Embedding Scenario Analysis into S&OP

Managing Demand Uncertainty through Capacity Optimization Using Linear Programming and Monte Carlo Simulation

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ABSTRACT

This thesis has researched how analytical tools can be used to assist in balancing supply and demand at the global telecommunications company Ericsson. The project stems from a need to manage demand uncertainty in Sales and Operations Planning in order to make scenario analysis both standardized and data-driven. Consequently, the purpose was to develop a practical scenario planning framework and tool for modeling uncertainty to support rational decision-making. To maintain a reasonable scope, the thesis was limited to study capacity planning and a single production facility.

Given this purpose, and in accordance with the Operations Research Modeling Approach, a literature review, open-ended interviews, observations, and benchmarking were carried out to map the current state and establish the modeling requirements. Thereafter, two models were developed: a linear programming model for cost-optimal capacity planning under a known demand change, and a Monte Carlo simulation that stress-tests production configurations across a range of uncertain demand realizations. The models quantify delays and investment requirements by providing cost breakdowns, utilization heatmaps, and service level distributions across demand scenarios.

The findings in this thesis demonstrate that linear programming and Monte Carlo simulation can together operationalize scenario planning by standardizing and quantifying decision alternatives. Furthermore, a five-stage scenario planning process map is proposed to formalize and integrate the tools into the S&OP cycle.

PREFACE

This master thesis marks the end of our five-year education in Industrial Engineering and Management (M.Sc.Eng.) at Lund University, a period that has involved both personal and academic development.

During our years in Lund, engaging courses and lecturers have led us to develop a strong interest in the field of Operations Research. Ultimately, this interest brought us the opportunity of writing this thesis in collaboration with Ericsson, developing analytical models in a real-world setting.

We wish to take this opportunity to thank the people who made this thesis possible. First and foremost, we want to thank our supervisor Danja Sonntag for her continued support, creativity, and engagement in our project. We also want to thank Ericsson for giving us this opportunity. In particular, we thank our supervisor Louise Läckström for guiding us through the hoops and hurdles of a global company. Lastly, we also want to show our appreciation for everyone who has supported us during this spring: colleagues in our thesis group, friends, and family.

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1 INTRODUCTION

Since the 1980s, supply chains have become increasingly global due to activities such as offshoring and outsourcing (Norrman & Olhager 2023, p. 1). Norrman and Olhager (2023, p. 5) describe that being able to source from a less expensive manufacturer in a low-cost country and the unlocking of economies of scale have become what is considered the main benefits of global supply chains. However, while global supply chains have opened up new markets and can lower manufacturing costs, globalization presents challenges. Such challenges arise since widespread operation-networks increase the amount of possible points of failure. Furthermore, factors such as geopolitical instability, climate change, and economic instability create uncertainty in the supply network (United Nations Trade & Development 2024). These uncertainties affect the volume and timing of what a company is able to supply its customers. As a result, the relationship between supply and demand may not be balanced. If demand exceeds supply, customer satisfaction may suffer and high costs occur if products need to be expedited (Jacobs et al. 2011, p. 89). Similarly, if supply exceeds demand, inventory related costs can increase. Therefore, uncertainty must be carefully considered to make rational operational decisions.

One company that must handle uncertainty when making decisions regarding production and inventory levels is Ericsson. Founded in 1876, Ericsson is one of the world's leading companies within the telecommunication sector (Ericsson n.d.-a) and aims to enable connectivity by providing hardware, software, and service to communication service providers, enterprises, and the public sector. The company operates across multiple international markets, and is currently managing a complex global supply chain with their main production located in the US, Brazil, Mexico, India, China, Malaysia, Poland, Romania, and Estonia (Ericsson n.d.-b). Consequently, their supply chain is often characterized by having long lead times and multiple tiers of partners and suppliers. Additionally, Ericsson's supply chain is exposed to geopolitical instability as well as demand and supply volatility, potentially leading to imbalances between the latter.

In order to better align supply and demand, organizations can utilize Sales and Operations Planning (S&OP). S&OP is a business process that intends to align an organization's supply capabilities with market demand over a planning horizon usually defined at 1-18 months, with monthly refinements to the plan (Jacobs et al. 2011, pp. 94–95; Grimson & Pyke 2007, p. 323). In practice, the process aims to balance the sales forecast with production resources in a way that synchronizes different functional areas, such as manufacturing, sales, and marketing. Thus, S&OP aims to mitigate the risks of overstocking, stock-outs, or other consequences of imbalances between supply and demand. The monthly S&OP process is divided into five steps and aims to make decisions regarding production and inventory levels for each product family (Jacobs et al. 2011, p. 94). The exact definition of each of the five steps varies in different research papers (for instance Grimson and Pyke (2007) and Jacobs et al. (2011)), although they share the objective of creating a unified operations plan. Below is the description of the process as defined by Jacobs et al. (2011, p. 95), which is illustrated in Figure 1.

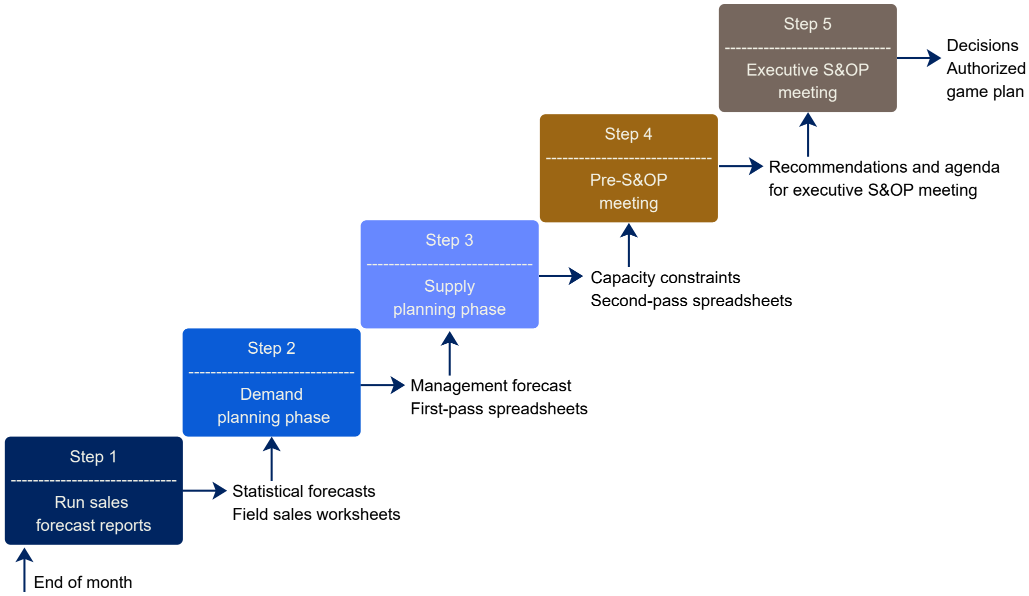


Figure 1. *The monthly sales and operations planning process. Adapted from Figure in 4.2 Jacobs et al. (2011, p. 94)*

In the first step, data from the preceding period from various departments, such as sales and production, is gathered and a statistical forecast is created. In the second step, a new forecast is generated for the upcoming 12 months. The forecast is derived from data from step one as well as possible outcomes of marketing campaigns, new product introductions, and phase-outs. If needed, it is possible to override the statistical forecasts in this step. Once complete, the third step ensures that the production plan is adapted to the new forecast. Thereby, this is where the supply and capacity planning takes place. If the production plan needs to be modified to fit the new forecast, this is discussed in the fourth step of the process: the pre-S&OP meeting. If there are different recommendations from various departments on how to align, these are discussed here. If various recommendations cannot be resolved, they are brought up in the last stage of the process, the executive S&OP meeting. Here, senior management formally approves the new production plan.

Ericsson has implemented S&OP, however, their current process does not follow the order described in the literature. Instead, Ericsson follows a 12-step process which is compared to the theoretical process in Figure 2. The process-step names and explanations contain Ericsson-specific abbreviations that are not explained in detail here, since they are not essential to understanding the S&OP cycle in the context of this thesis. For the purpose of the analysis, it is sufficient to highlight that Ericsson's S&OP cycle is a monthly recurring 12-step process that integrates customer prognoses, phase-outs, new product introductions, material constraints, and production capacity, similar to the process as described in the literature. However, Ericsson's process does not follow the same sequence as the one presented in the literature. Ericsson begins with collecting forecast and demand data from each customer, then consolidates locally. Thereafter, new product introductions are considered, followed by a demand consolidation on market area level, as well as conducting a preliminary operations planning. Following this are the pre- and executive S&OP meetings, before the operations plan is finalized in three consecutive steps. In Ericsson's process, decisions about the supply plan are made based on the demand forecasts and customer knowledge, meaning that the current process is reactive, adjusting supply to match shifts in demand, and making it less dynamic to changes.

Figure 2. *Ericsson's S&OP process categorized according to the theoretical process by Jacobs et al. (2011)*

To manage the reactive nature of its current S&OP process and create a basis for strategic and rational decision making, Ericsson has initiated the Integrated Business Planning (IBP) transformation. The IBP transformation can be described as a re-branding of the S&OP process. When studying the definitions of IBP and S&OP respectively as presented by the Association for Supply Chain Management, the main difference highlighted is that IBP includes more tools to handle uncertainties and risks, specifically Scenario Planning and Supply Chain Risk Management (ASCM / SCOR n.d.). Scenario planning is defined as "a planning process that identifies critical events before they occur and uses this knowledge to determine effective alternatives" (ibid). Thus, scenario planning is a tool that can complement processes such as S&OP and IBP by providing organizations with a structured way of developing responses to uncertainties and risks. For instance, the impacts of a machine breakdown or a black swan event such as a hurricane can be analyzed (Singh & Lee 2013, p. 6). Thus, organizations can work to reduce the impact of uncertainty on their operations. Ericsson aims to utilize scenario planning in order to enhance the ability to make proactive and well-informed decisions under uncertainty.

1.1 Problem Formulation

Standardizing scenario planning in the S&OP process has been identified as one of the goals in the transition towards IBP and more rational decision making. Currently, Ericsson has a scenario planning process, however, it operates with limitations. Firstly, there is no formal scenario definition. Ericsson has no standardized process for conducting scenario analysis and therefore has no set definition for which parameters to analyze, what time horizon to consider, how the analysis should be performed and ultimately, how to make decisions based on the scenarios. Secondly, the decision cycles are slow. As there is no structured process for scenario analysis within S&OP, such analyzes are performed differently every time the need arises. Consequently, the process currently requires manual information gathering from multiple departments, manual execution of the analysis, and additional time to consolidate and present the results before a decision can be made. Thirdly, the trade-offs between demand, supply, and inventory levels are handled case-by-case. Instead, Ericsson aims to have a standardized way of evaluating the trade-off between costs and service level, which the company defines as the percentage of demand fulfilled on time. Lastly, there is minimal use of data-driven scenario modeling. All of these issues show that there is no structured method to handle uncertainties present in global supply chains. To minimize issues that emerge when demand exceeds supply or vice versa, a more standardized way of handling uncertainty would be beneficial to Ericsson. This creates an opportunity to design a structured, repeatable methodology for embedding scenario planning into the S&OP cycle, supporting operational planning (0–18 months).

1.2 Purpose of the Thesis and Research Questions

The goal of the thesis is to develop a practical, data-driven scenario planning framework that supports decision-making in the S&OP process. The framework should enable planners and leaders to assess trade-offs between costs and service level, be able to evaluate demand–supply impacts, connect trade-offs to financials, as well as make faster, rational decisions. The framework is based on the following research questions:

1. How can data-driven analytical tools for modeling uncertainty operationalize scenario planning to support rational decision-making in the S&OP process?
2. What uncertain factors need to be considered, and how can they be structured and quantified?
3. What data, tools, and processes are required to support scalable scenario planning in IBP?

1.3 Report Structure

Chapter 2 presents the used methodology. Following, Chapter 3 explains theory behind rational decision making through decision analysis, how uncertainty can be managed within S&OP, scenario planning, and analytical tools. Thereafter, Chapter 4 applies the theory to Ericsson's case. To determine what should be included in the modeling framework, a current state mapping is performed. Thereafter, the construction and interpretation of linear programming and Monte Carlo models is discussed. Lastly, the conclusion and future research areas are presented in Chapters 5 and 6, respectively.

2 METHODOLOGY

An analytical research project distinguishes between three main types of analysis: descriptive, predictive and prescriptive analytics.

Descriptive analytics aims to answer the question "what happened?" using past data to identify changes that have occurred in the business (Sharma et al. 2022, pp. 4–6). Analyzing raw data, in addition to conducting a comprehensive review of past decisions, their outcome, and efficiency, valuable conclusions can be drawn and presented to stakeholders. These conclusions can further become the basis for evaluation and potential change of the current strategy. Descriptive analysis requires aggregation and data mining where data is gathered and sorted in order to extract meaningful information, followed by visualizing the data using relevant charts and graphs. The general idea with the analysis is to check whether business targets are being achieved most proficiently given past activities that occurred. For Ericsson, this means analyzing, for instance, past deals' costs, lead times, demand changes, production speeds, and capacity constraints, as well as identifying other constraints that were previously unaccounted for.

Predictive analytics, on the other hand, uses historical data to identify key patterns and trends to forecast future events, using techniques ranging from classical statistical methods to machine learning and artificial intelligence (Sharma et al. 2022, pp. 7–8). By identifying patterns in historical data, the forecasting model can be used to anticipate potential future risks and opportunities. Additionally, covariances between features, which are individual, measurable characteristics of a data sample used as an input to the model, can be identified. By identifying these relationships, the threat of unrecognized dependencies is limited in decisions. At Ericsson, such forecasting models are already implemented although heavily reliant on the sales departments insights and understanding of the market development.

Lastly, prescriptive analytics emphasizes the discovery of the best decision given available information, converting the data into actionable insights (Sharma et al. 2022, pp. 9–10). While descriptive analytics provides insights into past events and predictive analytics forecasts possible results, prescriptive analytics presents statistical techniques to locate the best decision and expected outcome among a variety of options. Essentially, it is an extension of the descriptive and predictive analysis which takes into consideration the probability of different scenarios and how they would impact the business. Consequently, prescriptive analytics allow stakeholders to be informed regarding the consequences of each decision option and thus create a rational strategy.

This thesis is of prescriptive nature with the aim of improving data-driven decision-making and will be used to present the best result given a set of possible scenarios and available resources. Given this focus, the research questions were addressed using the Operations Research Modeling Approach defined by Hillier and Lieberman (2010, pp. 8–19). The method is described in more detail below and summarized in Figure 3. Step 5 and 6 regarding the process of implementing the model is considered to be beyond the scope of the thesis and will therefore not be further discussed.

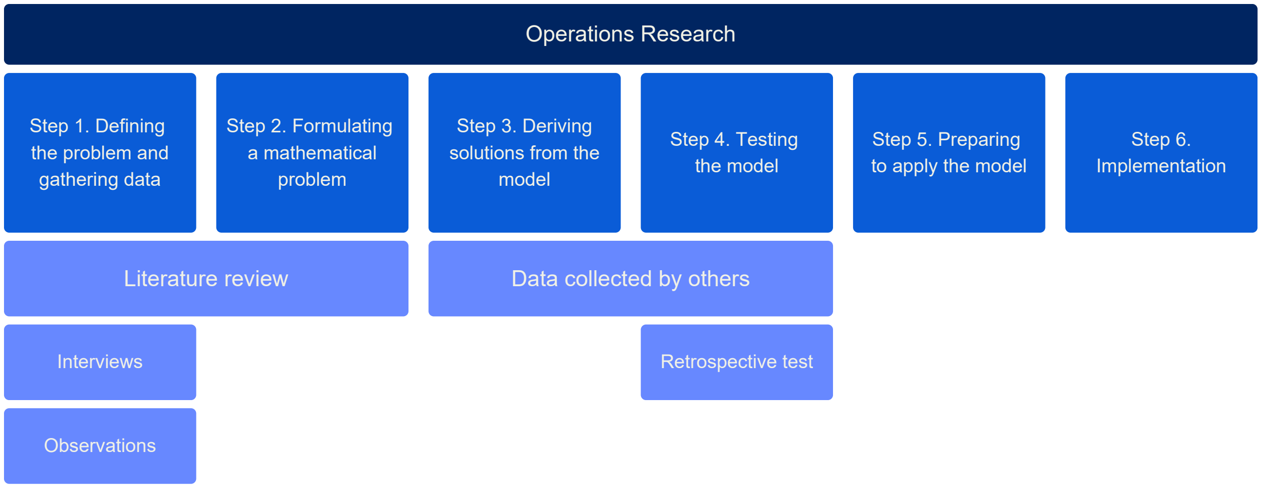


Figure 3. *Visualization of methodology*

Step 1. Defining the problem and gathering data

The first step includes determining appropriate objectives, constraints, and interrelationships between the research area and other areas of the organization. Consequently, a current state mapping is performed, involving the mapping of decision-making processes, escalation points, and information flows. In addition, current ways of working related to scenario planning are mapped, with the aim of identifying gaps and challenges in existing scenario-related practices. Through this process, it is determined which factors of uncertainty need to be considered in the scenario analysis.

