Pattern recognition in the Early Warning generation process

Master's thesis in Quality and Operations Management

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Due to anonymity reasons, the highlighted individuals who remain at the company are only mentioned by first name.

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SUMMARY
This paper covers an analytical study of Early Warnings - a data object that is automatically generated when a customer order is created. Early Warnigns are then continuously created any time there is a change in expected delivery.

Every day, a huge amount of Early Warnings is generated. The amount of data makes it difficult to evaluate and predict changes. A recognition of patterns in Early Warnings could support the planning process and also reduce uncertainty or stress regarding the huge wave of data that daily washes ashore.

The study has been conducted by mainly considering the aspects of lead time, delivery date, Early Warning generation date and quantity. By alinging collected data based on the delivery date, a new perspective of the analysis was acheived. Instead of considering dd.mm.yy or week X of the lead time, the data points are sorted as "delivery date - X weeks of lead time". This has been referre to as Temporal variable analysis. Additionally, a grading of Early Warnings was set up to evaluate the accuracy of each update compared to final delivery. The results were presented in color-based scales and in compiled graphs for easy overview and analysis.

The five main findings of the paper are that;
(1) there is in fact consequent patterns in the analysis set up.
(2) The utilization of several order lines, mainly due to partial consignments, strongly increase the number of Early Warnings generated.
(3) Expedited delivery dates appear during all parts of the lead time, contrary to initial beliefs.
(4) The total sum of shifts of Early Warnings is largely negative, this is due to the increased number of Early Warnings at the late stages of lead time that coincide with the gradually negative values of Early Warnings.
(5) The finding can be visualized in a model that is easy to scale up for more empirical results.

The main findings for the researcher can be summarized as;
- Expected delivery is expedited for orders until a certain lead time until final delivery. After this point, the majority of Early Warnings are postponements of the expected delivery date.
- More partial deliveries for an order strongly increases the number of Early Warnings generated and appears to lower the overall accuracy of the Early Warning compared to final delivery.

Keywords: Early Warning, temporal variable analysis.

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1. Introduction

In this section, the reader will get an insight in why this is an interesting topic, which problems it poses and the sought-after outcome by the researcher.
The study was a case study within the Supply Chain department at a large industrial company. During an internship leading up to the master thesis, the researcher was introduced to the topic of Early Warnings. An Early Warning is a datapoint that is generated if the Order Promise to a customer is changed. Several research projects regarding Early Warnings have previously been executed within the department. Therefore, before initiating this project, the focus of the researcher was not to find a new solution, but rather to find a new approach.

The data considered for this study revolves around the Confirmed Material Availability Date, hereafter CMAD, which together with quantity and product information constitutes the latest Order Promise. The Order Promise is planning information that is conveyed internally or to the customer about the deliveries to fulfill the customers actual or expected demand. The Order Promise is re-evaluated every day at the company by comparing current available and planned supply with forecasted and active customer orders, and if the a promise does not match the last, this generates a change in Order Promise. Within the company, these changes are referred to as Early Warnings.

The Order Promising process creates more than half a million changes to previous Order Promises per week. This vast data generation is stored in databases and reports that remain unutilized to a large extent. To quote the head of the researcher's department within the company, "It is counterproductive, reduce the problems or make the information useful!". Thus, this project aims to establish the Early Warnings as a resource within the company and increase the usefulness and value creation of Early Warning data.

The Order Promises are generated from is a highly complex algorithm that makes a lot of wrongful predictions when comparing to the actual delivery dates and quantities. Since the data contains all these wrongful predictions of the Order Promising process, it should be analyzable for patterns to support in how the Early Warnings can be interpreted or rated, rather than simply "wrong or more wrong".

Previous projects regarding Early Warnings have mainly focused on analyzing Early Warnings in group constellations, examples are; Negative Early Warnings in a certain time frame or all Early Warnings at a certain date/week to measure the total performance of the Supply Chain. This study instead breaks down the data into individual orders and compares the dates of events based on when Early Warnings are triggered compared to the delivery date and disregards other events during that specific date. Thus, revealing Early Warning reliability at a certain time before delivery, rather than delivery reliability across all orders or during a set of dates, see Figure 1.

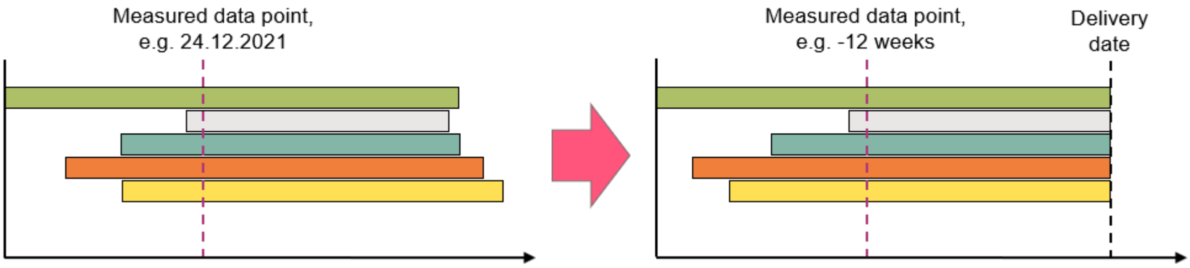


Figure 1. Research Approach compared to previous research

Currently, there is a gap in how and where the causes of all Early Warnings are located in the Supply Chain processes. Due to the lack of understanding of the concept, the data is largely accepted as it is, even though it is sometimes volatile. Providing a more profound understanding of the patterns of Early Warnings and how the development of new Early Warnings tends to unfold can increase the interest in the data in general. Further, an accurate model with a representative sample size could support decision making, short term forecasting and which information that is conveyed regarding the Early Warnings. Both internally and towards the customer. Although, this project would only form a small basis for a long-term outlook.

That is the outlook, but why are the Early Warnings currently a problem? Well, the Order Promising process is fully automated and, on a frequency decided from contractual agreements, the new CMAD is communicated to the customer. However, this constant flow of information is often not seen as information at all, since the CMAD is often expected to be updated repeatedly until the order is delivered, meaning the data generation is considered highly unreliable.

If there are patterns in when the Early Warnings are generated and the accuracy of updates for certain periods, these potential patterns should be obtainable by investigating the updates of CMAD already from the start of lead time, meaning the Order Date, to end, meaning the Customer Delivery Date. Further, the researcher wishes to create a visualization of the data to enable pattern recognition. A successful and conclusive result of the project will support the ability to predict future scenarios based on current updates, this will both improve the response in case of customer escalations and also support lead time-based pricing, which are both highly relevant topics within the Supply Chain of the company.
The hypothesis statements for this project were developed after gaining a basic understanding of the Early Warnings, surrounding processes and the data that was successfully extracted. The statements are then compared to the results for acceptance or rejection. The hypothesis regard number of Early Warnings generated, the values of Early Warnings and possible pattern recognition.

The chapters of this thesis are structured as

- Introduction: The background, problem and research questions
- Research setting: The environment of the project
- Literature review: Relevant models referenced by the research framework and study of methods for the data analysis

- Research Framework: Definition of Early Warnings at the company and related processes
- Methodology: How the research was conducted
- Results: Summary of results and highlighting of points of interest
- Evaluation: Answering the RQs and evaluating the hypotheses
- Discussion: The researcher's thoughts on the project and the results

The data collection was two-folded, followed by development and application of the analysis model. One data collection was a theoretical review to understand the research environment of the concept and typical methods for data analysis. The other part involved understanding the processes, by studying internal documentation and complementing with input from process experts. After this, an abstract model was created followed by data retrieval. Next the analysis model was created according to the availability and format of data, then the model was run and the data compared through visual and numerical analysis.

Research questions

The research questions are transitioning from exploratory to descriptive research. The first research question aims to explore the data on an abstract level to understand the dynamics between and within processes. If there is a failure in understanding what Early Warnings are and the relations to other processes, wrongful conclusions might be drawn, disregarding the quality of the data analysis in the descriptive part. Therefore, the first research question is formulated as:

1. *What are Early Warnings and how are Early Warnings currently generated within the Supply Chain at the company?*

For the statistical analysis part of the research, the questions are heavily implying the new research approach, illustrated in Figure 1, regarding Early Warnings and concepts that are expected to be used during the data analysis. Successfully answering the research questions will create a good foundation for a deeper understanding of the "behavior" of Early Warnings and thereby how an update in the Order Promise can be interpreted, rather than just being viewed as a random change. As no specific pattern is sought after, but predetermined data is analzed, the next research question is explorative in its approach and descriptive in the answer. Thus, the second research question is formulated as:

2. *Which, if any, patterns can temporal variables analysis reveal in Early Warning generation?*

The third research question is largely derived from the second question, which further implies the importance of a meticulous study. The quality of the results of RQ2 depend on RQ1, and the results of RQ3 depend on RQ1 and RQ2. As the setup of the temporal variables are explored according to Figure 1, RQ2 focuses on the general impression, while RQ3 focuses on the specific relationship between lead time and Early Warning accuracy within the process. So, the final research question is purely descriptive and formulated as follows:

3. *Does the timing of the generation of the Early Warning compared to the actual delivery date correlate with the accuracy of Order Promising?*

2. Research setting

This chapter introduces the industry and environment of the research project. This allows the reader to understand the context of the project, but also some of the challenges that the company and industry faces with emphasis on the need for predictive order management.

2.1 The semiconductor industry

Semiconductors are one of, if not the, most important electrical component in most modern electrical devices. The industry is constantly challenged by frequency of innovation, quality standards, long lead time and product value loss over time. This is largely due to the industry being subject to Moore's law – "the number of transistors in a dense integrated circuit doubles about every two years" (Corporate Finance Institute, 2022). In a world where digitalization is growing faster and increased its field at an aggregated pace, the strains on semiconductor focuses heavily on both functionality and quality, but also minimization of physical size. The rapid innovation cycles in combination with long lead times results in products that are being outdated and quickly losing value to competition before reaching the stage of a finished product. This fact discourages actors within the industry to keep an excessive storage of shelfed products. The common approach is to instead plan production pace according to forecasts with alternate outsourcing to enable rapid ramp-up.

2.2 CSC – E – Innovation

This project is being conducted at a global company in the semiconductor industry with its headquarters in Europe. Within the company, this project is being conducted within the Corporate Supply Chain (CSC) department. More detailed in the sub-department Engineering (E) and further, the sub-department Innovation (IN), shortened CSC-E-IN. The CSC-E-IN department has a wide experience of leading and supporting projects on both bachelor, master and doctorate level and a clear majority of employees are students. The current (20.10.2021) employment in the department is constituted of twelve bachelor thesis students, 21 master thesis students, seven PhD students, 40 working students, 22 interns and five additional long-term employees with administrative roles. Side note; working students is a mandatory internship of several university educations in Germany. Working students are studying while working part time at a company.

Order management is a neighbouring department and the Order Management process at the company is the function that matches incoming customer and forecasting orders is ever-updating and generates a massive stream of information that is seldom utilized in any corporate function. The CSC-E-IN department has had several projects regard the topic over the years for a deeper understanding of the effects of the process which creates a broad offset for this project.

2.3 Covid-19 impact

During the initial period of the pandemic Covid-19, many industries took caution and reduced production because an expected drop in revenue and consumption.

This created a bullwhip effect towards the semiconductor industry. A large amount of work-in-progress had no longer an end-customer, and the production was drastically reduced in order to reduce stockpiling and mitigate product value loss.

However, the loss of revenue recovered faster than expected and downstream actors to the semiconductor industry increased production. This created a reversed bullwhip effect towards the semiconductor industry, where there was a sudden demand for a product with lacking available supply and long lead times. This encouraged several actors within the semiconductor industry to simultaneously ramp up production which featured outsourcing, there was not enough available capacity for the industry to operate at full capacity.

The global shortage of semiconductors is still not resolved and poses a constant reminder of the value of accurate predictions and quick reactions.

3. Literature review

For this project, focus lies heavily on data analysis. A literature review is often used to establish a theoretical framework to support conclusions to the observations and results. This literature review instead explores concepts and methods to set up the data analysis and how to approach the obstacles, such as classification and mining of data and understanding the results.

Therefore, this section explains the theory behind the setup of the research. It does not cover the actual steps of the research, but rather the motivation and theory of the methods.

3.1 Data analysis literature review

Data analysis is often referred to as the process of using statistics to explain the results of an experiment or investigation (Dowdy, Wearden & Chilko, 2004). The result of a statistical analysis needs to be reliable and verifiable to constitute any ground for decision making. "Probability is basic to statistical decision making" – Dowdy, Wearden & Chilko (2004).

3.2 Probability measurement

The four mostly used rules of probability are (a) simple probability, (b) mutually exclusive events, (c) independent events and (d) conditional probability (Johnson and Kuby, 2004).

(a) Simple probability features a discrete set of equally likely outcomes, often with only one parameter.
(b) Mutually exclusive events feature variables that are unable to create a certain outcome unless another variable has a certain value and vice versa. Thus, the outcomes that give the same result can be added up, meaning the results are not equally likely.
(c) Independent events are when parameters act independently of each other. Each parameters probability can be seen as a factor that is multiplied with another parameter for the likeliness of a certain result.
(d) Conditional probability is a several-stage process of independent values. What is the probability of parameter 1 outcome "X" if parameter 2 has value "Y".

3.3 The null hypothesis

As a researcher in data analytics, it is important to not keep searching for what is not there. A study should therefore include the *null hypothesis*, meaning that any observed differences are because of chance rather than an impact of the parameter values (Dowdy, Wearden & Chilko, 2004). To be properly evaluated, the null hypothesis needs a level of difference where it can no longer be considered chance. If the results compared to the hypothesis has statistical proven significant value differences, the null hypothesis can be rejected and the result analysis continued (Dowdy, Wearden & Chilko, 2004).

Another important aspect to consider when setting up a data analysis is the *target population*, meaning where the result of the analysis will be applied

(Dowdy, Wearden & Chilko, 2004). This in turn affects sample selection to ensure that the data can reliably represents the target population.

3.4 The scientific method

The most common procedure when performing a statistical study is "the scientific method", consisting of six steps (Freedman, 1985).

1. State the problem
2. Formulate a hypothesis
3. Design the experiment
4. Make observations
5. Interpret data
6. Draw conclusions

Statistical analysis is mainly used in the fifth step, but also heavily influences step two and three (Freedman, 1985).

3.4.1 State the problem

Even with a deep understanding of the topic beforehand, the problem statement can be an iterative and very time-consuming process (Freedman, 1985). If the researcher is unable to properly formulate the problem, the projects increases the risk of losing focus because of vaguely formulated wanted effects and the collection of unnecessary data (Dowdy, Wearden & Wilko, 2004).

3.4.2 Formulate a hypothesis

A hypothesis is necessary to compare the outcome of the experiments to the researcher's speculations (Freedman, 1985). The hypothesis should contain enough detail to drive the experiment in a direction that yields a result that enables an evaluation of the hypothesis. It should predict unknown facts while being stated in a simple way (Dowdy, Wearden & Wilko, 2004).

The null hypothesis is not used until step five, interpret data. It is however important to state before observations, so as to not be bias (Freedman, 1985). Bias in this situation could lead to a lower acceptance of correlation to force a result, rather than iterating the design of the experiment or evaluating the lack of impact of the parameter (Freedman, 1985). One problem can have several hypotheses, including the null hypothesis.

3.4.3 Design the experiment

This step features a series of decisions, such as sampling sizes and objects, measured variables, granularity of investigation and how data extraction and analysis is done (Freedman, 1985). A sample size should be Representative, Random and Sufficiently Large (Dowdy, Wearden & Wilko, 2004). Random refers to randomness within a defined and limited sample size to ensure data quality thereby the validity or the results. To validate the representativeness of the samples and retain non-bias is a common problem in research design (Freedman, 1985). Especially if the sample size is small, as a large sample size is more likely to also be representative. Experiments require iterations to ensure reliability and this can also imply the scalability of the experiments, meaning that an output model can be "trained" to achieve higher accuracy as a continuation of the project (Dietterich, 1995).

3.4.4 Making observations

The main focus of this step is to ensure rigorousness of the experiment and avoid bias (Freedman, 1985). Bias is the influence of external factors, such as differently calibrated measurement instruments or leading questions in an interview (Bryman et al, 2019). If data appear to be unusual, it should be investigated to see if it is an error that needs correction. If it is not an error, the datapoint should be especially considered in the analysis (Dowdy, Wearden & Wilko, 2004). For this reason, the experiment should always be able to backtrack itself and for this reason keep all data samples until the end of the report.

3.4.5 Interpret data

The first action is to compare the null hypothesis and accept or reject it (Freedman, 1985). However, even if the null hypothesis is rejected, it does not mean that it is invalid. The decision to accept or reject the null hypothesis is based on the significance level of the results (Freedman, 1985). If significance is higher than the level, the null hypothesis is rejected and vice versa.

3.4.6 Draw conclusions

If the procedure is followed, the results will be completely calculated by probability and uniform with the data samples (Dowdy, Wearden & Wilko, 2004). If the null hypothesis has been rejected, it should again be considered that the null hypothesis can be correct. However, there is also the risk that the null hypothesis is falsely accepted (Freedman, 1985). Please note that different hypotheses should be evaluated individually, as the researcher's hypothesis does not need to be different from the null hypothesis. If no hypothesis is accepted, this should still lead to conclusions for the researcher if the research design and data are understandable with a good level of validity and reliability (Freedman, 1985).

3.5 Data classification

Analytical skill is a crucial factor of the researcher to set up categories and break down and classify data (Karlsson, 2016). Classification enables a standardized method to aggregate data and communicate information from the data in an easily perceivable way (Fortune, Short & Madden, 2020). The classification process supports the connection of different data in a meaningful way.

In statistical classification, one or several variables are vectorized to create the foundation for the classification (Fortune, Short & Madden, 2020). Along these vectors' categories are set up, covering a set of values or a specific one. During the analysis phase, each data point that matches the variable is sorted into the specific category, or class. This enables the researcher to investigate the data in clusters. Cluster analysis and statistical classification are suitable if input data is non-linear and extensive by creating an overview of the results, but also for application of the model as new instances does not need to be exactly matched with data to be subject to the probability model, but match the class instead (Fortune, Short & Madden, 2020).

Before classification is set up, the researcher needs to understand the variables that are investigated (Fortune, Short & Madden, 2020). Different types of classification need to be applied depending on how the data can be measured – there are three exclusive data categories that require different classification parameters. Input data is either (a) Continuous, meaning the data follows a linear scale, an example of a parameter is weight, classification is either setup in intervals or ratios, (b) Discrete – Ordinal, are input that can be placed in some order on a scale but without exact numerical values. A good example is a mood poll (good/ok/bad) or (c) Discrete – Nominal, meaning data categories have no hierarchy, e.g. apples and oranges (CareerFoundry, 2021).

4. Research framework

The framework for this project is mostly empirical and features a review of internal material to understand what an Early Warning is, how it is generated, where it is generated and the surrounding context of possible influencers. The internal material consists of training material for new employees, previous thesis projects and complementary information from topic experts or process owners.

The section starts with a summary of the definition of Early Warnings. After the summary, a more detailed explanation of the defeiniton, generation and history of Early Warnings is provided. This information is aquired to answer research question 1. For a broader understanding of the context and processes surrounding the Early Warnings, please see Appendix A.

4.1 Early Warning summary

Order promising is an order management process. In the Order Promising process, available capacity and actual demand are matched. The matching of demand and supply is called the Order Promising process and is the source of Order Promises. This process compares the available supply, new orders and planning data, and the matching if optimized through an automated daily process that generate the Order Promises. The delivery promise is calculated and split or merged between Schedule Lines in the process. The matching between capacity and demand is transferred to SAP. If the new matching is different from the last Order Promise, there is a mismatch, resulting in an Early Warning.

