5.3.1. Key assumptions and input parameters of the base models
For SC case study 2 we made the following key assumptions:

a. All customer orders are deterministic and based on historical data, including all SKUs within this supply chain scope for a time period of two years and two months (01.2012 – 03.2015).

b. All forecasts per SKU are deterministic and based on historical data.

c. The percentage internal orders are deterministic and based on the historical data.

d. The cost price per SKU is deterministic and based on the historical data.

e. All end product SKUUs are produced through production step 2 (see Figure 6, sub-Section 3.2.1.). There are no replenishments on end products done by external parties.

f. There is one raw material SKU that is the precursor material of intermediate products. The BOM for each intermediate product consist of solely this raw material in the proportion 1:1.

g. All options to pay early in the AP module are deterministic and set to 0 ( EP_j = 0 for all j | j ∈ J)

h. Payment terms to external suppliers and customer are deterministic.

i. Payment terms to internal suppliers and customers are zero.

The main input parameters for SC case study 2 are set as shown below in Table 6. For parameter definitions of the AP module see Section 4.2.1., of the inventory module see Section 4.1.2., and of the AR module see Section 4.2.2. Similarly to SC case study 1, the ROP is the total sum of all SKUs, and the input parameters MLS, FP, BS, GRPT, CO are averages of all SKUs.

Table 6: Input parameters baseline integrated OWC model SC case study 2
(This table is omitted for confidential reasons)

5.3.2. Results Integrated OWC model supply chain case study 2
As shown in SC case study 1, the right representative time should be chosen for the validation of the results. Figure 14 shows the total values of the total inventory position, the AR position, and the AP position over the simulated time for SC case study 2. It can be seen that the system is stable throughout the entire simulation time. This is most likely due to the completeness of master data. Therefore, for the sake of clarity it is chosen to create results for all days in 2014. Hence, we define a warm-up period of 365 days (1-1-2014) and a number or representative days of 365 days (final date: 31-12-2014). When simulating the %OWC over the representative time we find the results presented in Figure 15.
The next two sub-sections show the mean results and variance results. In Section 5.4 these findings are interpreted and the three main hypotheses are statistically tested based on these results.

Figure 14: Total inventory position (€), AR position (€), and AP position (€) over simulated time in SC case study 2

Figure 15: %OWC position over representative time for SC case study 2

5.3.2.1. Mean results supply chain case study 2

The results of the simulation run of the integrated OWC model with the base scenario input parameters are presented in Table 7. This table shows that the average %OWC over the representative time for this base model is equal to 14.9% if measured daily, and is equal to 14.3% if only measured at the end of each month belonging to the representative time period. On daily basis, the 14.9% consists of -1.3% OWC AP, 6.0% OWC INV, and 10.2% OWC AR. On end-of-month basis, the 14.3% consists of -2.3% OWC AP, 6.4% OWC INV, and 10.2% OWC AR.

For the real figures and bottom-up computations we refer to year 2014. Table 7 shows the results of the bottom-up computations and real figures. They correspond with the values in Appendix C. For the real inventory level of 2014 it can be seen in Figure 41 (Appendix C) that the %OWC INV was equal to 5.4%, and according to the bottom-up %OWC INV it could have been 5.3%. Furthermore, Figure 44 in Appendix C shows that the %OWC AR for the real figures in 2014 was 10.8%, and the bottom-up %OWC AR for 2014 is 11.3%. Finally, the %OWC AP requires some modifications as result of assumption f. (Section 5.2.1.). This is due to the fact that also in this SC case study there is only one raw material considered in the system, which is mostly bought from an internal supplier. Again, there don’t exist AP positions on internal supplies. Though, in case of out-of-stock situation at the internal supplier, then the company decides to buy the raw material from a ‘back-up’ external supplier. In 2014 this has
happened for roughly 18% of the company's raw material supplies. This has resulted in a %OWC AP on raw material supplies of -1.14%. This -1.14% is also taken as substitute of the bottom-up %OWC AP value.

Table 7: OWC validation report supply chain case study 2

<table>
<thead>
<tr>
<th></th>
<th>Integrated OWC model</th>
<th>Real Figures</th>
<th>Bottom-up</th>
<th>Dev. from Real Figures</th>
<th>Dev. from Bottom-up</th>
<th>Difference [%]</th>
<th>Difference [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>%OWC AR [%]</td>
<td>10.2%</td>
<td>10.2%</td>
<td>10.8%</td>
<td>11.3%</td>
<td>0.6%</td>
<td>1.1%</td>
<td>-0.056</td>
</tr>
<tr>
<td>%OWC INV [%]</td>
<td>6.0%</td>
<td>6.4%</td>
<td>5.4%</td>
<td>5.3%</td>
<td>-1.0%</td>
<td>-0.7%</td>
<td>0.185</td>
</tr>
<tr>
<td>%OWC AP [%]</td>
<td>-1.3%</td>
<td>-2.3%</td>
<td>-1.1%</td>
<td>-1.1%</td>
<td>1.2%</td>
<td>0.1%</td>
<td>1.033</td>
</tr>
<tr>
<td>%OWC [%]</td>
<td>14.9%</td>
<td>14.3%</td>
<td>15.1%</td>
<td>15.5%</td>
<td>0.8%</td>
<td>0.5%</td>
<td>-0.052</td>
</tr>
</tbody>
</table>

In summary, we find that for SC case study 2 the real figures based on the end-of-month positions showed an 0.8% higher average %OWC than the results of the integrated OWC model. This implies a relative difference of -5.2% of the simulation results versus the real figures. Further, we find that the sum of the bottom-up values of each of the OWC elements shows a daily average that is 0.5% higher than the daily average of results of the integrated OWC model. This corresponds to a relative difference of -3.4% of the integrated OWC model results versus the bottom-up calculations.

Finally, in our integrated OWC model we find an On Time in Full (OTIF) percentage of 91.8%, whilst the OTIF in the time period 1-1-2014 through 31-12-2014 was on average 95.0% (Table 8). This implies that the integrated OWC model showed a relative difference of -3.4% versus the real figures.

Table 8: OTIF validation report supply chain case study 2

<table>
<thead>
<tr>
<th>OTIF</th>
<th>Integrated OWC model</th>
<th>Real figures</th>
<th>Deviation</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>91.8%</td>
<td>95.0%</td>
<td>-3.2%</td>
<td>-0.034</td>
<td></td>
</tr>
</tbody>
</table>

5.3.2.2. Variance results supply chain case study 2

Table 9 shows the variance report of SC case study 2 to support the statistically hypothesis testing of hypothesis 1.1. In Figure 16 it can be seen that the first months until August delineate the correlation statement about the two variables simulated %OWC per end-of-month and the actual end-of-month %OWC of the company. However, in the real situation the OWC position starts to decline towards the year’s end, whilst the simulated OWC position keep increasing. This is due to the fact that in reality in this time period the BU puts a lot of pressure on customers to make the outstanding payment, such that the accounts receivable position could be lowered substantially for the end-of-the-year financial reports. The integrated OWC model is not expected to simulate these special types of practices, and thus, doesn't follow this decline in the last months of 2014 [Sargent, 2011]. Therefore, to test hypothesis 1.1 for SC case study 2 we only test the observed difference between the simulated %OWC
per end-of-month and the actual end-of-month %OWC of the company for the months January through August.

The 95%-confidence interval is constructed by making use of Formula 10 (sub-Section 5.2.2.). Where, \( n \) is the number of end-of-months, \( \mu \) is the simulated mean difference per end-of-month, \( \sigma \) is the simulated standard deviation of the difference per end-of-month, and \( t_{\alpha/2,n-1} \) is the critical value from the t-distribution for the given level of significance and \( n-1 \) degrees of freedom. It is shown in Table 9 that the 95%-confidence interval around the mean difference is [4.60%, 6.76%].

![Figure 16: %OWC simulated and actual %OWC per end-of-month](image)

**Table 9: Variance report of the difference in %OWC simulated vs. actual figures based on end-of-month figures**

<table>
<thead>
<tr>
<th>( n )</th>
<th>( \mu )</th>
<th>( \sigma )</th>
<th>Confidence coefficient</th>
<th>Margin</th>
<th>Lower bound (a)</th>
<th>Upper bound (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>5.68%</td>
<td>1.56%</td>
<td>1.96</td>
<td>1.08%</td>
<td>4.60%</td>
<td>6.76%</td>
</tr>
</tbody>
</table>

Moreover, Table 10 shows the variance report to support the statistically hypothesis testing of hypothesis 1.2. The simulated %OWC mean is tested against the fixed bottom-up %OWC value. The \([a,b]\) interval is constructed according to Formula 10 (pg. 35). Table 10 indicates that the 95%-confidence interval around the simulated mean %OWC is [11.38%, 18.48%].

**Table 10: Variance report of %OWC measured daily**

<table>
<thead>
<tr>
<th>( n )</th>
<th>( \mu )</th>
<th>( \sigma )</th>
<th>Confidence coefficient</th>
<th>Margin</th>
<th>Lower bound (a)</th>
<th>Upper bound (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>14.93%</td>
<td>1.81%</td>
<td>1.96</td>
<td>3.55%</td>
<td>11.38%</td>
<td>18.48%</td>
</tr>
</tbody>
</table>

Similarly to SC case study 2, it is impossible to compute the variance of the OTIF. The alternative way of testing this hypothesis is presented in sub-Section 5.4.2. In the next section we draw conclusions for the validation and verification of the input-output transformation of the integrated OWC model. We finish next section with the accreditation of the integrated OWC model.
5.4. Conclusions validation, verification & accreditation

Validation, verification, and accreditation are processes that help to ensure that models and simulations are correct and reliable [Pace, 2004]. First of all, in Section 5.4.1. we concentrate on the validation of the integrated OWC model. To support the validation section we test the hypotheses about the base model, described in Section 5.1., with the mean and variance results found in Section 5.2. and 5.3. Thereupon, Section 5.4.2. focuses on the verification of the integrated OWC model, in which we argue if the right simulation model has been built. Finally, in Section 5.4.3. we summarize the management decision on the approval of the integrated OWC model. Both the verifications and the validation sections are taken into consideration in the accreditation decision.

5.4.1. Validation

Pace [2004] defines two aspects of validation: conceptual validation (when the anticipated fidelity of the conceptual model is assessed) and results validation (when results from the implemented model are compared with appropriate referent to demonstrate that the model can in fact support the intended use). The conceptual model is elaborately described in Chapter 4 ‘Integrated OWC Modeling Approach’. During the development of the conceptual model, it is frequently assessed by the stakeholders within the firm under study. The conceptual model is successfully approved in this respect.

The results validation is based on hypotheses 1.1, 1.2, and 1.3 in Section 5.1. The following three paragraphs each focus on one of the three hypotheses, respectively. For hypothesis 1.1, in addition to the 95%-confidence intervals, the p-values are calculated using MS Excel’s left-tailed student distribution test (x=0), and a significance level (α) of 5% [Banks, Carson, Nelson, & Nicol, 2010; Sargent, 2011]. The statistical test for hypothesis 1.2 is performed by using the 95%-confidence interval and a two-tailed student distribution test with a significance level (α) of 5% [Banks, Carson, Nelson, & Nicol, 2010; Sargent, 2011]. And, the statistical test for hypothesis 1.3 is based on face validity techniques [Holden, 2010].