To fully understand the current approach to scenario management, as well as if and how it can be improved, information has to be gathered. Höst et al. (2006, p. 84) introduces surveys, interviews, observations, measurements, and data collected by others as the main methods for data collection when conducting a thesis. As the thesis aims to create a data-driven scenario planning framework that supports decision making, it is vital to understand how decisions are being made and which factors influence these decisions. Therefore, to identify and understand the problem, interviews and observations are chosen as the primary means of data collection. Furthermore, a literature review is conducted to gain understanding of examples in which similar issues have been approached and how they have been solved. The literature review enhances the theoretical foundation for the development of the model.

Interviews

To conduct interviews which ensure the necessary information is obtained, an interview guide has to be created. According to Höst et al. (2006, p. 90), there are three main types of interviews: open-ended, semi-structured, and structured. Open-ended interviews are based on an interview guide that contains questions split into different categories. The questions do not need to be phrased in the same way or asked in the same order across interviews. In a semi-structured interview, fixed questions that are always phrased in the same way with corresponding, predetermined alternatives for answering are mixed with open-ended questions. Lastly, structured interviews contain the same questions with the same response alternatives for each respondent. As the primary purpose of the interviews is to understand the scenario management, open-ended interviews are chosen, as they allow respondents to elaborate freely on topics beyond the interview guide, and to provide in-depth descriptions and perspectives of processes. The interview guide can be found in Appendix B.

The interviews aim to produce a qualitative understanding of the current setup of the S&OP process, scenario management, and the current decision-making structure. In such a situation, Höst et al. (2006, p. 89) explains that the interviewees can be selected in a way that ensures variation in the population is covered. By dividing the relevant division of Ericsson's Group Supply organization into categories, a comprehensive selection is made, ensuring interviews are conducted with individuals from every category. Three main categories are defined and analyzed to understand the current scenario planning setup: demand, supply, and coordination. This categorization allows for an analysis of how assumptions or changes in demand and supply may create challenges within S&OP, as well as how coordination between these areas influences scenario planning and, consequently, decision-making. The categorization and selection of interviewees is presented in Table 1.

Table 1. *Selection of interviewees across category and team*

Category	Team
Coordination	Scenario Planning
Coordination	Supply Chain Planning
Coordination	Integrated Business Planning
Coordination	Sales & Operations Execution
Coordination	Sales & Operations Execution
Coordination	Supply Chain Costs
Coordination	Scenario Planning
Demand	Demand Planning
Supply	Capability Planning
Supply	Inventory Planning
Supply	Inbound (Material Planning)
Supply	Capability Planning
Supply	Capability Planning
Supply	Capability Planning

To ensure the information gathered through the interviews can be used properly for the current state mapping and hence the model construction, the interviews are recorded. In order to ease the search of information, notes that highlight particularly important parts are taken as a complement to the recordings.

Observations

As a complement to the interviews, observations are conducted to gain an understanding of the current ways of working. Observations can be divided into four categories: complete observer, observer as participant, participant as observer, and complete participant (Höst et al. 2006, p. 93). A complete observer is a researcher who is neither seen nor noticed by the participants. The idea is that if the participants are unaware that they are being observed, they will in turn act more naturally. On the other hand, an observer as participant is known and recognized by the participants but the interactions are still limited. For this category the participants are also aware of the research goals of the observer. Moreover, participating as observer entails that the researcher is fully engaged with participants, interacting with them as a friend or colleague. However, the participants are still aware of the research goal and their participation. Lastly, a researcher who is a complete participant, is fully embedded and engaged with the participants' activities. For this category of observation, the participants are not aware of the research conducted nor their participation in it. In the case of this thesis, observations are used mainly through the participation in meetings in the S&OP cycle to understand current processes. Therefore, the observations belong to the observer as participant category. The relevant data is collected through taking notes.

Literature Review

The review draws on academic literature on scenario planning, decision-making under risk, and S&OP. The main objective is to identify scientific approaches to the aforementioned, in addition to industry best practices, and organizations that have succeeded in implementing scenario analysis in their supply planning. A literature review is an iterative process that can be revisited as the researcher's understanding of the research area deepens (Höst et al. 2006, p. 67). Höst et al. (2006) recommends conducting the literature review in three steps. Firstly, a wide search is performed. To do this, multiple channels are utilized, for instance, Google Scholar and the Lund University library database, Finn. Additionally, artificial intelligence is utilized through Scopus AI, a tool developed by Elsevier that assists in identifying relevant scientific publications for further exploration (Elsevier 2026). Since Scopus AI only includes publications from 2003 and onward, it is mainly used as a complement to the other search procedures. In the second step, a selection of the most relevant sources is conducted. This selection is the basis for the deep search that is performed in the third and last step. In practice, the method for the literature is applied by firstly identifying four main topics that assist in answering the research questions: decision analysis, uncertainty in S&OP, scenario planning, and analytical tools for modeling uncertainty. Accordingly, separate keyword searches are conducted for each of these areas, starting with the broad terms just presented, and progressively narrowing the search as more specific subtopics are identified. Besides utilizing keyword searches, the snowball method is applied through backward and forward chaining. Backward chaining entails studying the references of a relevant article that has been identified to find further literature (Högskolan Väst 2025). On the contrary, forward chaining allows for the identification of more recent publications, by looking at publications that have cited the article in question.

A literature review requires a detailed examination of the credibility of each article (Höst et al. 2006, pp. 59–70). Therefore, in this thesis, peer reviewed research papers are used to the greatest extent possible. Consequently, due to the great number of journals available and the complexity of navigating their credibility, the Norwegian Register for Scientific Journals serves as a tool for assessing and selecting credible sources. Journals in this register can be scored 0, X, 1, or 2 (Direktoratet for høyere utdanning og kompetanse n.d.). Score 2 is the highest level, representing the most high-quality publication channels. Score 1 represents journals that meet the minimum requirements to be considered scientific. Score X are journals under review and score 0 are journals that do not meet the requirements to be considered scientific. Consequently, journals scoring 1 or 2 have been used for this thesis to the largest extent possible. If the journal does not exist in the register, it is assumed that it corresponds to a score 0.

Step 2. Formulating a mathematical model

The defined problem needs to be reformulated in a way that is convenient for analysis. This is done by constructing a mathematical model that captures the essence of the problem. Two models are used in the analysis: a linear programming (LP) model and a Monte Carlo simulation. The linear programming model schedules production while ensuring that capacity constraints are satisfied and operational costs are minimized through an objective function. The Monte Carlo simulation is used to evaluate the robustness of the system under uncertain demand by sampling from predefined probability distributions.

By constructing a mathematical model, the problem can be described in a concise and precise manner. This helps identify important cause-and-effect relationships, which further clarifies what additional data are relevant to the analysis. Approximations and simplifications are necessary to ensure tractability. For instance, the model assumes constant cycle times in production, which may not always be the case. However, it is essential that the model remains a valid representation of the decision problem. This is assessed through testing and validation to ensure that the model's recommended actions lead to outcomes that closely align with observed real-world behavior. To enhance the credibility and functionality of the model, its structure builds upon the literature review of previous approaches to similar situations.

Step 3. Deriving solutions from the model

Once a mathematical model has been constructed, the next step is to develop a procedure to derive solutions from the model. To generate solutions from the models formulated in this thesis, the software Gurobi is used, which implements algorithms that are well established in the field of Operations Research. The procedure used to obtain solutions with these tools is described in more detail in Section 3. As mentioned previously, the optimal solution is only optimal with respect to the formulated model and not necessarily for the real-world problem, since the model represents an idealized rather than an exact depiction of reality. Hence, at this stage, a post-optimality analysis is required to address questions regarding how the optimal solution would change if different assumptions were made. In doing so, the parameters that are most critical in determining the solution can be identified.

Step 4. Testing the model

The following phase includes testing and refining the model by identifying edge cases, bugs, and making sure we obtain reasonable results. This process is commonly known as model validation. To ensure that the model reflects reality, an ongoing discussion is kept with the company. To further validate the model, a retrospective test was planned with the aim of reconstructing the past to determine how well the model would have performed during that period. In such a test, the model should perform at least equally well, but preferably yield a significant improvement, since this is a fundamental requirement for the model's development. Furthermore, this helps identifying shortcomings that must be addressed. However, a retrospective test could not be performed due to data unavailability. Lastly, the values of the parameters and decision variables are varied in order to examine whether the model behaves in a plausible manner. This is especially true for extreme values, as it assists in revealing inconsistencies.

Limitations and Outlook

Although the models provided are a proof-of-concept, there has been an ongoing discussion with Ericsson to ensure scalability. The mathematical procedures used are rational and can be expanded to include more market areas and production facilities. Despite this limitation, the methodology provides a thorough foundation of how to approach the problem at hand, and consequently facilitates the structuring of models that aims to help the user make more informed decisions under uncertainty. To determine what analytical tools should be used to obtain these objectives, the theory chapter follows. Once this has been determined, the analysis is carried out to apply the theoretical knowledge to Ericsson's case.

3 THEORY

The theory chapter forms the foundation of this thesis, providing a theoretical framework through which the research questions can be analyzed. The four areas outlined in Section 2 are addressed separately. Firstly, Section 3.1 explains how decision analysis provides the foundation for making rational decisions under uncertainty. Then, Section 3.2 studies how uncertainty is managed in the context of S&OP. Building on these findings, Section 3.3 analyzes how scenario planning can be used to structure uncertainty into a set of possible outcomes. Finally, Section 3.4 analyzes how scenarios can be studied analytically. For each demand scenario, a linear programming model is used to find optimal production configurations. To account for uncertainty, Monte Carlo analysis is utilized. These methods are discussed in Section 3.4.1 and 3.4.2 respectively. Figure 4 visualizes how the theoretical areas relate to each other.

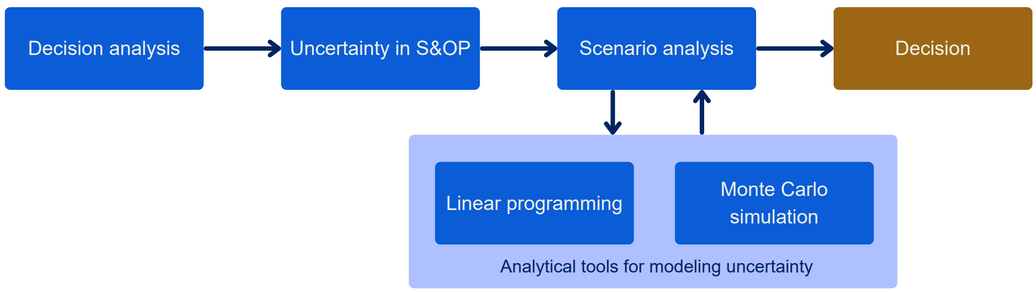


Figure 4. *Structure of theoretical framework*

3.1 Decision Analysis

Since the aim of the first research question is to establish a way for Ericsson to make more rational decisions within S&OP, finding a structured approach to decision making under uncertainty is vital. As noted by Hillier and Lieberman (2010, p. 672), "Decision analysis provides a framework and methodology for rational decision making when the outcomes are uncertain". Therefore, decision analysis is presented as a foundation for rational decision making. Howard (1996, p. 98) presents a three step decision analysis logical procedure which consists of a deterministic phase, a probabilistic phase, and a post-mortem phase.

In the deterministic phase, the decision and the various alternatives to choose between are defined. Furthermore, values are assigned to the decision alternatives. This step aims to answer the question "How are you going to determine which outcomes are good and which are bad?" (Howard 1996, p. 99). Additionally, the state variables, which signify the uncertain parameters associated with the outcome, their possible values, and their relationship to the outcome must be determined. Often, this is done by creating a function to represent the value being studied. In the context of Ericsson, a deterministic function representing the cost of a production schedule is created, where the state variable is the demand level of a certain product.

Once the decision problem is modeled through a deterministic model, the next step is to enter the probabilistic phase (Howard 1996, p. 100). The probabilistic phase consists of two major parts: firstly, determining underlying distributions of state variables and developing the probability distribution for each decision alternative. The latter can, for instance, be approximated using Monte Carlo simulation. When the outcome is not certain, the output is represented by an expected value (Hillier & Lieberman 2010, p. 674). Bayes' Decision Rule states that the decision with the highest expected value should be selected (Hillier & Lieberman 2010, p. 677).

The last step of the decision analysis logical procedure as presented by Howard (1996, p. 102), is the post-mortem phase. This phase takes place after the best decision alternative has been selected by analyzing the value of reducing uncertainty. The purpose of the analysis is to determine if the gain of retrieving better information in order to reduce uncertainty would be worth the cost.

3.2 Uncertainty in S&OP

There is a broad range of variables within S&OP that involve uncertainty (Fakhry et al. 2025, p. 7). In the context of S&OP, uncertainty can be divided into three main categories: internal, supply network, and environmental (Dittfeld et al. 2021, p. 569). Internal risks refer to those happening within a company, such as machine failures in production, or IT malfunction. Supply network risks include suppliers not delivering as agreed, or demand deviating from projected levels. Lastly, environmental risks include factors completely outside of the supply network, that still can affect both supply and demand. Dittfeld et al. (2021) present political situations and earthquakes as examples of environmental risks. Ericsson is exposed to all categories of uncertainty, but as will be determined in the analysis in Section 4, the most prevalent uncertain factor in the context of scenario management is demand.

To study how uncertainty can be managed in the context of S&OP, Fakhry et al. (2025) conducted a systematic literature review. The articles analyzed uncertainty management in S&OP from six different perspectives that were identified based on previous research on the subject: process, tools, people, objectives, decisions, and key performance indicators. The two dimensions of most relevance for this thesis are process and tools.

Fakhry et al. (2025, p. 15) conclude that uncertainty management has been identified as vital aspect to ensure an effective and efficient S&OP process. Despite this, literature shows that uncertainty management generally is not an integrated part of the S&OP process. Several solutions are provided on how to manage uncertainty to avoid destabilization of the S&OP output. Mainly, the effects of integrating a risk-oriented process are discussed. This involves methods such as scenario planning and creation, as well as extra S&OP meetings with the purpose of creating a platform for making informed decisions and handling risks to avoid destabilization of the S&OP plan. Furthermore, the authors discuss that adaptable frameworks that can be tailored to specific organizations can be valuable. However, the study discovers a gap: multiple authors discuss the critical need to manage uncertainty, but concrete, practical solutions to achieve this are not presented. Hence, it is concluded that a standardized way of integrating risk and uncertainty analysis into the S&OP process is not present in the literature (Fakhry et al. 2025, p. 10).

In order to answer the research questions and fulfill the purpose of this thesis, it is vital to understand how literature addresses the use of tools for managing uncertainty in S&OP. In general, the literature review shows that tools for managing uncertainty in S&OP have evolved from being reactive, meaning acting on given information, to utilizing stochastic programming as well as advanced simulation techniques to proactively anticipate outcomes (Fakhry et al. 2025, p. 10). However, the literature does not present an adaptable way of managing the full range of uncertainties present in the supply chain to create a basis for rational decisions. Specifically, in connection to the research questions, no standardized uncertainty management tools have been defined. Nonetheless, the research shows that a deeper understanding of how various uncertain factors could affect the S&OP output could be attained through the usage of stochastic planning to conduct scenario analysis.

3.3 Scenario Planning

All business decisions, such as those made within S&OP, rely on a certain expectation of the future. Regardless of whether complicated forecasting techniques or other methods of projecting the future business environment are utilized, the outcome remains uncertain. Therefore, as concluded in Section 3.2, it is important to incorporate uncertainty planning into business decisions (Singh & Lee 2013, p. 5). A good plan can be defined as one whose outcome remains within a specified range around a predetermined target value. If any resulting parameter falls outside this range, the plan must be revised. To prepare for situations that may cause a need for re-planning, it can be beneficial to conduct what-if scenario planning within the scope of the S&OP process. There is no widely accepted definition of scenario planning (Cordova-Pozo & Rouwette 2023, p. 9). However, studying various definitions, it can be concluded that scenario planning is a process where the practitioner identifies possible uncertain factors, the effect these might have on the company's future operations, and what strategies exist to handle the uncertainty.

Cordova-Pozo and Rouwette (2023, p. 14) describe that scenario planning improves decision-making processes by enabling the opportunity to study possible future events and consequently create strategies to reduce the risk or handle the impact of them. According to the literature review performed by Cordova-Pozo and Rouwette (2023), scenarios can be both qualitative and quantitative. Neither approach is without limitations. Qualitative approaches to scenario generation can, for instance, be limited by the knowledge of the participating individuals, whereas quantitative approaches can be limited by lack of imagination. Consequently, quantitative analysis should be balanced with creative qualitative analysis to avoid a too narrow set of scenarios. The article also discusses that the type of scenario that is generated depends on the scope of time that is analyzed. For short term scenarios, a deterministic perspective can be utilized, whilst for longer term scenarios, non-deterministic analyzes should be made (Cordova-Pozo & Rouwette 2023, p. 18). No matter which technique is used, Singh and Lee (2013, p. 6) present the following list of criteria that what-if scenarios should be evaluated against.