An Early Warning is often referred to as the change of expected delivery due to a disruption in the Supply Chain sub-processes. The scope of this project focuses on OM Early Warnings, but considers other versions of Early Warnings as OM Early Warnings are the most down-stream and therefore affected by other types. Therefore, the definition of Early Warnings in this project are redefined as "change in Order Promise due to a mismatch between planned supply and demand".

The pivotal attributes of the Early Warning to enable this project are the SAP order number, Schedule Line, KTU (oldCMAD), KTN (newCMAD), and quantity.

4.2 Early Warnings

Order promising is part of the validation process of order management at the company. The order management process, environment and relations to surrounding processes are described in Appendix A. In Order Promising, the current capacity and Work-In-Progress is checked in the tools Demand Fulfillment (DF) and Disional Model (DM) to calculate the available supply and is then compared to actual orders in the Open Order Book in SAP, hereafter OOB. The matching of demand and supply is the core of Supply Chain planning and also the source of Early Warnings. The process of demand and supply matching in DM has two goals: scheduling orders into the capacity plan to generate the Production Program, and to provide OM with the Supply Picture for Order Promising. The available Supply Picture is optimized through a daily process, the

Batch Run Order Confirmation, hereafter BROC, conducted automatically in DF. This process compares the available supply to the OOB, where the OOB features all new orders and planning data while considering Finished Product parameters such as minimum delivery quantity. The delivery promise is calculated and split or merged between Schedule Lines, hereafter SLs, through the BROC. DF compares actual demand to the Supply Picture and promises the optimal supply and demand match back to the OOB in SAP. If the new CMAD or quantity for an SL is different from the last Order Promise, there is a mismatch, resulting in an Early Warning that is subsequently recorded in SAP. This process is described in further detail in subsection 4.2.2.

4.2.1 Definition of Early Warnings

An Early Warning is the change of expected delivery due to a disruption. The disruptions can affect either or both the expected capacity and demand, thus creating the aforementioned mismatch. The disruptions resulting in Early Warnings have origins in both Supply Planning and OM and is indirectly affected by all Plan Process sub-processes (Appendix A). Therefore, the exact tracing and origins of the trigger of an Early Warning is often difficult to achieve and all possible root causes of Early Warnings being triggered are not known according to the department head of CSC-E-IN.

The data in this project is collected from DMOP. DMOP is a data universe within OM. Therefore, due to the data mining source, Early Warnings emitted in OM defines the scope of Early Warnings in this project. Since the Supply Planning and OM processes are in sequence, the Early Warnings from Supply Planning are one of the direct triggers of OM Early Warnings (Appendix A). Thus, the known origins of Supply Planning Early Warnings will also be covered in subsection 4.4.2, Early Warning generation.

Accordingly, the definition of Early Warnings for this project is redefined as “change in Order Promise”, or rather the outcome of individual changes in expected capacity or demand that then affects the internal Order Promise in the OM process. The data point of an Early Warning includes many attributes, however, featured in this project the following attributes are considered;

- The order number in SAP that the change of promise regards. This number is never changed and is bound to a specific customer, quantity, request date and additional data submitted upon order creation.
- A specific Schedule Line (SL) of the regarded order. One Early Warning can only be associated to one SL. However, quantity can be transferred between two SLs within the same order, and thus emits two Early Warnings, one for the subtraction of a quantity of SL1 and one for addition of quantity to SL2.
- A KTU. The KTU is order specific and never changes. The KTU is the original expected delivery date of the order. Upon consignment however, the order is moved to SL 9900 as a newly created demand of the order, thus the KTU for SL 9900 equals the actual delivery date. The difference between SLs are explained further in subsection 5.5.2.2.

- A KTN. An order has one KTN per SL and the values often change. The KTN is the current expected delivery date. The KTN is translated to, Confirmed Material Availability Date, or CMAD, in much of the available material and is also the primary reference in this thesis. However, when referring to the DMOP or the extracted dataset, KTN is used as that is the name of the parameter. After every BROC, KTNs are updated, and Early Warnings are issued in case the new KTN, or newCMAD, is different from the last promised one. When the newCMAD is closer in time than the previous, ergo a" pull-in" of an order, it is referred to as a "positive Early Warning" and vice versa.
- A quantity. An Early Warning can only contain one quantity. The quantity can be positive, negative or even zero depending on the origin of the Early Warning. Unless the ordered quantity is adjusted by the customer, a change of promise quantity is registered as a subtraction of quantity with the previous CMAD and addition of the quantity to the newCMAD, and thus generates two Early Warning data points.

4.2.2 Early Warning generation

In this subsection, the steps from DM to end customer through the Order Management process is described in detail. After gaining this overview, the explanation of how and where Early Warnings emerge from is provided.

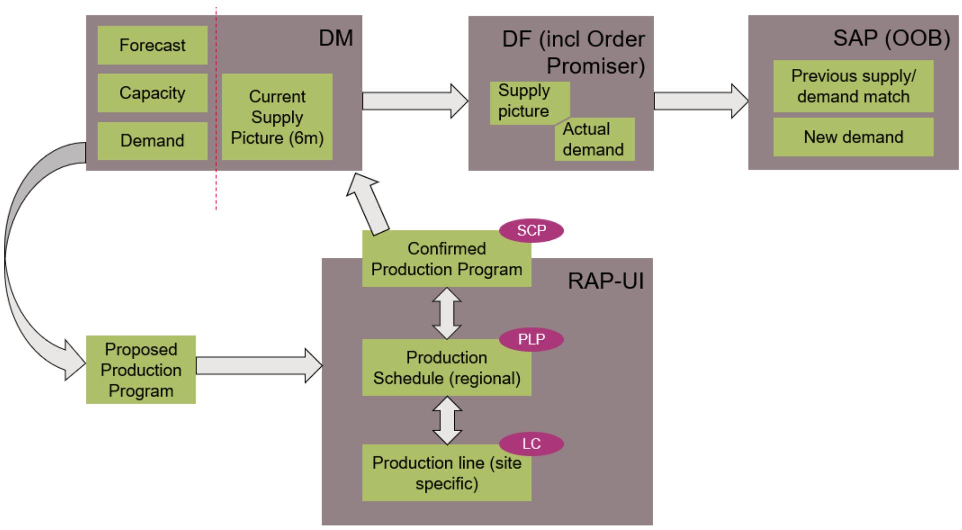


Figure 2. Data flow in the OM process from DM to OOB

We start by describing from DM and disregards the information flow until this point, as it has only indirect impact on the described process steps. Firstly, DM compiles information of demand, capacity and forecasting to generate the proposed Production Program which is then sent to RAP-UI for confirmation. In RAP-UI, the Production Logistics Planner, or PLP, assigns the proposed production program to production lines on a regional level in the detailed schedule. This detailed schedule is then sent for confirmation at a local level to the Line Controller who can accept or reject the detailed schedule based on feasibility of the plan within the plant. If the detailed schedule is rejected, the

PLP is consulted and a new detailed schedule is generated that can be accepted by the Line Controller. The PLP can then release the order for execution at the regional level, the SCP updates the DM with the detailed schedule. The DM-tool applies the Production Program to generate the Supply Picture and sends it to DF. In the DF-tool, the Supply Picture and the Open Order Book in SAP, OOB, are compared. In this comparison, Order Promises are generated and sent to SAP and is then available as order confirmation when updates are sent to customers.

For changes within the Freeze Fence, the SCP and PLP enters a negotiation to agree on adjustments. In this scenario the SCP represents the demand-side and PLP the supply side. This can occur if a customer changes their request and the Back End planning sends an updated request to Front End. The change of request is specified by SCP and sent to PLP who can (1) accept and adjust or (2) reject and make no changes.

These changes within the OM process does not generate Early Warnings unless the Order Promise is affected. Note that Early Warnings can be both positive and negative, if demand exceeds capacity, an order can be pre-allocated to the customer, resulting in a positive Early Warning, and vice versa. Within the company there are three main sources of Early Warnings, further illustrated in Figure 3.

- **New information about orders and planning are affecting the re-optimization process**.

The first main trigger of Early Warnings is located in DF when there are mismatches between a previous and a new Order Promise due to new order information from the OOB. This heppsn e.g. due to new customer requests, internal order changes or customer updates on an order, push-out or pull-in of orders due to prioritizing, division of a quantity over several CMADs, resulting in additional SLs, or merging of quantities from different SLs due to the same new CMAD. This triggers OM EWs.

- **Allocation of products assigned to ATP and AATP in order to prevent customer escalations**.

The second main trigger is located in SPL-UI (demand planning) and can be described as an override of the Supply Picture, where products are manually allocated to a customer in order to prevent customer escalations, meaning that a customer is taking action to discontinue the collaboration. These forced deliveries to customer and partial fulfillment of orders radically changes the prioritizing process in the BROC, as some of the customers demand is suddenly fulfilled and therefore not seen as critical. Allocation of products is only applied in periods of critically lacking supply.

In other words, this is a manual division of products between customers which then affects the re-optimization as the customers that receive allocated products has a higher demand fulfillment and gets lower priority in the following re-optimization cycle. This triggers OM EWs.

- **Disruptions in supply or production, leading to changes in supply fulfillment and in turn affecting the Supply Picture and thus, the re-optimization process.**

The third main trigger is located in RAP-UI (production planning), in physical production or in transit and is often referred to as Supply Early Warnings and Production Early Warnings. The cause for Early Warnings in RAP-UI can be both due to internal issues e.g. in production, or external supplier issues, such as a failed delivery or machine breakdown. If the Supply or Production Early Warnings affect the Supply Picture, an OM Early Warning is also triggered as Order Promise is also changed.

The type of Early Warning depends on the abstraction level, resulting in one of the two definitions of Supply EW or Production EW. However, a Supply EW or Production EW is not guaranteed to trigger an OM EW, unless the Order Promise is changed.

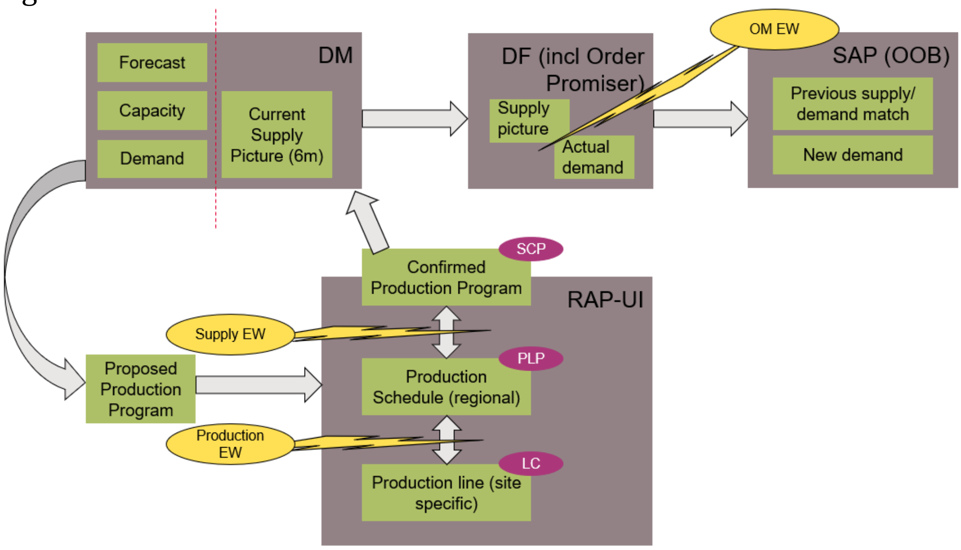


Figure 3. Early Warning generation in the OM process from DM to OOB

As Early Warnings in this study are defined as a change of Order Promise, all Early Warnings considered are generated where the Order Promise is generated, in the DF-tool.
However, for the versions of Early Warnings not under consideration, Production EWs are not documented, while Supply EWs are documented for performance review of the Supply Chain. In contrast OM Early Warnings are documented in the database 'DMOP' and in the Early Warning report.

4.2.3 History of Early Warnings

The original purpose of Early Warning reporting was to get an understanding of the daily rescheduling process of matching supply and demand through a fast and automated process. The benefit would be internal transparency in terms of possible revenue, supply and allocation updates. However, there is currently no Early Warning reporting that is considered useful to its end-users. The only identified direct usage of the report is in certain cases of customer escalations where Customer Logistics Managers can consult the report to trace and inform the customer of the reason for the fluctuations of lack of Order Promise and delivery.

In 2015, an OM Early Warning had to be manually accepted by a Customer Logistics Manager (CLM) for the new Order Promise to get transferred to SAP. However, the BROC prioritizes confirmed orders over late orders and the CLMs often ignored Early Warnings to keep a high priority for an extended part of the lead time. Thus, mismatches between supply and demand was discovered at a later stage and last-minute changes could result in a domino effect across the OOB. All Early Warnings are today accepted automatically which has increased the amount of changes in Order Promise drastically, but also shows the most recent, and hopefully most accurate, updates. However, the huge increase in data has affected the runtime of the BROC and it currently exceeds 24 hours of execution time. This has not caused any apparent effect on the Order Promising process, but as DF is updated at the end of the BROC and the OOB in SAP is up to date, meaning that the available supply in the SAP is based on the past day, see Figure 4.

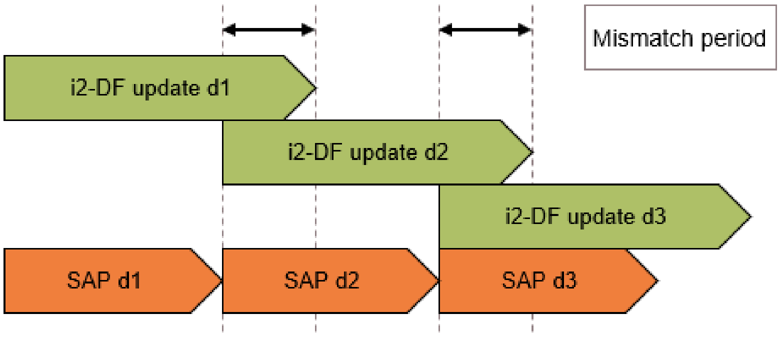


Figure 4. SAP and DF mismatch

The large number of reschedules in the BROC is one of the issues with Early Warnings as it creates high volatility in the Order Promising and delivery, thus lowering reliability. The unreliable supply schedule has led to occasional customer complaints as per a source in the OM-department. Moreover, customers can act on the change of promise and update their order requests which further triggers the BROC to a new optimized picture of demand fulfillment. Thus, creating an iterative cycle of Early Warning generation. Additionally, a majority of the Early Warnings are generated within one quarter of delivery with a strong decrease outside this scope. The long-term perspective is therefore not of interest to neither planning functions nor customers as the Early Warning generation sends many changes in the near term so that the customer cannot trust the Early Warning, while it in the long run sends unrealistically few changes so that neither the long-term planners cannot trust the Early Warning.

5. Methodology

This section covers how the project was conducted, decisions before and during the process and the reasoning behind them.

5.1 Research strategy

“Reality exists objectively and externally” is a fundamental viewpoint in quantitative research, as hence the world can be studied and measured and phenomenon can be verified or falsified (Bryman et al, 2018). This is the ontological position called objectivism, that independent of the observer different phenomena exists (Bryman et al, 2018). Constructionism, the ontological position of qualitative research on the other hand assumes knowledge can be subjective and reality is being interpreted by the viewer (Bryman et al, 2018).

This study investigates a dataset from business processes at a company, which motivates the project to not be purely theoretical. Empirical results for an empirical setting. It is assumed that the data given from these processes can be further studied objectively, hence an objectivist viewpoint is taken, which is well suited for this study. Additionally, the study has some qualitative aspects, as it is exploratory in its design and only feature a small sample of datasets from a large database.

5.2 Research design

When designing the study, using quality criteria for quantitative research was one part of the study, which according to Bryman et al (2018) are reliability, replicability and validity.

5.2.1 Reliability

This quality criteria deals with whether the same results of the study would be rendered if the study would be run again, ergo, that the results are repeatable and have consistency (Bryman et al, 2018). As data retrieval is a very time-consuming process, more so than expected, only a small set from a very large database was investigated. To start with, one product line was investigated, out of several dozens. This product line is used as a baseline for several studies within the department, as it is from a midsized department. Moreover, this product line has to a smaller extent been affected by the tight supply situation that is currently facing the semiconductor industry. The product line is therefore considered more representative than an extremely fluctuating one.

The sample data was selected from one of the earliest extractions of datasets of the project, while the database was still being explored. The dataset featured a collection of all order registered in the business intelligence system during a randomly selected period of time. The selected orders for the analysis were the first seven orders from the period, which would eliminate some bias in choosing data. However, some representativeness might be lost due to the orders being active in the same period of time and therefore being simultaneously impacted by external events.

5.2.2 Replicability

Replicability concerns if the study would be replicable by other researchers (Bryman et al, 2018). The business processes creating the investigated Early Warnings are specific to the case company. Moreover, what is causing the changes is also company specific, as it is based on very specific business processes. This is further complicated as the business processes are everchanging, meaning that a dataset used from different times might render different results because of changes in the system between these two times. However, a minute documentation of the steps of the data analysis provides high replicability under the same circumstances and data access.

5.2.3 Validity

Research validity concerns how well the experiment represents reality (Bryman et al, 2018). The everchanging business processes affects the validity as well as replicability. The generation of Early Warnings is highly affected by external events, such as outsourcing flexibility, export and import regulations or natural disasters that affect the Supply Chain. This can be overcome with a large enough sample size. For this project however, the sample size remains small, mainly due to a late initiation of data extraction. However, the model is designed to easily be scaled up for a result with increased validity.

When exploring internal sources, it became apparent that previous research on the topic of Early Warnings has been largely affected by the supporting function by creating bias toward the supervisor. An objective approach was sought after for this project by studying several projects, functions and consulting experts from several different departments connected to Early Warnings. However, the influence of supporting aspects is a plausible risk. For example, the explored relationships that has been indicated by previous work or experts might be independent variables and the results emerge from causality rather than correlation.

5.3 Internal collection of theoretical data

The theoretical data collection is mainly grounded in previous master thesis projects within the company on similar topics and follows a fishbone approach, where one thesis is used as a backbone with input from other sources to confirm and validate claims and explanations of the thesis. The complementary information was collected from thesis projects, internal learning modules and documentation or, in cases of contradicting material, process experts. The thesis selected as the backbone was completed during the spring of 2021 and takes an abstract approach to the Supply Chain to explain the processes between production and customer delivery.

The selected thesis contained several vague statements and was inconsequent in its nomenclature. After reviewing several internal thesis projects, it became apparent that there is an information asymmetry regarding order management which created confusion both for previous thesis authors and the researcher of this project. Several functions within the Supply Chain therefore had to be cross-referenced to fully understand if certain expressions or abbreviations had different meanings or scope, depending on the context where it was used. From this observation, another master thesis topic emerged that has been executed in parallel to this one.

5.4 Data analysis literature review

The data analysis literature review has been complemented as more knowledge was gained about the sample data and the scope of the literature increased slowly over time. Relevant literature has been found from the reference lists of similar master theses, personal recommendation from the project supervisor at the company and from search engines Google Scholar and EBSCOhost via Chalmers library website.

The process has included combinations of or individual searches for following phrases and words: Data analysis, Logistic regression, Data classification, Time series analysis, Regression analysis, Pattern recognition, Data collection methodology, Statistical analysis.

5.5 Research conduct

This sub-section will explain preparatory decisions, data retrieval and analysis of the project in a chronological order.