First of all, the results of the integrated OWC model for SC case study 1 shows a 95%-confidence interval around the mean difference between the simulated end-of-month %OWC positions and the real historical end-of-month %OWC levels of [11.04%, 13.57%]. For SC case study 2 this interval is [4.60%, 6.76%]. The left-tailed student distribution test (x=0) for SC case study 1 showed a p-value of $8.74 \times 10^{-10}$. The left-tailed student distribution test (x=0) for SC case study 2 shows a p-value of 0.0041. Hence, we accept the null-hypotheses ($H_{1.0}$’s) of hypothesis 1.1 for both SC case studies. This means that the difference of the real historical end-of-month %OWC levels minus the simulated end-of-month %OWC positions is significantly higher than 0.

Secondly, the results of the integrated OWC model for SC case study 1 shows a 95%-confidence interval around the simulated mean %OWC (daily) of [22.47%, 29.09%]. For SC case study 2 this interval is [11.38%, 18.48%]. The sum of all bottom-up values of each of the OWC elements denotes 26.2% (p-value=0.576) and 15.5% (p-value=0.591), for each SC case study respectively. Thus, based on statistical ground, we can safely accept the null-hypothesis ($H_{2.0}$) of hypothesis 1.2 for each of the SC case study. Bottom-up %OWC values approximately lie in the middle of each interval, and are thus statistically indistinguishable from the simulated %OWC level by the integrated OWC model.
Lastly, the integrated OWC model indicates a 3.8% and a 3.4% lower OTIF performance than the actual OTIF performance for SC case study 1 and 2, respectively. It is impossible to define the variance of the OTIF KPI, because the integrated OWC model is historical demand driven. This implies every simulation run with the 2014 demand data results in the same OTIF performance. Though, it can be seen that the OTIF simulation has a face validity, because it simulates the OTIF performance within a 5% tolerance. Hence, the null-hypothesis \((H_{1.0})\) of hypothesis 1.3 is accepted according to face validity techniques. [Holden, 2010]

Based on positive (statistical) test results of the hypotheses 1.1, 1.2, and 1.3 we conclude that the integrated OWC model is validated successfully.

### 5.4.2. Verification

Research questions 3 and 4 in the assignment formulation (Section 1.3.) are the two main questions that need to be addressed by the integrated OWC model. The simulation model simulates the %OWC level of a firm in the simulated time. Tables 2 (sub-Section 5.2.2.) and 7 (sub-Section 5.3.2.) show that the integrated OWC model simulates a %OWC level for both SC case studies in this study that is close to bottom-up computations. For both case studies, hypothesis 1.2 is tested positive. Hence, the integrated OWC model simulates the minimum required OWC level given the tactical and strategy boundaries of the firm, and by doing so it succeeds to answer research question 3. Moreover, the input parameters of the model are easily changeable such that the integrated OWC model is very suitable for sensitivity analyses. The sensitivity analysis of OWC main drivers is done in Chapter 6 and successfully address research question 4. In sum, all specifications are included in the model.

### 5.4.3. Accreditation

Accreditation is a management decision that may include schedule and other considerations as well as technical verification and validation information [Pace, 2004]. Responsible stakeholders have indicated to accept the integrated OWC model as tool to address research question 3 and 4, and they have allowed it for scale-up. This scale-up provides answer to research question 5 and be presented in Chapter 8.

Though, there are a few observations that need to be taken into consideration before using the integrated OWC model. We summarize these observations as follows:

- The integrated OWC model simulates in both case studies a %OWC AP position that is higher than bottom-up values and real figures.
- The integrated OWC model simulates in both case studies a %OWC INV position that is higher than bottom-up values and real figures.
- The integrated OWC model simulates in both case studies a %OWC AR position that is lower than bottom-up values and real figures.
- The integrated OWC model simulates in both case studies an OTIF performance that is lower than real OTIF performance.

Hence, there seems to exist a consistent deviation in each of the simulated OWC elements and the OTIF performance. Therefore, it is unrecommendable to pin oneself on absolute results, but rather
look for the appropriate interpretation of results. For instance, if we find consistently 1% lower %OWC INV than the referent, then we might argue to filter out this 1% deviation when defining the appropriate absolute %OWC INV value.

Based on this chapter we conclude that the integrated OWC model is suitable for running simulations with the main objective to simulate the OWC performance and OTIF performance. As mentioned in sub-Section 5.4.2. it is used to execute a sensitivity analysis of the OWC main drivers. The sensitivity analyses for various OWC main drivers is presented in the next chapter. The demand parameters are analyzed more elaborately on the impact on OWC and OTIF performances in Chapter 7.
Six

Sensitivity Analysis of OWC Main Drivers

In Chapter 2 it is illustrated what drivers majorly influence the OWC in each of the OWC elements, and eventually via these OWC element influence the total OWC level of a firm (see Figures 30, 31, and 32 in Appendix A). In this chapter we select a couple of these main drivers and see their impact on the %OWC levels and OTIF performance. All analyses are done for both SC case studies. All results are presented in relative terms. This implies that any main driver (x-axis) is changed on a multiplication factor scale, in which 1 refers to the initial input parameter setting. The y-axis presents the relative change in the outcome parameter.

Firstly, in Section 6.1. we analyze one-dimensional changes, which implies that only one input parameter is changed and other input parameters are kept constant. As part of the one-dimensional analysis, we take as main OWC drivers (input parameters) the reorder point, minimal lot size, production wheel length, the percentage external (3rd party) sales, and payment run cycle setting for AP. Secondly, in Section 6.2. we analyze two-dimensional changes, which implies that two input parameters are changed and the other input parameters are kept constant: in this thesis we consider the change of the reorder points and payment term on AR at the same time. All findings in this chapter are found by using historical demand data.

6.1. One-dimensional main OWC driver changes

6.1.1. Reorder points
The reorder point is the sole main driver of the OTIF performance, and it also greatly influences the OWC position of a firm. For the company the reorder points and safety stocks are undistinguishable. In this section the reorder point (ROP) for SC case study 1 is changed from 0 times the initial ROP setting until 2 times the initial ROP, with step size 0.2. The ROP for SC case study 2 is changed from 1 times till 2 times the initial ROP setting. It starts at 1 because this SC case study operates without safety stocks (initial ROP is zero), and ROPs cannot be lower than zero. Furthermore, the step size in kilograms for SC case study 2 is set equal to the step size in kilograms for SC cases study 1. ROPs are equally changed per SKU.

Reorder point vs. %OWC

Figure 17 shows the ROP versus the relative difference in %OWC. It can be seen that for both SC case studies the ROP and %OWC follow a strong positive linear relationship. The correlation coefficients are respectively 0.406 and 0.117. This implies that if the ROP levels are set 1 time higher, then the %OWC increases by 40.6% and 11.7%, for each of the SC case studies respectively. Moreover, Figure 46 in Appendix D.1. shows that this relationships is caused by a strong linear relationship between %OWC INV and ROP (ROP vs. %OWC AR or %OWC AP showed no correlation). The observation that the ROPs only affect the %OWC INV explains why the ROP has a greater effect on the %OWC in SC case study 1 than in SC case study 2. Namely, because as shown in Tables 2 (sub-Section 5.2.2.) and 7
(sub-Section 5.3.2.) the stake of %OWC INV in the total %OWC is significantly bigger in SC case study 1 (i.e. 18.5% INV in 25.8% total %OWC) than in SC case study 2 (i.e. 6.0% INV in 14.9% total %OWC). Hence, the bigger the stake of the inventories in the total OWC, the higher the impact of ROP on the total OWC.

**Figure 17: ROP vs. %difference in %OWC**

**Reorder point vs. OTIF**

Furthermore, Figure 18 shows the ROP versus the relative difference in OTIF. It indicates in both case studies that the ROP and OTIF follow a strong positive relationship. Besides it is non-linear, because it reaches a limit in which no further OTIF improvement can be obtained with increases in reorder points. This graph in combination with Figure 17 enables the firm to select desired level for one of the three variables considered (ROP, %OWC, or OTIF) and find the corresponding values of the other two variables.

**Figure 18: ROP vs. %difference in OTIF**
**Ratio $\Delta OTIF \,(\%) / \Delta OWC \,(\%)$**

It seems that SC case study 2 can obtain a higher increase in OTIF per percentage extra money invested in OWC than SC case study 1. This statement is delineated by Figure 19. First of all, the KPI %OWC has a perfect linear relation with the OWC value in euros if the 3rd party sales is the same. This implies that each relative $\Delta$%OWC is equal to relative $\Delta$OWC value in euros, and thus, each ROP setting corresponds linearly to an OWC value (€). In fact this is expected, because putting one euro extra in safety stock should lead to one euro extra in OWC. This linearity is underlined by Figure 17. This linearity implies that we may assume that the ratio ‘percentage difference in OTIF over percentage difference in %OWC’ is equal to the ratio ‘percentage difference in OTIF over percentage difference in OWC value (€)’. In sum, Figure 19 shows that per percentage extra money invested in OWC both OTIFs increase, that the positive relative change in OTIF diminishes per euro extra invested, and that SC case study 2 shows a consistently higher percentage increase in OTIF per percentage extra money invested in OWC than SC case study 1.

![Figure 19: ROP vs. ratio ‘difference in OTIF/ difference in %OWC’](image)

**Key conclusions ROP sensitivity**

It is shown that ROP has a strong positive linear effect on the %OWC of a firm. This effect is stronger when the stake of %OWC INV in the total %OWC is bigger. Furthermore, it is shown that the ROP has strong non-linear effect on the OTIF of a firm with a certain maximum OTIF performance.

Finally, SC case study 1 represents a business that produces according to mixed Make to Stock and Make to Order principles (see Section 3.1.), and SC case study 2 represents a firm that produces fully according to a Make to Order principle (see Section 3.2.). Expectedly, and shown in this study, the strategic decision to operate according to a MTO structure leads to a significant lower stake of inventories in the total OWC of the firm. Hence, in a MTO driven business, the ratio ‘percentage difference in OTIF over percentage difference in OWC value (€)’ is expected to be bigger than in a MTS driven business. Though, worth mentioning, if ROPs are applied in a MTO driven business, then the business starts to shift to a business driven by both MTO and MTS production orders.
6.1.2. Minimal lot sizes

Manufacturers are often faced with a minimal lot size (MLS) in production or in procurement. It is often set in such a way that it minimizes costs [Shine & Chin, 2013]. MLS is defined in Section 2.2. as main driver of OWC. In this section the MLS for SC case study 1 and SC case study 2 are changed from 0.2 times the initial MLS setting up to 2 times the initial MLS, with step size 0.2. MLSs are equally changed per SKU. The initial MLS of SC case study 2 is substantially lower than the initial MLS of SC case study 1.

**MLS vs. %OWC**

Figure 20 shows the MLS versus the relative difference in %OWC. The figure shows that both relationships are positive and non-linear. In SC case study 1 there exist a significantly stronger relationship between the two variables than in SC case study 2. Figure 47 in Appendix D.2. indicates that this positive relationship is caused by the effect of MLS on OWC in inventories.

Increasing the MLS leads to more cycle stock, because of higher production lot sizes. If we look closely at the results of SC case study 1, it seems that this non-linear relationship only exists for minor small MLSs. It gets seemly linear for higher MLSs. This is explained by the fact that MLS changes only affect those sales orders that are lower than the MLS, and thus, are produced in a lot size equal to the MLS. The amount of sales orders lower than the MLS is smaller for low MLS settings, and therefore, the business would be less affected on OWC if MLS settings are low. For instance, if the MLS is extremely high, then all production lot sizes are equal to the MLS. Increasing the MLS would affect all production lot sizes. If, hypothetically, the MLS is extremely low, than increasing the MLS would only affect a few of the production lot sizes. Hence, until the MLS is greater than the highest sales order quantity, the effect of MLS on OWC is compounding, and thereafter, this is linearly increasing. This also explains the stronger effect of MLS on the OWC in SC case study 1 than in SC case study, because as mentioned before, the MLS is substantially bigger in SC case study 1 than in SC case study 2.