1. Is the change significant enough to require re-planning?
2. Does the change affect multiple tiers of the supply chain?
3. Is the impact system-wide or confined to a local area?
4. What data and information are required to assess the impact?
5. Does the change invalidate any underlying assumptions of the current supply chain setup?
6. How can re-planning be performed without modifying master data?
7. Once scenarios are generated, how should they be evaluated, and which trade-offs must be analyzed?
8. How can scenario outcomes be assessed in terms of financial performance?
9. How should escalation thresholds triggering re-planning be defined?
10. How should the results of the what-if analysis be presented within the S&OP process?
11. How are the results of the what-if analysis translated into actionable decisions?

Points 1-3 answer questions in regards to the potential outcome of the scenario. Although this information may not be known when initiating a scenario, a qualified guess may be necessary in order to determine whether a scenario should be created at all. Points 4-6 consider how the analysis of the scenario can be conducted. Once the analysis is complete, points 7-11 define how the results should be evaluated and how decisions can be made based on them. Additionally, these points consider how the information can be consolidated in a way that allows for actionable insights.

In addition to the evaluation criteria, Singh and Lee (2013, p. 9) provide a list of software functions required to evaluate the impact of different scenarios. The software must be capable to perform the necessary calculations and analyses while not altering the master data. It should also be able to store assumptions, handle multiple scenarios simultaneously, and allow for quick adjustments in the setup to allow for changing conditions. Furthermore, the software should be able to connect the analysis to financial outcomes and allow for updates in scenario configurations, for instance, if a certain scenario becomes true. Lastly, the software needs to be able to communicate the scenario analysis, often using graphical representations, to the decision-makers within the S&OP process.

3.4 Analytical Tools for Modeling Uncertainty

To answer the research question regarding how analytical tools for modeling uncertainty can be used to operationalize scenario planning, it needs to be established what data-driven analytical tools for modeling uncertainty there are to choose from. As the framework developed in this thesis aims to analyze how the supply and production system can handle demand-changes, the paper "Models for production planning under uncertainty: A review" written by Mula et al. (2006) is used as theoretical foundation. The authors have conducted a literature review of 87 papers studying what uncertainty modeling approaches have been used in production planning. The study identifies four main approaches for modeling uncertainty: conceptual models, analytical models, artificial intelligence based models, and simulation models (ibid p.272). Conceptual models utilize descriptive analysis to understand problems and prescriptive analysis to provide guidelines to solve them. Analytical models are mainly based on techniques that stem from Operations Research, such as linear and stochastic programming, that are used to find optimal solutions to complex problems. Artificial intelligence based models use techniques such as reinforcement learning, neural networks, and fuzzy logic to predict results and support decisions. Lastly, simulation models utilize techniques such as Monte Carlo simulation to study system behavior under uncertainty.

Among the four approaches, analytical models are the most suitable for this thesis. According to the second step of the Operations Research methodology presented in Section 2, a mathematical model representing the problem needs to be constructed. One method that is used when incorporating scenario analysis into S&OP for making decisions about production, capacity, and investments is Mixed-Integer Linear Programming (MILP) (Lucas et al. 2001). Linear programming models are suitable for deterministic problems where values of ingoing parameters are known. For instance, it can be used to determine when and where to produce while minimizing costs across a supply chain. In Ericsson's situation, a supply chain configuration is already set: the supply chain specifications such as production and holding costs, lead times, and capacity levels are known, and a baseline production and location planning has already been established. Thus, while demand is considered an uncertain parameter, determining when and where to produce in response to a demand scenario can be considered a deterministic problem. Therefore, rather than incorporating uncertainty directly into the optimization model, this thesis adopts a scenario-based deterministic modeling framework. Demand uncertainty is modeled through a structured set of scenarios, each solved as a deterministic linear programming problem. This allows the user to compute comparisons of various production plans across demand realizations.

In the context of scenario planning, Ericsson is not only interested in managing sudden demand changes. It is also of interest to study the robustness of production schemes when exposed to demand changes during the S&OP cycle. For such an analysis, Monte Carlo simulation is a valuable tool as it allows for studies of a range of possible demand levels from an estimated distribution. By using both linear programming and Monte Carlo simulation, this thesis captures the strengths of two types of uncertainty modeling: analytical and simulation. This section describes the linear programming model and its adaptation to Monte Carlo simulation in further detail.

3.4.1 Linear Programming

Linear programming is a mathematical tool that is used to solve a problem given a set of constraints (Hillier & Lieberman 2010, pp. 23–36). Fundamentally, the problem revolves around allocating limited resources among competing activities in the best way possible. Using complex and efficient algorithms, the optimal configuration is obtained given that the problem is solvable considering its constraints. As the name indicates, all constituent mathematical functions, the objective function and constraints, are required to be linear.

The linear programming model, consisting of an objective function and its associated constraints, can generally be expressed as in Equation (1). When some variables are restricted to integer values as in this expression, the model is called mixed-integer linear programming. In this example, the objective function $Z = c^T x + d^T y + e^T z$ is to be minimized and is defined as the sum of contributions from all decision variables: continuous variables x, integer variables y, and binary variables z. Specifically, x represents quantities such as production amounts; y represents countable decisions, such as the backorder volume per period; and z represents binary decisions, such as whether to use a production facility or not. Each term in the objective function is weighted by coefficient vectors $c,\ d,\ e$, which correspond to costs or penalties associated with these aforementioned decision variables. Moreover, the objective function is subject to constraints represented by $Ax + By + Cz \leq b$, where $A,\ B,\ C$ are matrices, which enforce limitations such as production capacity and speed, lead times, and geopolitical limitations. Together, the constraints define a feasible region, or constraint space, that specifies all combinations of $x,\ y$, and z that satisfy the capacity and operational restrictions. A solution is feasible if all constraints are satisfied. Conversely, if at least one constraint is violated, the solution is infeasible. An optimal solution is a feasible solution that attains the minimum value of the objective function Z.

$$\begin{aligned} \min_{x,y,z} \quad & c^T x + d^T y + e^T z \\ \text{s.t.} \quad & Ax + By + Cz \leq b \\ & x \in \mathbb{R}^{|K|}, \quad y \in \mathbb{Z}^{|I|}, \quad z \in \{0,1\}^{|J|} \end{aligned} \tag{1}$$

The fundamental algorithm for linear programming is called Simplex (Hillier & Lieberman 2010, pp. 89–94). As its underlying mechanisms are geometric, a simplified two dimensional linear problem can be visualized to better understand the concept, see Figure 5. This problem contains 5 constraints that collectively define the feasible region. The objective function is highlighted in brown. Intersections between constraints that are not dissected by other competing constraints are called corner-point feasible (CPF) solutions, here represented by dots.

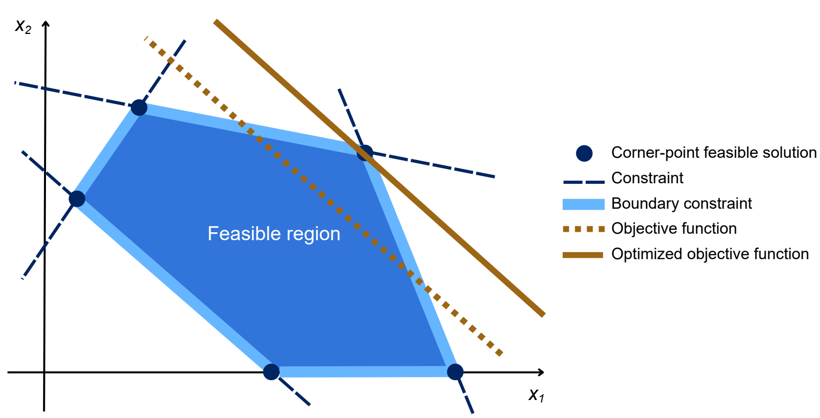


Figure 5. *General example of a two dimensional linear problem*

The algorithm is initiated by calculating the value of an initial CPF solution using the objective function Z. Thereafter, the solution's optimality is checked by investigating whether adjacent CPF solutions yield better values. If such solutions are identified, the search proceeds to an adjacent CPF solution in the direction of the steepest increase in Z. This point is then checked for optimality before progressing to the next point. This process is iterated until an optimal solution is found; in other words, when none of the adjacent solutions provide a better value. In reality, the problem described in this thesis contains multiple dimensions as it contains more than two decision variables, why a graphical visualization is not possible. Regardless, the general approach remains the same.

In practice, there are several programs that can solve linear programming problems. For this thesis, the Python software package Gurobi Optimizer is used. However, other linear programming software packages would also be viable options for this application.

A linear programming model makes several assumptions about the problem at hand. The most critical assumption for this research area is the certainty assumption which states that the value assigned to each parameter of a linear programming model is assumed to be a known constant (Hillier & Lieberman 2010, pp. 36–42). Since one of the objectives of the thesis is to evaluate configurations under demand uncertainty, it is evident that such an assumption does not hold for at least the demand parameter. Although the demand parameter values used for each scenario are initially treated as deterministic and fixed, the values are based on predictions of future conditions which inevitably introduces some degree of uncertainty. Consequently, a robustness analysis will be conducted using Monte Carlo simulation.

3.4.2 Monte Carlo Simulation

Monte Carlo simulation is a method used to study how uncertainty in the input of a model affects the output. The method is useful when it is not feasible to test all possible values of uncertain parameters (Clemen & Reilly 2014, p. 483). In the case of Ericsson, an analysis of how robust a certain production plan is to demand changes is needed. It is not possible to test for all demand levels within the relevant range, but if the demand distribution can be estimated, Monte Carlo simulations can be conducted to identify the outcome and impact on the total expected cost of the production setup.

Simply put, Monte Carlo simulations consist of three main components: inputs (Y), a mathematical model $g(Y)$, and outputs (X) (Amelin 2013, p. 2). To conduct a simulation, the possible ranges of the various input values must first be established. From these ranges, individual random samples are drawn one at a time. Then, each sample value is put into a deterministic mathematical model that consequently produces one output. This is called one iteration. The process of selecting a random sample and putting it into the deterministic model is then repeated N times. Once enough iterations have been performed, the outputs can be consolidated and the distribution, mean, and variance of them can be studied.

For the robustness analysis in this thesis, the Monte Carlo procedure is initiated by estimating the probability distribution of the demand. A common approach to distribution fitting is to analyze historical data. However, in this thesis, the triangular distribution, $T(a, b, c)$ is used to study uncertainty around a demand forecast. The triangular distribution is commonly used in business decision analysis when information about the underlying data is insufficient to perform a statistical analysis for distribution fitting (Kissell & Poserina 2017, p. 122). Furthermore, the triangular distribution is practical in the sense that it is bounded. To use the triangular distribution, a minimum (a), maximum (b), and most likely, i.e., mode (c) value is required. Since a demand forecast is commonly presented as a single value, the forecast level is considered the mode of the triangular distribution. Then, the minimum and maximum values can be set by selecting a percentage deviation that reflects the degree of uncertainty around the forecast value. In cases where multiple scenarios exist, for instance different variants of a forecast, this approach can be extended by running separate simulations for each demand scenario. Rather than combining multiple possible demand scenarios into one single distribution, which would require knowing the probabilities for each outcome, each scenario is modeled with its own triangular distribution. Then, the results of the simulations can be compared.

The next step of constructing a Monte Carlo simulation is to create a deterministic representation of the problem at hand (Clemen & Reilly 2014, pp. 488–492). This has already been done during the construction of the linear programming model. For each demand sample value in each scenario, the linear programming model determines a production plan based on minimizing cost. This model will be used for each iteration but with varying demand levels, and it is therefore vital that the deterministic model it tested for accuracy before being used as the foundation for the Monte Carlo simulation. Once the model has been constructed, the simulation can begin and the output studied. Based on the distribution, the Monte Carlo simulation draws N independent demand realizations. For each value, the production plan is optimized using the linear programming model. By consolidating the optimized value from each iteration, consequences of varying demand on total cost, backlog, investment needs, and other outputs can be studied.

An important aspect when simulating is the number of iterations, which reflects the number of demand samples, N, inserted into the model. More iterations increase the accuracy of the sampling toward the underlying probability distributions, but also result in more time-consuming simulations, requiring a balance between the two (Clemen & Reilly 2014, p. 492).

To study the accuracy of the simulation, confidence intervals can be analyzed using Equation 2. Here, $\overline{x}$ is the sample mean, s is the sample standard deviation and N the number of iterations (Devore et al. 2021, p. 459). In accordance with the Central Limit Theorem it is assumed that the sample means are normally distributed due to the large number of iterations. Hence, the confidence interval represents the interval in which the true mean, μ, would be 95% of the time, if the same procedure were repeated many times. Assuming normally distributed sample means, a 95% confidence interval corresponds to using the critical value of 1.96.

$$CI = \overline{x} \pm 1.96 \frac{s}{\sqrt{N}} \tag{2}$$

To determine a sufficient number of iterations, a pilot simulation is first run with a small initial N to obtain a preliminary estimate of the sample standard deviation, s. Given this estimate, the half-width of the confidence interval, $\varepsilon = 1.96 \cdot s/\sqrt{N}$, can be used as a convergence criterion (Devore et al. 2021, p. 457). The simulation is considered to have run a sufficient number of iterations when ε falls below a pre-specified threshold. Rearranging for N yields the minimum number of iterations required to achieve the desired precision ε, see Equation (3).

$$N \geq \left(\frac{1.96 \cdot s}{\varepsilon}\right)^2 \tag{3}$$

Once a sufficient number of iterations has been determined and the simulation has been run, a confidence interval (CI) is constructed for each demand scenario to study whether there is a statistically significant difference in production cost between scenarios. If the confidence intervals for demand scenarios do not overlap, it can be concluded that the mean production costs are statistically different. If any confidence intervals are close or overlap, a z-test could be used to confirm the results.

4 ANALYSIS

The analysis chapter aims to integrate the Operations Research Modeling Approach with theoretical findings from literature as well as empirical insights from interviews and observations to create a basis for answering the research questions. Evaluating Ericsson's uncertainty management process against the theoretical S&OP dimensions identifies scenario planning as the main uncertainty management mechanism in place. In order to improve the scenario planning process, it is essential to understand current operational practices. Therefore, the analysis continues by examining Ericsson's scenario definition, as well as by conducting a current state mapping of Ericsson's scenario management to identify gaps against theory and potential efficiency enhancements. To address these gaps, mathematical models are developed in line with theory to establish a more data-driven way of conducting scenario planning in S&OP. Finally, the requirements for making the proposed analysis structure a scalable process for Ericsson are discussed.

4.1 Defining the Problem and Gathering Data

This section aims to establish how Ericsson's scenario planning process can be improved. Consequently, it needs to be understood how scenarios are defined, and how they are currently analyzed. All together, this discussion defines the problem at hand.

4.1.1 Scenario Definition

The interviews and observations from participation in meetings in the S&OP cycle concluded that Ericsson's supply organization conducts scenario analysis but lacks a standardized process and scenario definition. Scenarios are triggered by sudden, significant changes in demand or supply. The objective of the analysis is to determine suitable actions to manage the consequences of the scenario, as well as associated risks. For instance, identifying required investments and corresponding risks such as unnecessary capacity lock-in if forecasted demand does not materialize.

Based on the current objectives of the scenario planning process, it can be concluded that the scenario planning process is mainly reactive, though Ericsson intends to expand it to include a proactive perspective to study the robustness of an operations plan. In both cases, demand is the most relevant uncertain factor; supply disruptions are out of scope in this thesis. In fact, the interviewees argue that resilience mechanisms such as safety stocks and spot-market component purchases are in place to handle such cases. Since large demand changes are difficult to forecast, the focus is on handling sudden changes rather than predicting specific levels. Consequently, two scenario analyses are needed: one to accommodate a known demand change, defined as the *reactive* scenario, and one to analyze how stochastic demand impacts the S&OP production plan, defined as the *proactive* scenario.

4.1.2 Current State Mapping of Scenario Management in the S&OP Cycle

Scenario planning at Ericsson originates from the Covid-19 pandemic, where a standardized process was established to handle large demand variations. However, after the pandemic, scenarios have evolved to being managed ad-hoc, and Ericsson now wants to incorporate scenario planning into the monthly S&OP cycle. Market area forecasts are consolidated into a demand plan by the demand planning team, but despite well performing forecasts, sudden changes in demand levels and product mix are common. Given the high degree of market concentration, it is crucial to assess investments, capacity adjustments, and operational changes required to accommodate such demand shifts. These are the situations that the reactive scenario is designed to address.

Although the current reactive scenario planning process is not standardized, it can be characterized by four main components, visualized in Figure 6. A scenario is initialized when a demand change occurs, but it is not defined how large the change must be to trigger escalation.