5.5.1 Databases

Order data for the company is stored in SAP BusinessObjects Web Intelligence. This is a web-based tool that enables report creation and analysis functions via a drag-and-drop interface (SAP, 2021). SAP Business Objects Web Intelligence features several options as data sources for report creation, allowing the use of both local or global data, the main source being ”business universes”. For this project, two business universes have been studied.

5.5.1.1 AATP_v2

The Early Warning report is generated in this universe. The report is a weekly generated report with the latest order confirmations for all orders that has experienced a change. The report features 31 available data columns with information about product information, quantities, dates and a on a medium level of granularity also dispatch information and customer data.

Data from this universe was not utilized in the end, mainly due to three reasons

1. The report does not save previous Order Promises
2. Reports are only available for ten months
3. All available data from the Early Warning report is also available in DMOP

5.5.1.2 DMOP.unx

The Data Mart Order Promising (DMOP) is the main data universe for storage of data regarding Order Processing, and features an enormous and complex amount of data. The sheer number of different report designs and parameter combinations is extreme with the 827 different parameters (as per 10.12.21) available to add as data columns. The variation for the parameters is also highly differing, with for example Export Control Flagging for certain materials featuring only three different values 'Yes/No/Unknown', to goods issue dates on the form 'YYYY/MM/DD hh:mm:ss' with all orders since January 1988. Each of these 827 parameters can also be applied as a filter to make the amount of data more manageable or feasible to extract.

Due to the complexity of the data universe, few employees that have access to the universe can operate it well or have an understanding beyond the standardized report that they extract. This process of setting up and executing the data extraction is explained in the following chapter.

5.5.2 Data extraction

In this subsection, an explanation of the data extraction process and the parameters included in the data extraction is provided.

5.5.2.1 Dataset "recipe"

When getting familiar with the DMOP, the researcher started with an explorative approach of 'trial by error'. Experiences from previous and current theses or internship projects that was utilizing the DMOP was the main support to create a basic understanding of the universe. During the project, this approach had to be adjusted since other project owners active within DMOP could only support in the usage and understanding of the parameters utilized in their project, ergo, their dataset "recipe". From conversations with the consulted individuals, it became apparent that no one learns DMOP through experimentation, but the recipe for their datasets is in most cases compiled after a request to the IT and reporting department of the company. However, this requires an extremely detailed request for every desired parameter. After seeking support from the IT department for this project a deeper understanding of the relevant parameters were obtained. However, several iterations of different dataset designs were extracted to find the parameter selections that yielded not only the correct information, but at certain granularities and in the correct format, e.g. for time and date formats. Another issue that was discovered during these iterations is that not all parameters are compatible for combined extraction. This created a lot of fruitless extraction results as several extractions yielded no return from the database, ergo, a blank slate. This uncertainty led to a continued explorative approach for setting up the final design of the analysis model, as adjustments to data formats and availability had to be made. However, this process is not properly documented. The final parameter selections for extraction are seen as in SAP BusinessObjects Web Intelligence in *Figure 5*. Detailed descriptions of the parameters can be found in *Table 1* and *Table 2*.

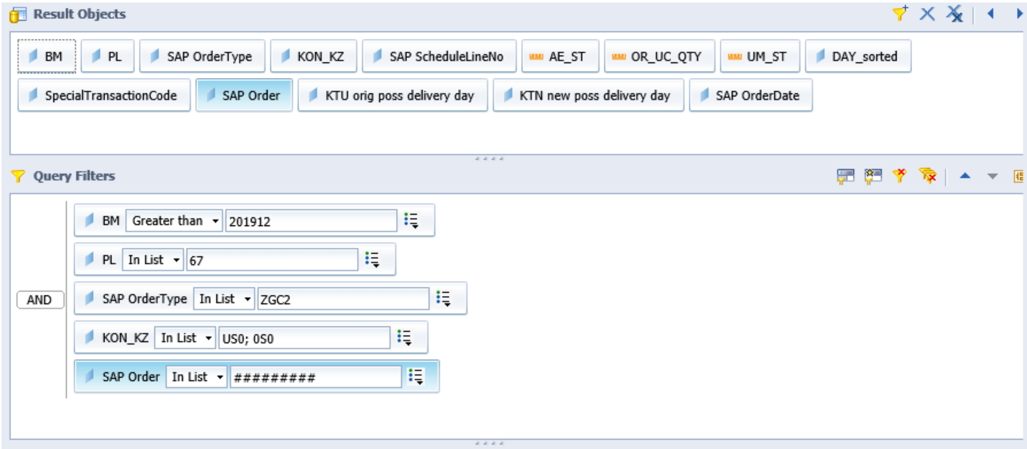


Figure 5. Parameter selection in SAP BusinessObjects Web Intelligence

Due to the huge selection of available parameters for data extraction in DMOP, the design of the dataset was important in order to both include potentially necessary information, but also to exclude noise. The dataset should also be extracted in a format that is easy to run in via the data analysis model (Dietterich, 1995). For this reason, an approach of *unbalanced multiple response permutation procedure*, hereafter unbalanced MRPP, was applied. I contrast, balanced MRPP means to collect data by frequency, meaning all variables has the same amount of measurements. Unbalanced MRPP instead adapts another trigger that is not balanced between the variables. Unbalanced MRPP is therefore suitable when there are large portions of static data. This project focuses on the changes in Order Promise on a daily granularity. Thus, the data collection was limited to events with a new CMAD and/or shift in quantity.

A basic understanding of the parameters of the dataset was achieved through internal literature review and support from process experts from IT and reporting. Derived from this knowledge, the process of descaling and cleaning the data before extraction was enabled, this further supported to stabilize the data and reduce the size of the data extractions while maintaining the high level of detail required to make a desirable analysis.

The data extraction featured four fully generated versions of the datasets that proved insufficient or too complex for the analysis model. The extraction iterations also included a larger number of undocumented versions of the dataset that contained no data, as parameters cancelled each other out or that the DMOP report generation timed out, thus yielding no return. Timeouts in DMOP occur due to either too broad filtering, meaning that not all data can be filtered through, or due to too extensive data results. The final version of the dataset features 14 columns, five of which are used as filters. These are described in *Table 1* and *Table 2*.

5.5.2.2 Dataset parameters description

The parameters that are included in the extracted dataset AND used as filters are presented in *Table 1* by the name used in DMOP, with a short description and also the used filter values.

Parameter name	Description	Filter values
BM	Business Month – is featured as the month that a datapoint is created	FROM: 201912
KON_KZ	Is an internal reporting code to indicate in which region of the company's warehousing the accounting to external customers is located	OR: US0; 0S0
SAP OrderType	The order type describes the purpose of the order, which also is one of the main impactors on prioritization rules	EQUAL TO: ZGC2
PL	Product Line – is a hierarchical level in a business division. E.g. industry -> business line -> product line.	EQUAL TO: 67
SAP Order	The order number is connected to an internal or customer order, and further links this to a scheduled quantity to support calculation of e.g. expected delivery	EQUAL TO: *10-digit code, unique per extraction

Table 1. Used parameters in DMOP also used as filters

BM, KON_KZ, SAP OrderType and PL are applied as filters to minimize the data searched to create the data extract. This speeds up the data extraction and mitigates database timeout. A database timeout was one of the early struggles with the DMOP as searches for data were too broad or extensive. From the early versions of the extractions from DMOP, each SAP Order was represented by a single data row and further included the values of BM, KON_KZ, SAP OrderType, PL and information about when the order was created and delivered, but disregarding the events between. For the orders in this dataset, it was therefore confirmed that the orders were delivered, ensuring that the entire lead time could be assessed for these order numbers in SAP. It was from this early extraction that the sample size was then selected. However, the final extraction of the dataset featured a much higher level of detail, where every update in dates or quantity was represented by an individual data row. This unfortunately made it impossible to extract more than one order at a time.

The earliest creation date for any of the selected orders was in December, 2019, so to reduce search along the time parameter, the BM was filtered from that point onward. For filter KON_KZ, US0 and 0S0 represents unconfirmed and confirmed orders, respectively, for accounts in the regions Americas and Asia-Pacific, this filter was added after consulting the IT and reporting expert. For OrderType, ZGC2 represents "standard ordering", which confirms that it is an order from a customer, that is not subject to any special prioritizing rules which makes the order more stable, thus, generating relatively few Early Warnings. Examples of other order types are forecast orders, which mostly have low priority and faces many changes and zero confirmations, or allocated orders, where the order often is fragmented into smaller shipments, resulting large volatility in prioritizing and therefore many delivery updates. For filter PL, number 67 was recommended by several employees who have experience with Early Warnings because it is (a) relatively stable and (b) still of significant size. For filter SAP Order, the selection of order numbers is previously explained in this chapter.

The parameters that are included in the extracted dataset and not used as filters are presented in *Table 2* by the name used in DMOP, with a short description.

Parameter name	**Description**
SAP ScheduleLineNo	The schedule line is an abstract concept that is used to keep track of orders when deliveries are split or merged by the order re-promising process.
AE_ST	Auftragseingang in Stück – incoming orders in SAP measured in product quantities
OR_UC_QTY	Orders Received with Unconfirmed Quantity – includes any eventual quantity that is ordered (AE_ST) but has no planned delivery date
UM_ST	Umsatz in Stück – Sales (billings) measured in product quantities
TransactionCode	Describes the reason of the change on the order row
SAP OrderDate	The date when the order is entered in SAP
KTU orig poss delivery day	Ursprünglischer Kanntermin – The original Order Promise or CMAD. This date is static during the lead time
KTN new poss delivery day	Kanntermin neu – The updated Order Promise date or CMAD. This date is often shifted during the lead time
DAY_sorted	The issue date of the update

Table 2. Used parameters in DMOP not used as filters

A Schedule Line (SL) can take the value of 1, 2, 3, 9900 or 9901. SL 1, 2 and 3 are the regular SLs that contain the quantities and delivery dates during the lead time, and therefore record all changes. Splitting of an order is conducted by adding quantities to different SLs. However, this has no effect on the physical production, as the SLs are purely abstract. Upon dispatch or "goods issue date" the quantity is subtracted from the SL and added to SL 9900 or in specific cases also to 9901. According to one OM expert, SL 9901 is only used on rare instances and that one possible reason is when a warehouse from a different business region complements an order.

AE_ST, OR_UC_QTY and UM_ST are the parameters that measure order quantities. The order quantity parameters are closely connected and are compared during the analysis. Most importantly is that the total sum of AE_ST and UM_ST are balanced, to ensure that all delivieries are accounted for during the lead time.

The transaction code is a one or two letter string that indicate why the order is changed (e.g. cancellation, currency change or change of promise) and if it is a new order entry. Upon goods issue date, the regular SL is closed and SL 9900 is entered as a new order line, according to the transaction code, but preserves the order number to still having enabled order tracking. The consequence is that the KTU remains the same for the order until the good issue date, it is then updated to the new Order Promise, ergo, the KTN date. The exact reason for this remains a mystery to the researcher.

DAY_sorted was the final parameter added and the only parameter that is not included in any of the previous versions of datasets. The addition of this parameter was paramount as it extended the dataset with a new row for every update of date or quantity during order lead time.

AE_ST or OR_UC_QTY, and SL 1, 2 or 3 are used up until the goods issue date, meaning that these values can be traced during lead time, but generate no updates afterwards. UM_ST and SL 9900 or 9901 are only shown in data upon goods issue date and show no updates prior. Further, AE_ST can also appear as an ordered quantity on SL 9900 in rare cases. According to an OM expert, these cases are quite chaotic and has been manually tampered with, meaning it does not follow the standardized order re-promising process.

5.5.3 Data analysis

The data analysis focuses on steps 2, formulate a hypothesis, and step 3, design the experiment, of the scientific method.

5.5.3.1 Analysis approach

As stated in the introduction; the focus of the research was not to find a new solution, but to explore a new approach. Previous projects have mainly focused on analyzing Early Warnings in group constellations. This study instead breaks down the data into individual orders and compares the dates of events based on when Early Warnings are triggered compared to the delivery date and disregards other events during that specific date. Thus, revealing Early Warning reliability at a certain time before delivery, rather than delivery reliability across all orders or during a set of dates, see Figure 6.

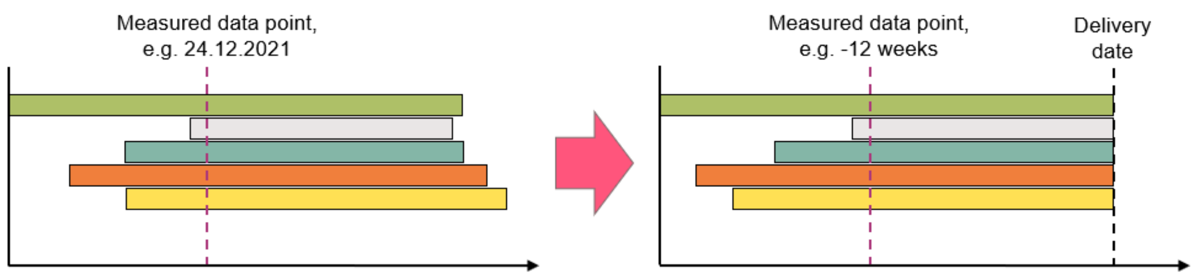


Figure 6. Research approach compared to previous research.

5.5.3.2 Hypothesis development

The hypotheses for this project are defined in chapter 5.6. This subchapter explains the basis and reasoning behind the hypotheses.

In order to formulate a hypothesis, it has to be considered what value the project is designed to create and to synchronize the value creation with the research questions. The research questions focus on understanding what Early Warnings are and the environment where this data is generated and how it acts. This is done via internal, exploratory research, meaning it proves difficult to test and before understanding what the Early Warnings are, the researcher decided that a hypothesis at this stage would be too vague or random to provide value to the results. Further, the research questions require a data analysis of Early Warning generation based on temporal variables and features a results analysis to enable answering the research questions. In order to conduct the analysis, a deeper understanding of Early Warnings is required. Assuming this information is acquired, more well-founded hypotheses can be formulated at this point of the project rather than in the beginning.

No hypothesis was formulated until the concept of Early Warnings and its environment was explored. The data extraction was an iterative process with a new run per SAP Order and the large amount of data that was extracted did not look conclusive at first glance. So, in parallel with the data extraction, and before the analysis was initiated, the null hypothesis was formulated. The null hypothesis should indicate if there is a result to be gathered based on the current setup or if the results appear to be random. Due to the small sample size, there is an insufficient basis to completely exclude the possibility of random data. So, in order to create a result, focus of the null hypothesis lies instead of proving that the Early Warnings can be measured for different time scopes and shows different trends of values depending on when the Early Warning is generated. Thus, if the variation of Early Warnings for specific fragments of the lead time across several orders proves to be inconclusive or negligible the null hypothesis will be accepted. Further, the data analysis will be inconclusive and accordingly rejected.

The researcher's hypothesis statements are derived from the null hypothesis and research questions 2 and 3. The four hypothesis statements features one aspect each that the researcher aims to claim as a conclusive result based on both the data that was successfully extracted and the prior knowledge about the data from research framework in chapter 4. Therefore, the hypothesis statements were not formulated until after the complete data extraction and are purely derived from the researcher's own impressions and learnings from the project and data until that point.

The impression that the researcher's hypothesis statements were derived from can be summarized as; Early Warnings are generated mainly within the last three months of the lead time with a majority of negative values, meaning "push-outs" or postponement of promise. However, as it is close to the delivery time, the negative values are quite small.

5.5.3.3 Design of analysis

Every order was extracted individually. After this the dataset was cleansed of irrelevant datapoints, and key numbers for the order was calculated. After this the order was separated into new data sheets depending on the SL and the analysis model was applied to yield data for result analysis. The data from each SL was then compiled in the *graph analysis dataset* (see example in Appendix B). Data extraction is covered in the previous chapter. This section describes the subsequent steps in detail.

5.5.3.3.1 Data cleaning

Data cleaning was made easier by the inclusion of all parameters mentioned above and they were subsequently removed after their purpose had been fulfilled. The following procedure is identical for all seven orders sampled. First, the dataset was sorted for unconfirmed orders. As the orders were not confirmed, no CMAD was generated for these data points. The dataset was therefore sorted after KTN and for occasions where the value equaled "NULL". Inclusion of these data points would possibly affect the final numbers as the rows carry a quantity and KTU, and they were therefore deleted. The rows should correlate with the rows carrying a value for OR_UC_QTY and for rows of KON_KZ carrying the value of "US0" as they both represent unconfirmed values.

Next, the dataset was sorted for orders that carried no quantity. These rows would have no effect on the final numbers as the calculations of Adjusted oldCMAD and Adjusted newCMAD requires a quantity factor to generate a value. These values are explained later in this section. The sorting was done on parameter AE_ST and all rows with value equaling "0" were deleted. This correlated with rows carrying the value "W" for TransactionCode. TransactionCode W indicates an adjustment due to currency exchange and carried neither quantity not shift of CMAD. Sorting for AE_ST thus reduced the steps of the data cleaning process.

After this parameter OR_UC_QTY was checked for any remaining values. The parameter was subsequently emptied for all samples and the parameter could then be removed completely. In order to ensure data quality, the orders and billings was compared after each of these deletions to make sure no ordered quantity was lost in the process. This was done by applying the Autosum function for parameters AE_ST and UM_ST and comparing the results. If the sums equaled each other no quantity was lost in the cleaning.

The cleaning process reduced the number of data points per set by ~25% depending on the order, without reducing any relevant data for the analysis.

5.5.3.3.2 Calculation of order specific performance

After the data extraction, it was discovered that the sample orders often had a single delivery date, but quantity in UM_ST was divided across several KTNs. Another discovery was the frequent split and merging of quantities between SLs. For example, during the lead time, a quantity of AE_ST could therefore be assigned to SL 1 for one month, shifted to SL 2 for one month before being partly reassigned to SL 1 and then partly dispatched to SL 9900. A different example is visualized in Figure 7.

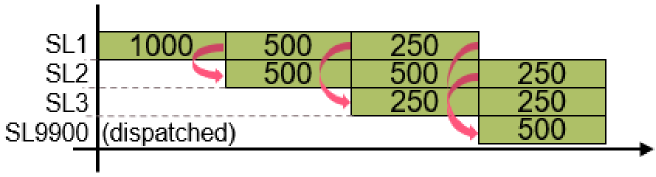


Figure 7. Example: quantity shift between Schedule Lines

Note that the quantity for each SL is summarized in the example. In the dataset, the quantity is often divided into smaller quantities with different KTN-values within the same SL. Meaning that in the second step of the sequence SL 2 could carry five separate quantities of 100 pieces each.