![Figure 20: MLS vs. difference in %OWC](image-url)
**MLS vs. OTIF**

Moreover, it is shown in Figure 21 that MLS might lead to minor changes in the OTIF, but there is no significant relation observed. Moreover, changes are small and within an observed maximum change of 3.1% and observed minimum change of -1.7%.

![Figure 21: MLS vs. difference OTIF](image)

**Key conclusions MLS sensitivity**

In sum, the effect of MLS on OWC compounding until it reaches a point in which all production lot sizes are equal to the MLS. Thereafter, the effect of MLS on OWC is linear. This implies that if the initial MLS of a business is low, then the business’ OWC is relatively less affected by MLS increases. Finally, the effect of MLS on the OTIF performance of a firm is non-significant.

6.1.3. **Production wheel length**

Figure 30 in Appendix A indicates that the production wheel length is also one of the OWC main drivers. The bucket size (BS) per SKU (see Section 4.1.) is defined in the integrated OWC model, which is equal to the production wheel length in days. In this sub-section, we vary for both SC case studies the BS from 0.2 until 2 times the initial BS. BSs are changed equally per SKU. In the initial situation, SC case study 1 has the same BS for all SKUs, but in SC case study 2 not all BS are the same per SKU.

Figure 48 in Appendix D.3 shows the production wheel length (bucket size) versus the difference in %OWC. For SC case study 2 a line is observed that shows linear properties, but SC case study 1 shows a rather clear non-significant relation between the two variables. Similarly, Figure 49 in Appendix D.3. shows that the non-significant relationship also exists for the relation between BS and the difference in OTIF. We conclude this section by stating that we cannot find a significant effect on %OWC or the OTIF performance due to the production wheel length.

6.1.4. **Proportion internal sales /external sales**

Demand from 3rd party sales is often observed by a firm and cannot be changed, with the exception of rejecting demand. Meanwhile, multinational firms often decide to sell goods internally as well. Internal customer sales typically do not have payment terms. Moreover, firms often define the %OWC as the
main OWC KPI. For more information see sub-Section 2.1.3. Due to the fact that this KPI is applied, it is important for the firm to understand the influence of the percentage 3rd party sales when setting OWC targets. Therefore, in this section we manipulate the demand by randomly nominating a sales order as a sales order from a 3rd party customer. The percentage 3rd party sales are varied from approximately 50% till 100%. For each SC case study, 1 times the percentage 3rd party sales corresponds to the initial situation. The initial percentages of 3rd party sales are roughly 75% and 95%, for the two SC case studies respectively.

**Percentage 3rd party customer sales vs. %OWC**

Figure 22 shows that the relationship between percentage 3rd party sales and the relative difference in OWC is strong, negative, and non-linear. The observed diminishing effect might be expected, because the variable 3rd party sales is in the denominator of the %OWC KPI, see Formula 1.1. Furthermore, Figures 50 and 51 in Appendix D.4. show that this effect is caused by the effects of percentage 3rd party sales on OWC in AP, and OWC in inventories. OWC in AR remains the same, which implies that the relative change in AR is equal to the relative change in the percentage 3rd party sales. Finally, we observe that the relation is stronger in SC case study 1 than in SC case study 2, which is due to the fact that the affected variables %OWC INV and %OWC AP have a greater contribution to the total %OWC in SC case study 1 than in SC case study 2. Hence, firms that are characterized by lower proportions of AR are less affected the percentage 3rd party sales.

![Figure 22: Percentage 3rd party sales vs. the %OWC KPI](image)

**Key conclusions percentage 3rd party customer sales orders sensitivity**

First of all, if there is no priority applied to either 3rd party customer sales orders or internal customer sales orders, then the percentage of 3rd party sales should not affect the OTIF performance of a firm. Though, the percentage of 3rd party sales does have an diminishing effect on the %OWC of the firm, and the effect is greater for businesses characterized by high proportions of inventories and AP in the total amount of OWC.
Finally, it can be observed that if a business group consists of two business units (in this case SC case studies 1 and 2), then it can reduce the total %OWC of the business group by strategically decide to produce the internal sales orders at the business unit that operates with lower proportions of inventory. As mentioned before, expectedly, and shown in this study, the strategic decision to operate according to a MTO structure, versus a MTS structure, leads to a significant lower stake of inventories in the total OWC of a business. Hence, a MTO driven business is lesser affected by the changes in the percentage 3’d party customer sales over total sales. Therefore, as a business group that strives to lower the %OWC KPI, it is theoretically better to deliver the internal sales order (i.e. sales order between the BG’s BUs) from the business unit that is set up according to the MTO structure.

6.1.5. Payment run cycle settings on payables

Within the field of AP management, there are two important variables next to the payment term that affect the average AP position over time. These two OWC main drivers are the ‘payment run cycle identifier (rci)’ and the ‘days in payment run cycle (PRC)’. Typically firms do not pay every day, but rather once in a specified number of days. We define (see 4.2.1.1.) this number of days at the company as the ‘days in payment run cycle (PRC)’. Hence, the company pays its suppliers every end of the PRC. A firm may choose to structurally pay its suppliers in the PRC that contains the payment due date (rci=0), or to structurally pay them in one PRC earlier (rci=1). The first decision would lead to mostly late payments to the supplier, and the latter decision would ensure that the purchasing firm always pays it suppliers in time.

**Days in payment run cycle (PRC) vs. %OWC**

Currently both SC case studies pay their creditors in the payment run cycle that surround the payment due date (rci = 0). This implies that they always pay late, and thus by increasing the days in the payment run cycle, the firm increases the overdue per payment. Figure 23 (next page) shows the relationship between the days in payment run cycle and the difference in %OWC is significant and negative linear. For SC case studies 1 and 2, the %OWC increases by 0.51% and 0.82% per day extra in the payment run cycle, respectively. Hence, the effect on the OWC in SC case study 2 is greater than in SC case study 1. This is due to the fact the AP element of OWC in SC case study 2 has a higher stake in the total OWC than in SC case study 1.

**Payment run cycle identifier (rci) vs. %OWC**

Finally, Figures 52 and 53 in Appendix D.5. show that the average AP position lowers by changing the run cycle identifier from 0 (rci = 0) to 1 (rci = 1), in which the change means that the firm starts paying creditors one run cycle before the payment due date instead of the payment run cycle that contains the payment due date. This change would increase the supplier’s satisfaction, because they would always receive payments in time. The consequence would be a 2.5% and 4.9% lower average OWC position, per SC case study respectively.
Key conclusions payment run cycle setting sensitivity

We find that businesses can influence the OWC level by changing the payment run cycle setting (i.e. rci and PRC), but these effects are relatively low in comparison with other OWC main drivers. It only affects the business’ AP position. Thus, businesses that are characterized by higher stakes of AP in the total OWC are more affected by changes of the payment run cycle settings.

6.2. Two-dimensional changes: AR payment term & safety stock

So far the impact of one-dimensional changes of certain input parameters on OWC and OTIF performances are presented. These insights add value in the field of operations management, supply chain management, and trade credit management. The analyses of one-dimension OWC main driver changes are obvious and mostly support decision making with regard to one of the three OWC elements (AR, INV, or AP). However, OWC management concerns integrated decision making as well. The two-dimensional changes may look less obvious but indicate what can be achieved if OWC decision making concerns main driver changes in more than one areas (AR, INV, and AP).

AR payment term & reorder points

A good example of two-dimensional changes of OWC main drivers in OWC management is simultaneously changing the reorder points in kilograms and AR payment terms (customer payment term) in days. By making use of the integrated OWC model we analyze scenarios in which the firm offers a higher service (in terms of OTIF performance) to its customers, but in return receives a faster payment. The objective of this sub-section is to find the resulting OWC and OTIF performances when these two variables are changed.

Figures 54 and 55 in Appendix D.6. show the results for SC case study 1 and SC case study 2, respectively. The two OWC main drivers are represented by the x-axis (ROP) and by the size and pattern fill of the circle (AR). The ROP is varied from 0.6 times the initial ROP until 1.4 times the initial ROP. The AR payment term (PT) is varied from 0.4 times the initial payment term until 1.6 times the initial payment term, see the figures’ legends. Unrealistic scenarios are excluded, such as negotiating a higher
PT and increasing the ROP (i.e. increase the service levels). Expectedly, the OTIF performance is only dependent on the ROP and not the PT. Therefore, we find one OTIF performance per ROP setting, which also correspond to the OTIF performances as result of ROP, defined in Figure 18, sub-Section 6.1.1.

**Customer payment term (AR) & Reorder point vs. %OWC**

If we consult the results of SC case study 1 presented in Figure 54 (Appendix D.6.), then we find what kind of customer payment term reduction should be realized per increased ROP scenario in order to have a similar level of OWC. For instance, if we look at the scenario in which the ROP are set 1.2 times as high as the initial situation, then we find that the OTIF performance is increased by 1.8%, and that with 0.78 times the initial PT, the %OWC is preserved. This implies that if the company offers a 1.8% higher service to its customers, and meanwhile negotiates a payment term reduction greater than 22%, then the company is better off. Furthermore, to preserve the OWC level, it is computed that for ROP changes of -40%, -20%, +20%, and +40%, a payment term change is required of +60.5%, +32.7%, -21.8%, and -45.1%, respectively.

Moreover, Figure 55 (Appendix D.6.) shows the results with regard to SC case study 2. As is indicated in Section 6.1. the ROP of SC case study 2 can only be increased, since in the initial situation they operate without safety stocks (i.e. ROP of the system). It can be seen immediately that in SC case study 2 the changes in ROP can be compensated with smaller changes in the customer payment term than in SC case study 1. To keep an equal total OWC level, it is calculated that for ROP changes of +20%, +40%, and +60%, a payment term change is required of -2.7%, -5.7%, and -9.9% respectively. In return the business could offer the customer a 1.9%, 2.7%, and 3.5% higher OTIF performance, respectively.

**Key conclusions customer payment term (AR) & reorder points sensitivity**

In sum, we find that the OWC position of SC case study 2 can be significantly faster compensated by negotiating payment terms if the ROP is changed, than in SC case study 1. This is due to the fact that the AR position in SC case study 2 has a significantly higher stake in the total OWC than in SC case study 1. Finally, it can be seen that businesses can even reduce their OWC position by optimizing the balance between the customer payment term and the ROP. For instance, SC case study 1 could strategically decide to increase the ROPs by 20%, therefore offer her customers a 1.8% higher OTIF performance, knowing that in return they could negotiate a reduction in payment terms higher than 22%. Then, they would lower the total OWC of the business.
An important OWC driver of any manufacturing firm is the variable demand. A manufacturer employs OWC to fulfill the demand requests of its customers [Muckstadt & Sapra, 2010; Caballero, Teruel, & Solano, 2014]. Therefore, this chapter’s sole focus lies on the impact analysis of changing demand parameters (i.e. mean demand and volatility of demand) on the OWC and OTIF performances. Before doing so, we need to model the demand, since in the previous chapters only historical demand data is used. Only SC case study 1 is chosen to be analyzed. We use a tool, written in Excel’s VBA, to create a piecewise empirical distribution based on observations for both the demand inter-arrival times and the quantities per sales order. We use an empirical demand distribution since no significant fit can be found with a theoretical distribution (all significances below 0.02). We later use the tool to create numerous samples of demand.