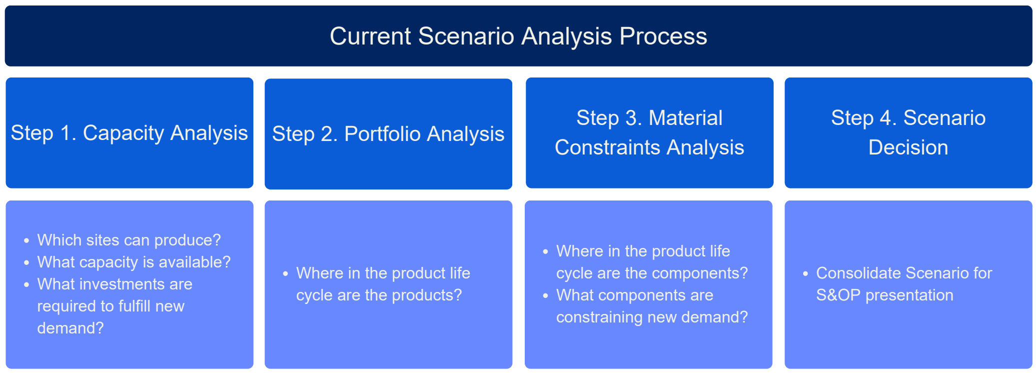


Figure 6. *Visualization of the current scenario planning process*

When a scenario is initialized, the first step is to conduct a capacity analysis to identify feasible production locations for the new demand. Ericsson's supply chain follows a strict product flow scheme. When a new product is introduced to the market, a supply chain design is created for the product and the corresponding customers. This plan is designed to minimize total cost across production, bill of materials, transport, and tariffs, while respecting geopolitical constraints. For instance, products with sensitive electronic components cannot be produced in China for US customers. Consequently, the set of viable production sites for a given demand change is often limited. Once identified, available capacity and feasible delivery dates must be determined. Production consists of two main stages: assembly and testing, where assembly equipment is generally more expensive.

Currently, the capacity analysis is performed manually by the capability planning team. Feasible production sites are first identified, after which the new demand is compared with available capacity at each site. This is complicated by the lack of real-time capacity data, requiring employees to rely on monthly capacity plans and preceding S&OP decisions. The analysis is further complicated by the need to study each production step individually, as routing and cycle times vary by product, and some products require additional fixture equipment, meaning both production steps and fixtures can be the limiting factor. When planning capacity for scenarios, the main KPIs that Ericsson wants to analyze are service level and cost. If it is not possible to meet the new demand request with a satisfying service level within the current production scheme, investments in new capacity are evaluated. Feasible solutions are then consolidated for the Pre-S&OP meeting.

In the second step, a portfolio analysis is conducted to determine where the relevant products are in their life cycle. This is particularly important when investments are required, as it may not be rational to invest in equipment for a product soon to be phased out, whereas increasing capacity for a product approaching full-scale production may be justified.

In the third step, a material constraint analysis is performed by the inbound team, covering both component and life cycle analysis. The objective of the material requirements analysis is to determine whether the planned changes are feasible given supply levels, bill of material relationships, and lead times. By comparing the current supply plan with the demand changes, it is determined whether components are available within the necessary lead time. Material constraints can be resolved through airfreight, product redesign, or spot-market purchases, though the latter is not always possible for Ericsson-specific components. The outcome is an estimate of the potential cost of meeting the demand scenario, including financial liability if demand does not materialize.

Lastly, the analyzes performed are consolidated to be presented in the pre-S&OP meeting. In rare and urgent cases, extra S&OP meetings can be held. There is no standardized way of presenting the consolidated results, and there are no set guidelines for how decisions should be made. Currently, it is the scenario planning employee's responsibility to consolidate the information from steps 1-3 in the scenario analysis process.

4.1.3 Benchmark with Volvo

Ericsson is not the only company that must manage uncertainties and variations in their S&OP process. In order to study how uncertainty can be managed in S&OP not only from a theoretical perspective, benchmarking interviews were conducted with employees who participate in the process at Volvo Group. The interviews concluded that Volvo has integrated scenario planning as a proactive and standardized part of their supply planning in S&OP. Scenarios are used mainly to explore different ways to fulfill a given level of demand from the sales teams. Non-standardized, ad-hoc scenario analysis also exists among demand planners. For instance, the effect on total demand if all customers increase their forecast levels is studied. Such an analysis is a basis for determining what demand level to present to the supply team. Thus, scenario analysis at Volvo involves both the demand and supply part of S&OP, with results consolidated to management when major decisions are required.

Although Volvo has integrated scenarios as a regular part of their S&OP cycle, no dedicated software or analytical tool is used to support the analysis. The primary supporting tool is manual and deterministic using Excel. Larger decisions, mainly regarding changing capacity levels, depend on whether it can be determined that a potential change in the plan is a trend or a one-time event. Moreover, decisions are highly dependent on experience and knowledge about operational flexibilities. Similarly to Ericsson, Volvo recognizes the need for a higher degree of financial integration into decision making in S&OP. Mainly, a higher degree of risk assessment for irreversible investments and capacity changes could be of value. Additionally, Volvo acknowledges the need to manage uncertainty in S&OP, especially given the large degree of volatility in the global environment. There have been efforts and discussion of developing data models to aid with decision-making. However, it has been concluded that it is difficult to construct a model that can manage a high degree of complexity without being too rigid.

4.1.4 Definition of the Problem

The current scenario management process indicates that capturing both capacity and material availability perspectives is vital. Capacity constraints in production mainly appear when demand suddenly increases. Typical fluctuations are handled through safety stock and production flexibility. However, when demand changes exceed normal variation, the analysis is performed manually, requiring data collection from both the ERP system and suppliers. A systematic approach would therefore improve efficiency and reduce the risk of arbitrary, ad-hoc decisions. Currently, no step in the process ensures cost-efficiency, meaning sub-optimal decision-making is possible. An analytical model for capacity allocation would support a decision-making process that approaches cost-optimality.

The degree of complexity is higher among material requirements planning than capacity planning. Ericsson's portfolio spans hundreds of products, each with thousands of components, managed through sourcing, procurement, and planning processes. Given this scale and complexity, optimizing material planning is not prioritized at this point, as material issues are already addressed through supplier coordination, inventory buffers, and continuous monitoring of escalated components.

Capacity analysis, in contrast, involves a limited number of production sites and a structured set of constraints, making it a high-impact and tractable target for analytical optimization. Focusing on capacity therefore provides a feasible way to reduce manual effort, improve response time, and support cost-optimal decision-making. The material requirements are equally important to analyze, but will within the scope of this thesis not be part of the mathematical models due to the increased degree of complexity and risk of reduced clarity. However, the portfolio analysis and material requirements are not neglected. Conversely, they are derived from and aligned with the results from the capacity analysis, while maintaining a manageable scope of the modeling.

4.2 Formulating a Mathematical Model

The current state analysis in the previous section determined that the mathematical models should focus on the impact of demand variation on capacity requirements. Other than finding cost-optimal production schedules for additional demand, the main objective of the scenario analysis is to find the best course of action when the previously installed capacity is not enough. The reactive model is constructed as an linear programming model. The proactive model also uses the linear programming model but introduces uncertainty by integrating it into a Monte Carlo simulation, where each iteration performs the optimization but for a different demand value. Hence, the proactive model can study a range of possible demand realizations. In this section, the reactive model is described, followed by the proactive model.

4.2.1 The Reactive Scenario Analysis: Linear Programming Model

The reactive scenario model seeks to determine the following:

- Feasibility of meeting the demanded quantity by the requested date
- Production configuration required to meet demand
- Expected delay if demand cannot be met on time
- Additional cost of investment required to avoid the delay

The linear programming model determines the production schedule for the new demand based on minimizing the expected cost. The model mimics the flow of components through a production line, taking into account capacity constraints and costs. The new production is scheduled on top of the already set production plan, which is determined in the S&OP process from the previous month. If demand cannot be satisfied in the set production schedule, there are two options. Firstly, the model can allow for demand to be satisfied late through the creation of a backlog with a corresponding backorder cost. Secondly, demand can be satisfied through investment in equipment in the constraining production steps.

When demand cannot be met by the requested date, choosing between backlog and equipment investment as decision alternatives means that the rational decision, under Bayes' Decision Rule, is the one with the lowest expected cost. Therefore, the initial goal was for the model to be able to balance the cost of unmet demand (backlog) with the cost of investment in the needed equipment, to be able to make a direct comparison and evaluate expected cost. However, during interviews, this turned out to be an infeasible approach for two reasons. Firstly, Ericsson does not have a defined backorder cost for each of its products. The penalty of not being able to satisfy an order can vary depending on many factors, such as who the customer is or what market it is located in. Secondly, it is not realistic that the cost of the investment should be distributed only on the products in one order, as investments of this scale typically benefit multiple products over several years. Therefore, two separate linear programming models are constructed: one in which the recourse strategy if demand cannot be satisfied is to carry backlog, and one where backlog is not allowed, but capacity can be increased. While a direct cost comparison between the two recourse strategies is not possible, the models can still quantify the outcome of the demand scenario: either the expected delay, or the required investments. In this section, the models are described separately, starting with a detailed description of the backlog model. Then, Section 4.2.3 presents the investment model, where only the differences from the backlog model are described in detail.

4.2.2 Linear Programming Model with Backlog Allowed

The objective of the linear programming model is to create a production plan that minimizes cost for a certain set of products, production steps, and periods. The backlog model is presented in its entirety in Appendix A. Latin letters are used to represent indices and decision variables. Greek letters represent parameters with fixed input values. Table 2 presents the sets and indices in the backlog model. The reactive scenarios are most commonly performed when there is a substantial demand change request from one customer on a single or small number of products, each denoted by $i \in \mathcal{I}$. To produce these products, a set of production and testing steps, denoted by $k \in \mathcal{K}$, is required. However, as previously discussed, not all products are processed in all steps. This is represented by the subset $\mathcal{K}_i$. Moreover, the subset $\mathcal{K}_i^{wip}$ denotes all steps in a production line except the last one, meaning all steps that are succeeded by a work-in-progress (WIP) storage. In other words, $\mathcal{K}_i^{wip} + k_i^{final} \equiv \mathcal{K}_i$. A time period is denoted by t.

Table 2. *Sets and indices*

Symbol	**Description**
$i \in \mathcal{I}$	Set of products
$k \in \mathcal{K}$	Set of production steps
$\mathcal{K}_i \subseteq \mathcal{K}$	Set of production steps in the route of product i
$\mathcal{K}_i^{wip} \subseteq \mathcal{K}_i$	Set of non-final production stages of product i
k_i^{final}	The final production stage of product i
$t \in \mathcal{T}$	Set of time periods

Table 3 presents the input parameters. All parameters except demand, $\delta_{i,t}$, are held constant across scenarios, ensuring that differences in output reflect demand variation alone. The remaining parameters are explained in greater detail when introduced in their corresponding equations.

Table 3. *Parameters*

Parameter	Description	Indexes	Unit
$\delta_{i,t}$	Demand	$i \in \mathcal{I},\ t \in \mathcal{T}$	pieces
$\mathcal{Z}_{k,t}$	Total production capacity	$k \in \mathcal{K},\ t \in \mathcal{T}$	hours
$\zeta_{k,t}$	Occupied production capacity	$k \in \mathcal{K},\ t \in \mathcal{T}$	hours
$\mathcal{E}_{i,k,t}$	Total fixture capacity	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	hours
$\epsilon_{i,k,t}$	Occupied fixture capacity	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	hours
$\tau_{i,k}$	Processing time	$i \in \mathcal{I},\ k \in \mathcal{K}_i$	hours
γ_i	Production cost	$i \in \mathcal{I}$	cost/piece
β_i	Backlog cost	$i \in \mathcal{I}$	cost/piece
η	Holding cost rate	–	%
ψ	Capacity utilization factor	–	%
Q	Sufficiently large constant	–	–

With the production line set, the model can determine how much to produce of each product in each step and period. Table 4 represents the decision variables.

Table 4. *Decision variables*

Variable	Description	Indexes	Unit
$x_{i,k,t}$	Production time allocated	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	hours
$p_{i,k,t}$	Production quantity	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	pieces
$w_{i,k,t}$	WIP inventory after step k	$i \in \mathcal{I},\ k \in \mathcal{K}_i^{wip},\ t \in \mathcal{T}$	pieces
$f_{i,t}$	Finished goods inventory	$i \in \mathcal{I},\ t \in \mathcal{T}$	pieces
$b_{i,t}$	Backlog	$i \in \mathcal{I},\ t \in \mathcal{T}$	pieces

The decision variable $x_{i,k,t}$ represents the production time allocated to product *i* at step *k* in period *t*, while $p_{i,k,t}$ is the corresponding number of pieces produced. Moreover, if there is constraining capacity in a following production step, a WIP storage can be built. This is expressed as $w_{i,k,t}$. In case of pre-production, the resulting finished goods stock is represented by $f_{i,t}$. In the opposite case, capacity restrictions that result in a backlog at the end of a period are represented by $b_{i,t}$.

Objective Function

The objective function minimizes the cost of the production schedule needed to meet the additional demand and is presented in Equation (4).

$$\begin{aligned} \min \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} \Big(\gamma_i \, p_{i,k_i^{final},t} + \beta_i \, b_{i,t} + \gamma_i \, \eta \, f_{i,t} \Big) \\ + \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i^{wip}} \sum_{t\in\mathcal{T}} \frac{|\mathcal{K}_i^{\leq k}|}{|\mathcal{K}_i|} \gamma_i \, \eta \, w_{i,k,t} \end{aligned} \tag{4}$$

The first term in the first set of sums, $\gamma_i \, p_{i,k_i^{final},t}$, evaluates the production cost of all completed products. Here, γ_i represents the production cost for each product. It is assumed that the production cost is only realized once the product has passed through the final production step, whereupon the index k_i^{final} is used in $p_{i,k_i^{final},t}$.

Next, the cost of backlog is evaluated. If the installed capacity is not adequate, a backlog, $b_{i,t}$, is created. This is not necessarily a critical issue. It can be acceptable as long as the corresponding service level is satisfactory. However, since delays are undesirable, backlog comes at a cost per delayed unit, $\beta_{i,t}$. Hence, the backlog cost is evaluated by multiplying the unit backorder cost, β_i, by the amount of unfulfilled demand for each product in each period $b_{i,t}$. This ensures that the backlog penalty is accumulated until demand is fulfilled, allowing for a cost that considers both the size and duration of the backlog.

Then, the cost of pre-production is set by multiplying the unit cost, γ_i, by the internal holding cost rate, η, and the amount of finished goods inventory for each product and period, $f_{i,t}$. It is assumed that there are no limits for the finished goods inventory. The holding cost rate, η, is relevant as it penalizes pre-production. However, pre-production is an option to allow for a more evenly distributed production in cases of demand peaks.

The second set of sums represents the cost of WIP inventory for each product over all periods. Therefore, the production steps are only summed over the set $k \in \mathcal{K}_i^{wip}$, which includes all intermediate steps and excludes the final step. This distinction is made because any inventory held after the last production step is classified as finished goods inventory rather than WIP, and is consequently already penalized with cost. As it was not possible to obtain information on how each production step contributes to the final product value, and to maintain scalability of the model, it is assumed that the value added at each step is evenly distributed across all production steps. Therefore, the cost of holding WIP at step k is determined by multiplying the product value by the fraction of the route completed up to and including that step, given by $|\mathcal{K}_i^{\leq k}|/|\mathcal{K}_i|$. This value is then multiplied by holding cost rate and the number of pieces in WIP storage of each product, between each production step, across all periods.

Constraints

The production plan is limited by a set of constraints related to capacity, production flow, and inventory balance. These constraints ensure that the minimization remains feasible by considering operational limits.

Production and testing capacity constraint

The capacity constraint limits how much production can take place in a production step in a certain period. Since production capacity is independent of product type, production hours, $x_{i,k,t}$, are summed over all products. Together, the added production, $x_{i,k,t}$, and the occupied capacity in each step and period, $\zeta_{k,t}$, cannot be greater than the total installed capacity, $\mathcal{Z}_{k,t}$. The total installed capacity is multiplied by the capacity utilization factor, ψ, which allows the user to limit capacity allocation to preserve resilience in the production system. The resulting capacity constraint is shown in Equation (5).

$$\sum_{i \in \mathcal{I}} x_{i,k,t} + \zeta_{k,t} \leq \mathcal{Z}_{k,t} \, \psi \quad \forall \, k \in \mathcal{K}_i, \; t \in \mathcal{T} \tag{5}$$

Fixture capacity constraint

The capacity can also be constrained by the fixture availability, which is displayed in Equation (6). Fixtures are product specific pieces of equipment that are sometimes required in addition to the main production step. The constraint shows that for all products, production steps, and periods, the production, $x_{i,k,t}$, and the occupied fixture capacity, $\epsilon_{i,k,t}$, cannot be larger than the total installed fixture capacity in hours, $\mathcal{E}_{i,k,t}$. Additionally, as in the main production stages, the total fixture capacity is multiplied by the utilization factor, to allow for flexibility in production.

$$x_{i,k,t} + \epsilon_{i,k,t} \leq \mathcal{E}_{i,k,t}\,\psi \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T} \tag{6}$$

The sufficiently large constant, Q, replaces $\mathcal{E}_{i,k,t}$ when the fixture capacity does not constitute a constraint, as all production steps do not require them.