In order to adjust the analysis to this, the new parameters Adjusted newCMAD, Final Adjusted newCMAD, Adjusted oldCMAD and Final Adjusted oldCMAD were introduced. The "Adjusted" indicates that the datapoint is evaluated by impact on total delivery reliability for that update. "Final" indicates that it is the ultimate value for the analyzed order. These parameters were calculated based on a formula that was developed through of a project regarding delivery reliability at the company from 2020 and is formulated through the following steps:

1. Subtract KTU from KTN to get the shift of CMAD
2. Multiply shift with quantity assigned to the shift (AE_ST)
3. Divide the number by total order quantity (Autosum AE_ST or UM_ST)
4. Iterate and sum up every datapoint for the same DAY-sorted

This is further shown in Formula 1, 2 and 3

$$\frac{\sum_n(\Delta CMAD_1 * Qty_1 + \Delta CMAD_n * Qty_n)}{\sum Qty}$$

Formula 1. Adjusted CMAD shift calculation

The result indicates how much the average of all quantities that are affected has shifted. For example, if an Early Warning is triggered without changing the CMAD, this indicates that the order was split and that parts of the quantity are still expected to be delivered on the previous CMAD. The shifted quantity will also trigger an Early Warning with a shifted CMAD. Suppose that the unchanged quantity is 75 units and the shift regard 25 units and a CMAD change of four days. Applying the formula for delivery reliability would appear as follows in Formula 2.

$$\frac{(0*75 + 4*25)}{\sum 100}$$

Formula 2. Example of Adjusted CMAD shift calculation

Thus, the Adjusted newCMAD shift is 100 divided by 100 = 1. The delivery reliability in this case is thus pushed out by one day. The formula was added to better represent delivery reliability, rather than seeing a shift of four days when the impact on total delivery is less significant. If another shift is issued during the same DAY_sorted, it can be calculated as shown in Formula 3.

$$\frac{(0*50 + 4*25 + (-4)*25)}{\sum 100}$$

Formula 3. Second example of Adjusted CMAD shift calculation

Further, the Final Adjusted newCMAD and oldCMAD were to be used as comparative values for the performance of the SLs. In order to calculate the Final Adjusted values, only the input at order creation and delivery were required as input. For this assortment, the parameter TransactionCode was done to filter out the value "N", showing all newly created orders. Upon order creation, new orders are assigned to a standard SL with an order quantity, AE_ST, and an original expected delivery date, the oldCMAD, as parameter KTU. As this is a constant value, the ΔCMAD could not be calculated. For this reason, the formula that was applied converted the date on KTU to a numerical value that was multiplied with assigned AE_ST into a new column, cleverly named "KTU*Qty". The KTU*Qty column was then summed up and divided by the total sum of AE_ST and converted to a date, resulting in Final Adjusted oldCMAD.

Upon delivery, a new order is assigned to SL 9900 with an order quantity, UM_ST, and the final delivery date. To verify that the delivery date was correct, four of the orders were separately extracted with the parameter "SAP GI Date System". GI stands for Goods Issue and represents when the order was shipped for delivery. This was not done for all orders as the inclusion of SAP GI Date System returned a blank dataset due to incomompatability with some of the other parameters.

The same calculation that was conducted for KTU*Qty was also done with the factors KTN and UM_ST into a new parameter, equally cleverly named "KTN*Qty". These values and calculations were saved in a separate sheet for future reference, named "Only N-SL" (short for Only New Schedule Line). The final addition in Only N-SL was "Final Average KTN", which was added under the KTN-column with an average-formula. These are the "final" values for the specific order, disregardless of the SL.

Additionally, another column was added in the first datasheet named "Adjusted newCMAD-KTN. If no change=0". The formula of the column compared the KTN and KTU for every remaining data entry. If the values correspond, meaning there is no shift of CMAD, the column returned a value of zero. If the KTN and KTU did not match, the formula would collect the value of the Final Adjusted oldCMAD and subtract the KTN, thus comparing how many days the new expected delivery differs from the actual Adjusted delivery date. See dependents illustrated in Figure 8.

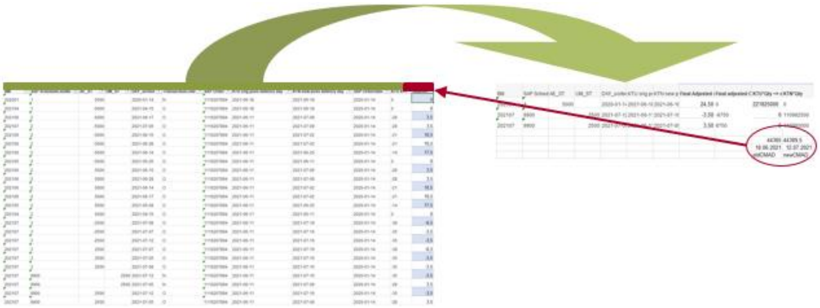


Figure 8. Data transfer or dependency between dataset and Only N-SL

5.5.3.3.3 SL separation and performance calculation

The following step was to sort the dataset on SL. Each SL-segment was then copied into a new sheet that was named as SL#, e.g. SL1. No further action was taken in handling this sheet.

After this, an analysis sheet was created adjacent to each separated SL. The analysis compares the update accuracy and volatility compared to Adjusted order behavior and is thus, Analysis 1 is dependent on the sheets “SL1” and “Only N-SL”. This procedure was identical for all SLs, including SL 9900. See Figure 9 for the final setup of data sheets per individual order.

Figure 9. Setup of datasheets per dataset

From SL#, the column DAY_sorted was copied into Analysis # and all duplicate values removed. This created a list of every day that there was a change in Order Promise for that specific SL. The removal of duplicates enabled the column to be treated as a timeline for the SL. Next in Analysis #, two columns where set up by the names of “Final Adjusted oldCMAD/issue date delta”, and “Final Adjusted newCMAD/issue date delta”. The formula for each row is the respective Final Adjusted CMADs, retrieved from Only N-SL, subtracted by DAY_sorted. This value indicates how many days before the expected and actual delivery date that the change in Order Promise was generated.

Further, columns where set up for Average KTN. The formula calculates the average KTN of the rows in SL# that correspond to the DAY_sorted in Analysis #. The result is the average expected delivery date during that DAY_sorted. This was then compared to the Final Adjusted newCMAD in an adjacent column named “Final Adjusted newCMAD-KTN” to calculate the margin of error when reviewing the total change of Order Promise for the considered DAY_sorted, or the issue date.

Next, columns for “Average CMAD shift” and “Adjusted average CMAD shift” was set up. The formula for Average CMAD shift searches SL# for every row that correspond to the DAY_sorted in Analysis #. If the date corresponds, the formula calculates the difference between KTU and KTN for those rows and then averages the difference. The result is the average shift of CMAD during the DAY_sorted. The total average of the new column was calculated, the result enables comparison of the shift to the average shift of the SL.

The Adjusted average CMAD shift calculates the average of the column Adjusted newCMAD-KTN in SL# where the row corresponds to the DAY_sorted in Analysis #. The result is the average of the Adjusted CMAD shifts issued during the DAY_sorted. The total average of the new column was also calculated, the result enables comparison of the shift to the average Adjusted shift of the SL.

The following column that was set up is named "Final Adjusted newCMAD-(Adjusted oldCMAD-Adjusted CMAD shift)". The formula retrieves the Final Adjusted CMADs from Only N-SL and calculates the difference, ergo, the absolute shift of CMAD according to the adjustment formula for delivery reliability. This shift was then subtracted from the Adjusted average CMAD shift. The result is the difference in number of days between the Adjusted CMADs for the order as a whole and for the Adjusted CMAD for that SL on the specific DAY_sorted.

The following three columns to be explained are used as reference for the "Graded table results" in Chapter 6.1. These columns evaluate the values from the SL on a scale from 0-5. The graded value 10 was also included for 100% accuracy. The three columns returned a grade and a color, for easy evaluation and overview, depending on the sum of days derived from the combination of variables. The grade scale, color scale and triggering value is seen in table 3. The values of the grades are not related to any previous order or production performance, though this was considered. Lead times and freeze fences are specific for each type of Finished Product, and as the production selection for this project was near random, it was not good basis for the grade scale. Order performance is too volatile when looking at singular orders to conclude a good measurement value. As is, the grades are set up to cover one week, two weeks, one month, two months and finally six months, before reaching grade =0.

Grade	+/- Difference in days
10	0
5	3
4	7
3	14
2	30
1	91
0	91<

Table 3. Analysis # calculations grade scale

The three evaluating columns are name as (a) average KTN-Average^2 CMADshift-Final Average newCMAD, (b) Adjusted newCMAD-KTN and (c) average KTN-Average^2 Adjusted CMAD shift-Final Adjusted newCMAD. If KTN is not accurate, we expect the average shift to affect the KTN again to move towards the final KTN. As the shift of KTN always is derived from the previously promised date, and therefore represents the true shift of that date, the original expected or the average delivery date does not affect the evaluation.

(a) The first evaluation was calculated without any Adjusted values, meaning quantities and impact on order performance was disregarded. The calculation compares the Final Average newCMAD with the Averge KTN, combined with the average shift of CMAD for the SL. The result shows how close the new expected delivery date is to the actual delivery date if it is subject to the average impact of changes from from the specific SL.

(b) The second evaluation compares the Final Adjusted newCMAD with Average KTN. Thus, showing the difference between the actual delivery date and the new expected delivery date, ergo, Early Warning accuracy.

(c) The third evaluation compares the Final Adjusted newCMAD with the Averge KTN combined with the average Adjusted shift of CMAD for the SL. The result shows how close the new expected delivery date is to the actual delivery date if it is subject to the impact of Adjusted changes from the SL on average.

If the results of (a) and (c) appear accurate, it means that the Order Promising process is not making radical changes across the SL in total and that it is pushing the KTN or newCMAD closer to actual delivery date. Thus, making the Early Warning somewhat reliable. An example of Analysis 2 for SAP Order 1116207894 is shown in Figure 10. For a more thorough example, Appendix B shows all sheets of data explained in this chapter, for one of the sample orders.

DAY_sorted	Final Adjusted oldCMAD/issue date delta	Final Adjusted newCMAD/issue date delta	average KTN	Adjusted newCMAD-KTN	average CMADshift	Average Adjusted CMADshift	Final Adjusted CMAD-(Adjusted oldCMAD-CMADshift)	average KTN-average^2 CMADshift-Final Average newCMAD	Adjusted newCMAD-KTN	average KTN-Average^2 Adjusted CMAD shift-Final Adjusted newCMAD	10=genau. 5=>3d difference, 4=>1w, 3=>2w, 2=> 4w, 1=1qrt
2021-06-17	1	25,5	05.07.2021	7	-24,5	-18	7	2	3	4	
2021-07-05	-17	7,5	09.07.2021	3,5	-28	-21	3,5	2	4	3	
2021-06-15	3	27,5	05.07.2021	7	-24,5	-18	7	2	3	4	
2021-06-28	-10	14,5	05.07.2021	7	-24,5	-18	7	2	3	4	
2021-06-14	4	28,5	28.06.2021	14	-17,5	-11	14	3	2	5	
2021-05-25	24	48,5	11.06.2021	31,5	0	0	24,5	4	1	2	
2021-05-28	21	45,5	25.06.2021	17,5	-14	-7	17,5	3	2	4	
2021-04-15	64	88,5	11.06.2021	31,5	0	0	24,5	4	1	2	
				Average ^2	-17	-11					

Figur 10. Analysis sheet example

All relations and dependencies are shown in Figure 11. The original dataset and SL# are shown as one, as the columns are the same and there are no dependencies, only copies, between the two.

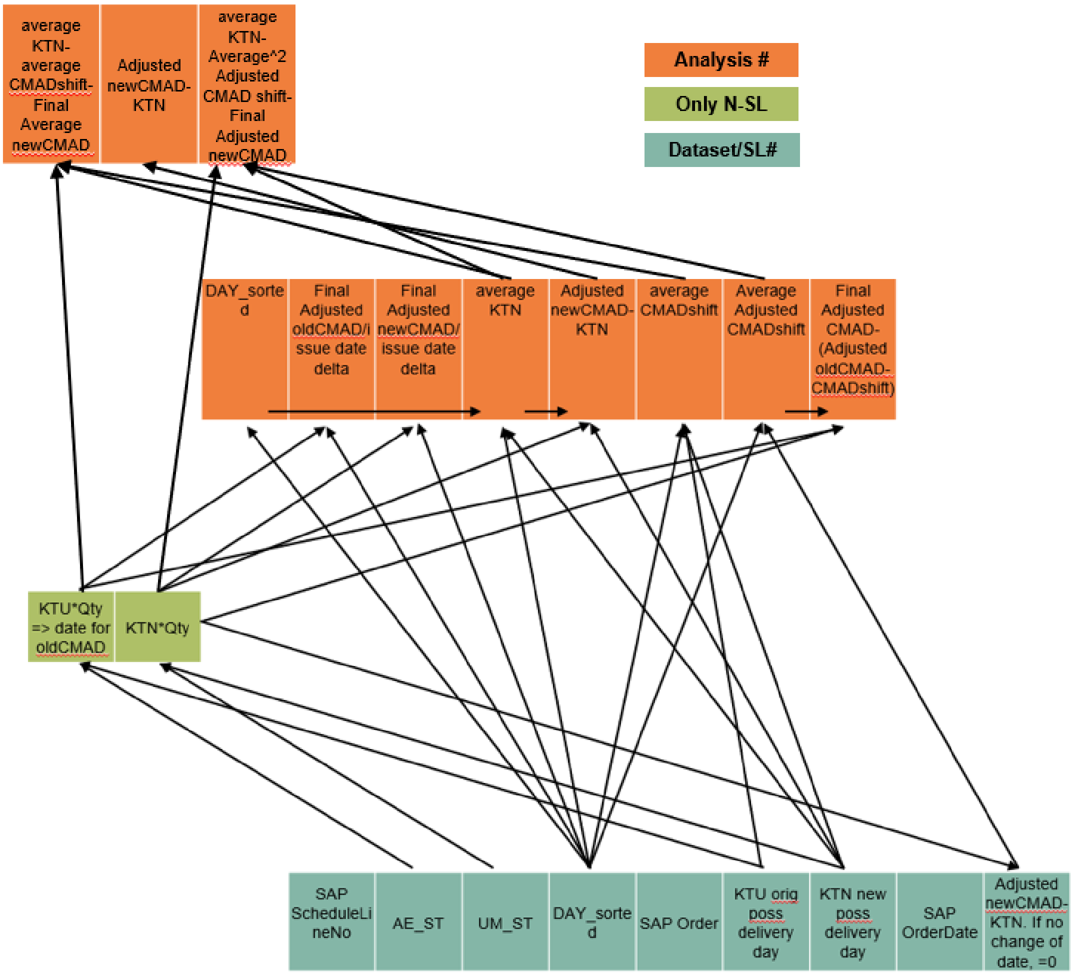


Figure 11. Column relations between SL#, Only N-SL and Analysis #

5.5.3.3.4 Compilation of SL performance in the *graph analysis dataset*

After this process had been conducted for each SL in every SAP Order of the sample size, two compiled analyses were conducted, one between Final Adjusted newCMAD/issue date delta and Adjusted newCMAD-KTN and the other featured the graded parameters of each SL, also seen in the top left corner of Figure 11. The selection of parameters for the analysis was based on the hypothesis, and were considered to be sufficient input for evaluation of the hypotheses.

The compiled results were grouped into two different sheets depending on standard SL (1, 2 and 3) or delivery SL (9900 and 9901). The Final Adjusted newCMAD/issue date delta was divided into weeks for a more easy to assess timeline. After this, the maximum and minimum values were identified and set as extreme points of the timeline and was in turn implemented as the X-axis. For the Y-axis, the Adjusted newCMAD-KTN was entered with one line for each SL. The values of the columns were sorted to match the week they were generated. As the assortment was done in weeks, one SL could have several updates in the same data point. In these cases, the average value was calculated. Assortment according to those axes enabled the visual comparison of orders with a retroactive viewpoint, as all orders were lined up according to the Final Adjusted newCMAD as illustrated in Figure 7 (page 26), and a clustered column chart was generated with each SL as a singularity. Additionally, the average value for each week was calculated and set up in a line chart. This chart shows the weekly movement of the average margin of error of expected delivery and, thus, supports evaluation of hypothesis statements 2 and 4.

Adjacent to the calculation of the average value per week, another column was set up to count the number of SL generating a new value input for the week. This column converted into a line chart following the timeline creates visualization of the development of number of Early Warnings generated per week. This supports the evaluation of the first hypothesis statement. The third hypothesis statement can be evaluated by summing up the complete table of Order Promise changes. The total value can then be compared to the total number of Early Warnings generated for analysis of average values.

The parameters for the second analysis was chosen as they form the top-hierarchy in terms of dependability and are already graded, indicating that they can be considered for analysis of Early Warning performance. The results were compiled into three tables, one for each graded result. The table counts the number of Early Warnings per grade per order, the total Early Warning times grade product and the average grade per Early Warning per order and the total average. However, SL 9900 and SL 9901 are not included as they are to a much higher extent accurate with new promises and an order with many partial deliveries would then have a worse grades than an order with fewer deliveries.

5.6 Hypotheses

This chapter presents the null hypothesis and the researcher's hypothesis statements that will be evaluated in the results chapter. Thus, it is also an excellent Segway to the results in chapter 6.

5.6.1 Null hypothesis

It is confirmed within the company's Supply Chain that Early Warnings impact the performance measurement, but this impact is not defined with neither how nor how much. Therefore, the hypothesis is that the impact can be measured for specific time fragments of the lead time. Further, the null hypothesis is formulated as the inconclusiveness if positive Early Warnings and negative Early Warnings negate each other in the studied parts of the lead time. This would be shown as that the sum of shifts of CMAD for the fragments of the analyzed period being equal to, or near, the value of zero.

Therefore, the null hypothesis is defined as; *The study of any fragment of the lead time for several orders shows that the negative and positive Early Warnings can be summed up to a near-zero value.*

5.6.2 Researcher's hypothesis

From previous projects regarding Early Warnings, it is perceived as that the majority of Early Warnings are generated close to the delivery date. This implies that the sum of CMAD shifts due to Early Warnings are negative, since large pull-ins of orders cannot be generated close to the delivery date. For example, one week before delivery, a pull-in of maximum one week can be made, however, push-out possibilities are infinite. The total available supply should remain

similar between updates of the Supply Picture, which should indicate that the total push-out of orders due to Early Warnings is equally compensated by pull-ins of other orders due to prioritizing. However, as priority can be affected by completely new created orders that does not appear as positive Early Warnings, the total sum of quantity and date shifts in Early Warnings should be slightly negative. It is also the researcher's belief that the order can be broken down into SLs that are run through the model individually to then be summed up in visual presentations. If there is a pattern regarding the Early Warning generation, it should be made visible through this approach.
The hypothesis for this project therefore states that:

1. *The number of generated Early Warnings increase close to delivery date*
2. *Significant positive Early Warnings appear only at early stages of the lead time*
3. *The total sum of CMAD shifts is negative, but not significant*
4. *Visual comparison of orders with a retroactive viewpoint from delivery date shows a clear pattern of generated Early Warning values*

6. Results

This section compares the results from the data analysis with the hypothesis and presents partial results from the individual SL analysis. The full set of data for one SL is provided as an example in Appendix B.

6.1 Graded table results

Firstly, the compiled results of the graded parameters are presented.

6.1.1 Average CMAD-Average^2 CMAD shift-Final Average newCMAD

The first table that is presented, features the difference between the compiled Average CMAD per SL and the Final Average newCMAD for the order as a whole, then subjected to the average CMAD shift of the order as a whole. These values are completely independent of the quantity, as long as the quantity does not equal zero. The results are graded according to Table 3 and the results are compiled in Table 4.

average KTN-average^2 CMADshift-Final Average newCMAD								No of EW	EW * grade	Average grade per EW
OrderNo	0	1	2	3	4	5	10			
1116202411	56	6	1	0	0	0	0	63	8	0,13
1116211443	0	3	8	0	0	1	0	12	24	2,00
1116214141	13	13	4	7	2	0	0	39	50	1,28
1116207894	0	4	6	2	2	0	0	14	30	2,14
1116214145	27	11	10	4	0	0	0	52	43	0,83
1116214146	30	16	8	3	0	4	0	61	61	1,00
1116214144	29	9	10	3	4	2	0	57	64	1,12
Tot sum	155	62	47	19	8	7	0		280	0,94

Table 4. Results not influenced by quantity

When considering the results, it is important to recognize the affecting factors. The Average^2 CMAD shift, refers to that the average shift of CMAD per day is calculated and then averaged for those values, resulting in the total average shift. If the difference between the oldCMAD and the newCMAD is significant, the shift will also be higher. Therefore, if the newCMAD is close to the actual delivery, the subtraction of the shift will make the formula emit a low grade. This formula evaluates and grades the Early Warning as a trendsetter rather than accurate value. Another big factor is partial delivery, if the difference in days between the first and last delivery is significant, the Final Average newCMAD will not be a good reference point as new Order Promises will move towards the two different values. Since the grade disregards the number of deliveries, delivered quantities or when the specific deliveries are delivered, the grade will show poor performance even though accuracy and trend would show good results. Further, the Average KTN is based on the Early Warnings, or new promises, that were issued on a specific date. If the Early Warning is issued long before the Final Average newCMAD the changes should be incremental and numerous to yield a good grade and represent an accurate trend.