In Section 7.1, we present the classification of the SKUs. In Section 7.2, we focus on the introduction of piecewise empirical distributions and the development of the two piecewise empirical distributions for the two discrete variables inter-arrival times and the quantities per customer sales order. Thereupon, we validate the integrated OWC model for the created empirical distributions in Section 7.3. Then, in Section 7.4, we develop methods to manipulate one of the two demand parameters (i.e. mean demand or volatility of demand) whilst preserving the other. Finally, we perform a sensitivity analysis of the mean demand and the volatility of demand in the last section.

### 7.1. Classification of the stock keeping units

In order to develop a probability distribution that models the demand for all SKUs we choose to classify the SKUs into different classes according to their value (i.e. cost price) and according to the state (intermediate- and end products). The reason behind this value-based classification is that the cost price of a SKU drives the simulated OWC AP position and simulated OWC INV position of the firm (see Formulas 7.1 and 9); the firm’s prices are entirely cost price driven, and thus, the simulated OWC AR position is cost price driven as well. Moreover, it is important to distinguish the SKUs according to their state because the intermediate products are the precursor materials for the end products (note: external sales also exist on intermediate products). Hence, the classification of SKUs based on their cost price and state suffices for a OWC simulation. This results in the four classes of SKUs as follows:

<table>
<thead>
<tr>
<th>Class</th>
<th>Class cost price type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Intermediate products; low cost price</td>
</tr>
<tr>
<td>2</td>
<td>End-product; low cost price</td>
</tr>
<tr>
<td>3</td>
<td>End-product; Medium cost price</td>
</tr>
<tr>
<td>4</td>
<td>End-product; High cost price</td>
</tr>
</tbody>
</table>
7.2. Empirical distributions per class

By consulting the demand master data of SC case study 1 it can directly be observed that the demand within each class behaves according to a stochastic inter-arrival time and a stochastic quantity of demand. In IBM’s Analytics-software, SPSS, these two discrete random variables (i.e. inter-arrival time and quantity) are tested for theoretical distributions, based on distribution fitting techniques presented in the book by Field [2009]. None of these tests resulted in significant results (all test significances lower than 0.02). Therefore, we continue this section by using the observed data themselves to specify directly a distribution rather than fitting a theoretical distribution to the data. This is called an empirical distribution. [Law, 2007]

Empirical distributions are the solutions for modelers that simply cannot find a theoretical distribution that fits the date adequately. The empirical distribution always finds a perfect fit with the observation. However, the disadvantage is that it might become more challenging for variance analyses of the distribution [Law, 2007]. Though, this challenge is solved by the methods developed in Section 7.4.

In sub-Section 7.2.1. we present the theory behind the piecewise empirical distribution. Thereupon, sub-Section 7.2.2. shows the specification of the empirical distributions for the inter-arrival times per class. Finally, in sub-Section 7.2.3. we specify the empirical distributions per class for the quantity of demand.

7.2.1. From observations to piecewise empirical distribution

The two random variables ‘inter-arrival time’ and ‘quantity of demand’ are discrete variables and can each be assigned to several specified intervals (called grouped data). All observations are grouped into k adjacent intervals \([a_0, a_1], [a_1, a_2], ..., [a_{k-1}, a_k]\), so that the \(j\)th interval contains \(n_j\) observations, where \(n_1 + n_2 + ... + n_k = n\), and \(X_j\) tells the discrete value that belongs the interval. Each interval \(X_1, X_2, ..., X_k\) is used to define the probability mass function (pmf) and piecewise cumulative distribution function (cdf) by first sorting the \(X_j\)'s into increasing order. [Law, 2007]

We assume that \(a_j\)'s are equally spaced for each random variable, implying that each interval is equal in size and that \(X_j\) is equal to \((a_j - a_{j-1})/2\). Then, the empirical pmf \(P(X=X_j)\) could be defined as follows:

\[
P(X = X_j) = \frac{n_j}{n} \quad [11.1]
\]

And, the piecewise empirical cdf \(G(X_j)\) could be specified as follows:

\[
G(X_j) \begin{cases} 
0 & X_j < a_0 \\
G(X_{j-1}) + \frac{n_j}{n} & \text{if } a_{j-1} \leq X_j \leq a_j \\
1 & X_j \geq a_k
\end{cases} \quad [11.2]
\]
7.2.2. Empirical distribution of the inter-arrival times
The empirical pmf and cdf for the inter-arrival times in number of days are presented in Table 16 in Appendix E.1. The table indicates for each class the number of observations, and the probability and cumulative probability of the \( j \)th interval (\( X_j \)).

7.2.3. Empirical distribution of the quantity per sales order
The empirical pmf and cdf the quantity per sales order in kilograms are presented in Table 17 in Appendix E.1. The table indicates for each class the number of observations, and the probability and cumulative probability of the \( j \)th interval (\( X_j \)). The intervals that do not contain observations are excluded from the table.

7.3. Validation of the empirical distributions
Based on the empirical distribution of the inter-arrival times (7.2.2.) we can create a sample of sales order arrivals to the system. Then, per sales order arrival we can create the quantity in kilograms, based on the empirical distribution of the quantity per sales order (7.2.3.). These two empirical distributions are assumed to be independent of each other. Before using these empirical distributions to analyze the sensitivity of the mean demand and the variance of the demand, we need to validate the results of the integrated OWC model based on these empirical distribution samples. This validation section is organized similar to Chapter 5. In order to statistical test the appropriateness of the empirical distributions we define hypotheses 1.4 and 1.5 as follows:

**Hypothesis 1.4:** The base model based on empirical demand data simulates an overall OWC position that is statistically indistinguishable from the overall OWC position simulated by the base model based on the historical demand data.

\[ H_{4.0}: \text{the integrated OWC model measure of OWC using the empirical demand distributions} = \text{the integrated OWC model measure of OWC using historical data} \]

\[ H_{4.1}: \text{the integrated OWC model measure of OWC using the empirical demand distributions} \neq \text{the integrated OWC model measure of OWC using historical data} \]

**Hypothesis 1.5:** The base model based on empirical demand data simulates an OTIF performance that is statistically indistinguishable from the OTIF performance simulated by the base model based on the historical demand data.

\[ H_{5.0}: \text{the integrated OWC model measure of OTIF using the empirical demand distributions} = \text{the integrated OWC model measure of OTIF using historical data} \]

\[ H_{5.1}: \text{the integrated OWC model measure of OTIF using the empirical demand distributions} \neq \text{the integrated OWC model measure of OTIF using historical data} \]

We created 10 samples (n=10) to test these hypotheses. The results are shown in Table 18 in Appendix E.2. In order to find the 95% confidence intervals we applied Formula 10 (sub-Section 5.2.2.2). This resulted in the 95% confidence interval of the simulated %\%OWC(\%) of [23.2\%, 26.8\%] and the 95% confidence interval of the simulated OTIF(\%) of [88.9\%, 91.8\%]. The results are shown in Tables 12 and 13 (next page), respectively.
Table 12: 95% confidence interval of the simulated %OWC (using empirical distributions)

<table>
<thead>
<tr>
<th>n</th>
<th>μ</th>
<th>σ</th>
<th>Confidence coefficient</th>
<th>Margin</th>
<th>Lower bound (a)</th>
<th>Upper bound (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>25.0%</td>
<td>2.8%</td>
<td>1.96</td>
<td>0.90%</td>
<td>23.2%</td>
<td>26.8%</td>
</tr>
</tbody>
</table>

Table 13: 95% confidence interval of the simulated OTIF performance (using empirical distributions)

<table>
<thead>
<tr>
<th>n</th>
<th>μ</th>
<th>σ</th>
<th>Confidence coefficient</th>
<th>Margin</th>
<th>Lower bound (a)</th>
<th>Upper bound (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>90.4%</td>
<td>2.4%</td>
<td>1.96</td>
<td>0.75%</td>
<td>88.9%</td>
<td>91.8%</td>
</tr>
</tbody>
</table>

The simulated %OWC and OTIF based on the historical demand data (2014) is 25.8% and 89.2%, respectively (see sub-Section 5.2.2.). It can be seen that these two results both lie within the corresponding 95% confidence interval. In addition to that, if performed a two-tailed student t-test, then we find a p-value for the hypothesis 1.4 (x=25.8%) of 0.367 and for the hypothesis 1.5 (x=89.2%) of 0.216. This would imply that we accept both the null-hypotheses H₄₀ and H₅₀ (p-values > 0.05). This means that the integrated OWC model based on the demand data from the empirical distribution simulates a %OWC and OTIF performance similar to the results of the integrated OWC model based on historical demand data. Therefore, we may use the empirical distributions of the inter-arrival times of the sales orders, and of the quantity per sales order, for the sensitivity analysis of the demand parameters.

7.4. Methods empirical distribution manipulation

To analyze the impact of changing empirical distribution parameters we present in this section three methods that support in this regard. Firstly we develop Method I for the manipulation of the mean of the empirical demand distribution while preserving its volatility. Secondly, we define Method II to reduce the volatility in the empirical demand distribution and preserve the mean. And lastly, we develop Method III to increase the volatility whilst preserving the mean demand. Before we do so, we make one important assumption in this thesis with regard to the empirical distributions:

a. The mean of the empirical distribution is equal to the mid-point of the interval that contains the mean. i.e. μ₀ = X̅₀.

Where, μ₀ is the mean of the initial empirical distribution, and X̅₀ is the mid-point of the interval that contains the mean in the initial empirical distribution.

7.4.1. Method I: Manipulating the mean of the empirical distribution whilst preserving the variance

If we desire to manipulate the mean of this distribution whilst keeping an equal variance, then we need to shift the entire pmf function proportionally to the right or left. This implies that the histograms that can be made from pmf moves over the x-axis, whilst preserving it initial shape. [Law, 2007]

We define the change, m(x), as a function of the mean of each initial empirical distribution, X₀, and the multiplication factor (x) applied (see Equation 12.1). The change indicates how many units the pmf and cdf are moved to the right (positive change) or left (negative change). Then, each new interval,
$X_{1j}(x)$, as a function of the multiplication factor $(x)$ and the initial interval, $X_{0j}$, is found by Equation 12.2. In this way the intervals are shifted to the right or left proportionally to $x$, whilst preserving their probabilities, implied by Equation 12.3.

\[ m(x) = (x - 1)\bar{X}_0 \quad [12.1] \]
\[ X_{1j}(x) = X_{0j} + m(x) \quad [12.2] \]
\[ P(X = X_{1j}) = P(X = X_{0j}) \quad [12.3] \]

This method changes the mean by the multiplication factor $x$, since the equation below applies:

\[ \mu_1 = \sum_j P(X = X_{1j})X_{1j} = \sum_j P(X = X_{0j})(X_{0j} + (x - 1)\bar{X}_0) = \sum_j P(X = X_{0j})X_{0j} + \sum_j P(X = X_{0j})(x - 1)\bar{X}_0 \]
\[ \mu_1 = \mu_0 + (x - 1)\mu_0 = x\mu_0 \quad [12.4] \]

Where, $\mu_0$ is the initial mean, and $\mu_1$ is the new mean. Furthermore, it preserves the variance since Equation 12.4 is true and the following equation applies:

\[ \text{Var}_1 = \sum_j P(X = X_{1j})(X_{1j} - \bar{X}_1)^2 = \sum_j P(X = X_{0j})((X_{0j} + (x - 1)\bar{X}_0) - (\bar{X}_0 + (x - 1)\bar{X}_0))^2 \]
\[ \text{Var}_1 = \sum_j P(X = X_{0j})(X_{0j} - \bar{X}_0)^2 = \text{Var}_0 \quad [12.5] \]

Where, $\bar{X}_1$ is the interval that contains the mean of the new empirical distribution (equal to $\bar{X}_0$, proven in Equation 12.4), $\text{Var}_0$ is the initial variance, and $\text{Var}_1$ is the new variance.