Conversion of production in hours to pieces

As the capacity levels are given in hours, the processing time per product and production step, $\tau_{i,k}$, is needed to convert allocated production time into throughput. This is done using Equation (7), where the production time allocated to each product at a given step is divided by the corresponding processing time per piece and step. This distinction is important for several reasons. The demand factor, varied across scenarios, is inserted into the model in units of pieces. Furthermore, costs of production, inventory holding, and backlog are all defined per piece. The objective function also optimizes production based on pieces in production.

$$p_{i,k,t} = \frac{x_{i,k,t}}{\tau_{i,k}} \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T} \tag{7}$$

Work-in-progress flow constraints

The WIP flow constraint ensures that when the downstream step, k', has lower capacity than the preceding step, k, a WIP inventory is built between these steps. The WIP storage before each production step is equal to the WIP level from the previous period, plus the output of production in the previous step, minus the output in the subsequent step. This flow must hold for all products and all periods and is displayed in Equation (8). The WIP flow constraint enforces the order of production and tracks the amount of WIP stored between steps across all periods, which is necessary for determining the total WIP cost.

For each consecutive pair (k, k') in $\mathcal{K}_i$:

$$w_{i,k,t} = w_{i,k,t-1} + p_{i,k,t} - p_{i,k',t} \quad \forall\, i \in \mathcal{I},\ t \in \mathcal{T} \tag{8}$$

Inventory balance

The inventory balance keeps track of how many products are finished or how much demand is unfulfilled at the end of each period. The relationship is displayed in Equation (9). First, the finished goods of product i from the preceding period, $t-1$, must be considered. To that, the production of product i in the current period t is added, represented by $p_{i,k_i^{final},t}$, where k_i^{final} denotes the last production step. Next, the demand must be considered. This is done by subtracting the demand of product i in the current period t. It is assumed that backlog is carried over between periods. Consequently, the backlog from the previous period, $b_{i,t-1}$ is subtracted from the expression. This now leaves two variables that have undefined values: $f_{i,t}$ and $b_{i,t}$. If there is a surplus in production, $f_{i,t}$ will be larger than zero. Consequently, there is no backlog, and $b_{i,t}$ will be equal to zero. On the contrary, if there is a backlog, there is no finished goods inventory, meaning $f_{i,t}$ will be equal to zero, and $b_{i,t}$ will be larger than zero. Although the constraint does not strictly force this, the cost of having backlog and finished goods will entail that these are never positive simultaneously.

$$f_{i,t} - b_{i,t} = f_{i,t-1} - b_{i,t-1} + p_{i,k_i^{final},t} - \delta_{i,t} \quad \forall\, i \in \mathcal{I},\ t \in \mathcal{T} \tag{9}$$

Initial Conditions

For the model to work properly, some of the decision variables require initial values. Equation (10) displays that the WIP for all products must have an initial value of zero. Furthermore, the initial value for finished goods must be zero for all products. This is shown in Equation (11). The objective function does not penalize costs in period $t = -1$. Therefore, if these values are not set to zero, the model can satisfy all demand before entering the planning horizon, leading to an unrealistic solution.

$$w_{i,k,t\,=\,(-1)} = 0 \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i^{wip} \tag{10}$$

$$f_{i,t\,=\,(-1)} = 0 \quad \forall\, i \in \mathcal{I} \tag{11}$$

Non-negativity

None of the decision variables can obtain negative values, as that would for instance require negative production levels. Therefore, non-negativity is enforced for the production variables $x_{i,k,t}$ and $p_{i,k,t}$, as well as for WIP inventory levels, $w_{i,k,t}$, finished goods inventory levels $f_{i,t}$, and backlog levels $b_{i,t}$.

$$x_{i,k,t},\ p_{i,k,t},\ w_{i,k,t},\ f_{i,t},\ b_{i,t} \geq 0 \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T} \tag{12}$$

4.2.3 Linear Programming Model with Investment Allowed

The investment model uses the same sets and indices as the backlog model, described in Table 2. Additionally, the investment model uses the same parameters as the backlog model, except for two modifications. Firstly, no unit backlog cost, β_i is needed, as no backlog is allowed in this model. Secondly, a large constant, $Big\text{-}M$, is added to represent an arbitrarily large number to penalize investment costs. Since the investment option will not be directly comparable with the backlog option, it is not vital that the cost of investment is correct for this proof-of-concept, but it must just be sufficiently large for the model to avoid this option to the greatest extent possible. Once the optimization is done, the valuable output is instead how many additional hours of capacity is required in each production step, and when. Once the optimization is complete, this number can be converted to pieces of equipment and man-hours. The full investment model is presented in Appendix A.

To describe the investment option, decision variables for investments are added. There are two types of possible investments. Capacity can be added in a main production step or in fixtures. Sometimes, both types of investment are needed simultaneously. Consequently, two investment decision variables are required. Firstly, $a_{k,t}$ describes how many additional hours of capacity in each main production step that is required to satisfy the entire new demand change. Secondly, $q_{i,k,t}$ signifies how many additional hours of fixture capacity are needed. $q_{i,k,t}$ is product specific, which $a_{k,t}$ is not. The additional decision variables for the linear programming with investment option are shown in Table 5.

__Table 5.__ Additional decision variables for investment LP

Variable	Description	Indexes	Unit
$a_{k,t}$	Production capacity investment requirement	$k \in \mathcal{K},\ t \in \mathcal{T}$	hours
$q_{i,k,t}$	Fixture capacity investment requirement	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	hours

Objective Function

The investment model minimizes costs for production, finished goods inventory, WIP inventory, production capacity investments, and fixture capacity investments. The objective function for the linear programming investment model is displayed in Equation (13), where the last two set of sums are new. The production capacity investments are summed over all production steps and periods, whereas the fixture capacity investments are summed over all products, production steps relevant for each product, and periods.

$$\begin{aligned}\min \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} & \left(\gamma_i\, p_{i,k_i^{final},t} + \gamma_i\, \eta\, f_{i,t}\right) \\ & + \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i^{wip}} \sum_{t\in\mathcal{T}} \frac{|\mathcal{K}_i^{\leq k}|}{|\mathcal{K}_i|}\, \gamma_i\, \eta\, w_{i,k,t} \\ & + \sum_{k\in\mathcal{K}} \sum_{t\in\mathcal{T}} M\, a_{k,t} \\ & + \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i} \sum_{t\in\mathcal{T}} M\, q_{i,k,t}\end{aligned} \tag{13}$$

Constraints investment model

The constraints for the investment model are similar to those in the backlog model. However, all backlog decision variables are removed since this is no longer an option. Instead, variables for investment opportunities are added. Only altered constraints are commented below.

Production and testing capacity constraint

The production capacity is no longer strictly limited by the already existing capacity. It is now an option to add capacity in each production step. The constraint is presented in Equation (14). It is assumed that capacity investments accumulate over time. This means, for instance, that if capacity is added in production step $k = 1$ in period $t = 2$, the extra capacity will remain there for the remaining periods. The sum $\sum_{\hat{t}\in\mathcal{T}_{\leq t}} a_{k,\hat{t}}$ signifies just this: for every period $\hat{t}$ in the set of periods $\mathcal{T}_{\leq t}$, which denote all periods that have passed up to and including the current period, t, the capacity added for production step k is added and accumulated. The capacity utilization factor remains, and it is assumed that it applies to potential capacity investments as well.

$$\sum_{i\in\mathcal{I}} x_{i,k,t} + \zeta_{k,t} \leq \psi \left(\mathcal{Z}_{k,t} + \sum_{\hat{t}\in\mathcal{T}_{\leq t}} a_{k,\hat{t}} \right) \quad \forall\, k \in \mathcal{K}_i,\ t \in \mathcal{T} \tag{14}$$

Fixture capacity constraint

As for the production steps, fixture capacity can also be added in this model. The fixture capacity constraint adapted to the investment case follows the same logic as the production capacity constraint above, and is shown in Equation (15).

$$x_{i,k,t} + \epsilon_{i,k,t} \leq \psi \left(\mathcal{E}_{i,k,t} + \sum_{\hat{t} \in \mathcal{T}_{\leq t}} q_{i,k,\hat{t}} \right) \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T} \tag{15}$$

Finished goods balance

The finished goods balance no longer needs to consider backlog, whereupon the backlog decision variables are removed from this constraint. The resulting finished goods balanced constraint is presented in Equation (16).

$$f_{i,t} = f_{i,t-1} + p_{i,k_i^{final},t} - \delta_{i,t} \quad \forall\, i \in \mathcal{I},\ t \in \mathcal{T} \tag{16}$$

Non-negativity

Non-negativity is enforced for all decision variables.

$$x_{i,k,t},\ p_{i,k,t},\ w_{i,k,t},\ f_{i,t},\ a_{k,t},\ q_{i,k,t} \geq 0 \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T} \tag{17}$$

4.2.4 The Proactive Scenario Analysis: Monte Carlo Simulation

The reactive demand scenario analysis aims to determine how a demand increase can be managed, and it considers the demand value as deterministic. In most cases however, the exact demand level may not be known, because forecasts are not always accurate. If investment decisions are made on single value estimates of demand, the decision may not lead to a robust production plan, as a production plan that is optimal in one scenario can be infeasible in another. The sensitivity is particularly important to study when making investment decisions, to determine whether one should take the risk of delivering products late, or make very expensive investments that are irreversible. To do this, Monte Carlo simulations are used to stress test production configurations and investment decisions across a range of demand levels. In addition, it can be used completely standalone to generate an idea of how future capacity levels might have to change to accommodate for demand uncertainty.

Ericsson experiences two main types of demand uncertainty: volume and timing. The uncertainty can be expressed as minor deviations around a largely known demand volume, or as completely different demand scenarios that differ in volume, timing, or both. When uncertainty relates to volume, Ericsson aims to consider three scenarios: a base case defined as the market area forecast (MAF), a conservative variant of the MAF, and a stretch of the MAF. Considering these three values as the mode, minimum, and maximum of a triangular distribution is not straightforward, as that requires knowing the probability of each outcome. Therefore, each forecast level is treated as its own demand scenario, and for each scenario, a separate simulation is run. Minor volume uncertainty around each forecast value is modeled by the triangular distribution, described in Section 3. Consequently, for each of the three scenarios, *N* demand values are independently sampled from the corresponding triangular distribution. The three resulting outcome distributions can then be compared and statistically analyzed to assess the sensitivity of decisions across demand scenarios.

Studying three separate demand scenarios allows the user to analyze the corresponding consequences, without having to know the probabilities for each demand scenario. Using expert judgment, such as input from the market area which is the department working closest to the customer, the most likely demand scenario can be given extra attention. The analysis is conducted for both the backlog and investment models. Due to not being able to correctly distribute the backlog and investment costs on a product level, a direct comparison of costs between the two models is still not possible. However, incorporating stochasticity into both models can help decision-makers visualize risk exposure for different options for managing additional demand.

4.3 Deriving Solutions From the Model

Most commonly, a scenario is not run for the full product portfolio, but for a limited number of products and facilities. Therefore, it is justifiable and intentional that the models in this thesis are developed with a limited scope as a proof-of-concept. The limited scope is meant to ensure that there is theoretical and computational validity to the approach before it is decided to invest in front-end development and integration of the concept into Ericsson's organization. Accordingly, the current implementation of the models is based on a situation with one production facility. Furthermore, to illustrate the models' output, an exemplary situation with four products, four production steps, and a planning horizon of six periods is presented.

Despite having a limited scope, it was not possible to obtain empirical values for all input parameters. Therefore, the input values used for the implementation of the models in Gurobi are made up to illustrate how they can support decision making. A hypothetical demand scenario is presented in Equation (18), where each entry $\delta_{i,t}$ represents the demand for product i in period t.

$$\Delta = \begin{pmatrix} 0 & 0 & 0 & 0 & 1000 & 0 \\ 0 & 0 & 10000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 16000 \\ 0 & 3000 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{18}$$

For these four products, the product routing is visualized in Equation (19), where a value 1 indicates that the product visits a production step, and 0 that it is skipped. For instance, product 4 skips production step 3, as $K_4 = (1, 1, 0, 1)$. Furthermore, in the production line exemplified in this thesis, it is previously known that only production steps 3 and 4 require product specific fixtures to function. The remaining input values are not presented as they are non-essential for interpreting the models' output.

$$\mathcal{K} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 1 \end{pmatrix} \tag{19}$$

4.3.1 Reactive Scenario Output

The output of the reactive scenario models can be described as production plans in which all the previously determined decision variables specify where, what, when, and how much should be produced in each production step, and for each product. As previously mentioned, other than finding cost-optimal production schedules for additional demand, the main objective of the reactive scenario analysis is to find the best course of action when the previously installed capacity is not enough. The deterministic models take on two perspectives on how to deal with an upcoming demand change resulting in an infeasible solution given previously existing capacity; either by allowing backlog or by investing in additional capacity. Their respective optimal solutions result, of course, in different outcomes which are thereafter compared. To ensure a standardized way of interpreting the results, a decision-support chart is presented in Figure 7.

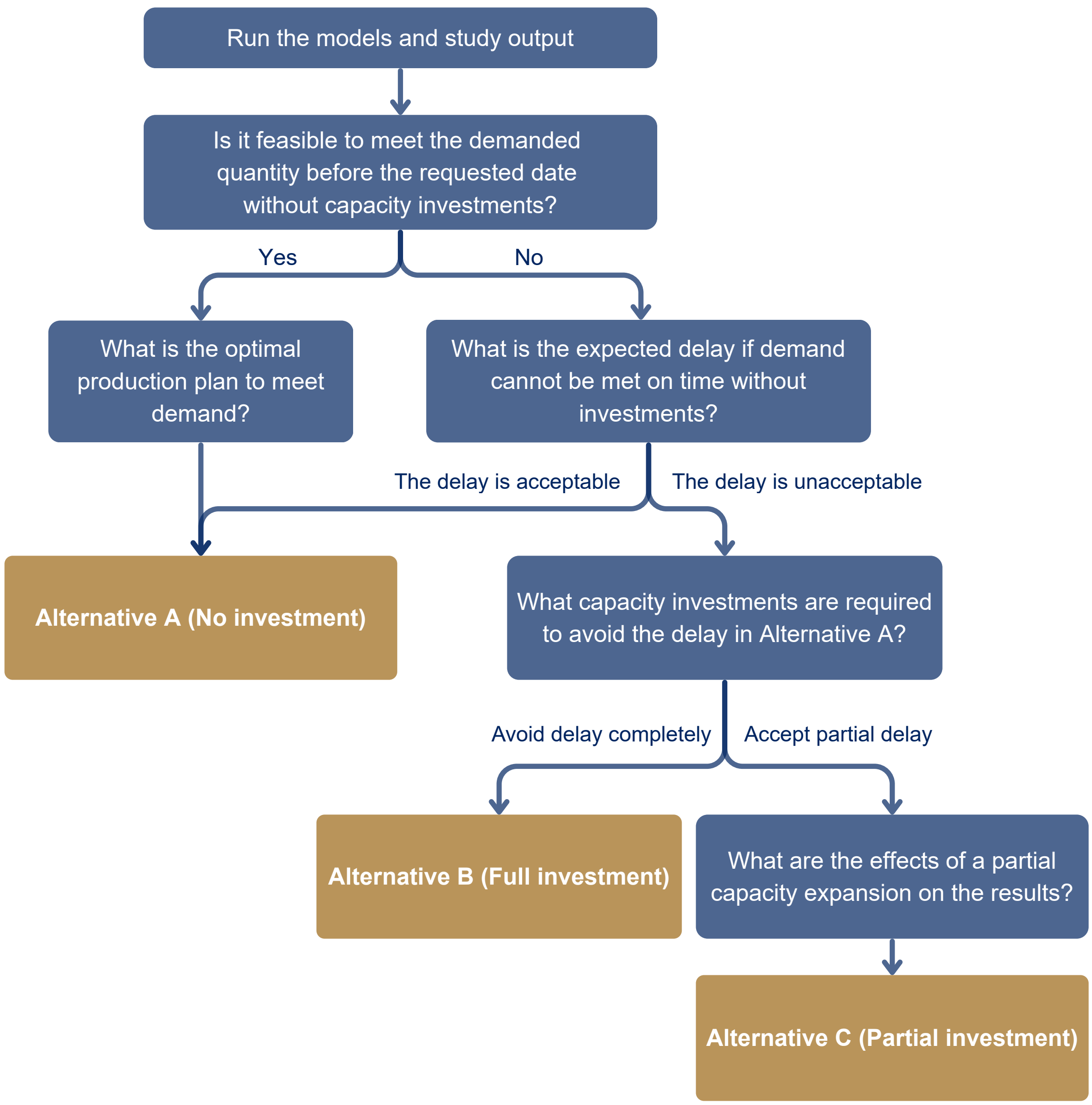
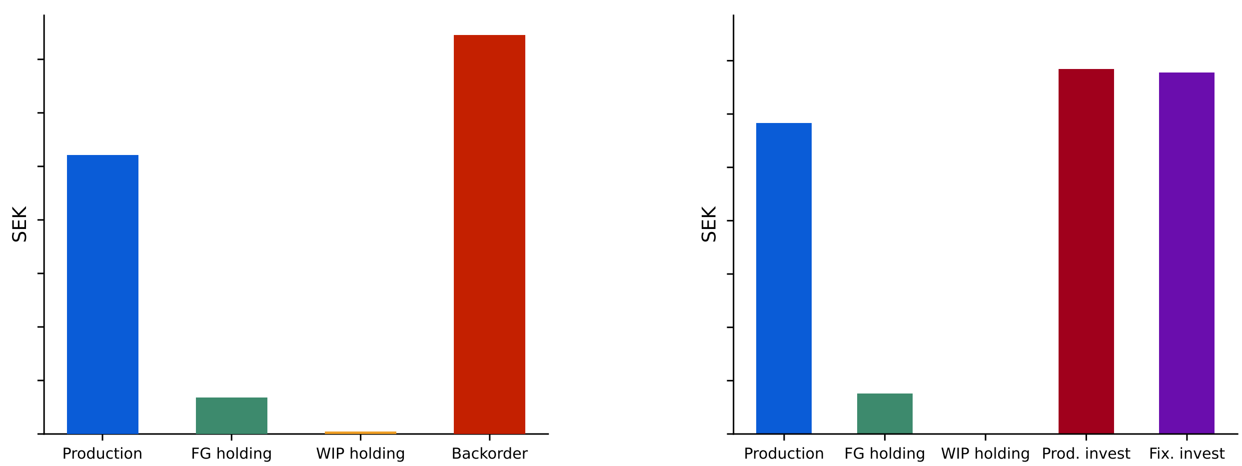


Figure 7. *Decision-support chart for reactive scenario models.*

This decision-support chart addresses the questions that need answers in the capacity analysis, and also presents three decision alternatives that can be brought to the S&OP cycle. Firstly, Alternative A maintains the current installed capacity levels with the production schedule determined by the backlog model. Alternative B completely eliminates any potential backlog through capacity investments. Thereby, the service level reaches a level of 100%, but likely means high investment costs. Lastly, decision Alternative C allows for incremental capacity investments in the steps suggested by the investment model to reduce the backlog, while not entirely eliminating it. The chart does not automatically tell the user what decision to make, but gives a structure to how to approach the decision-making while analyzing the trade-off between costs and service level.