In Table 5, three orders are strong deviators from the average, ##2411 with a relatively low grade but also ##1443 and ##7894 with a relatively high grade. In the table we can see that the highest graded orders have fewest Early Warnings emitted. This should indicate that the total shift and the total average shift are also low. In the sheet "Only N-SL" for the orders, we can see the first delivery promise, or CMAD, compared to the delivery dates. For the higher grades, the final shift of CMAD is approximately one month and kept as one or two deliveries. In contrast, ##2411 has the highest number of generated Early Warnings in the sample size. The order features almost one year between the first promised and the last actual delivery date, additionally, the delivery is split into seven consignments with a total difference of more than six months between the first and last delivery date. However, though the number of Early Warnings is high, it is not significant compared to other orders with average grades.

6.1.2 Adjusted newCMAD-Average KTN

The second table that is presented, features the difference between the Final Adjusted newCMAD for the order as a whole and the daily Average newCMAD, extracted as KTN. The Final Adjusted newCMAD considers the quantity of the order changes, while the KTN does not, unless the quantity equals zero. The results are graded according to Table 3 and the results are compiled in Table 5.

Adjusted newCMAD-Average KTN										
OrderNo	**0**	**1**	**2**	**3**	**4**	**5**	**10**	No of EW	**EW * grade**	**Average grade per EW**
1116202411	40	20	2	0	1	0	0	63	28	0,44
1116211443	2	3	1	0	3	1	2	12	42	3,50
1116214141	7	18	6	6	2	0	0	39	56	1,44
1116207894	0	2	4	3	5	0	0	14	39	2,79
1116214145	18	15	5	5	5	1	3	52	95	1,83
1116214146	22	17	9	1	1	2	9	61	142	2,33
1116214144	22	15	9	5	1	1	4	57	97	1,70
Tot sum	111	90	36	20	18	5	18		499	1,67

Table 5. Result from average updated CMAD compared to Final Adjusted newCMAD (delivery date)

Again, it is important to recognize the affecting factors. One important aspect is that the KTN is not adjusted to quantity. If large quantities are shifted on a certain date, this would affect the performance more than indicated by the KTN, and the same is true if the total quantity between two different dates of updating is fluctuating. Another important aspect is that the Final Adjusted newCMAD is not the exact delivery date. Even though it is a weighted value in order to better represent the order reliability, it is still not the exact delivery date. This means that even a KTN that perfectly matches an actual delivery might not yield a high grade, especially if the first and last delivery are many days apart. Or vice versa, if the result yields a high grade, the new expected delivery date is close to the Final Adjusted newCMAD, but perhaps not an actual delivery date.

In Table 6, three order are again stronger deviators, the same ones as in the previous order. The orders with the fewest updates, and also with few deliveries, show the highest grade. Especially ##1443 is having a high grade and only one delivery, indicating that the new order date of the Early Warnings for this order is not volatile, but close to the actual delivery. Although, two Early Warnings show a date more than a quarter year off (grade equals zero). For order ##7894, no newCMAD is yields value equal to zero, but still has a significantly lower grade since no new promise is issued in the same week.

##2411 is showing a grade significantly lower than the average, as explained in the previous section, it is due to the large timespan between the first and last delivery and the many updates. However, order ##4146 is showing a high grade even though having nearly as many Early Warnings issued. This order is delivered as one, and the high grade is achieved by the many KTN correlating with the exact delivery date. By reducing the grade factor of a KTN showing the exact value from 10 to, for example 6, reduces the grade to slightly below average, while the grades for other orders remain largely the same. Thus, proving the flaws of the analysis setup.

6.1.3 Average KTN-Average^2 Adjusted CMAD shift-Final Adjusted newCMAD

The third table that is presented, features the difference between the Final Adjusted newCMAD for the order as a whole, and the daily Average newCMAD per SL, then subjected to the Adjusted CMAD shift of the order as a whole. The Final Adjusted newCMAD and the Adjusted CMAD shift considers the quantity of the order changes. The results are graded according to Table 3 and the results are compiled in Table 6.

average KTN-Average^2 Adjusted CMAD shift-Final Adjusted newCMAD								No of EW	EW * grade	Average grade per EW
OrderNo	0	1	2	3	4	5	10			
1116202411	51	9	0	2	1	0	0	63	19	0,30
1116211443	2	3	3	0	1	1	2	12	38	3,17
1116214141	7	19	5	1	6	1	0	39	61	1,56
1116207894	0	4	4	1	4	1	0	14	61	2,90
1116214145	39	8	0	2	3	0	0	52	26	0,50
1116214146	36	12	10	3	0	0	0	61	41	0,67
1116214144	44	8	1	0	0	0	4	57	50	0,88
Tot sum	180	64	24	10	16	4	7		296	0,97

Table 6. Results of KTN performance compared to delivery, adjusted by quantity

The affecting factors for this result largely feature the formula for Adjusted CMADs to better represent delivery reliability. However, the Average KTN is not weighted by the quantity. This would cause an issue if a large quantity is delivered at one period and many smaller quantities in another, thus emitting a larger amount of Early Warnings closer to the smaller deliveries while the Final Adjusted newCMAD is pushed towards the delivery with a large quantity.

The Average^2 Adjusted CMAD shift is the average value of the Adjusted CMAD shift per SL per order and thus faces similar issues as the Average parameter in subsection 6.1.1. This concerns significant difference between oldCMAD and newCMAD, but also the difference in days between original expected and actual delivery date in cases of partial deliveries. Further, the Average KTN is based on the Early Warnings that were issued on a specific date. If the Early Warning is issued long before the Final Average newCMAD, in order to represent the trend, the changes should be incremental and numerous to yield a good grade. Therefore, this result is also rather measuring the accuracy of the trend, rather than the accuracy of the Early Warning itself.

In Table 6, we again see the high grades of ##1443 and ##7894 and low grade of ##2411. However, ##4145 and ##4146 also have low grades. ##4144 have four Early Warnings with an exact match with the Final Adjusted newCMAD, meaning that the factor ten is having a large impact. Looking at the EW * grade in Table 6, the four times ten has a huge impact on the grade and reducing the factor from ten to e.g. six also reduces the average grade per Early Warning to 0,60 and this order should actually be considered as low performing. All these three orders have a single delivery date and a high number of generated Early Warnings. Another similarity is that the orders have one well-performing SL, yielding the higher grades, and two SLs, mostly yielding grade zero.

Regarding the performance of ##1443, ##7894 and ##2411, the same affects as in subsection 6.1.1 apply. The higher grades are correlating with few Early Warnings and a relatively small total shift of CMAD. The lower grade correlates with multiple consignments over a long period of time and a large total shift of CMAD.

6.2 Compiled graphs result

In this subsection, the temporal variable analysis of the data is presented in graphs. All data is sorted chronologically and the graphs therefore feature a timeline on the horizontal axis.

6.2.1 Column: Difference between newCMAD and Final Adjusted CMAD

The first graph presented is derived from the difference between the Final Adjusted newCMAD and the KTN, or newCMAD. Added to this, the Early Warnings are sorted on two parameters, firstly the difference between the delivery date and the date that the Early Warning is issued. Secondly the order number and SL within the order, however excluding SL 9900 and SL 9901. As the order lines for SL 9900 and SL 9901 are created upon delivery, the difference between KTU and KTN is therefore often zero and the effect of including the updates would increase the average performance, but can hardly be argued to better represent the actual reliability of Early Warnings. The graphs result of SL 9900 and 9901 are isolated in subchapter 6.2.4.

Firstly, the column graph in Figure 12 shows how the generation of positive Early Warnings is more common and even dominant in the early stages of order lead time. However, from the point in time with 38 weeks left of the lead time this starts to shift and during the last 32 weeks of lead time, negative Early Warnings are generated in large clusters and becomes clearly dominant in both individual impact and total number of emitted Early Warnings.

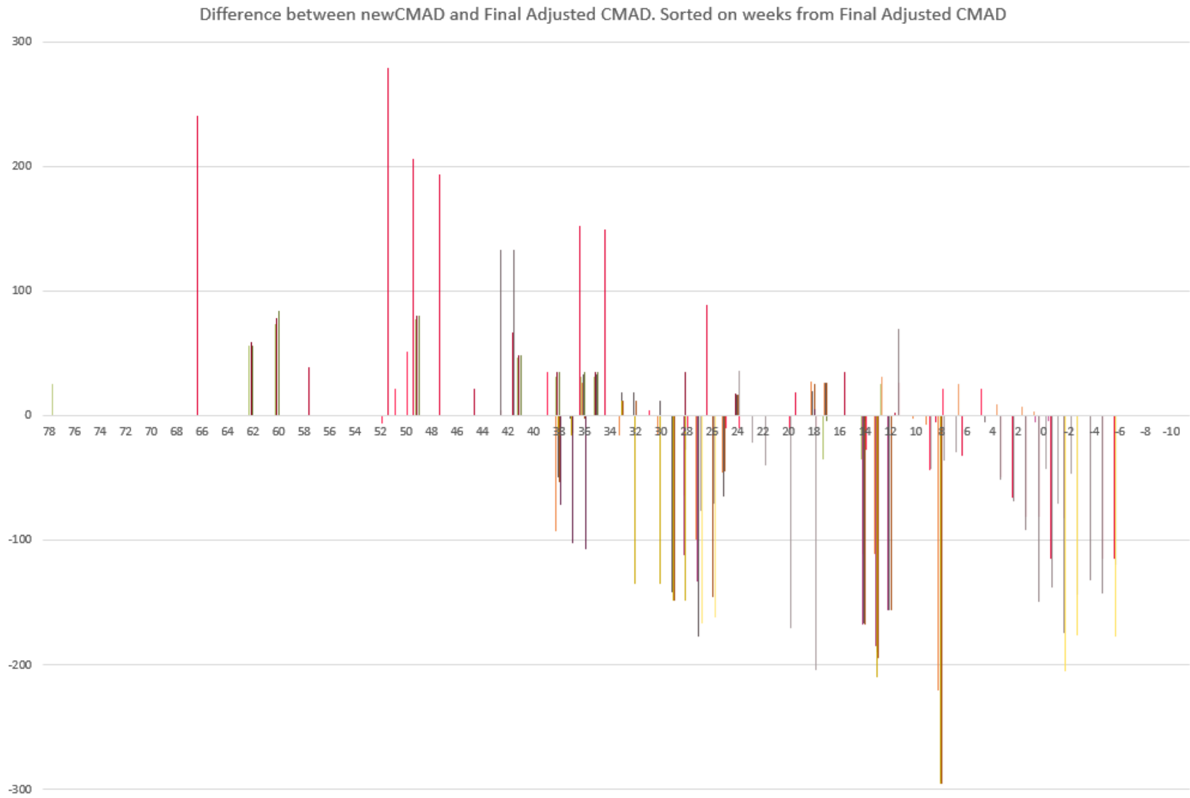


Figure 12. Column graph of newCMAD accuracy for different time periods as compared to the Final Adjusted CMAD

Focusing before the last 38 weeks of the lead time, there is only one Early Warning with a negative value. Additionally, the positive Early Warnings have large values. The most inaccurate of the newCMADs generated in this scope predicts the product to be available for delivery 279 days before the Final Adjusted newCMAD, with several Early Warnings with similar values. This is highly inaccurate and indicates some optimism by the Order Promising process in early stages of lead time.

Inside the last 38 weeks of lead time there are several clusters with an increased number of changes in Order Promise, the majority of which are negative and with relatively high values compared to the positive Early Warnings in the same scope. The exact scope of the clusters is better represented in Figure 13, which shows the number of Early Warnings generated per week. Noteworthy is that this graph includes the completely accurate Early Warnings, where the difference between Final Adjusted newCMAD and newCMAD is zero, meaning that these are not visible in Figure 12.

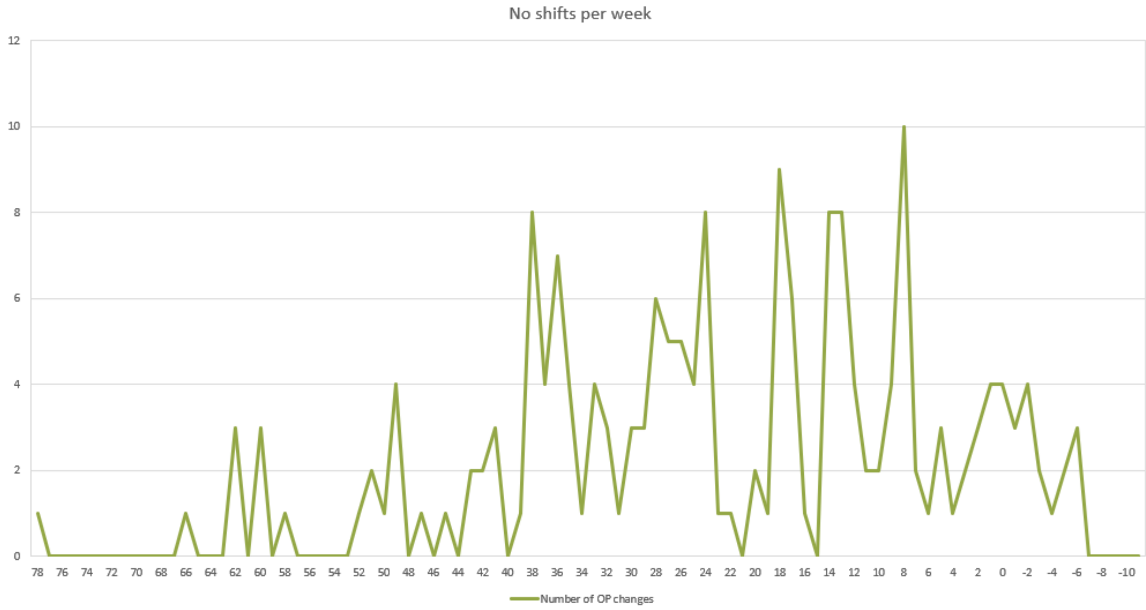


Figure 13. Number of Early Warnings generated per week

However, Figure 13 displays no indication of the value of the Early Warning. Although, a cross-analysis of Figure 12 and Figure 13 allows a good overview of the clusters sorted in weeks (until delivery);

Weeks 36 to 38

The Early Warnings are distributed as eleven negative and eight positives. However, the average accuracy of the positive Early Warnings is higher, meaning they are closer to a value of zero, with one exception. It should be suspected that this exception is the converging newCMAD associated to the SL with the highest positive Early Warning value from week 51.

Weeks 24 to 28

The Early Warnings are distributed as 19 negative, six positive and three that match the Final Adjusted newCMAD. Compared to previous periods, this is when the negative Early Warnings become clearly dominant. The orders that generate negative Early Warnings of large values also generates highly accurate Early Warnings with a difference of ten or less. Thus, the order reliability is still on a decent level.

Weeks 17 to 18

The Early Warnings are distributed as four negative, seven positive and four that match the Final Adjusted newCMAD. This cluster stands out as it is relatively close to the Final Adjusted newCMAD, but with both majority positive Early Warnings and, very high accuracy over all with all newCMADs within 35 days of the Final Adjusted newCMAD, with one exception of -204.

Weeks 13 to 14

The Early Warnings are distributed as twelve negative, two positive and one that match the Final Adjusted newCMAD. This cluster follows the same trend as clusters 36 to 38 and 24 to 28. The negative Early Warnings are decreasing in accuracy, while the positive are converging towards zero. Positive Early Warnings cannot be generated at the Final Adjusted newCMAD or after. Thus, a decline of the positive values is not surprising and highly inaccurate positive values can no longer be generated.

Week 8

The Early Warnings are distributed as six negative, one positive and three that match the Final Adjusted newCMAD. Even though the highest values of negative Early Warnings are generated in this week. Three different orders generated at least one Early Warning with a difference of more than 200 compared to the Final Adjusted newCMAD. However, all three orders also had one SL that generated an Early Warning that match the Final Adjusted newCMAD.

6.2.2 Line: Difference between newCMAD and Final Adjusted CMAD

The graph presented in this sub-section is also derived from the difference between the Final Adjusted newCMAD and the newCMAD. The Early Warnings are sorted on two parameters. Firstly, the difference between the delivery date and the date that the Early Warning is issued. Secondly, the order number and SL within the order, however excluding SL 9900 and SL 9901. As the order lines for SL 9900 and SL 9901 are created upon delivery, the difference between KTU and KTN is therefore often zero and the effect of including the updates would increase the average performance, but can hardly be argued to better represent the actual reliability of Early Warnings.

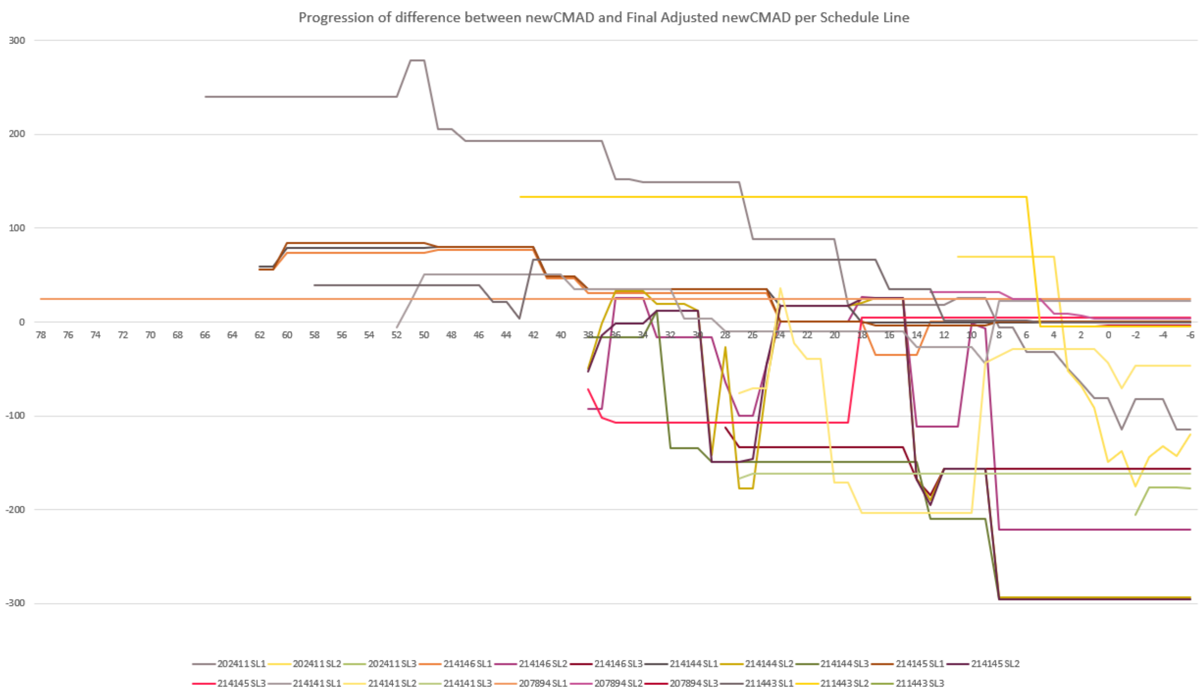


Figure 14. Line graph of newCMAD accuracy for different time periods as compared to the Final Adjusted CMAD

In contrast from the column graph of Figure 12, Figure 14 is a line graph. Even though based on the same data as Figure 12, Figure 14 follows each individual SL rather than isolated Early Warnings. Unless a new Early Warning is issued for the SL, it retains its value until the right edge of the graph. This visualization also allows to follow the development of a certain SL across the lead time. However, it is not visualized when the order is delivered. Therefore, the final, or rightmost, part of each order contains no updates and is therefore not considered in the analysis.