7.4.2. Methods II & III: Manipulating the variance in the empirical distribution whilst preserving the mean

The previous method shows a way to shift the mean to the right or left on the x-axis, whilst the variance remains constant. This sub-section focuses on the contrary, i.e. changing the variance of the empirical distributions, whilst preserving the mean. This implies that the histograms that can be made from a pmf function needs to be manipulated such that the probability mass around the mean reduces (for more variance) or increases (for less variance). [Law, 2007]

The variance of a discrete random variable $X$ with a probability mass function is the expected value of the squared deviation from the mean ($\bar{X}$). The formula for the initial variance ($\text{Var}_0$) of the empirical distribution of the quantity per sales order can be expressed as follows:

\[ \text{Var}_0 = \sum_j P_0(X = X_j)(X_j - \bar{X}_0)^2 \quad [13.1] \]

We present a consolidated method (a combination of Method II and III) in which we take mass from the outside and compress it into the center (Method II), or take mass from the center of the pmf
and spread it out (Method III), such that we manipulate the variance and preserve the mean of the empirical distribution.

**Method II: Reducing the volatility and preserve the mean of the empirical distribution for all** $0 \leq x < 1$

Figure 24 illustrates Method II. To reduce the variance of the empirical distribution we can multiply each initial probability $P_0(X = X_j)$ with the factor $(1-x)$ for $0 \leq x < 1$, except for $P_0(X = \bar{X}_0)$. The probability of the interval that contains the mean of the distribution, i.e. $P_0(X = \bar{X}_0)$, is equal to its initial probability plus all the reductions of the other probabilities. This results in the new probabilities $P_1(X = X_j)$ as shown in the Equation 13.2 below.

$$P_1(X = X_j) = \begin{cases} xP_0(X = X_j) & : j \neq J \text{ and } 0 \leq x < 1 \\ P_0(X = X_j) + (1 - x) \sum_{j \neq J} P_0(X = X_j) & : j = J \text{ and } 0 \leq x < 1 \end{cases}$$ [13.2]

Where $J$ is the index that indicates the $j^{th}$ interval that contains the mean ($J = j : X_j = \bar{X}_0$). By making use of the new probabilities, we find that the mean demand is preserved since the Equations 13.3 through 13.6 apply:

$$\mu_1 = \sum_j P_1(X = X_j)X_j = \sum_{j \neq J} xP_0(X = X_j)X_j + \left(P_0(X = \bar{X}_0) + (1 - x) \sum_{j \neq J} P_0(X = X_j)\right)\bar{X}_0$$ [13.3]

$$\sum_{j \neq J} P_0(X = X_j)X_j = P_0(X \neq X_j)\bar{X}_0 \quad \text{(since } \bar{X}_0 \text{ divides the probability mass into 2 equally sized masses)}$$ [13.4]

$$\mu_1 = xP_0(X \neq X_j)\bar{X}_0 + \left(P_0(X = \bar{X}_0) + (1 - x) P_0(X \neq \bar{X}_0)\right)\bar{X}_0$$

$$= xP_0(X \neq X_j)\bar{X}_0 + \bar{X}_0 - P_0(X \neq \bar{X}_0)\bar{X}_0 + (1 - x) P_0(X \neq \bar{X}_0)\bar{X}_0 = \bar{X}_0$$ [13.5]

$$\mu_1 = \mu_0 \quad \text{for all } 0 \leq x < 1$$ [13.6]

Moreover, we find a new variance ($Var_1$) of the empirical distribution equal to $x$ times the initial variance ($Var_0$), since Equation 13.6 is true and Equations 13.7 through 13.9 apply:

$$Var_1 = \sum_j P_1(X = X_j)(X_j - \bar{X}_1)^2$$ [13.7]

\[\text{Figure 24: illustration of Method II}\]
\[
= \left( \sum_{j \neq \emptyset} x P_0(X = x_j) (X_j - \bar{X}_0)^2 \right) + \left( P_0(X = \bar{X}_0) + (1 - x) \sum_{j \neq \emptyset} P_0(X = x_j) (\bar{X}_0 - \bar{X}_0)^2 \right) \tag{13.8}
\]

\[\text{Var}_1 = x \text{Var}_0 \quad \text{for all } 0 \leq x < 1 \tag{13.9}\]

**Method III: Increasing the volatility and preserve the mean of the empirical distribution for all \(1 < x \leq 2\)**

To increase the volatility in the empirical distribution it becomes a bit more complicated. Figure 25 illustrates the method that is developed to increase the volatility, whilst preserving the mean. Figure 25 shows a simple hypothetical pmf histogram with the seven intervals \(X_1\) to \(X_7\), where \(X_4\) contains the mean of the distribution. In words, we want to take mass from a \(X_i\)'s probability and equally divide it over the \(X_j\) that contains the mean (i.e. \(\bar{X}_0\)), and the \(X_k\) that lies one time farther from the mean. In the hypothetical example we use an multiplication factor of \(x=1.33\), such that we take one third of the probability mass of \(X_3\) and add half of it to \(X_4\) (mean) and half of it to \(X_5\) (one time farther), with each of the masses illustrated by the areas \(b\) and \(c\), respectively. Subsequently, we take one third of the probability mass of \(X_6\) and we add half of it (area \(b\)) to \(X_4\) again, and half of it (area \(c\)) to the new \(X_6\) (one time farther).

This explained manipulation of the empirical distribution can only be done for all \(X_j \in X_\alpha\), where \(X_\alpha = \{X_0j \mid \bar{X}_0 < 2X_j\}\). This implies that if the difference between initial \(X_j\) and \(\bar{X}_0\) is greater than the size of \(X_\alpha\) then we cannot perform the manipulation, because it would add probability mass to a negative \(X_j\).

In sum, this method is formulated in the Equation 13.20 below, where \(x\) indicates the multiplications factor applied, \(X_\alpha\) is the set of affected \(X_i\)'s, and \(X_b\) is the set of non-affected \(X_i\)'s \((X_b = \{X_0j \mid \bar{X}_0 \geq 2X_j\}\)).

\[
P_1(X = x_{ij}) = \begin{cases} 
\frac{(x - 1)}{2} P_0(X = \left( X_{ij} - \frac{X_{ij} - \bar{X}_{ij}}{2} \right)) + (2 - x) P_0(X = \bar{X}_{ij}) : X_{ij} \in X_\alpha, j \neq j, \text{and } 1 < x \leq 2 \\
\frac{(x - 1)}{2} P_0(X = \left( X_{ij} - \frac{X_{ij} - \bar{X}_{ij}}{2} \right)) + P_0(X = \bar{X}_{ij}) : X_{ij} \in X_b, j \neq j, \text{and } 1 < x \leq 2 \\
P_0(X = \bar{X}_{ij}) + \frac{(x - 1)}{2} \sum_{X_{ij} \notin X_\alpha} P_0(X = \left( X_{ij} - \frac{X_{ij} - \bar{X}_{ij}}{2} \right)) : j = j \text{ and } 1 < x \leq 2
\end{cases} \tag{13.20}
\]
Before we use Method 3 we show that the mean of the empirical distribution is preserved and the variance is manipulated for a scenario in which all \( X_j \)'s are affected, implying that the size of the smallest \( X_j \) is bigger than the difference the mean and that \( X_j (\forall X_j; \overline{X}_{0j} < 2X_{0j} ) \).

**Mean of the empirical distribution is preserved**

To find the relation between \( x \) and the mean of the empirical distribution after applying Method 3 we first look at what happens to one bar that contains \( X_j \). The weighted average mean of that bar after using Method 3 can be calculated with a reas (mean), c (moves one time farther), and d (preserved) as weightings (Figure 25):

\[
\frac{b\overline{X}_j + c(2X_j - \overline{X}_j) + dX_j}{b + c + d} = \frac{x - 1}{2} P_0(X = X_j)\overline{X}_j + \frac{x - 1}{2} P_0(X = X_j)(2X_j - \overline{X}_j) + (2 - x)P_0(X = X_j)X_j}{P_0(X = X_j)} = X_j
\]

for all \( X_j \)'s and \( 1 \leq x \leq 2 \) \[13.21\]

Then, it can be shown that the initial mean is preserved after applying Method 3, since we find that the weighted average of all areas (\( b, c, \) and \( d \)) after applying the Method III for all \( X_j \)'s, i.e. \( \mu_1 \), is equal to the initial mean, i.e. \( \mu_0 \). This is shown in the following Equations 13.22 through 13.24:

\[
\mu_1 = \sum_{j \neq j} \left( \frac{x - 1}{2} P_0(X = X_j)\overline{X}_0 + \frac{x - 1}{2} P_0(X = X_j)(2X_{0j} - \overline{X}_0) + (2 - x)P_0(X = X_j)X_{0j} \right)
\]

\[
+ P_0(X = \overline{X}_0)\overline{X}_0 \]

\[13.22\]

\[
\mu_1 = \sum_{j \neq j} \left( P_0(X = X_j)X_{0j} \right) + P_0(X = \overline{X}_0)\overline{X}_0 \quad (following\ Equation\ 13.21) \]

\[13.23\]

\[
\mu_1 = \sum_j \left( P_0(X = X_j)X_{0j} \right) = \mu_0 \]

\[13.24\]

**Variance in the empirical distribution is increased by \( x \)**

To find the relation between \( x \) and the variance in the empirical distribution after applying Method 3 we first focus again on what happens to one bar that contains \( X_j \). However, now we show the weighted average variance of only the areas \( b \) and \( c \) (Figure 25):

\[
\frac{b(\overline{X}_j - \overline{X}_j)^2 + c\left( (2X_j - \overline{X}_j) - \overline{X}_j \right)^2}{b + c} =
\]
\[
\frac{x-1}{2}P_0(X = X_j)(\bar{X}_j - \bar{X}_1)^2 + \frac{x-1}{2}P_0(X = X_j)((2X_j - \bar{X}_j) - \bar{X}_1)^2
\]
\[
= 2(X_j - \bar{X}_j)^2
\]

for all \(1 \leq x \leq 2\) \[13.25\]

Thereupon, it can be shown that the new variance is equal to \(x\) times the initial variance after applying Method 3, since we find that the weighted average variance of all areas \((b, c,\) and \(d)\) for all \(X_j\)'s, i.e. \(\mu_1\), is equal to \(x\) times the weighted average variance of all initial areas for all \(X_j\)'s, i.e. \(\mu_0\). This can be proven since Equation 13.25 is true, and Equations 13.26 through 13.28 apply:

\[
\text{Var}_1 = \sum_{j \neq 1} \left( \frac{x-1}{2}P_0(X = X_j)((2X_{0j} - \bar{X}_0) - \bar{X}_1)^2 + \frac{x-1}{2}P_0(X = X_j)(\bar{X}_0 - \bar{X}_1)^2 \right)
\]
\[
+ (2 - x)P_0(X = X_j)((X_{0j} - \bar{X}_1)^2) + P_0(X = X_j)(\bar{X}_0 - \bar{X}_1)^2
\]
\[
= \sum_{j \neq 1} \left( 2(x - 1)P_0(X = X_j)(X_{0j} - \bar{X}_0)^2 + (2 - x)P_0(X = X_j)(X_{0j} - \bar{X}_0)^2 \right)
\]
\[
\text{Var}_1 = \sum_{j \neq 1} xP_0(X = X_j)(X_{0j} - \bar{X}_0)^2 = x\text{Var}_0
\]

7.5. Sensitivity analysis of demand parameters

To analyze the impact of changing demand parameters on OWC and OTIF performances we analyze two parameters of the empirical distribution of the quantity per sales order: (1) the mean demand, and (2) the variance of demand. The empirical distribution of the inter-arrival times remain unchanged. We show how the OWC and OTIF performances are affected by varying the mean of the empirical distribution of quantity per sales order through Method I in sub-Section 7.5.1. Thereupon, the impact of changing the variance of the empirical distribution of quantity per sales order via Methods II and III is presented in sub-Section 7.5.2.