With the decision chart framework in place, the comparison between the backlog and investment strategies proceeds as follows. Two production schedules are created but not included in this thesis to maintain readability. The analysis is supported by studying a set of relevant graphical outputs. Since the input data are based on a hypothetical case, the exact magnitude of the output values is not of interest. Consequently, graphs are not numerically labeled. Nevertheless, scaling remains intact between the graphs that need to be compared.

To gain a general oversight, the cost components of the production plans are compared, see Figure 8.



(a) *Backlog model*

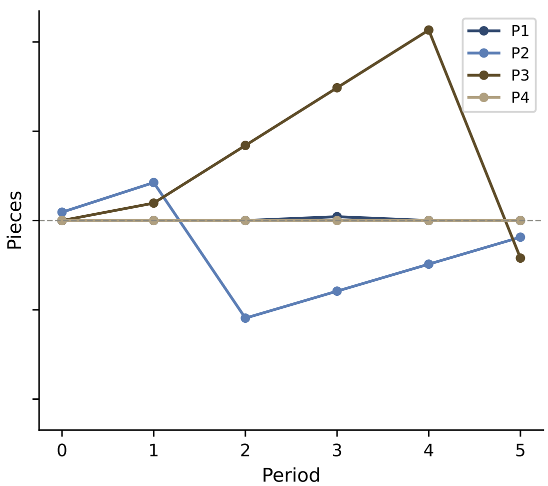
(b) *Investment model*

Figure 8. *Cost components of results in linear programming models.*

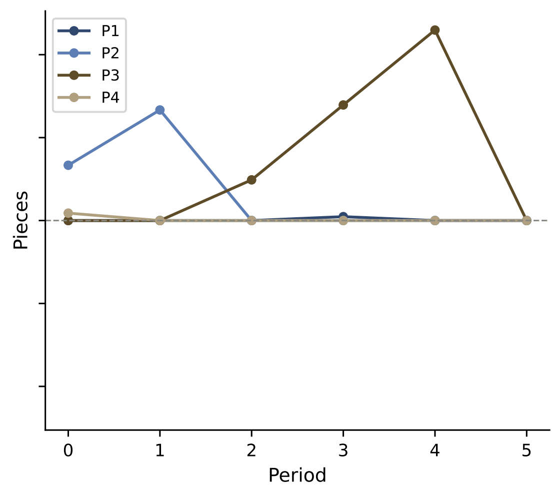
The substantial backorder cost in Figure 8a indicates that the current capacity is insufficient to fulfill demand on time. In reality, this means that the production plan is infeasible. However, the backlog model remains valuable because rather than returning no solution when the production schedule is infeasible, it allows for unmet demand, although penalized by the backorder cost. Consequently, the magnitude of delays can be quantified. The backlog model not only shows whether existing capacity is enough to satisfy demand on time, but also how severe the delays will be if no capacity is added. The capacity shortage in this example is also reflected by the high investment costs across both main production steps and fixtures in Figure 8b, which indicate that capacity is constrained in multiple stages. Naturally, the production component will be lower for the backlog model if the capacity is inadequate, as all products cannot be produced.

The accuracy and meaningfulness of this comparison depend heavily on the ability to estimate backlog costs per unit and per product with sufficient precision, as well as to define the investment cost parameters accurately. As of now, the cost associated with both backlog and investment are set to large arbitrarily numbers to penalize such actions. A more detailed discussion of these parameters is presented in Section 6. Despite this, the graphs give the user an overlook of the amount of backlog created, or the amount of investments needed. Hence, it is possible to get an initial understanding of what recourse actions might have to be taken.

When capacity is constrained, the finished goods and WIP holding costs are relatively small compared to the backlog and investment costs, respectively. This suggests that under capacity constraints, the primary cost drivers are not inventory related. Nevertheless, to better understand how inventory and backlog costs arise on a per product level, a comparison can be made between the models' inventory levels over time, according to Figure 9. These graphs make it possible to study which products are prioritized in being manufactured prior to their delivery date and stored as finished goods, as well as which will not be finished on time and consequently accounted for as a backlog. Note that Figure 9b has no negative inventory, as no backlog is allowed for the investment model.



***(a)** Backlog model*

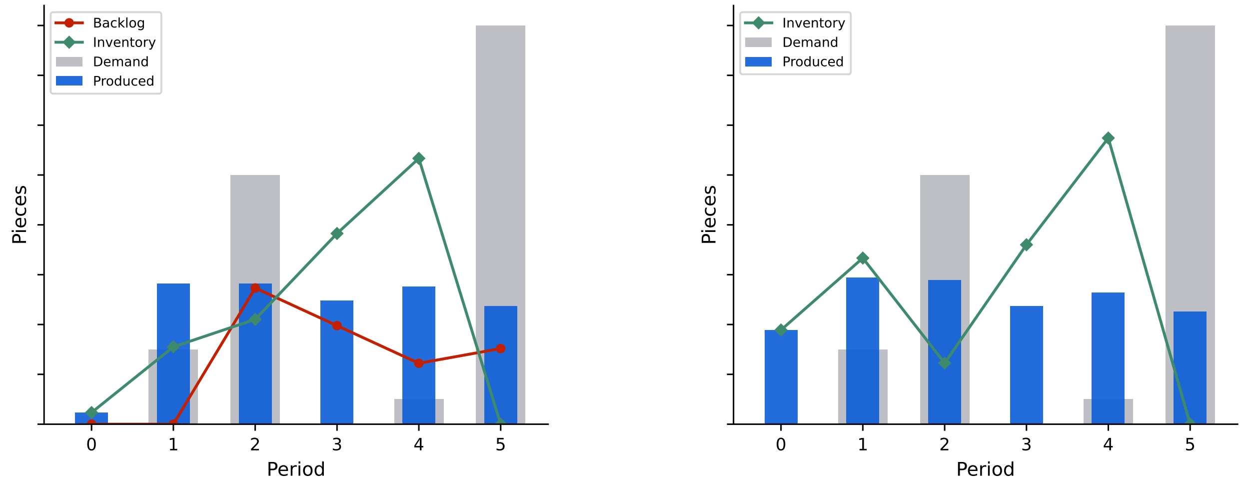


***(b)** Investment model*

Figure 9. *Backlog and finished goods comparison. Note that negative inventory, below the center line, represents backlog.*

As can be seen in Figure 9a, limiting capacity does not result in a backlog for all products, nor all the time. Some products are prioritized over others, since the model balances production, backorder, and holding costs against the size and timing of demand. In this case, product 3 accumulates a high level of finished goods in both models to meet demand in period 5. Although finished goods inventory incurs costs, the alternative of carrying backlog is more expensive. For product 2, pre-production also occurs, but a combination of capacity being inadequate and the model favoring other products means the demand in period 2 cannot be fulfilled. While the backlog gradually recovers during the planning period, capacity is insufficient to fully meet demand for products 2 and 3, meaning a backlog remains. In contrast, in the investment model, the possibility for additional capacity avoids the backlog for product 2 by enabling more pre-production and inventory build up in early periods.

To further display how production, demand, and inventory levels relate to each other over time, two additional graphs are introduced in Figure 10.



***(a)** Backlog model*

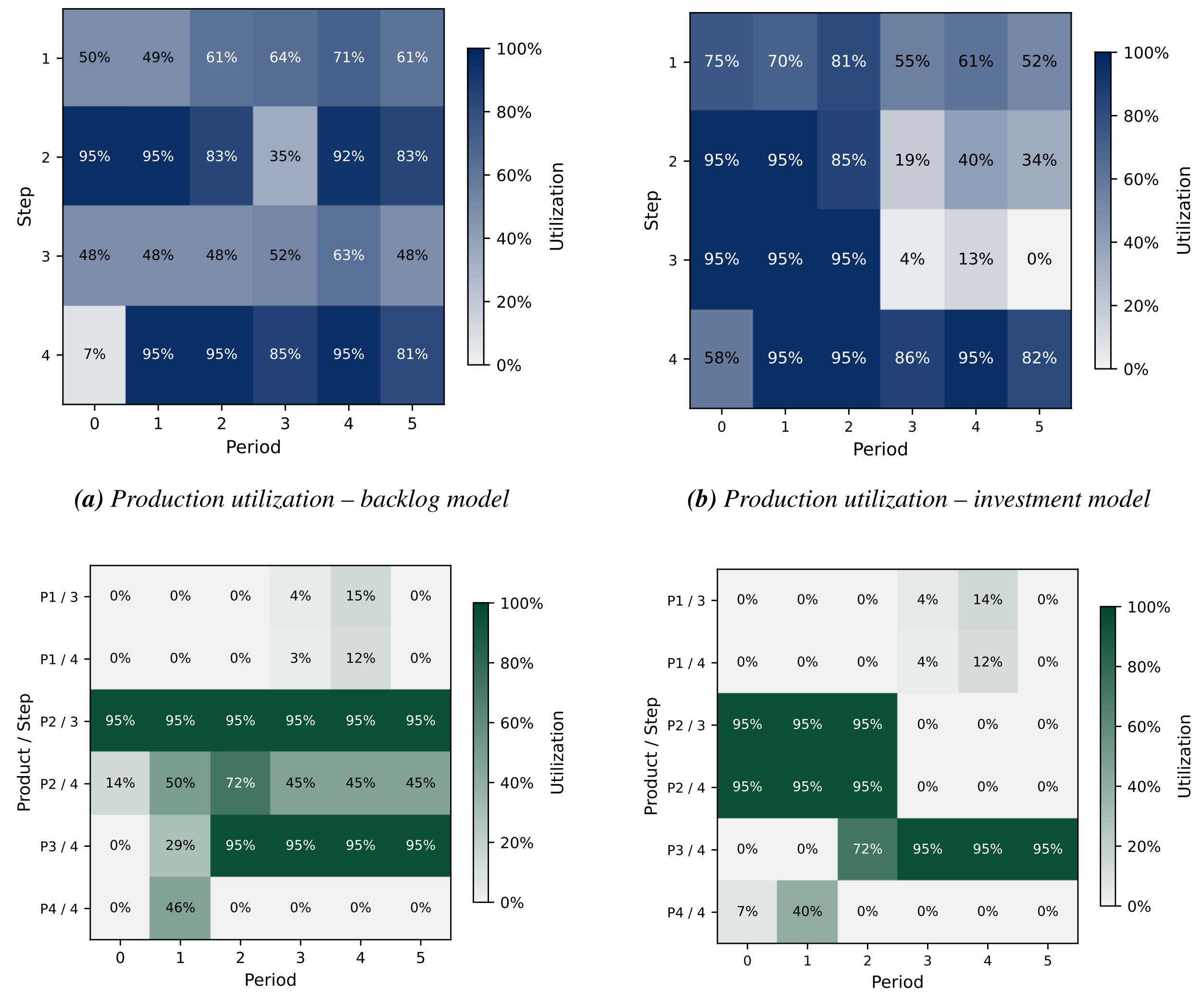
***(b)** Investment model*

***Figure 10.** Visualization of demand and production levels in final production step across periods.*

It should be noted that the production bar only refers to the output in the final production step. For instance, this is shown in period 0 in the backlog model, where production does occur, but all output remains as WIP, which is not reflected in the graphs.

The graphs highlight that periods of imbalance between production and demand propagate both forward and backwards. Demand peaks propagate backwards since they cause production in earlier periods, despite there being no demand there. For instance, production takes place in both periods 0 and 3, even though there is no demand in these periods. In contrast, the effects can also propagate forwards. In the backlog model, the demand peak in period 2 is too large for the installed capacity, causing a backlog that must be recovered during later periods. This consumes capacity that could have been used to manage the period 5 demand peak. In the investment model, this is avoided, resulting in more consistent production levels and earlier production of finished goods to meet later demand peaks.

The previous graphs have clearly established that capacity is inadequate in this hypothetical case. Consequently, a detailed overview of capacity constraints and subsequently utilization rates should be analyzed. To best understand the bottlenecks, heatmaps are presented in Figure 11, showing the utilization rate of each production step for each period. Note that in this case, a maximum allowed utilization rate of 95% is set. These graphs demonstrate which machines are limiting the whole production system and which are currently underutilized. Note that some production steps are not shown in the graphs for the fixtures in Figures 11c and 11d as they are not required for that production step. Currently, Ericsson usually analyzes one production step at a time, but the heatmaps allow for a visualization of the whole production line at the same time.



(a) *Production utilization – backlog model*

(b) *Production utilization – investment model*

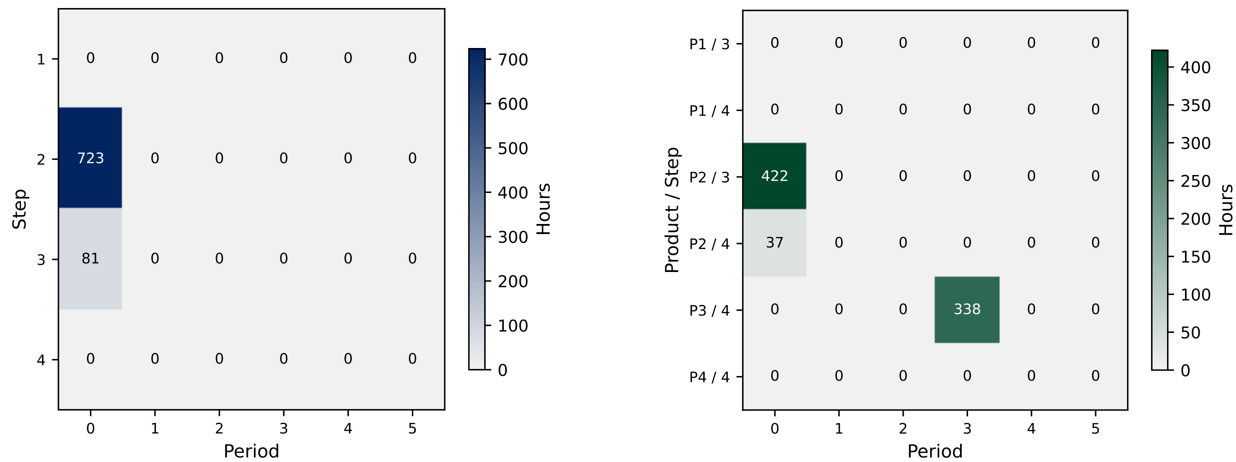
(c) *Fixture utilization – backlog model*

(d) *Fixture utilization – investment model*

Figure 11. *Utilization rates for production and fixture resources.*

Comparing the utilization rate charts of the backlog model with the investment model, it becomes apparent how targeted investments can result in a higher degree of utilization throughout the production system. Studying Figure 11a, the low utilization in production step 4 in period 0 stands out. The 7% utilization is not due to there being no demand, but is rather a consequence of the bottleneck present in step 2. This bottleneck starves the downstream production steps, whereupon they cannot produce, and installed capacity is left underutilized. By investing in bottleneck production steps, utilization rates improve earlier across the entire production system, which can result in a higher throughput from the start. This is visualized in Figure 11b.