In Figure 14, we can confirm that the extreme values of the positive Early Warnings (>100 days inaccuracy) are associated to only two different orders. SL1 for order ##2411 has the lowest accuracy of the orders, which is also confirmed in chapter 6.1, and is the only order that generated positive Early Warnings with a value over 150 days. Additionally, when approaching the Final Adjusted newCMAD, all three SLs for the order generates negative Early Warnings with a value lower than -100.

All Early Warnings with a positive value higher than 100 days are associated to only two of the orders. However, outside the last 38 weeks of lead time, six out of the seven order in the sample size emits Early Warnings with a positive value higher than 50 days.

6.2.3 Line: Average CMAD accuracy per week

The graph presented in this sub-section features the average values of Table 12. The y-axis shows the average of all individual values for difference between the newCMAD from the Early Warning and the Final Adjusted newCMAD of the related order for each SL. The x-axis shows the difference from when the Early Warning is issued to the Final Adjusted newCMAD, measured in weeks. However, the order lines for SL 9900 and SL 9901 are excluded as these Early Warnings are created upon delivery. Therefore, the difference between KTU and KTN is often zero and the effect of including the updates would increase the average performance, but can hardly be argued to better represent the actual reliability of Early Warnings.

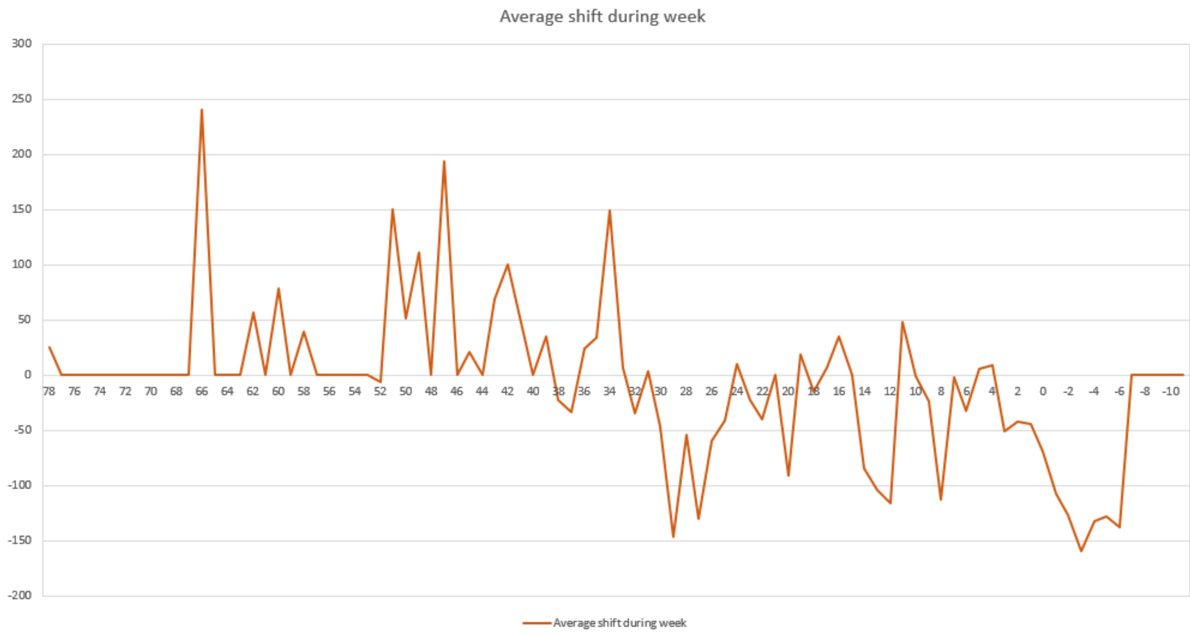


Figure 15. Average difference between newCMAD and Final Adusted newCMAD per week

If there is only one value per measured point, a line graph is more suitable to look for patterns. From Figure 13, we can confirm that outside of week 38, there are fewer Early Warnings generated per week. And seven out of the 14 weeks where Early Warnings are generated, before week 38, features only one Early Warning, meaning the average value is not really of interest and that value has already been evaluated. However, the generation of Early Warnings is increased after this period. Also notewirthy, the average of the Early Warnings remains mainly positive until week 31.

From week 30 until week -6, the average value is mainly negative. This period can also be compared with Figure 13 to see that the weeks where the average is positive features few Early Warnings, and the weeks where the average is negative often features a higher number of Early Warnings generated. This indicate that, inside week 30, either the total number of negative Early Warnings, or the total sum of the negative Early Warnings, is significantly higher than that of the positive Early Warnings.

6.2.4 Column: Difference between newCMAD and Final Adjusted CMAD for SL 9900 and SL 9901

The graph presented is derived from the difference between the Final Adjusted newCMAD and the newCMAD, exclusively for SL 9900 and SL 9901. The graph is set up with the same settings as Figure 12, with columns based on the parameters of difference between Final Adjusted newCMAD and the newCMAD from the Early Warning, and the issue date of the Early Warning compared to Final Adjusted newCMAD. For relevance, the extreme points of both axes are adjusted.

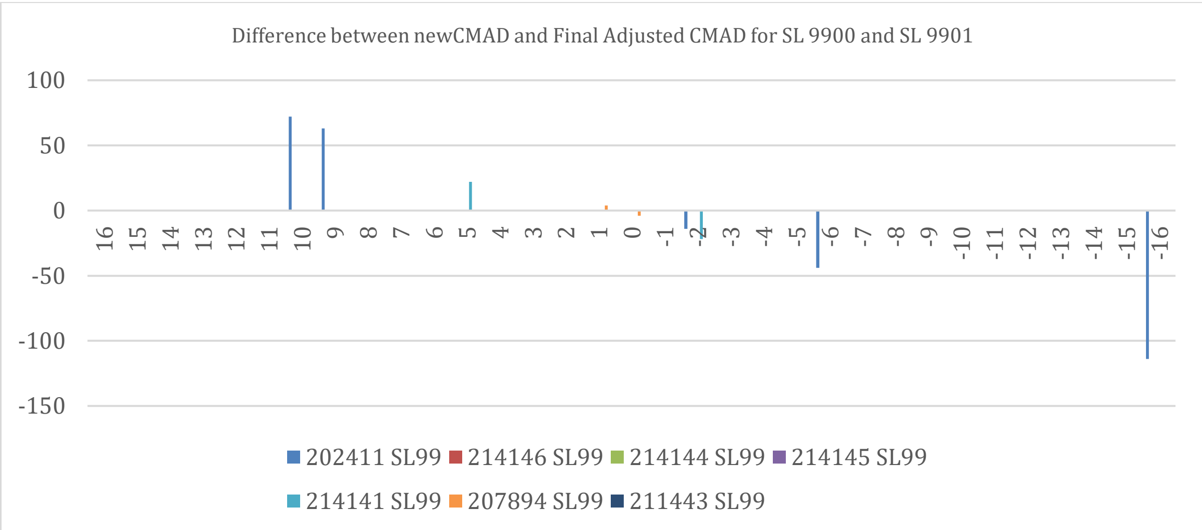


Figure 16. Column graph of newCMAD accuracy for different time periods as compared to the Final Adjusted CMAD for SL 9900 and SL 9901

For SL 9900 and SL 9901, the order line is created upon delivery, and the KTN, or newCMAD, therefore always correlates with an actual delivery. If an order is split into partial consignments, the Final Adjusted newCMAD is located between these dates, with a higher attraction to deliveries of high quantities. The Early Warning generation when comparing to the Final Adjusted newCMAD of these SLs therefore follow Newton's third law; *for every action there is an equal and* *opposite reaction*. This relation explains the linear regression of the values in the graph.

SAP order ##2411 has been singled out in all seections of the result. In this graph we notice that this order has consignments spread over a period of 27 weeks and, in Figure 16, it can be concluded that it is from ten weeks before Final Adjusted newCMAD to 16 weeks after. This confirms that the majority quantity is delivered to customer in the first half of the delivery time period.

For the seven orders in the sample size, there is a total of 15 individual deliveries to customer. As ##2411 represent seven of these deliveries, it can also be concluded that at least two orders are represented by only one delivery, thus both compared parameters equals the Final Adjusted newCMAD, thus equaling zero therefore not visible in the graph.

7. Evaluation

In this chapter, the hypotheses will be evaluated and the answer to the research questions defined.

7.1 Hypotheses

In this chapter, the null hypothesis and the researcher's hypothesis statements will be evaluated and compared to the results of the project. As outcome, the hypotheses will be rejected, accepted or partially accepted.

7.1.1 Null hypothesis

In subchapter 5.6.1, the null hypothesis is formulated as the inconclusiveness if positive Early Warnings and negative Early Warnings negate each other in the studied parts of the lead time. This would be shown as that the sum of shifts of CMAD for the fragments of the analyzed period being equal to, or near, the value of zero.

From Figure 12 to 16, it is visible that the values of generated Early Warnings follow a trend of positives turning to negatives and increasing in numbers, as the delivery date gets closer. Therefore, fragments of the lead time can be summed up as being negative, positive, near zero. This indicate that time periods can be classified and are therefore not inconclusive. Thus, there is an analyzable impact of the time periods and the null hypothesis can be rejected for the samples of this project.

7.1.2 Researcher's hypothesis

The researcher's hypothesis consists of four statements. These will be evaluated individually and accepted or rejected accordingly.

7.1.2.1 Researcher's first hypothesis statement

"The number of generated Early Warnings increase close to delivery date"

The delivery date and the Final Adjusted newCMAD equal each other when the order is completed through only one delivery. However, in case of partial consignment, the Final Adjusted newCMAD is guaranteed to be located between the different delivery dates and therefore proves a good measurement point for measuring the number of Early Warnings generated.

According to Figure 13, the number of Early Warnings generated is somewhat stable during the lead time from order creation, but doubles with 38 weeks left of lead time until Final Adjusted newCMAD. However, it is a sudden increase, instead of a trending value and inside the 38^{th} week, the generation is again fairly consistent.

With seven weeks of lead time left, the number of generated Early Warnings drops. However, this can be explained by the usage of Final Adjusted newCMAD as the reference point. With this measurement, orders can be delivered before week zero, and this could indicate several orders were completed at this breakpoint. Thus, the orders that remain active are using fewer SLs and consequently have fewer means of generating Early Warnings. The same argument holds true prior to week 38. All orders of the sample size have generated at least one Early Warning with 58 weeks of lead time until Final Adjusted newCMAD. However, the orders are not split into several SLs until later. The first time that orders are split into several SLs are at week 43, 38 (for three orders), 27, 13 and 11. This does not correlate with any specific spikes in Figure 13, but helps understand the sudden increase.

Thus, the first hypothesis statement is neither rejected nor accepted. The generation of Early Warnings experience one strong increase, but the correlation is more related to the setup of SLs.

7.1.2.2 Researcher's second hypothesis statement

"Significant positive Early Warnings appear only at early stages of the lead time"
"The early stages of the lead time" is a rather undefined period. For this evaluation, we consider the lead time as the lead time where Early Warnings are generated in the sample size, ergo, up to 78 weeks prior to Final Adjusted newCMAD. By regarding early stages as the earliest 50% of the studied lead time, the assumption is that the early stages of the lead time are defined as the weeks 78 to 39 prior to Final Adjusted newCMAD. Further, "significant positive Early Warnings" is also rather undefined and can also be regarded as relative to the remaining lead time. In this project, there is a scale for Early Warnings used for the graded table results which can be found in Table 3 at page 32. For consistency of the analysis, a value selected from this scale should be used as a reference point in significance. Grade 2 indicates a difference on less than 30 days and grade 1 indicates a difference of less than 91 days. Both will be considered when evaluating this hypothesis statement.
The individual generation of Early Warnings are presented in Figure 12 on page 40. Derived from Figure 12, the largest positive Early Warnings are generated prior to week 39. However, there are significant Early Warnings generated in later weeks accordingly;

- Grade 2: week 38, 36, 35, 34, 28, 26, 24, 16, 13 and eleven
- Grade 1: week 36 and 34

Thus, significant positive Early Warnings appear also in later stages of the lead time. However, not all orders have a lead time that exceed 78 weeks. The argument behind the hypothesis can therefore not be fully rejected. It has been previously stated that all orders of the sample size have generated an Early Warning by week 58. The definitions of "the early stages" can then be adjusted as week 58-29 or, by averaging 78 and 58, as week 68-34. Through either of these adjustments, the positive Early Warnings of significant value according to grade 1 are included in the early stages of the lead time.

However, for significance according to grade 2, several Early Warnings are generated at a later stage. Especially the significantly positive Early Warning of week 11 (see Figure 12) makes a strong case against the researcher's hypothesis. The Early Warning is issued approximately 77 days prior to Final Adjusted newCMAD and holds a value of +70 days, ergo, the Early Warning is issued maximum one week before the newCMAD.

While the exact cause of this strong positive Early Warning is difficult to trace, the possible scenario of unexpected available supply cannot be denied. Therefore, the second hypothesis statement is rejected. The possibility of a significant positive Early Warning appears to be higher, but is not exclusive to, the early stages of the lead time.

7.1.2.3 Researcher's third hypothesis statement

"The total sum of CMAD shifts is negative, but not significant"

The CMAD shift should be defined as the difference from the penultimate newCMAD to the newCMAD of the latest Order Promise. However, as quantities shift SLs during the lead time, each individual shift is complicated to track and has not been an implemented feature of this study. We therefore need a replacement reference point.

KTU-KTN is not considered as a replacement parameter, as the original expected delivery date is seldom kept and an order that is delivered later than the KTU will emit a higher number of Early Warnings with increasingly negative values. The Final Adjusted newCMAD regards the deliveries and is the best reference point for delivery, when only one date per order can be considered, as in this project. The difference between newCMAD and Final Adjusted newCMAD is therefore used as a parameter as the sum total should have a value close to that of the CMAD shift.

In the compilation of data into average weeks, if two Early Warnings were emitted from the same SL in the same week, the Early Warnings were averaged into one data point. Thus, the total number Early Warning and the total sum of the Early Warnings will not be completely accurate. However, the sample size is considered large enough to give a strong indication of the validity of the hypothesis. After the compilation of data points, the sum total of the number of Early Warnings is **187**. The sum total of the difference between newCMAD and Final Adjusted newCMAD for these 187 Early Warnings is **-5690**. The total sum of -5690 days over the small sample size of seven orders can seem significant, but the average newCMAD has a difference of -30 days. According to the grade scale in Table 3 at page 31, this is barely significant according to grade 2 and not significant according to grade 1.

However, as the Early Warning generation is increased, the majority of Early Warnings are negative, and the total sum of CMAD shifts appear significantly negative. As this appears to be the trend, an increased sample size is expected to also increase the negative values. Thus, the researcher's third hypothesis statement is rejected.

7.1.2.4 Researcher's fourth hypothesis statement

"Visual comparison of orders with a retroactive viewpoint from delivery date shows a clear pattern of generated Early Warning values"

This evaluation of this hypothesis statement is best referred to Figures 12, 14 and 15 from chapter 6.2. These are shown as miniatures in Figure 17.

Figure 17. Compiled figures 12, 14 and 15 respectively

All three graphs indicate the same pattern, which indicate that there is a conclusive pattern to be recognized. The positive Early Warnings are strongly dominant until 38 weeks left of lead time until Final Adjusted newCMAD. After this period the Early Warnings are mixed between positive and negative values with a weak majority of negative values. However, as the total number of generated Early Warnings per week is increased, the negative Early Warnings increase in both number and value when enclosing the Final Adjusted newCMAD. The negative Early Warnings develop a strong dominance of both total value and total number of data points compared to the positive Early Warnings. This pattern is especially recognizable in Figure 15, which shows the average value of the Early Warnings per week.

Therefore, the researcher's fourth hypothesis can be accepted for the selected sample size.

7.2 Answering the research questions

What are Early Warnings and how are Early Warnings currently generated within the Supply Chain at the company?

This is answered in Chapter 4, Research framework, with the addition of Appendix A for an extended context upon interest. However, even though the processes within the Supply Chain are mapped, there are still blind spots when it comes to Early Warning generation and only the most common causes are traced at this point. Today there are three different kind of Early Warnings identified and explained, but there is expected to be more categories that can be traced. Although, the shift is often not noticed until the automated processes of the OM, and the changes are difficult to trace upstream due to the complex Supply Chain.

Which, if any, patterns can temporal variables analysis reveal in Early Warning generation?

Positive Early Warnings are mainly generated in the early stages of lead time. The values are relatively large but seldom accurate. There are basically no negative Early Warnings until the splitting of order lines about halfway through the lead time. At this point, the number of Early Warnings is doubled but stays balanced between negative and positive. Eventually the negative Early Warnings dominate, and before the Final Adjusted newCMAD, positive Early Warnings are no longer generated.

Does the time of the generation of the Early Warning correlate with the accuracy of Order Promising?

Yes, there are definitely patterns for certain clusters of Early Warnings. Most orders emit Early Warnings that are close to the Final Adjusted newCMAD already in week 33, and makes only small adjustments for weeks 24 and 18. However, this accuracy is not concise for all SLs within the order and the pattern is not concise for all orders of the sample size. A better linkage between the delivered quantities the Early Warnings should be established and a more orders need to be evaluated to validate any conclusions.

8. Discussion

This section compares the results from the project with personal insight from the researcher and presents assumptions and speculations that are supported by the result.

8.1 Project summary

In this project, an understanding of Early Warnings was gathered in order to execute a comprehensible data extraction and analysis with the relevant parameters. After a hypothesis was stated, the extraction and analysis were conducted with several output parameters that could then be both compared between the individual samples and compiled to analyze for trends in the data points. The results were then compared to the hypothesis statements.

8.2 Result indications

The results indicate that

- Orders in SAP initially generate positive Early Warning and starts emitting negative Early Warnings with a certain lead time left until Final Adjusted newCMAD
- The number of partial consignments for an order strongly increase the generation of Early Warnings while reducing the overall accuracy
- The sample size needs to be increased for sufficient validity to support any decision making at the company

8.3 Researcher's observations

In this subchapter observations made during and after the analysis are discussed.

8.3.1 Early Warnings generation

An unexpected result from the graphs generation was the clear shift from positive to negative. The researcher expected a dominance of negative Early Warnings at the end of lead time as was confirmed, however, the absolute dominance of positive Early Warnings in the early stages of lead time (26 to one) was not expected. This might be connected to the BROC algorithm. The suspicion is that if orders are not postponed, the algorithm has a higher priority of retaining order stability. However, once the order is pushed out of the original delivery window, priority is lowered and it is easier for the algorithm to further split and postpone the order.

Additionally, the number of generated Early Warnings per time period appears to be dependent mainly on the number of active SLs for the order. However, by looking at the extreme difference between newCMAD and Final Adjusted newCMAD in Figure 14 on page 42, there are clusters with several Early Warnings of the similar value. This especially refers to the following weeks; 8, 12-14, 25-29 and 49. One interesting aspect is that the pattern can be divided into months or quarters. Which could indicate that if e.g. one or two quarters remain until the expected delivery date, the evaluation of the Order Promise features more parameters and/or a more critical prioritization. This would then depend on the BROC and shows that a better understanding of the algorithm would have benefitted predictions and assumptions of the project.