7.5.1. Sensitivity mean demand

In this sub-section we vary the multiplication factor, \(x\), in Method I, from 0.95 to 1.10 with step size 0.025 (in Equations 12.1, 12.2, and 12.3). Each factor indicates an increase or decrease of \((x-1)\) in the mean demand (kg). The range is kept small due to the high impact of the quantity of demand on the OWC and OTIF performances. For each factor applied to all four empirical distributions we create 15
samples (n=15), and take the sample average of the OWC and OTIF performances. The results are presented below.

**Mean of demand vs. %OWC performance**

First of all, when we look at Figure 56 in Appendix E.3. we find that the annual sales to 3rd party customers relates seemly linear to the mean of the demand distribution. However, this figure also shows that the OWC value (€) decreases when the mean demand either decreases or increases. The result of these two changing variables ‘annual 3rd party sales’ and ‘OWC value (€)’ is the relative difference in %OWC presented in Figure 26 below. Per point we show (µ ; σ₁5), i.e. the average change in %OWC (µ), and the standard deviation of the change in %OWC (σ₁5).

It can be seen that if the mean demand decreases, then the %OWC slightly increases. This is due to the fact that the OWC value (€) decreases, but the annual sales to 3rd party customers decreases in higher amounts (shown in Figure 56, Appendix E.3.). Furthermore, the effect of mean demand on %OWC is compounding. This is due to the fact that the OWC value (€) decreases, whilst the annual sales to 3rd party customer increases. Since the OWC value is the numerator and annual sales to 3rd party customers is the denominator in Formula 1.1 (sub-Section 2.1.3.), this leads to the compounding effect observed in Figure 26.

![Figure 26: mean demand vs. relative difference in %OWC](image)

We expect to find to find a positive linear relationship between the mean demand and the annual sales to 3rd party customers, but the decrease in OWC value as results of increasing the mean demand might seem unexpected. What might be the case, is that the increased mean demand pulls out all stock in the system, whilst the system has no capacity left to refill these stocks. If this were to be true, then it should involve a decreasing OTIF performance of the system. This is described in next paragraphs.

**Mean of demand vs. OTIF performance**

Figure 27 shows that increasing the mean demand leads to a lower OTIF performance and there exists a non-linear negative relation between these two variables. Per point in the chart we show (µ ;
σ₁₅), i.e. the average change in OTIF (µ), and the standard deviation of the change in OTIF (σ₁₅). As mentioned one paragraph earlier, this is most likely because the system has not sufficient capacity to fulfil all demand requests and simultaneously ensure the appropriate safety stocks per SKU.

Figure 27: mean demand vs. relative change in OTIF

**Key conclusions mean demand sensitivity**

SC case study 1 seems to be appropriately set up to maintain the current demand request. Decreasing the mean demand leads to less OWC in the system, but a higher %OWC. Increasing the mean demand also leads to less OWC in the system, and this effect is compounding, because the system’s capacity is not sufficient to handle the increased average demand size. This is delineated by the negative non-linear relation between the mean demand and the OTIF performance.

### 7.5.2. Variance of the empirical distribution of the quantity per sales order

In the remainder of this chapter we vary the multiplication factor x in Method II from 0 to 1, and in Method III from 1 to 2, with step size 1/3, for all four empirical distributions of the quantity of demand for each class. Each factor corresponds to a ‘variance change multiplier’ of the empirical quantity of demand distribution per class. This value is not always equal to x (shown Equation 13.28), since the number of affected $X_j$’s can alleviated the effect of Method 3, and because of the assumption that the mean demand is equal to the mid-point of the $X_j$ that contains the mean demand (assumption a.). Therefore, Table 14 contains the ‘variance change’ after numerical analyses (i.e. by manually computing the variance of demand, based on the new pmf). The weighted average is the total variance change of all four distribution, where the weightings are equal to the specific class’ mean demand divided by the total mean demand of all classes. This gives a good indication of the overall demand volatility change for all classes. For each of these volatility scenarios we run 20 samples (n=20) to create results. The results are presented in the next two sections.
Table 14: Variance change of the empirical quantity of demand distribution per class per applied factor x

<table>
<thead>
<tr>
<th>Factor (x)</th>
<th>0</th>
<th>0.33</th>
<th>0.67</th>
<th>1</th>
<th>1.33</th>
<th>1.67</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>0</td>
<td>0.33</td>
<td>0.67</td>
<td>1.28</td>
<td>1.47</td>
<td>1.65</td>
<td></td>
</tr>
<tr>
<td>Class 2</td>
<td>0</td>
<td>0.33</td>
<td>0.67</td>
<td>1.27</td>
<td>1.53</td>
<td>1.82</td>
<td></td>
</tr>
<tr>
<td>Class 3</td>
<td>0</td>
<td>0.33</td>
<td>0.67</td>
<td>1.26</td>
<td>1.51</td>
<td>1.75</td>
<td></td>
</tr>
<tr>
<td>Class 4</td>
<td>0</td>
<td>0.33</td>
<td>0.67</td>
<td>1.28</td>
<td>1.56</td>
<td>1.74</td>
<td></td>
</tr>
<tr>
<td>Weighted average</td>
<td>0</td>
<td>0.33</td>
<td>0.67</td>
<td>1.27</td>
<td>1.50</td>
<td>1.72</td>
<td></td>
</tr>
</tbody>
</table>

**Variance of demand vs. %OWC**

Figure 28 shows the simulated relation between the change in variances of the empirical quantity of demand distributions and the %OWC, based on the weighted average (wa) change as shown in Table 14. Per point we show \( (\mu ; \sigma_{20}) \), i.e. the average change in %OWC (\( \mu \)), and the standard deviation of the change in %OWC (\( \sigma_{20} \)). It can be observed that the variance of the demand quantity has a weak positive relation with the %OWC, and it shows aspects of linearity. Moreover, it can be seen that if all sales orders are equal to the mean demand (i.e. the variance is equal to zero), then SC case study 1 can realize a relative decrease in %OWC of 6.9% versus the initial %OWC.

![Figure 28: variance of demand vs. relative difference in %OWC](image)

**Variance of demand vs. OTIF**

Furthermore, Figure 29 shows that the variance of the empirical demand distributions relates strong, non-linear, and negative with the OTIF performance. Per point we show \( (\mu ; \sigma_{20}) \), i.e. the average change in OTIF (\( \mu \)), and the standard deviation of the change in OTIF (\( \sigma_{20} \)). If the variance of the quantities of the sales orders varies more, then the OTIF performance reduces. Furthermore, this negative effect is compounding.
**Key conclusions variance of demand sensitivity**

By applying the manipulated empirical quantity of demand distributions (varying the variance; preserving the mean) to the integrated OWC model, we find that the variance of the quantity demand distribution relates positively to the %OWC, and relates negatively to the OTIF performance. This implies that under lesser variance observed in the demand, the firm can be more efficient, providing a higher service to the customer whilst operating with less OWC. In contrast, an higher variance in the demand leads to a less efficient firm, providing customers with a lower service whilst operating with more OWC. This latter mentioned negative effect is compounding. In sum, it is worthwhile for a firm to emphasize the necessity of decreasing the volatility of the quantity demand in order improve the supply chain efficiency. Notwithstanding, these type of ‘volatility reduction practices’ lie within the responsibility of the sales department.

![Figure 29: variance of demand vs. relative difference in OTIF](image)
Conclusions, Implementation, & Reflection

We conclude this thesis by answering the first four research questions in Section 8.1. Thereupon, we describe the implementation of the integrated OWC model and the bottom-up model in Section 8.2. This provides answer to the last research question. Lastly, we focus on the limitation and we provide further research direction in Section 8.3.

8.1. Conclusions

Which model can be used to calculate the minimum required level of OWC?

In this thesis we define two different models that can be used to calculate the minimum required level of OWC: (1) the bottom-up model, and (2) the integrated OWC model. The first model explains an analytical and separate approach in which the minimum required OWC levels for each of the OWC elements (i.e. inventories, account receivables, and accounts payables) is computed from a theoretical perspective. The integrated OWC model is an integrated OWC simulation in which the total OWC level is explicitly simulated as result of input parameters.

The OWC drivers of the bottom-up OWC model are strategic and tactical decisions made by the company. For OWC in inventories this translates into the different stocking types chosen to apply, and if these stocking types are not static by nature (e.g. cycle stock and work in process stock), then the main decision variable must be defined (e.g. replenishment quantity for the cycle stock). For OWC in account receivables and in accounts payables, the OWC drivers are the negotiated payment terms and the sales order values (in AR) or purchase order values (in AP). In this model the key performance indicator, i.e. the dependent variable, is %OWC (i.e. OWC divided by third party customer sales).

The integrated OWC model (simulation) is also driven by the strategic and tactical decisions of a firm, but it simulates the independent variables, i.e. the business principles that define the strategic and tactical decision, explicitly. For instance, for the firm’s replenishment quantity, these independent variables are the min lot sizes, production wheel lengths, frozen periods, etc. Hence, the input (independent) variables of the integrated OWC model that drive the OWC of a firm are taken explicitly, whereas the bottom-up model’s OWC is implicitly driven by the independent variables. This enables the integrated OWC model to analyze the impact of OWC drivers on a higher level of detail. In addition to the dependent variable %OWC, this model also indicates the On Time In Full (OTIF) performance achieved according the independent variables. This helps the firm to find the appropriate balance between the customer satisfaction (OTIF) and OWC.

What is the current OWC performance on BU level?

This thesis focuses on two supply chain case studies. The first supply chain case study denoted a total %OWC of 31.2%\(^3\) in year 2014, in which 18.2% OWC existed in inventories, 15.1% existed in

\(^3\) Actual OWC figures are subject to modifications applied and explained in Chapter 3.
account receivables, and 2.1% existed in accounts payables. The second supply chain case study showed a %OWC of 13.5%\(^3\) in year 2014, in which 5.4% OWC existed in inventories, 10.8% existed in account receivables, and 2.7% existed in accounts payables.

**What is the minimum required OWC level given the tactical and strategic boundaries?**

1. **What is the bottom-up minimum required OWC in inventory, AR, and AP?**

   In order to answer this question we use the bottom-up model. For supply chain case study 1 we find a bottom-up total %OWC equal to 24.9%, defined by 16.7% in inventories, 10.2% in accounts receivables, and 2.0% in accounts payables. This implies a gap in operational efficiency of 6.6%. This gap is for approximately 75% caused by the efficiency gap in AR management. The efficiency gap in AR management is caused by two major bankrupt customers who still have outstanding sales payment, and it is caused by high amounts of overdue payments.