The improved utilization is the result of investments in both production capacity and fixture capacity. The exact investments are illustrated in the heatmaps in Figure 12. The ability to show exactly how much capacity is needed is something that Ericsson currently does not present in their scenarios.



***(a)** Production hours – investment model*

***(b)** Fixture hours – investment model*

***Figure 12.** Investments needed according to investment model.*

Note that both graphs refer to the investment model. The graphs illustrate the required investments expressed as additional hours of periodical capacity and assumes that once an investment is done the additional capacity remains onward. In general, the model invests when the need arises and tends to favor earlier investments since costs remain constant over time. Such is the case in Figure 12a, but not in Figure 12b, where additional capacity is not needed until period 3. The investments suggested in the graphs may not always be feasible, as there can be a delay between the investment decision and the machine becoming operational. Consequently, the model can be adjusted for such a scenario to ensure its validity.

The aforementioned investments are, however, often costly. For that reason, it is important to maintain a close dialogue with the sales department in order to develop as accurate an understanding of future demand as possible. If long-term demand is highly uncertain, it may be preferable to avoid additional capacity investments and instead accept temporary backorder costs. In this context, to analyze the trade-off between cost and service level, an additional graph is introduced, see Figure 13. As previously discussed, service level at Ericsson is defined as the percentage of demand fulfilled on time.

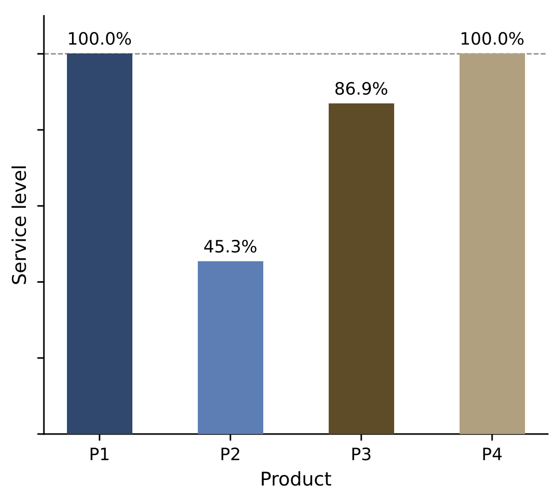


***Figure 13.** Service level per product*

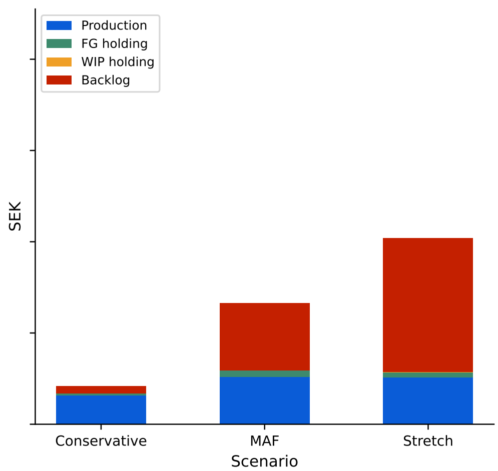
The graph provides an overview of how well demand is met per product over the entire time horizon using the backlog model. Naturally, the results match those discussed when studying the inventory graphs in Figure 9. As the demand of products 2 and 3 was not met on time, their service levels are reduced. This must not necessarily be a critical issue, as long as the resulting service level is satisfactory. If a different prioritization among products is desired, for instance due to some customer or product being more important or having higher margins, additional constraints must be created stating which product must be produced first. In summary, the consolidated analyzes from the various output facilitate assessing the practical implications of choosing between backlog and investment strategies in situations where capacity is inadequate.

4.3.2 Proactive Scenario Output

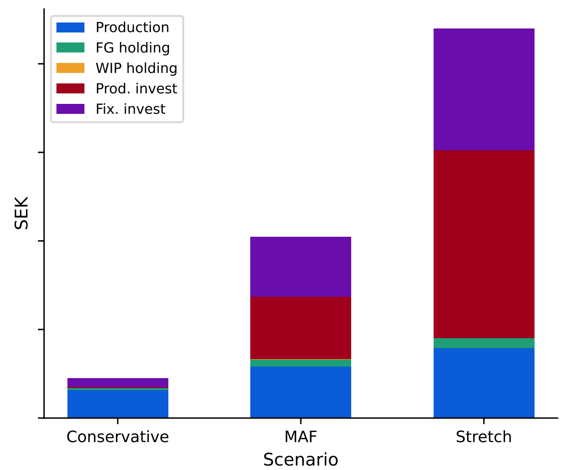
For the sake of presenting hypothetical demand scenarios, a situation where the timing of the demand is considered known, but the volume uncertain is analyzed. The outputs build on the same data as in the linear programming model but with additional conservative and stretch scenarios, as presented in Equation (20). Each demand value in the three matrices is considered the mode in its own triangular distribution, where the minimum and maximum values have been put to be $\pm 20\%$ from the mode.

$$\begin{aligned}
\Delta^{\text{cons}} &= \begin{pmatrix} 0 & 0 & 0 & 0 & 500 & 0 \\ 0 & 0 & 6000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 8000 \\ 0 & 2000 & 0 & 0 & 0 & 0 \end{pmatrix}, \\
\Delta^{\text{MAF}} &= \begin{pmatrix} 0 & 0 & 0 & 0 & 1000 & 0 \\ 0 & 0 & 10000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 16000 \\ 0 & 3000 & 0 & 0 & 0 & 0 \end{pmatrix}, \\
\Delta^{\text{stretch}} &= \begin{pmatrix} 0 & 0 & 0 & 0 & 2000 & 0 \\ 0 & 0 & 13000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 16000 \\ 0 & 4000 & 0 & 0 & 0 & 0 \end{pmatrix}
\end{aligned} \tag{20}$$

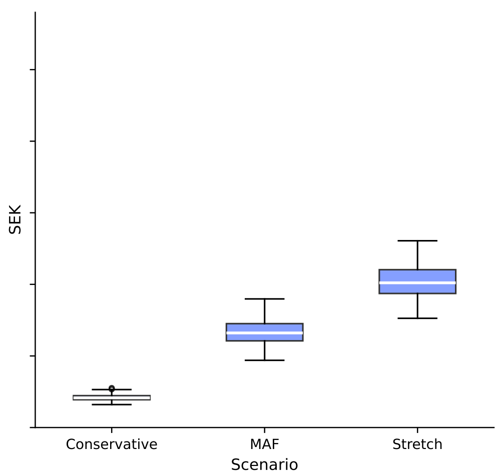
These demand scenarios are then used as input to the backlog and investment models respectively. Since thousands of iterations are performed, thousands of separate production configurations are generated for each model. Consequently, the output cannot be shown as a separate production schedules as in the deterministic models. Instead, the results are consolidated by studying the mean and distributions of the values. In Figure 14, the mean costs and distributions of the backlog and investment Monte Carlo simulations are presented.



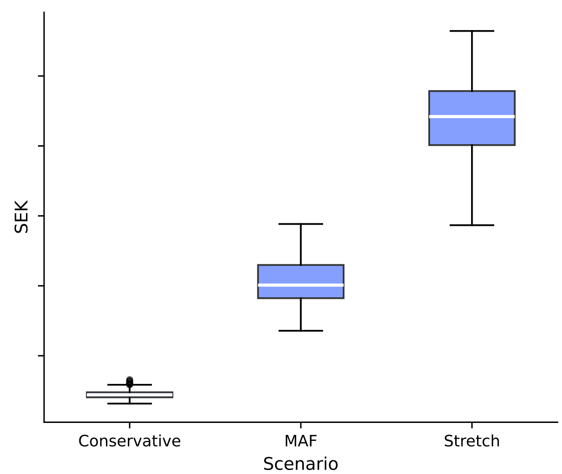
(a) Cost components – backlog model



(b) Cost components – investment model



(c) Cost distribution – backlog model



(d) Cost distribution – investment model

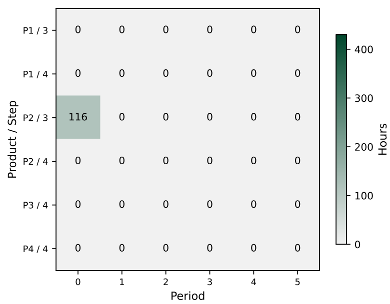
Figure 14. *Cost components and distribution under stochastic demand.*

Figures 14a and 14b break down the cost components of the different scenarios. Studying the conservative scenario it is apparent that almost no backlog, and subsequently no investments are required. Naturally, the production cost is lower for the conservative scenario since demand is also lower. The MAF and stretch scenario show similar production costs in the backlog model as they are both at their production capacity limit and no additional units can be produced, resulting in a additional backlog costs for every additional unit. In contrast, demand is always met in the investment model which is why production cost scales with demand.

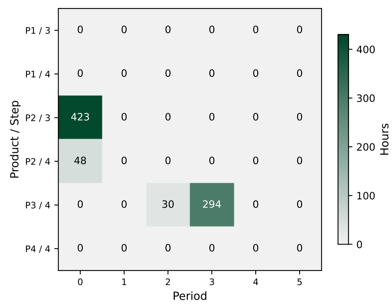
Figures 14c and 14d provide an additional perspective on the total costs of each scenario. Although demand volumes are largely known, minor deviations, here simulated as $\pm 20\%$ of the forecasted volume, are likely to arise. Hence, for larger demand volumes, a larger degree of cost variation is expected. Another source of cost variation is particularly noticeable in the investment model. As can be seen in Figure 14d, marginal costs are significantly higher in scenarios where capacity is heavily constrained, as is the case for the MAF and stretch scenarios. To meet additional demand, every additional unit requires investment. At this point, it is essential to evaluate whether it is worth accepting additional orders given the associated investment costs.

To get an overview of where the capacity is limiting in these scenarios, a set of heatmaps displaying fixture hour investments under different demand scenarios is illustrated in Figure 15. Take notice that all graphs refer to the investment model. The graphs in the upper row illustrate the mean fixture capacity invested in the simulations for each demand scenario, expressed as additional hours of periodical capacity. It is important to note that no individual simulation necessarily results in the investment pattern shown; rather, the values represent averages across all simulations and should be interpreted accordingly. It is of interest to compare the three scenarios and draw conclusions based on their differences and similarities, noting that each is optimized for a different demand level. For instance, it is clear that the fixture for product 2 in production step 3 is limiting across all three scenarios, indicating that even if the lowest demand level realizes, investment in this fixture will most likely be needed.

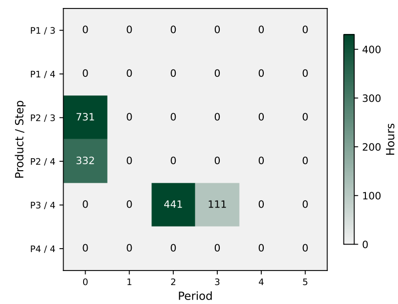
NB: corresponding graphs for how the conservative and stretch scenario breaks down are available but are not included in the thesis to preserve readability.



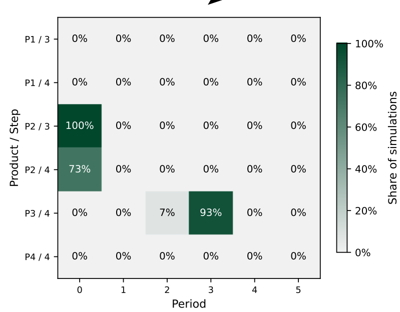
***(a)** Conservative – investment model*



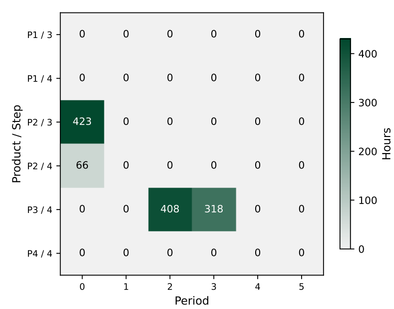
***(b)** MAF – investment model*



***(c)** Stretch – investment model*



***(d)** MAF – share of simulations with investment*



***(e)** MAF – mean invested capacity given investment*

***Figure 15.** Mean fixture hours invested across demand scenarios (top row). The MAF scenario **(b)** is broken down into investment frequency **(d)** and conditional magnitude **(e)**.*

To examine the simulation means more closely, Figures 15d and 15e provide a granular view of the MAF scenario. These correspond directly to Figure 15b through the law of total expectation according to Equation (21).

$$\mathbb{E}[H] = P(\mathcal{I}) \cdot \mathbb{E}[H \mid \mathcal{I}] \tag{21}$$

Here, Figure 15d shows $P(\mathcal{I})$, the share of simulations in which an investment is made, and Figure 15e shows $\mathbb{E}[H \mid \mathcal{I}]$, the mean capacity acquired conditional on investment occurring. Together, these two quantities recover the unconditional mean $\mathbb{E}[H]$ shown in Figure 15b. This decomposition reveals a perspective that the unconditional mean does not show. A low unconditional mean can happen in two ways: either by investments not being needed that often, but being large when they do happen, or by investments being needed frequently, but in smaller amounts. Although these situations present the same unconditional mean, they are very different from a decision-making perspective. In the first situation, large investments that may be difficult to predict or prepare for are needed. The required investment in $P3\,/\,4$ fixtures in period 2 is a clear example of this. Here, as shown in 15d and 15e, only 7% of iterations require investments. However, when investments are needed, a substantial 408 hours are invested on average. In contrast, a situation when a low conditional mean is caused by small but frequent investments signals that capacity is consistently close to its limit. Such a situation presents itself in period 0 for fixture $P2\,/\,4$ where 73% of the simulations result in an investment, but on average when such an investment is realized only 66 hours worth of capacity is needed. This indicates that this specific piece of equipment is sensitive to demand change and close monitoring is needed.

Another interesting perspective presented by the figures is that demand changes affect not only the required investment volume, but also its timing. Row $P3\,/\,4$ in Figure 15d shows that for 93% of the simulations, an investment is realized in period 3, whilst for 7% of the simulations, an investment is realized one period earlier. This indicates that an investment in the fixture is needed; however, depending on the exact demand realization, the timing might change. This is further confirmed by comparing Figures 15b and 15c, which show that as demand increases, the bulk of fixture investment shifts from period 3 to period 2. Being aware of this timing issue beforehand enables the user to lay out the groundwork for an investment and execute it immediately when forecast confidence improves. If no such indications are available in time, a risk averse company might invest in this fixture for period 2 to ensure that demand can be met regardless of the demand outcome.

To be able to finalize the analysis of consequences of planning for different demand scenarios, the service level needs to be evaluated. Figure 16 presents a box-plot showing the distribution of achieved service levels across simulations. As expected, the box-plot shows that there is a clear declining trend of service level when demand increases. A declining service level is not inherently problematic, as keeping a high service level is generally more expensive. As long as the service level is above the accepted target threshold, the decline can be considered acceptable. Furthermore, the box-plot reveals that there is a higher degree of variability in the MAF and stretch scenarios. This result is expected since the deviation from the mode in each triangular distribution is in percent. Hence, for larger demand volumes, the range becomes wider. However, the larger variability can also be explained by the fact that in the MAF and stretch scenarios, the production system operates close to its capacity limits. When the system operates at its limits, it makes the resulting service level more sensitive to demand fluctuations, as there is no remaining capacity left to handle situations where demand increases. Such a trend could, for instance, lead to conclusions of higher operational risks connected to certain demand scenarios.

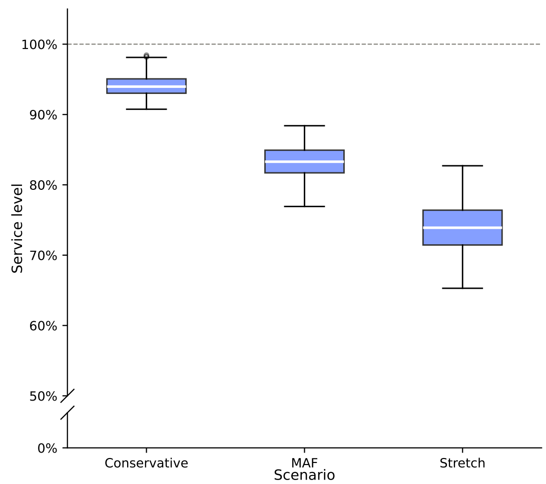


Figure 16. *Service level distribution for the backlog model under stochastic conditions.*

To summarize, the Monte Carlo simulations provide insights into potential shortfalls that are not visible when using a deterministic demand value. For instance, it can show not only the average size of investments, but also the frequency. Together, this can contribute to making decisions for a suitable risk profile. Furthermore, it can reveal trends in service-level and costs, which can support the trade-off discussion. Consequently, this analysis transforms the linear programming from being deterministic into a tool that can aid in making uncertainty and risk-informed decisions.

4.4 Scalable Scenario Planning

The quantitative models developed through the Operations Research Modeling Approach explore various ways of managing capacity for a demand scenario. However, the models are a proof-of-concept limited to one production site and manual data entry. Therefore, additional discussion beyond the mathematical framework is needed to address the broader applicability of this way of conducting scenario modeling in S&OP. This chapter begins by explaining how the scenario planning process can be standardized. Next, a discussion of what data is required for scalable usage of the provided models is provided.