8.3.2 Sum of Early Warnings

Ealry in the project, an insight was reached regarding the inevitable rejection of the researcher's third hypothesis. If an order stayed to only one Schedule Line through the entire lead time, the sum total of the shift would be the difference between KTU and KTN, or old and newCMAD. Due to the increased generation of Early Warnings closer to the Final Adjusted newCMAD, with a strong majority of them being negative. This, in combination with the splitting into different SLs being a feature only in later stages of the lead time, the density of the negative Early Warnings was a lot higher and a delayed order that is split into several SLs then amplify the negative shift.

Large positive values of Early Warnings appear to be common, but the CMAD keeps getting pushed back to reduced positive Early Warnings and eventually negative Early Warnings. The positive Early Warnings that are generated late in the lead time however, are often very close to a deliver date and thus highly accurate. However, the negative Early Warnings are often pushed out to a much later date than the Final Adjusted newCMAD and the accuracy of negative Early Warnings therefore decrease in the late stages.

Another important aspect is the allocation process. The sample size is limited to "standard orders" and should therefore not be affected by allocation, however, the available supply is. As the available supply and actual demand are the two main inputs for the BROC, this indirectly affects the standard orders. This might affect the generation of Early Warnings as available supply is moved for "allocation" and leaves a reduced Supply Picture.

Also, the orders of the sample size are from roughly the same time frame, and the trends of Early Warning generation might be explained by impact from large external events that affect the Supply Chain. For example, a Covid-outbreak at a large the company factory or delayed import processes would largely reduce the available supply and thus the BROC. Therefore, the sample size needs to be increased over a larger period of time to reduce external impact and validate any actual trends.

8.3.3 Reference points and measurements

The graphical results track the accuracy of each individual Early Warning compared to the Final Adjusted newCMAD. These values look more radical than the actual shift of the CMAD. In case an updated Order Promise differs 100 days to the Final Adjusted newCMAD and the next one differs 99 days, the shift is only one day between the Order Promises, but in the graphical results the inaccuracy is shown as 100 and 99. It should be considered if this is a fair evaluation, as the value of Early Warnings also could be considered to be the shift in CMAD from the last CMAD, or the total shift from the first promised delivery date, instead of, as in this study, the Final Adjusted newCMAD.

The usage of Final Adjusted newCMAD as the reference point for Early Warning accuracy appear to be functional when an order is limited to one consignment, or when all consignments of an order are near each other in terms of date. For example, if an order is split into two consignments of equal quantity. For each consignment there is an Early Warning generated which perfectly match this specific delivery date. The Final Adjusted newCMAD is then located right between the two actual deliveries. So, it the deliveries are 30 days apart, the accuracy according to this model will be 15 days for both Early Warnings, even though they are 100% accurate. In the graded result, ##2411 is singled out in every table as the lowest performing order. However, the consignments span a timeframe of approximately six months, or 183 days, and the Early Warnings span a timeframe from +279 to -177, a total difference of 456 days. Meaning in terms of total deviation, ##2411 still performs at a low level and the correlation between low Early Warning accuracy and partial consignments is still valid.

8.3.4 SL splitting

In the project, SLs are studied individually and the process of splitting into SLs is difficult to track. For logical reasons, only SL 1 features the Early Warnings prior to splitting of the order quantity. So, when the second SL is set up, it appears to only be impacted by the new Early Warnings, even though the Early Warnings prior to the order splitting also affected the same order.

The granularity level of SL to track the Early Warning development was decided in consensus with the supervisor from the company, but might not be the optimal parameter for the tracking. In later stages of the project, when the analysis was near completion, the researcher was made aware of another granularity known as "Line Item". The concept has been presented internally but is not a used concept within the Supply Chain. Line Item is supposed to trace the quantity as an individual item through the entire lead time. Thus, one SL can cover several Line Items and if the quantity is split with ten weeks of remaining lead time, the split is also made retroactively, so that both splitting and merging of SLs does allows Line Items to have the same CMAD, but they remain as two separate items until they are delivered. However, according the head of OM, tracking of this granularity is probably not possible in DMOP. Although, this is not fully confirmed.

New SLs are set up only when a consignment is split due to the order getting different delivery dates for different quantities. When looking into the time before orders of the sample size are split, there is an interesting pattern. The last Early Warning before the split is a large postponement of the Order Promise, in contrast to the Early Warnings until that point, who are only increasing its positive value. For example, order ##4146 generates three Early Warnings, gradually increasing the positive value from 56 to 77. The fourth Early Warning has a value of 47 and in the fifth Early Warning, the order is split. The pattern is very similar for five out of the seven orders of the sample size. Thus, indicating that order splitting and further order push out is easier for the algorithm after the first negative shift of the Order Promise.

8.3.5 Adjusted delivery reliability

The measurement of “adjusting” the dates of CMAD with respect to the quantity is developed to better represent the actual delivery reliability. The analysis of graded tables, is done both according to average (6.1.1) and adjusted values (6.1.3). Comparison of the grade between the two shows that the grading based on average values has a more levelled grading, the grades in the adjusted analysis rates the orders with fewer Early Warnings higher and the orders with many Early Warnings are rated lower. Assuming that all calculations and assumptions are correct, this means that the difference in performance between the orders is greater according to the adjusted model. But with the large impact of the number of Early Warnings, the company need to consider and refine the Adjusted formula depending if the want a larger impact from the magintude of individual Early Warnings, or the number of Early Warnings generated. However, an expanded sample size is need to prove and define or disprove this correlation.

The analysis of 6.1.2 features a mix of the average and adjusted values which reduces the validity of the exacts results, while the indications are still of interest. Adding further granularity, for example to calculate the adjusted values per SL, would require more layers of analysis. This increased effort and complexity of the analysis would yield a better representative result, but as the application of the adjusted formula is not fully implemented in the delivery reliability evaluation the possible value-creation is of developing the model cannot be proven.

8.3.6 Confirmed data loss

When the data was compiled into graphs, the Early Warnings were kept on separate SLs, but all dates within the same week were compiled into one average data point. This was done mainly due to a lack of time, as the process of sorting Early Warnings on the timeline was completely manual. However, this resulted in data loss where one SL had multiple Early Warnings in one week. These instances correlate with the clusters of Early Warnings, especially between weeks 14 to zero. Therefore, in this period, there are both more accurate and inaccurate Early Warnings, which would affect the appearance of the graphs. However, the analysis impact is perceived as negligable, as no radical shifts within the same week were observed when compiling the results.

The averaging of Early Warnings within the same week affect both the first and third hypothesis statement. *For the first hypothesis statement*: the data loss slightly reduces the number of generated Early Warnings for weeks 14 to zero. This strengthens the researcher’s hypothesis as the generation of Early Warnings experience another increase closer to Final Adjusted newCMAD than the one observed. *For the third hypothesis statement*: as the period of data loss is in the later stages of the lead time, the Early Warning values are mainly negative. Thus, the total sum of Early Warnings is suspected to be even lower if the average is separated into its individual values. Additionally, when calculating the average value per Early Warning, the denominator, ergo the number of Early Warnings, is higher which reduces the average. However, as the negative sum of Early Warnings is also increased, the effect might be negligible or even negative.

This consideration indicates that the researcher's hypothesis is even less likely to be accepted.

8.4 Limitations

The focus of the project was initially based on the outlook of a previous thesis project. However, when expanding the understanding of the Early Warnings and its environment by examining internal training material, other thesis projects and reaching out to process experts, it was discovered that the original thesis was based on a mix of current and outdated information.

Further, there appeared to be some confusion as to the different concepts, ontology and system relations within the OM process. Depending on the using function within the company, the same object can have different names, such as the Finished Product, which is referred to as both FP-number and MA-number depending on the using function. Another cause for confusion is that one word can be used by different functions, where they refer to different objects, or the same object at different abstraction levels. For example, the Early Warning as referred by the Early Warning report that is derived from AATP_v2 only refer to OM Early Warnings, while in another context an Early Warnings may refer to any possible cause of Early Warnings.

For this reason, statements in different material was often ill-defined and sometimes even contradicting each other. Only the words of the process owners have been considered absolute when reviewing the material. The process of creating a basic understanding therefore took longer than expected.

Another strong limitation is the researcher's lack of experience regarding statistical analysis. In the literature review for the data analysis, this caused a problem as it was difficult to grasp which kind of literature was sought after. For this reason, much time was spent on exploring data analysis concepts and methods that was considered unusable, or later disregarded due to lack of time.

8.5 Outlook

There are several adjustments that can be applied for the analysis model and data extraction.

More information could be gathered on the algorithm that runs the BROC and therefore the order re-promising process. It is expected that insight in the priority modes of the algorithm includes time parameters, which would help formulate better hypotheses. However, there is a strong risk of increased complexity with the addition of new parameters. For example, customer relation, size or the fiscal quarter could be affecting parameters that would then need to be considered. However, the current discussion features a lot of uncertainty that is suspected to be best traced to the algorithm.

In DMOP only 14 of the 827 available parameters were included in the data extraction. Hopefully the parameters included are the most relevant ones, but a further understanding and inclusion of parameters to enable cross-referencing for better tracking within the order would stronger conclusions from the result. Alternatives to tracking on order could for example be to investigate if there are patterns in the Early Warning generation

- Between customers
- Between FPs
- Within an FP
- Within a business segment
- Between Line Items
- Between orders with the same lead time
- Between orders with only one delivery

However, if retaining the current model, the sample size should be increased to fully explore the validity of the conclusions. Only eight out of approximately one billion orders are considered, meaning that there is a lot of data to extract in order to reach a sample size that can be considered representative.

References

Bell, E., Bryman, A. & Harley, B. (2018). *Business Research Methods* (5th edition). Oxford University Press, Oxford, Great Britain. ISBN: 9780198809876

Corporate Finance Institute (2022). *Moore's Law.* https://corporatefinanceinstitute.com/resources/knowledge/other/moores-law/

Dietterich, T. (1995). Overfitting and undercomputing in machine learning. *ACM Computing Surveys, Volume 27* (3rd issue), p.326-327. DOI: 10.1145-212094.212114

Dowdy, S., Wearden, S. & Chilko, D. (2004). *Statistics for Research*. (3rd edition). John Wiley & Sons, Inc., New York. ISBN: 9780471267355

Freedman D.A. (1985). *Statistics and the Scientific Method*. Mason W.M., Fienberg S.E. (eds) Cohort Analysis in Social Research. Springer, New York. DOI: 978-1-4613-8536-3_11

Fortune, N., Short, S. & Madden, R. (2020). Building a statistican classification: A new tool for classification development and testing. *Statistical Journal of the IAOS, Volume 36* (4th issue), p. 1213-1221. DOI: 10.3233/SJI-200633

SAP. (2021). *Business Intelligence Platform Administration Guide.* SAP Help Portal. https://help.sap.com/viewer/2e167338c1b24da9b2a94e68efd79c42/4.3.2/en-US/469d02e96e041014910aba7db0e91070.html

Thanda, A. (2021). *What is Logistic Regression? A Beginner's Guide*. CareerFoundry. https://careerfoundry.com/en/blog/data-analytics/what-is-logistic-regression/

Johnsson, R. & Kuby, P. (2004). *Elementary Statistics*. (9th edition). Brooks/Cole Publishing, California. ISBN: 978-0-534-39915-3

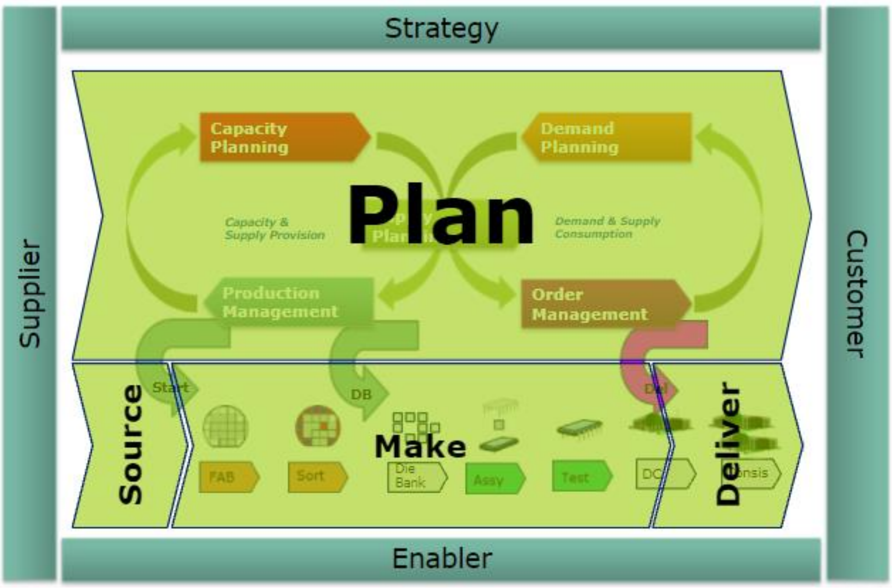
Karlsson, C. (2016) *Research Methods for Operations Management*. (2nd edition). Routledge, Abingdon-on-Thames. ISBN: 978-1-315-67142-0

Appendix A

This section covers a larger scope of the Early Warning generation processes and related processes. The section was orginally a part of Chapter 4. Research framework, but had negligible impact on the result and was therefore moved to this section of the paper.

1 Supply chain management at the company

The Supply Chain management tool SCOR, Supply Chain Reference Model, is a process reference model which considers the entire Supply Chain and all business activities related to satisfying customers demand. At the company, the SCOR model is used to increase visibility and harmonization of SC processes, for standardization through an inter-industrial reference model and to achieve reliable and efficient benchmarking.
The six major SC processes are Plan, Source, Make, Deliver, Return and Enable, as seen in Figure 3. The different interfaces described in the model are sourcing logistics (interface towards suppliers), production logistics (internal SC and production logistics), distribution logistics (interface towards customers), warehouse logistics (interface towards external partners) and transportation logistics (interface towards external partners). In between these interfaces there is a flow of material, information and value.



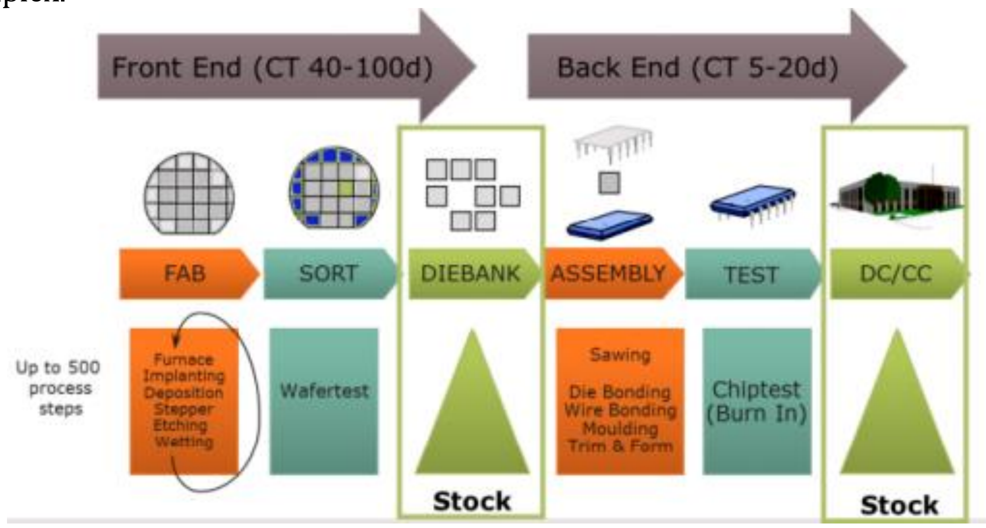
The SCOR model

1.1 Source

The source process includes all activities related to sourcing of material, such as purchasing activities, material acquisition, storing and shipment to production. By optimizing the sourcing processes, the trade-off between conflicting sub-targets of secure supply, high flexibility, quality and efficiency can be minimized. Most of the sourcing logistics concepts are driven by planning, forecasting and consumption, including inventory sourcing which is the most used concept within the company. For individual sourcing, on the other hand, procurement is event-driven.

1.2 Make

The Make Process considers production and production control, and the output is material to Die Bank from front end production and distribution centers from back end, as seen in Figure 4. The targets of the make process is to optimize the contradicting targets of low inventory levels and high delivery performance while also fulfilling market requirements and operational requirements. The KPIs address cost, quality and speed. The production sites and silicon foundries are distributed globally, and the production processes are complex and involves thousands of steps. This makes the production and the Supply Chain highly complex.



FE to BE facility mapping

1.3 Deliver

The Deliver Process includes order management, shipping, invoicing, order tracking and return. This also involves storage and transport of finished goods. The main target of the delivery process is to ensure high performance while keeping the distribution costs low. The KPIs are, among others, delivery performance, delivery capability and delivery reliability. Delivery reliability is of particular interest for this study and is the main KPI of the OM sub-process. The KPIs can be seen in Figure 5.

Overdue orders	$\frac{\text{Overdue line items}}{\text{Total line items}} * 100\%$
Overdue receivables	$\frac{\text{Overdues}}{\text{total account receivables}} * 100\%$
Order confirmation cycle time performance	$\frac{\text{Confirmed line items inside target (24h) per timeframe}}{\text{All incoming line items per timeframe}} * 100\%$
Delivery performance	$\frac{\text{\# of line items delivered according to last requested date (CRD)}}{\text{Total number of line items delivered}} * 100\%$
Delivery capability	$\frac{\text{\# of line items confirmed according to last requested date (CRD/WT)}}{\text{Total number of line items}} * 100\%$
Delivery reliability	$\frac{\text{\# of order line items shipped according to initially confirmed date}}{\text{Total number of order line items delivered}} * 100\%$

Delivery KPIs

1.4 Return

The return process is divided into different types: logistical returns due to logistical errors, technical returns due to quality issues and commercial returns due to customer failures.

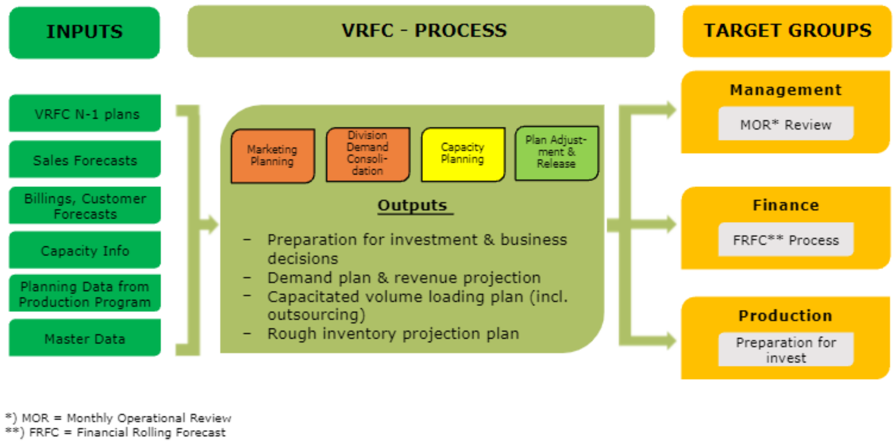
2 The plan process

The company distinguishes between four different levels of planning based on time and abstraction level. The levels are (long to short-term) strategic, tactical, operational and execution.

2.1 Planning levels

All planning steps are interconnected, and the information from lower levels is reused for planning in the higher levels. The execution step includes last-minute production plan changes in Front End and Back End, decisions are made locally in plant.