   For supply chain case study 2 we find a bottom-up total %OWC level equal to 13.5%, defined by 5.3% in inventories, 11.3% in accounts receivables, and 3.1% in accounts payables. This implies that SC case study 2’s performance in 2014 is equal to the bottom-up calculations.

2. **What is the integrated minimum required OWC level?**

   To answer this question we use the integrated OWC model. For the first supply chain case study we find an end-of-month average %OWC based on year 2014 of 25.4%, existing of 18.1% in inventories, 8.6% in accounts receivables, and 1.2% in accounts payables. Furthermore, when the integrated OWC model uses the empirical distributions for the demand, assuming 2014’s mean demand and variance of demand, then we find an average %OWC of 25.0%, existing of 17.4% in inventories, 9.0% in accounts receivables, and 1.4% in accounts payables. The modified real %OWC performance is 32.4%. Modifications are executed such that the referent complies with the assumptions made for the integrated OWC model. This implies a simulated gap in operational efficiency of 7.0% and 7.4%, respectively.

   The second case study is only analyzed according to historical master data and not according to empirical demand distributions. We find an end-of-month average %OWC based on year 2014 of 14.3%, defined by 6.4% in inventories, 10.2% in accounts receivables, and 2.3% in accounts payables. The modified real %OWC performance is 15.1%. This means a simulated gap in operational efficiency of 0.8%.

   Both approaches show that supply chain case study 2 performed better in terms of operational efficiency than supply chain case study 1 in year 2014. Furthermore, supply chain case study 2 requires a significantly lower %OWC level due to the tactical and strategic decisions of the firm. This strategic benefit is mainly caused by inventory management.

**What is the impact of OWC driver changes on the OWC level?**

The impact of OWC driver changes is analyzed with the integrated OWC model. Table 15 shows a summary of all findings from the sensitivity analysis in Chapter 6 and 7, where the second and third columns indicate the effect on the total %OWC and the OTIF, respectively. The definitions of the symbols used are as follows: ++ = strong positive related; + = weak positive related; -- = strong negative related; - = weak negative related; o = no significant relation. In addition, the star mark (*) indicates that
the two variables are linear related. All other cases which are not linear related have either a well-behaved compounding or diminishing effect, as can be seen in the graphs of Chapter 6 and 7.

Table 15: Summary findings sensitivity analysis of the OWC main drivers

<table>
<thead>
<tr>
<th>OWC driver</th>
<th>%OWC</th>
<th>OTIF</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reorder points</td>
<td></td>
<td></td>
<td>MTO driven businesses benefit more from reorder increases than in a MTS driven businesses, i.e. the ratio 'percentage difference in OTIF over percentage difference in OWC value (€)' is bigger.</td>
</tr>
<tr>
<td>Minimal lot sizes</td>
<td></td>
<td></td>
<td>The effect of MLS on the %OWC is compounding, because with higher levels of MLS, the number of production lot sizes equal to the MLS is bigger.</td>
</tr>
<tr>
<td>Production wheel length</td>
<td></td>
<td></td>
<td>There is no significant effect found on OWC or OTIF performances</td>
</tr>
<tr>
<td>Percentage third party sales</td>
<td></td>
<td></td>
<td>The effect is greater for businesses characterized by high proportions of inventories and AP in the total amount of OWC; A business group that strives to lower the overall %OWC KPI is theoretically better off by delivering the internal sales order (i.e. sales order between the BG’s BUs) from the business unit that is set up according to the MTO structure.</td>
</tr>
<tr>
<td>Days in payment run cycle</td>
<td></td>
<td></td>
<td>Businesses that are characterized by higher stakes of AP in the total OWC are more affected by changes in the payment run cycle settings</td>
</tr>
<tr>
<td>Payment run cycle identifier</td>
<td></td>
<td></td>
<td>Businesses that are characterized by higher stakes of AP in the total OWC are more affected by changes in the payment run cycle settings</td>
</tr>
<tr>
<td>Mean of demand distribution</td>
<td></td>
<td></td>
<td>If the capacity is almost saturated, then a lower mean demand observed leads to less OWC in the system, but a higher %OWC since the third party customer sales decreases more rapidly; then a higher mean demand observed also leads to less OWC in the system, and thus, an exponentially decreasing %OWC since the third party customer sales are increasing in addition.</td>
</tr>
</tbody>
</table>
| Variance of demand distribution|      |      | Less variance observed in the demand leads to a higher supply chain efficiency, providing a higher service to the customer whilst operating with less OWC; In contrast, a higher variance observed in the demand leads to a less efficient firm, providing customers with a lower service whilst operating with more OWC.
8.2. Implementation

**How to scale-up the models and methods to a larger scope?**

The objective of the firm under study is to scale-up all work done in this thesis to a larger scope in order to comprehensively set targets. This thesis is part of a company-wide OWC management improvement project, in which the implementation of the integrated OWC model plays a crucial role. In this section we describe our vision on how the model should be implemented in the company to serve its purpose, and by doing so, we provide answer to the last research question.

**Use the bottom-up OWC model for a business scope that cannot comply with the integrated OWC model’s assumptions**

This thesis shows that the bottom-up OWC model suffices in finding the gap in operational efficiency. The model can be used to analyze the current performance of a business and to find structural differences between business units as result of the company’s tactical and strategic decisions. Since the operational efficiency gap can also be found by the integrated OWC model, we recommend that during the scale-up, the bottom-up OWC model should only be used to analyze the current performance for either relatively less relevant business scopes to save time, or for business scopes that cannot comply with the assumptions of the integrated OWC model.

**Apply the integrated OWC model to improve OWC target settings; to give input to OWC optimization projects**

The integrated OWC model enables a company to analyze the OWC performance more thoroughly, since it simulates the OWC and service level performances based on all relevant input parameters in compliance with reality. In addition to a performance analysis, it enables the company to find the impact of OWC drivers (e.g. reorder points) on the total OWC. This enhances the company’s decision making in finding the right OWC optimization areas. Moreover, based on speculations, the company can use the integrated OWC model to analyze certain scenarios and predict future OWC changes. This supports the ultimate goal to set OWC targets more accurate and understandable.

**Use empirical demand distributions to cope with problems that might hinder the OWC target setting process due to the integrated OWC model’s historical demand data assumption**

Chapter 7 shows that the integrated OWC model’s assumption that all customer sales orders are historical can be ignored by creating the appropriate empirical distributions for the inter-arrival times and the quantity per sales order. The tool developed to create these empirical distribution should be used throughout the scale-up project to analyze and predict OWC changes as results of demand speculations.

**Appoint a team responsible for the use of the integrated OWC model with key users for each selected business scope**

To roll out the integrated OWC model over all desired business scopes, we recommend to appoint a key user per business scope who support his/her business to find the required OWC levels and predict the future. Moreover, the key user could support improvement/optimization projects by simulating the impact.
8.3. Limitations & Further research

The limitations of this thesis concern the integrated OWC model and the empirical demand distribution manipulation methods, due to their assumptions. In this section, the first four thesis limitations describe the most important assumptions that restrict the integrated OWC model’s applicability. Thereupon, the last limitation focuses on the empirical demand distribution manipulation method.

1. **Customer sales orders are historical based.** Throughout this thesis the integrated OWC model uses historical demand data as input. This might impede the representative aspect of findings. Although, Chapter 7 illustrates a method to cope with this assumption, and this method is used for a reduced scope.

2. **Production capacity is deterministic and constant.** The integrated OWC model assumes no volatility in the production capacity. Expectedly, this doesn't have a significant effect for the selected case studies because their capacity resources are fairly stable, but this might hinder the simulation of less stable production processes.

3. **No external supplier uncertainty.** The integrated OWC model shows that internal supplies might fail to deliver in time, but external supplies are always on time. This reduces the applicability of the integrated OWC model to situations with high external supply uncertainties.

4. **No customer payment uncertainty.** The integrated OWC model assumes that all customers pay their bills according to the negotiated payment term. This provides insight from a bottom-up perspective (i.e. determining the required OWC level if all policies are met), but it doesn’t provide the company with insight in the expected overdue per payment.

5. **The mean of the empirical distribution is equal to the mid-point of the interval that contains the mean.** Due to this assumption, the statements about the methodology that the mean demand of the empirical demand distribution is changed whilst the variance is preserved, or the variance is changes whilst the mean demand is preserved, is not fully accurate.

The first four limitations must be further researched by creating additional functionalities to the integrated OWC model and analyzing the impact of these additions.

The impact of the fifth limitation can first be analyzed numerically by comparing the realized variance and mean changes versus what is expected. If this leads to a significant difference, then it is recommendable to further develop the methodology, also incorporating the distance between the mean demand and the mid-point of the interval that contains the mean demand.
Appendices

Appendix A: Breakdown diagram OWC

Figure 30: Breakdown diagram OWC in Inventory

Figure 31: Breakdown diagram OWC in accounts receivable
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Appendix B: Supply Chain Case Study 1

Figure 33: Actual figures 2014 SC case study 1

Figure 34: Actual vs. bottom-up 2014 SC case study 1
Figure 37: Bottom-up calculation 2014 SC case study 1

Figure 35: Influence of internal company sales SC case study 1

Figure 36: Influence of deviating products

%OWC in Inventory

Intermediate & End Products
Raw Materials
Engineering Materials

Figure 35: Influence of internal company sales SC case study 1
Figure 38: %OWC in accounts receivable actual figures vs. bottom-up values SC case study 1

Figure 39: %OWC in accounts payable actual figures vs. bottom-up values SC case study 1
Appendix C: Supply Chain Case Study 2

%OWC in INVENTORY

Figure 40: Actual figure 2014 SC case study 2

%OWC in Inventory

Figure 41: Actual vs. bottom-up 2014 SC case study 2
Figure 42: Bottom-up calculation 2014 SC case study 2

Figure 43: Influence of internal company sales SC case study 2
Figure 44: %OWC in accounts receivable actual figures vs. bottom-up values SC case study 2

Figure 45: %OWC in accounts payable actual figures vs. bottom-up values SC case study
Appendix D: Sensitivity Analyses

D.1. Reorder points

Figure 46: ROP vs. %OWC in inventories, in accounts receivable (AR), and in accounts payable (AP)

D.2. Minimal lot sizes

Figure 47: MLS vs. %OWC in inventories, in accounts receivable (AR), and in accounts payable (AP)
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Figure 48: Bucket size (production wheel length) vs. difference in %OWC

Figure 49: Bucket size (production wheel length) vs. difference in OTIF
D.4. Proportion internal/external sales

Figure 50: Percentage third party sales vs. %OWC in inventories, in AR, and in AP (supply chain case study 1)

Figure 51: Percentage third party sales vs. %OWC in inventories, in AR, and in AP (supply chain case study 2)
D.5. Payment run cycle settings

Figure 52: Payment run cycle setting vs. %OWC SC case study 1

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D.6. Reorder points & customer payment term

Figure 54: Changing ROP & AR payment terms vs. %OWC & OTIF (SC case study 1)
Figure 55: Changing ROP & AR payment terms vs. %OWC & OTIF (SC case study 2)
Appendix E: Sensitivity Analyses for demand parameters