- In the operational step, the Production Program is developed and confirmed by advanced planning systems that calculate the demand/supply match on a daily basis and generates a weekly production plan to optimize the Supply Chain. The Production Program is further discussed in subchapter 3.5.2.
- For the tactical step, a scenario planning tool is used to create different business scenarios. By combining the information derived from the scenario planning and the Production Program, the Volume Rolling Forecast can be calculated to provide guidance for investment and business decisions, as well as to create demand plans and revenue projections, volume loading plans and inventory projection plans. A more detailed view of the Volume Rolling Forecast process is presented in Figure 6.



The VRFC process

- The planning processes is also divided into five different sub-processes, namely capacity planning, demand planning, supply planning, production management and order management.
    - Capacity planning features bottleneck analysis and scenario generation to support capacity investments and disbanding.
    - Demand planning controls prioritization demand which is sent as input for the Divisional Model, hereafter DM.
    - Supply Planning is the interface between the Plan sub-processes and is largely centralized around the DM. The DM is an IT tool that combine

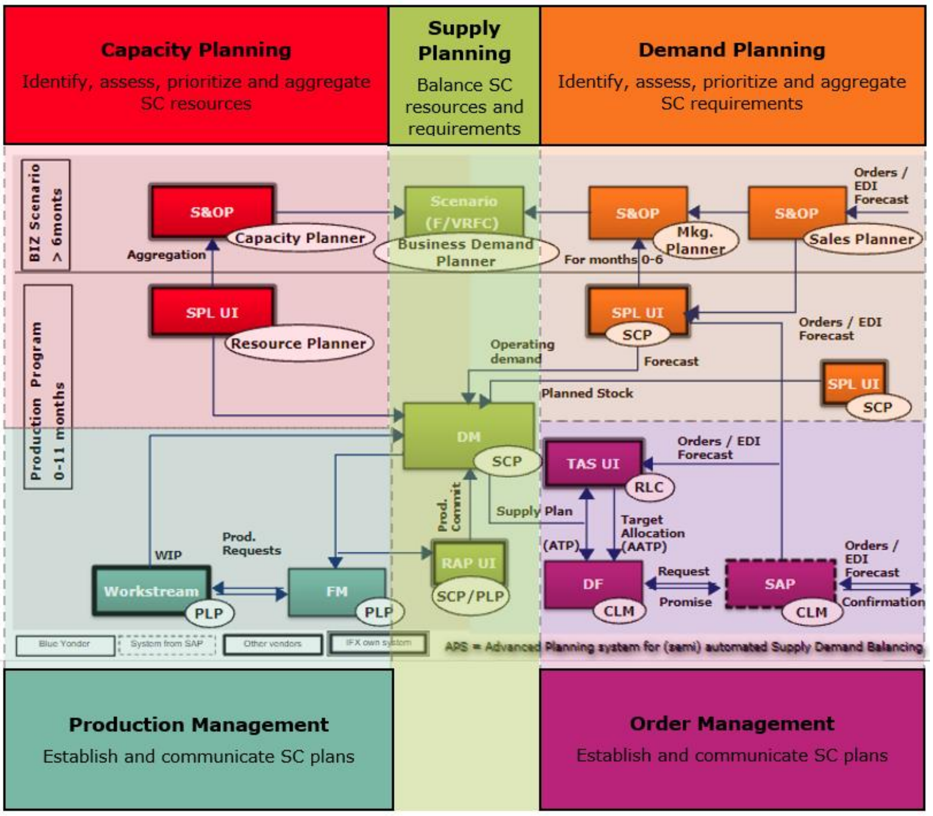
information about capacity, forecast and actual demand to create the Supply Picture, used for production planning and order confirmation.

- Production Management, acts according to the Production Program and confirms or adjusts the input plan ot its operations. The output is a detailed production plan which is sent back to the DM.
- Order management, hereafter OM, compares the Supply Picture generated in the DM with actual demand in the DF. OM also conveys information about order confirmation or changes to the customer and internal systems for forecasting.

2.2 Process flow overview

Most of the processes are automatized and work by rules defined by the Supply Chain Planners. In the supply planning process, a demand and supply matching is made daily by combining the information from capacity planning and demand planning, resulting in a plan containing available supply, defined as ATP and AATP, and production requests for production management. The Supply Demand Match process is done automatically. However, inside the back end freeze fence, changes of demand and production requests can only be done manually in the tool Requests and Promise User Interface, referred to as RAP-UI, in collaboration by the Supply Chain Planner and the Production Logistics Planner, hereafter SCP and PLP.

The information from the Divisional Model is used in Production Management to optimize inventory levels, utilize booked capacities, weekly process, and reserve capacity and resources, monthly process. It is also used as input to the OM tools, DF and TAS-UI, in the form of information about available supply. If there is not enough supply to confirm an order, a substitute product can be considered instead. The process of Order Management will be more thoroughly explained in the next chapter. For more detailed information, including the stakeholders responsible for the different processes, as well as tools, can be seen in Figure 7.



Supply chain sub-processes

3 Order Management at the company

Within the Planning process, OM is where Supply Chain plans are established and communicated to the customer. These plans are on a higher abstraction level than a defined Finished Product. The level is known as the Sales Product, a virtual object best described as an umbrella that covers Finished Products with the same fit and function. The main purpose is to seamlessly introduce new products to customers, thus enables ordering via the same Sales Product number for the customer with a guarantee that the product has the same fit and function. The OM planning for the upcoming 52 weeks is done on Sales Product level. The order management process consists of several processes, such as order handling and scheduling, the company refers to confirmed order and delivery dates as Order Promises. When the information is conveyed to a customer the Order Promise instead becomes the latest order confirmation.

3.1 Order types and entry

There are different kinds of orders, which has different implications in terms of changeability, priority and level of detail. The different order types can be seen in Table 1.

Sales document name	SAP document type	Purpose	ATP reservation	Confirmation relevant	Delivery relevant	Slides
Scheduling agreement	ZGZ2	› Contains customer specific contract information › Framework for forecast / buffer-stock / order concepts	No	No	No	11 - 16
Forecast	ZEF1/ZUF1	› Reserving supply for customer › Indicating customer demand for the next 26/52 weeks › Triggering production	Yes	Yes	No	17 - 24
Call-off order	ZEC1/ZUC1	› Transforms forecasted quantities into deliverable demand › Automatic consideration of in-transit shipment and update of old order quantities	Yes	Yes	Yes	25 - 29
Standard order	ZGC2	› Can be used in combination with forecast or as stand-alone order › Provides concrete demand according lead time, which has been agreed between IFX and the respective customer	Yes	Yes	Yes	30 - 35
MPS/JIT order	ZPS1	› Transforms forecasted quantities into deliverable demand on a short-term notice (usually placed 48 to 72 hours prior to requested delivery)	Yes	Yes	Yes	36 - 38
Buffer-stock	ZCS1	› Reserves inventory in our IFX warehouses for customer / material in case of increased short term customer demand › Contractual agreement with customer required	Yes	Yes	No	39 - 43

Order Types for OM

Customer order entry is done manually by a Customer Logistics Manager or transferred from customer input. The entry requires an extensive list of information where the most relevant to order management are product information, Wunschtermin or WT (customer request date) and quantity. After the order entry process is finished, the order validation in SAP starts. This consists of several sub-processes that an order must go through in order to be validated, e.g. financial and capacity aspects. Derived from the WT, the system calculates when products need to be available at a warehouse to have enable for pick and pack and transit time before the WT is passed. This date is referred to as the Requested Material Availability Date, RMAD.

3.2. The Order Management process

Once an order is validated, it is going through the Order Promising process. Here, the quantities that are Available to Promise, hereafter ATP, are checked. Available to Promise is the uncommitted supply in the time frame until the calculated RMAD, and includes information on quantity, Sales Product and the associated Finished Products. By matching the ATP with orders, the Order Promises are generated. An Order Promise confirms information about the Finished Product, quantity and Confirmed Material Availability Date, hereafter CMAD. The CMAD is the date when the order is expected to arrive to the customer according to current calculations, the Order Promise, and can thus be communicated towards the customer as order confirmation. The CMAD is the most volatile factor when investigating Early Warnings.
Examples of other OM processes include comparing product qualifications entered by the customer to Sales Products, or matched to package quantities and minimum order quantities.

Appendix B

This section shows the data sheets from one of the sample orders. The pictures follows the setup of the sheets in Excel going from SL 1 to 99##.

	BM	SAP ScheduleLineNo	AE_ST	UM_ST	DAY_sorted	TransactionCode	SAP Order	KTU orig poss delivery day	KTN new poss delivery day	SAP OrderDate	KTU-KTN	Adjusted newCMAD-KTN. If no change of date, =0
5	202001	1	5000		2020-01-14	N	1116207894	2021-06-18	2021-06-18	2020-01-14	0	0
6	202104	1	-5000		2021-04-15	O	1116207894	2021-06-18	2021-06-18	2020-01-14	0	0
7	202106	2	-5000		2021-06-17	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	3,5
8	202107	2	-5000		2021-07-05	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	3,5
9	202106	2	-5000		2021-06-15	O	1116207894	2021-06-11	2021-07-02	2020-01-14	-21	10,5
10	202106	2	-5000		2021-06-28	O	1116207894	2021-06-11	2021-07-02	2020-01-14	-21	10,5
11	202106	2	-5000		2021-06-14	O	1116207894	2021-06-11	2021-06-25	2020-01-14	-14	17,5
12	202105	2	-5000		2021-05-25	O	1116207894	2021-06-11	2021-06-11	2020-01-14	0	0
13	202106	2	5000		2021-06-15	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	3,5
14	202106	2	5000		2021-06-28	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	3,5
15	202106	2	5000		2021-06-14	O	1116207894	2021-06-11	2021-07-02	2020-01-14	-21	10,5
16	202106	2	5000		2021-06-17	O	1116207894	2021-06-11	2021-07-02	2020-01-14	-21	10,5
17	202105	2	5000		2021-05-28	O	1116207894	2021-06-11	2021-06-25	2020-01-14	-14	17,5
18	202104	2	5000		2021-04-15	O	1116207894	2021-06-11	2021-06-11	2020-01-14	0	0
19	202107	3	-2500		2021-07-08	O	1116207894	2021-06-11	2021-07-19	2020-01-14	-38	-6,5
20	202107	3	-2500		2021-07-07	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-3,5
21	202107	3	-2500		2021-07-12	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-3,5
22	202107	3	2500		2021-07-07	O	1116207894	2021-06-11	2021-07-19	2020-01-14	-38	-6,5
23	202107	3	2500		2021-07-05	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-3,5
24	202107	3	2500		2021-07-08	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-3,5
25	202107	9900		2500	2021-07-12	N	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-3,5
26	202107	9900		2500	2021-07-05	N	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	3,5
27	202107	9900	2500		2021-07-12	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-3,5
28	202107	9900	2500		2021-07-05	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	3,5
29												
30											-566	

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

BM	SAP ScheduleLineNo	AE_ST	UM_ST	DAY_sorted	SAP Order	KTU orig poss delivery day	KTN new poss delivery day	Final Adjusted newCMAD-KTN (0<)	Final adjusted CMAD shift	KTU*Qty => date for oldCMAD	KTN*Qty
202001	1	5000		2020-01-14	1116207894	2021-06-18	18.06.2021	24,50	0	221825000	0
202107	9900		2500	2021-07-12	1116207894	2021-06-11	16.07.2021	-3,50	-8750	0	110982500
202107	9900		2500	2021-07-05	1116207894	2021-06-11	09.07.2021	3,50	8750	0	110965000
										44365	44389,5
										18.06.2021	12.07.2021
										oldCMAD	newCMAD

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

BM	SAP ScheduleLineNo	AE_ST	UM_ST	DAY_sorted	Transaction Code	SAP Order	KTU orig poss delivery day	KTN new poss delivery day	SAP OrderDate	KTU-KTN	Adjusted oldCMAD-KTN. If no change of date, =0	KTN as val
202001	1	5000		2020-01-14	N	1116207894	2021-06-18	2021-06-18	2020-01-14	0	0	44365,00
202104	1	-5000		2021-04-15	O	1116207894	2021-06-18	2021-06-18	2020-01-14	0	0	44365,00

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

	B	C	D	E	F	G	H	I	J	K	L	M
4	DAY_sorted	Final Adjusted oldCMAD/issue date delta	Final Adjusted newCMAD /issue date delta	average KTN	Adjusted newCMAD-KTN	average CMADshift	Average Adjusted CMADshift	Final Adjusted CMAD-(Adjusted oldCMAD-CMADshift)	average KTN-average^2 CMADshift-Final Average newCMAD	Adjusted newCMAD-KTN	average KTN-Average^2 Adjusted CMAD shift-Final Adjusted newCMAD	10=genau. 5=>3d difference, 4=>1w, 3=>2w, 2=> 4w, 1=1qrt
5	2020-01-14	521,00	545,5	44365	24,50	0	0	24,5	0	2	2	
6	2021-04-15	64,00	88,5	44365	24,50	0	0	24,5	0	2	2	
7							0					

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

BM	SAP ScheduleLineNo	AE_ST	UM_ST	DAY_sorted	TransactionCode	SAP Order	KTU orig poss delivery day	KTN new poss delivery day	SAP OrderDate	KTU-KTN	Adjusted oldCMAD-KTN. If no change of date, =0	KTN as value
202106	2	-5000		2021-06-17	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	-21	44386,00
202107	2	-5000		2021-07-05	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	-21	44386,00
202106	2	-5000		2021-06-15	O	1116207894	2021-06-11	2021-07-02	2020-01-14	-21	-14	44379,00
202106	2	-5000		2021-06-28	O	1116207894	2021-06-11	2021-07-02	2020-01-14	-21	-14	44379,00
202106	2	-5000		2021-06-14	O	1116207894	2021-06-11	2021-06-25	2020-01-14	-14	-7	44372,00
202105	2	-5000		2021-05-25	O	1116207894	2021-06-11	2021-06-11	2020-01-14	0	0	44358,00
202106	2	5000		2021-06-15	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	-21	44386,00
202106	2	5000		2021-06-28	O	1116207894	2021-06-11	2021-07-09	2020-01-14	-28	-21	44386,00
202106	2	5000		2021-06-14	O	1116207894	2021-06-11	2021-07-02	2020-01-14	-21	-14	44379,00
202106	2	5000		2021-06-17	O	1116207894	2021-06-11	2021-07-02	2020-01-14	-21	-14	44379,00
202105	2	5000		2021-05-28	O	1116207894	2021-06-11	2021-06-25	2020-01-14	-14	-7	44372,00
202104	2	5000		2021-04-15	O	1116207894	2021-06-11	2021-06-11	2020-01-14	0	0	44358,00

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

DAY_sorted	Final Adjusted oldCMAD/issue date delta	Final Adjusted newCMAD/issue date delta	average KTN	Adjusted newCMAD-KTN	average CMADshift	Average Adjusted CMADshift	Final Adjusted CMAD-(Adjusted oldCMAD-CMADshift)	average KTN-average^2 CMADshift-Final Average newCMAD	Adjusted newCMAD-KTN	average KTN-Average^2 Adjusted CMAD shift-Final Adjusted newCMAD	10=genau. 5=>3d difference, 4=>1w, 3=>2w, 2=> 4w, 1=1qrt
2021-06-17	1	25,5	05.07.2021	7	-24,5	-18	7	0	3	4	
2021-07-05	-17	7,5	09.07.2021	3,5	-28	-21	3,5	0	4	3	
2021-06-15	3	27,5	05.07.2021	7	-24,5	-18	7	0	3	4	
2021-06-28	-10	14,5	05.07.2021	7	-24,5	-18	7	0	3	4	
2021-06-14	4	28,5	28.06.2021	14	-17,5	-11	14	0	2	5	
2021-05-25	24	48,5	11.06.2021	31,5	0	0	24,5	0	1	2	
2021-05-28	21	45,5	25.06.2021	17,5	-14	-7	17,5	0	2	4	
2021-04-15	64	88,5	11.06.2021	31,5	0	0	24,5	0	1	2	
				Average ^2	-17	-11					

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

BM	SAP ScheduleLineNo	AE_ST	UM_ST	DAY_sorted	TransactionCode	SAP Order	KTU orig poss delivery day	KTN new poss delivery day	SAP OrderDate	KTU-KTN	Adjusted oldCMAD-KTN. If no change of date, =0	KTN as value
202107	3	-2500		2021-07-08	O	1116207894	2021-06-11	2021-07-19	2020-01-14	-38	-31	44396,00
202107	3	-2500		2021-07-07	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-28	44393,00
202107	3	-2500		2021-07-12	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-28	44393,00
202107	3	2500		2021-07-07	O	1116207894	2021-06-11	2021-07-19	2020-01-14	-38	-31	44396,00
202107	3	2500		2021-07-05	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-28	44393,00
202107	3	2500		2021-07-08	O	1116207894	2021-06-11	2021-07-16	2020-01-14	-35	-28	44393,00

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

	A	B	C	D	E	F	G	H	I	J	K	L	M
1													
2													
3													
4		DAY_sorted	Final Adjusted oldCMAD/issue date delta	Final Adjusted newCMAD/issue date delta	average KTN	Adjusted newCMAD-KTN	average CMADshift	Average Adjusted CMADshift	Final Adjusted CMAD-(Adjusted oldCMAD-CMADshift)	average KTN-average^2 CMADshift-Final Average newCMAD	Adjusted newCMAD-KTN	average KTN-Average^2 Adjusted CMAD shift-Final Adjusted newCMAD	10=genau. 5=>3d difference, 4=>1w, 3=>2w, 2=> 4w, 1=1qrt
5		2021-07-08	-20,00	4,5	44394,5	-5,00	-36,5	-30	-5	0	4	1	
6		2021-07-07	-19,00	5,5	44394,5	-5,00	-36,5	-30	-5	0	4	1	
7		2021-07-12	-24,00	0,5	44393	-3,50	-35	-28	-3,5	0	4	1	
8		2021-07-05	-17,00	7,5	44393	-3,50	-35	-28	-3,5	0	4	1	
9								-29					
10													
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24													
25													

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

BM	SAP ScheduleLineNo	AE_ST	UM_ST	DAY_sorted	TransactionCode	SAP Order	KTU orig poss delivery day	KTN new poss delivery day	KTU-KT	Adjusted oldCMAD-KTN. If no change of date, =0	KTN as value
202107	9900		2500	2021-07-12	N	1116207894	2021-06-11	2021-07-16	-35	-28	44393,00
202107	9900		2500	2021-07-05	N	1116207894	2021-06-11	2021-07-09	-28	-21	44386,00
202107	9900	2500		2021-07-12	O	1116207894	2021-06-11	2021-07-16	-35	-28	44393,00
202107	9900	2500		2021-07-05	O	1116207894	2021-06-11	2021-07-09	-28	-21	44386,00

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

	A	B	C	D	E	F	G	H	I	J	K	L	M
4		DAY_sorted	Final Adjusted oldCMAD/issue date delta	Final Adjusted newCMAD/issue date delta	average KTN	Adjusted newCMAD-KTN	average CMADshift	Average Adjusted CMADshift	Final Adjusted CMAD-(Adjusted oldCMAD-CMADshift)	average KTN-average^2 CMADshift-Final Average newCMAD	Adjusted newCMAD-KTN	average KTN-Average^2 Adjusted CMAD shift-Final Adjusted newCMAD	10=genau. 5=>3d difference, 4=>1w, 3=>2w, 2=> 4w, 1=1qrt
5		2021-07-12	-24,00	0,5	44393	-3,50	-35	-28	-3,5	0	4	1	
6		2021-07-05	-17,00	7,5	44386	3,50	-35	-28	-3,5	0	4	2	
7								-28					

Report 1 | Only N-SL | SL1 | Analysis 1 | SL2 | Analysis 2 facit | SL3 | Analysis 3 | SL99 | Analysis 99

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