E.1. Pmf and cdf tables for the two empirical distributions of demand

Table 16: pmf and cdf table for inter-arrival times SC case study 1

<table>
<thead>
<tr>
<th>( X_j ) (j\textsuperscript{th} interval)</th>
<th>Class 1 (n=99) pmf</th>
<th>Class 1 (n=99) cdf</th>
<th>Class 2 (n=456) pmf</th>
<th>Class 2 (n=456) cdf</th>
<th>Class 3 (n=352) pmf</th>
<th>Class 3 (n=352) cdf</th>
<th>Class 4 (n=113) pmf</th>
<th>Class 4 (n=113) cdf</th>
</tr>
</thead>
<tbody>
<tr>
<td>( X_1 )</td>
<td>0.151515</td>
<td>0.151515</td>
<td>0.671053</td>
<td>0.671053</td>
<td>0.508523</td>
<td>0.508523</td>
<td>0.159292</td>
<td>0.159292</td>
</tr>
<tr>
<td>( X_2 )</td>
<td>0.070707</td>
<td>0.222222</td>
<td>0.08114</td>
<td>0.752193</td>
<td>0.150568</td>
<td>0.659091</td>
<td>0.159292</td>
<td>0.318584</td>
</tr>
<tr>
<td>( X_3 )</td>
<td>0.141414</td>
<td>0.363636</td>
<td>0.153509</td>
<td>0.905702</td>
<td>0.125</td>
<td>0.784091</td>
<td>0.035398</td>
<td>0.353982</td>
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<tr>
<td>( X_4 )</td>
<td>0.111111</td>
<td>0.474747</td>
<td>0.061404</td>
<td>0.967105</td>
<td>0.096591</td>
<td>0.880682</td>
<td>0.061947</td>
<td>0.415929</td>
</tr>
<tr>
<td>( X_5 )</td>
<td>0.030303</td>
<td>0.505051</td>
<td>0.017544</td>
<td>0.984649</td>
<td>0.079545</td>
<td>0.960227</td>
<td>0.053097</td>
<td>0.469027</td>
</tr>
<tr>
<td>( X_6 )</td>
<td>0.020202</td>
<td>0.525253</td>
<td>0.008772</td>
<td>0.993421</td>
<td>0.028409</td>
<td>0.988636</td>
<td>0.115044</td>
<td>0.584071</td>
</tr>
<tr>
<td>( X_7 )</td>
<td>0.070707</td>
<td>0.59596</td>
<td>0.004386</td>
<td>0.997807</td>
<td>0.002841</td>
<td>0.991477</td>
<td>0.070796</td>
<td>0.654867</td>
</tr>
<tr>
<td>( X_8 )</td>
<td>0.030303</td>
<td>0.626263</td>
<td>0.002193</td>
<td>0.997807</td>
<td>0.005682</td>
<td>0.991477</td>
<td>0.044248</td>
<td>0.769912</td>
</tr>
<tr>
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<td>0.717172</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.017699</td>
<td>0.787611</td>
</tr>
<tr>
<td>( X_{10} )</td>
<td>0.050505</td>
<td>0.767677</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
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<td>0.061947</td>
<td>0.849558</td>
</tr>
<tr>
<td>( X_{11} )</td>
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<td>0.002193</td>
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<td>0.026549</td>
<td>0.876106</td>
</tr>
<tr>
<td>( X_{12} )</td>
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<td>0.002841</td>
<td>0.994318</td>
<td>0.026549</td>
<td>0.902655</td>
</tr>
<tr>
<td>( X_{13} )</td>
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<td>0.858586</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.044248</td>
<td>0.920354</td>
</tr>
<tr>
<td>( X_{14} )</td>
<td>0.020202</td>
<td>0.878788</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.026549</td>
<td>0.946903</td>
</tr>
<tr>
<td>( X_{15} )</td>
<td>0.010101</td>
<td>0.888889</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.176999</td>
<td>0.964602</td>
</tr>
<tr>
<td>( X_{16} )</td>
<td>0.088889</td>
<td>0.909091</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.176999</td>
<td>0.982301</td>
</tr>
<tr>
<td>( X_{17} )</td>
<td>0.020202</td>
<td>0.909091</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.00885</td>
<td>0.99115</td>
</tr>
<tr>
<td>( X_{18} )</td>
<td>0.020202</td>
<td>0.929293</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.00885</td>
<td>0.99115</td>
</tr>
<tr>
<td>( X_{19} )</td>
<td>0.020202</td>
<td>0.959596</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.00885</td>
<td>0.99115</td>
</tr>
<tr>
<td>( X_{20} )</td>
<td>0.020202</td>
<td>0.969697</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.00885</td>
<td>0.99115</td>
</tr>
<tr>
<td>( X_{21} )</td>
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<td>0.989899</td>
<td>0.002193</td>
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<td>0.002841</td>
<td>0.994318</td>
<td>0.00885</td>
<td>0.99115</td>
</tr>
<tr>
<td>( X_{22} )</td>
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<td>0.999999</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.00885</td>
<td>0.99115</td>
</tr>
<tr>
<td>( X_{23} )</td>
<td>0.020202</td>
<td>0.999999</td>
<td>0.002193</td>
<td>1</td>
<td>0.002841</td>
<td>0.994318</td>
<td>0.00885</td>
<td>0.99115</td>
</tr>
</tbody>
</table>
Table 17: pmf and cdf table for quantity of demand SC case study 1

<table>
<thead>
<tr>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n=100 k=188</td>
<td>n=462 k=108</td>
<td>n=353 k=80</td>
</tr>
<tr>
<td>Xj (ith interval)</td>
<td>pmf</td>
<td>cdf</td>
<td>pmf</td>
</tr>
<tr>
<td>X1</td>
<td>0.010</td>
<td>0.010</td>
<td>0.019</td>
</tr>
<tr>
<td>X2</td>
<td>0.030</td>
<td>0.040</td>
<td>0.028</td>
</tr>
<tr>
<td>X3</td>
<td>0.020</td>
<td>0.060</td>
<td>0.028</td>
</tr>
<tr>
<td>X4</td>
<td>0.140</td>
<td>0.200</td>
<td>0.022</td>
</tr>
<tr>
<td>X5</td>
<td>0.020</td>
<td>0.220</td>
<td>0.169</td>
</tr>
<tr>
<td>X6</td>
<td>0.010</td>
<td>0.230</td>
<td>0.050</td>
</tr>
<tr>
<td>X7</td>
<td>0.030</td>
<td>0.260</td>
<td>0.041</td>
</tr>
<tr>
<td>X8</td>
<td>0.040</td>
<td>0.300</td>
<td>0.019</td>
</tr>
<tr>
<td>X9</td>
<td>0.050</td>
<td>0.350</td>
<td>0.030</td>
</tr>
<tr>
<td>X10</td>
<td>0.030</td>
<td>0.380</td>
<td>0.113</td>
</tr>
<tr>
<td>X11</td>
<td>0.010</td>
<td>0.390</td>
<td>0.028</td>
</tr>
<tr>
<td>X12</td>
<td>0.040</td>
<td>0.430</td>
<td>0.030</td>
</tr>
<tr>
<td>X13</td>
<td>0.010</td>
<td>0.440</td>
<td>0.015</td>
</tr>
<tr>
<td>X14</td>
<td>0.020</td>
<td>0.460</td>
<td>0.035</td>
</tr>
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<td>0.020</td>
<td>0.480</td>
<td>0.050</td>
</tr>
<tr>
<td>X16</td>
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<td>0.500</td>
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</tr>
<tr>
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<td>0.520</td>
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</tr>
<tr>
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<td>0.026</td>
</tr>
<tr>
<td>X19</td>
<td>0.020</td>
<td>0.560</td>
<td>0.037</td>
</tr>
<tr>
<td>X20</td>
<td>0.010</td>
<td>0.570</td>
<td>0.024</td>
</tr>
<tr>
<td>X21</td>
<td>0.020</td>
<td>0.590</td>
<td>0.009</td>
</tr>
<tr>
<td>X22</td>
<td>0.010</td>
<td>0.600</td>
<td>0.004</td>
</tr>
<tr>
<td>X23</td>
<td>0.080</td>
<td>0.680</td>
<td>0.013</td>
</tr>
<tr>
<td>X24</td>
<td>0.020</td>
<td>0.700</td>
<td>0.015</td>
</tr>
<tr>
<td>X25</td>
<td>0.020</td>
<td>0.720</td>
<td>0.013</td>
</tr>
<tr>
<td>X26</td>
<td>0.050</td>
<td>0.770</td>
<td>0.013</td>
</tr>
<tr>
<td>X27</td>
<td>0.010</td>
<td>0.780</td>
<td>0.002</td>
</tr>
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<td>X28</td>
<td>0.010</td>
<td>0.790</td>
<td>0.013</td>
</tr>
<tr>
<td>X29</td>
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<td>0.810</td>
<td>0.013</td>
</tr>
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<td>X30</td>
<td>0.010</td>
<td>0.820</td>
<td>0.009</td>
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<td>X31</td>
<td>0.030</td>
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<td>X33</td>
<td>0.020</td>
<td>0.880</td>
<td>0.006</td>
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<td>X34</td>
<td>0.020</td>
<td>0.890</td>
<td>0.006</td>
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<tr>
<td>X35</td>
<td>0.010</td>
<td>0.950</td>
<td>0.006</td>
</tr>
<tr>
<td>X36</td>
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<td>0.960</td>
<td>0.002</td>
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</table>
### E.2. Validation empirical distributions

Table 18: Integrated OWC model results of 10 samples from the empirical distributions

<table>
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<tr>
<th>Simulation run</th>
<th>OTIF</th>
<th>%OWC</th>
<th>%OWC AP</th>
<th>%OWC INV</th>
<th>%OWC AR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>93.23%</td>
<td>25.32%</td>
<td>-1.66%</td>
<td>17.86%</td>
<td>9.12%</td>
</tr>
<tr>
<td>2</td>
<td>90.30%</td>
<td>27.19%</td>
<td>-2.21%</td>
<td>19.15%</td>
<td>9.26%</td>
</tr>
<tr>
<td>3</td>
<td>90.99%</td>
<td>23.92%</td>
<td>-1.73%</td>
<td>16.93%</td>
<td>8.72%</td>
</tr>
<tr>
<td>4</td>
<td>92.26%</td>
<td>29.26%</td>
<td>-1.69%</td>
<td>21.72%</td>
<td>9.22%</td>
</tr>
<tr>
<td>5</td>
<td>91.58%</td>
<td>20.85%</td>
<td>-1.57%</td>
<td>13.31%</td>
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<tr>
<td>6</td>
<td>91.97%</td>
<td>23.09%</td>
<td>-1.55%</td>
<td>16.00%</td>
<td>8.64%</td>
</tr>
<tr>
<td>7</td>
<td>88.94%</td>
<td>24.38%</td>
<td>-1.75%</td>
<td>17.21%</td>
<td>8.92%</td>
</tr>
<tr>
<td>8</td>
<td>88.84%</td>
<td>24.08%</td>
<td>-1.59%</td>
<td>16.83%</td>
<td>8.84%</td>
</tr>
<tr>
<td>9</td>
<td>84.92%</td>
<td>22.48%</td>
<td>-1.52%</td>
<td>15.21%</td>
<td>8.79%</td>
</tr>
<tr>
<td>10</td>
<td>90.66%</td>
<td>29.43%</td>
<td>-1.70%</td>
<td>21.94%</td>
<td>9.19%</td>
</tr>
</tbody>
</table>
E.3. Mean demand sensitivity

Figure 56: Mean of demand vs. relative difference in total annual sales & relative difference in OWC value (€)

Figure 57: Mean of demand vs. relative difference in %OWC in AP, INV, and AR
E.4. Variance of demand sensitivity

Figure 58: Variance of demand vs relative difference in %OWC in AP, INV, and AR
Bibliography