4.4.1 Operationalizing Scenario Planning in S&OP

As discussed in the Theory in Section 3, rational decisions are made based on selecting the decision alternative with the highest expected value, and it has been established how the linear programming and Monte Carlo models can support this. However, as probabilities of demand levels are not always known, and as Ericsson operates in a volatile, global, and competitive business environment, additional guidelines may be needed to have a standardized way of making decisions. Therefore, the following scenario planning process map is suggested as a way to proceed when demand requests appear. The map combines processes or criteria already presented in this thesis: the S&OP process as the setting for scenario planning, the four step scenario planning procedure from the current state mapping, and the eleven evaluation criteria for what-if scenarios from 3. The resulting scenario planning process map is presented in Figure 17, and this section discusses each part of the map in further detail.

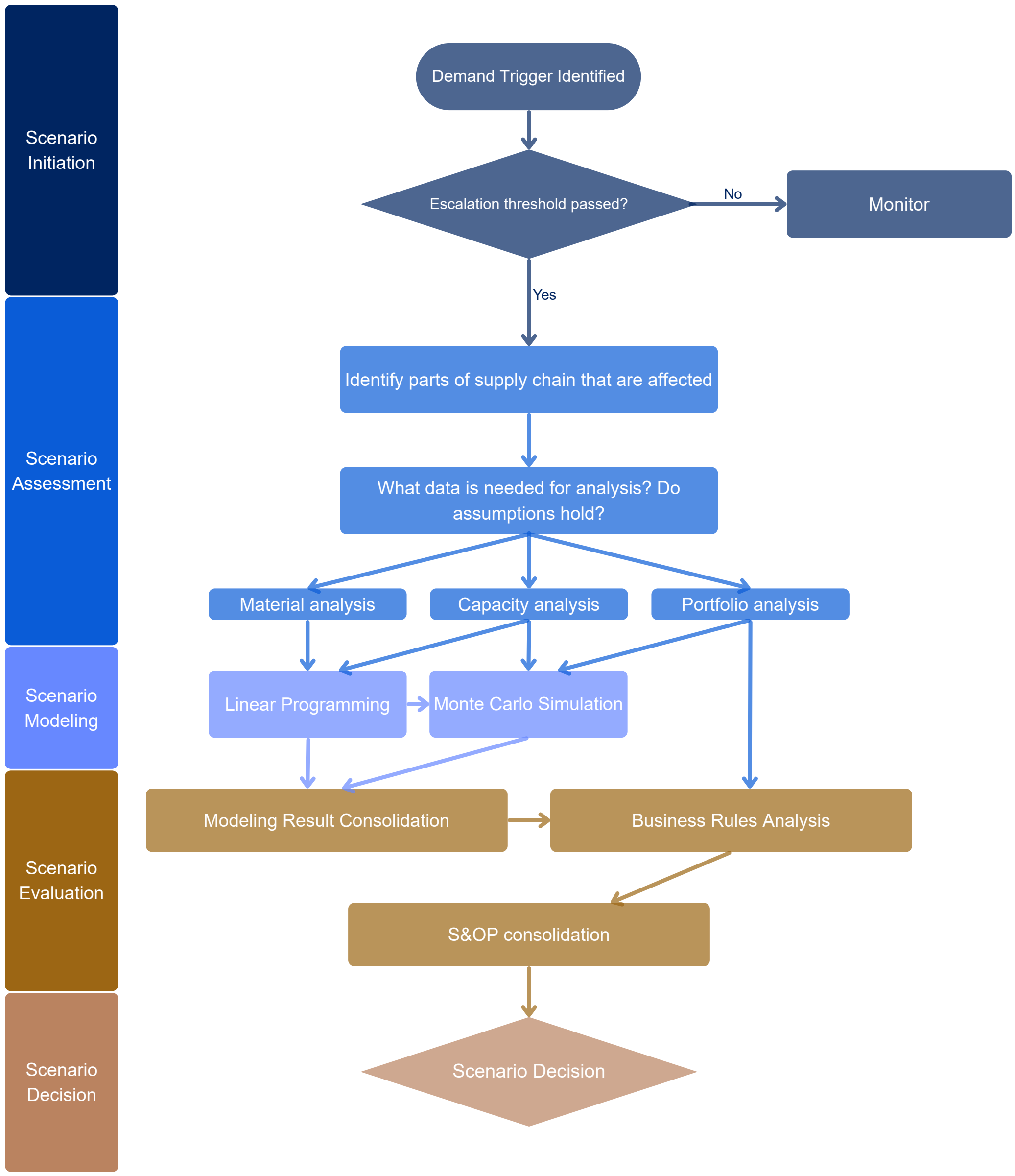


Figure 17. *Scenario planning process map*

The scenario planning process is divided into five main stages: initiation, assessment, modeling, evaluation, and decision. The purpose is to analyze and support decisions in response to demand changes that arise both within and outside of the normal S&OP cycle, whereupon the stages are not directly aligned with the S&OP process steps. This ensures that the process remains flexible and responsive to demand changes that arise between cycles. However, it can still be aligned with the five steps of the academic version of S&OP.

In the initiation stage, the demand change trigger is identified and a decision on whether to initiate a scenario needs to be made. As this decision must be made before any analysis is performed, it is important that it can be determined without further investigation. Currently, there are no set guidelines for such a decision. Therefore, it is recommended to integrate scenario thresholds into the scenario planning process. These can, for instance, be one or a combination of the points below:

- Volume threshold
- Product value threshold
- Potential loss/gain in revenue threshold
- Potential market share gain/loss threshold
- Hard demand change (actual order) vs soft demand change (forecast change)
- Trend vs one-time event

If the threshold is not exceeded, the situation should be monitored. If a scenario is initiated, the process moves to the assessment stage, where the scope is set by identifying the relevant customers, parts of the supply chain, or other significant details. Based on this, the necessary data can be determined. Additionally, it must be established whether assumptions about the current supply chain setup hold or not, for instance, whether geopolitical events restrict certain production facilities or transportation routes, before moving to the analysis. moving on to the actual analysis of how to solve the demand request.

Next, as discussed in Section 4.1.2, the most critical components of the scenario assessment are the material requirement analysis, capacity analysis, and portfolio management analysis. As this thesis focuses on the capacity analysis, no suggestions are provided on the material requirements and portfolio analysis. Should the material analysis identify a constraint, it can be incorporated into the capacity model as an earliest allowed production date, according to Equation (22), where t_i^{mat} is the earliest period in which material for product i is available.

$$x_{i,k,t} = 0 \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t < t_i^{mat} \tag{22}$$

Having conducted the material analysis, the capacity analysis is performed using the linear programming and Monte Carlo models, after which the modeling stage is complete. Before entering the evaluation stage, the portfolio analysis must be considered. The portfolio analysis establishes where in its life cycle a product is, which affects future expected demand levels, and thereby the material and capacity requirements. It is therefore treated as a separate pipeline parallel to the material and capacity analysis. If the latter establishes a need for investments, the product portfolio analysis can provide insights into whether an investment is justifiable based on the life cycle curve.

Having completed the modeling stage, the evaluation stage is entered and the various decision alternatives are established. The modeling results are consolidated to clarify trade-offs between cost and service level, necessary investments, and risks for each alternative. Following this, the business rules analysis can be entered.

Although rational decisions are based on selecting the decision option with the lowest expected cost, business decisions may have to be supported by qualitative analysis based on business rules. The IBP transformation aims to establish an S&OP process more adherent to the company strategy, whereupon company strategy should guide how to manage demand scenarios. The company strategy is broken down into granular plans that govern Ericsson's daily operations. In practice, this is often controlled through budgets. It must therefore be determined whether the decision alternatives adhere to the budget in terms of both cost and profit. For instance, if an order cannot be fulfilled satisfactorily, not only that volume but a full contract may be lost, destabilizing the S&OP plan and causing deviations from the budget. Moreover, values not directly reflected in the budget must also be considered, such as accepting negative margins to gain market share. Thus, scenario decisions require data-driven analysis, but must be supported by guidelines ensuring decisions are made in alignment with strategy.

Lastly, the decision alternatives that are deemed viable are consolidated to be presented in the pre-S&OP meeting. If possible, a decision is made here on how to manage the scenario. If there are various opinions, these can be presented for a final decision by management in the Executive S&OP meeting. Thus, the final stage of the scenario process is reached: a scenario decision.

The proposed scenario planning process is not significantly different from the way Ericsson already operates, but establishes a standardized flow of information and a larger degree of data-driven decision making. Together with the business rules, this creates a standardized framework for decision making under uncertainty within S&OP, making the process less vulnerable to sub-optimality, inconsistencies, and knowledge loss. To summarize, the proposed process does not replace the current way of conducting scenario analysis, but strengthens, standardizes, and formalizes it.

4.4.2 Data Availability and Structure

Although the concept of the models contribute to a more standardized way of conducting scenario planning, the exact models constructed for this thesis are limited in the sense that they only consider one production facility and manual data entry. As will be discussed in the next section, it is possible, and not overly complicated, to mathematically extend the models to incorporate more complexity. However, the limiting factor is the data availability.

Once the necessary input data is available, the models have a satisfactory computational speed. For scalable IBP integration of the presented models, the challenge is not the computational capacity, but ensuring accurate data supply. Some data is static and unlikely to require frequent updates, such as product routing, cycle times, and production cost/unit. Other values, such as total and occupied capacity per production step, must be updated before each scenario analysis, as not doing so compromises the output.

In addition to the process of gathering and updating data, access to it is a vital aspect. Several of the data points utilized in the model are, as previously discussed, not available in any ERP system as of today. In particular, the capacity values are not available in the level of detail required for the use of the models. Therefore, it is recommended that the upcoming IBP tool is designed to simplify the continuous collection of data on total and occupied capacity in all production sites on a production step level. It is acknowledged that this suggestion may not be viable for the suppliers to which Ericsson outsource production due to secrecy, but simultaneously highlighted that it would be a facilitator for fast and reliable scenario analysis.

Data availability is necessary, but not sufficient, for the scalability of the models. To use the suggested method for scenario capacity analysis in a larger scale, the inputs, underlying mathematical functions, and outputs need to be integrated into a usable interface. Integrating the models into an interface enables decision-makers to conduct analyzes of various demand scenarios without knowledge of the underlying models. Moreover, to expand the use case, the tool would have to be able to facilitate various scopes of analysis. Although in theory, the models are equipped to manage an unlimited number of products, all input values must currently be entered manually. For large scale usage, it must at a minimum, be possible to quickly adjust product-specific input values. This would ensure that the model is equipped for a larger set of products through automatic data pipelines.

5 CONCLUSION

This thesis aims to answer the following research questions in the context of Ericsson's supply chain planning organization:

1. *How can data-driven analytical tools for modeling uncertainty operationalize scenario planning to support rational decision-making in the S&OP process?*
2. *What uncertain factors need to be considered, and how can they be structured and quantified?*
3. *What data, tools, and processes are required to support scalable scenario planning in IBP?*

To improve the scenario planning process in S&OP, Ericsson needs a more standardized and data-driven approach. It was determined that it was most appropriate to focus the analytical tools on the capacity perspective of the scenario creation. Ericsson needs the scenario planning for two purposes. First, to determine how to manage sudden demand increases from a capacity perspective. This was named the reactive scenario. Secondly, to view the robustness of production configurations when demand is uncertain, which was named the proactive scenario. Consequently, to answer Research Question 2 - the most relevant uncertainty factor to consider is demand, both in regards to timing and volume.

Reactive scenarios are treated as deterministic problems for which linear programming was identified as a suitable analytical tool. The linear programming model allows the user to study what delays or investments are required to manage a demand increase. This presents an efficient method to get exact and cost-optimal values of what is required from a capacity perspective to solve a demand scenario. For the proactive scenario, Monte Carlo simulation was identified as a method for introducing stochastic demand into the analysis, allowing the robustness of the production plan to be studied across a range of demand outcomes. Together, in response to Research Question 1, the two analytical tools operationalize scenario planning by standardizing and quantifying decision alternatives for managing demand scenarios, both under certain and uncertain conditions. When applied to hypothetical demand scenarios and capacity situations, the tools produce tangible, actionable outputs on what capacity adjustments or delays are required. The stochastic analysis further allows the user to assess whether delays or capacity requirements differ significantly across demand levels.

In response to Research Question 3, a standardized scenario planning process map is suggested that formalizes the current way-of-working and incorporates the analytical tools developed in this thesis. The process map also shows how other dimensions of the scenario analysis, such as material requirements, portfolio analysis, as well as business rules, can be incorporated into the decision-making. To further enable a scalable scenario planning process using the suggested tools, pipelines for data collection need to be set up.

The practical results of the thesis benefit Ericsson primarily through the development of a data-driven decision-support tool that can improve the speed and consistency of their scenario analysis in the setting of S&OP. After setting up the necessary pipelines for data availability and gathering, it is possible to conduct the capacity analysis considerably faster and more consistently. However, the tools do not replace qualitative judgment. Adherence to company strategy and contextual knowledge must remain part of the decision-making process.

The findings of this thesis are tailored to Ericsson, but the modeling approaches can be adapted by other companies, particularly in sectors characterized by high demand variation that is difficult to forecast. The underlying purpose of the thesis is to develop methods to align supply and demand, which, if successful, could in the long run reduce overproduction and waste, as well as reliance on high-emission airfreight to solve sudden and urgent demand spikes.

Theoretically, the thesis validates and builds on the already existing, although limited, research of managing uncertainty within S&OP. As concluded during the literature review, the main approaches for managing uncertainty in S&OP are to conduct additional S&OP meetings, as well as scenario creation, which are both presented in this thesis. While linear programming and Monte Carlo simulation are well-established methods for modeling production planning, this thesis applies them to a specific industrial case. Consequently, the thesis contributes to empirical validation of the application of these analytical tools' in the setting of S&OP.

Limitations

A meticulous reader will have noticed that Step 4 in the Operations Research Modeling Approach, testing the model, has not been discussed, although it was described in the methodology. Initially, the intention was to conduct a retrospective test of the linear programming model, to ensure the output data reflected the outcome of previous decisions. However, this was not possible. As previously discussed, the recommended input data are not available as of today. This is the reason the models have been tested using hypothetical data, and also one of the reasons why a retrospective test could not be performed to ensure validity. However, this does not mean that the models have been developed completely without validation. Benchmarking against another company as well as to theory have been performed to ensure that suitable analytical tools were selected. Moreover, the models are developed based on conversations and interviews with employees at Ericsson. The actual construction of the code behind the models was developed iteratively with constant sanity checks as well as edge-case tests. Lastly, a rigorous validation meeting was held with the employee who currently makes the capacity analysis to ensure no vital mistakes were made, and that the analysis captures all necessary perspectives. To summarize, the inability to perform a precise quantitative validation through a retrospective test constitutes a limitation of the thesis. However, other forms of model validation have been performed throughout the thesis project.

6 FUTURE RESEARCH

Although it was concluded that it is possible to use analytical tools such as linear programming and Monte Carlo simulation to operationalize scenario planning in S&OP, work remains in order to integrate the way of working into Ericsson's day to day operations. This chapter discusses how a more rigorous analysis of certain input values can strengthen the robustness of the models' conclusions, as well as how the logic behind the models can be expanded to other planning processes within the company.

6.1 Determination of Costs Inputs

As previously mentioned, one limitation of the models presented in this thesis is the difficulty of making a direct comparison between the cost of not being able to satisfy demand, and the cost of investing in additional capacity. In the case of Ericsson, backorder costs are not utilized. Based on interviews, it is difficult to quantify a single backorder cost for each of Ericsson's products, as the consequences of not being able to deliver vary depending on a variety of factors. Firstly, Ericsson's has a number of focus markets where gaining or retaining market share is of extra importance. In these markets, the importance of being able to support demand changes is higher than in other markets. Moreover, being able to respond to a demand request can be the deciding factor on whether a contract is closed with a customer or not. In these instances, the consequence of not meeting demand can be a greater loss in sales than just the change of demand that is requested, since the full contract can be lost. Another factor is that different markets has different margins. Despite the difficulties, the possibility of quantifying a backorder cost could facilitate a more standardized way of making decisions on investing in additional capacity, especially if the investment cost can be determined.

Although there is difficulty in distributing the cost of investment on one single order or product, the actual cost is known or can be obtained. Currently, investments in capacity are modeled per hour. This allows for an assessment of how close the company is to having to invest in a full machine. However, in reality, investments are binary - either a full machine is bought or not. Despite the complicating factors, if both backorder and investment costs could be quantified on a product level, a direct comparison between delay and the cost of investment would be possible. Consequently, it would be possible to directly apply Bayes' Decision Rule as originally intended.

6.2 Model Extension

The analysis performed in this thesis can be expanded in various ways. For instance, it can be used to analyze other perspectives than demand. For example, if the demand volume remains, but a machine suddenly breaks down, the model can generate a new production schedule that accommodates the change. In the Monte Carlo analysis, another parameter can be selected for variation. Moreover, the analysis also allows for varying multiple factors simultaneously. For instance, to account for additional uncertainty in the production system, production cycle time can be varied at the same time as demand. The result of such an analysis would be a cost distribution based on expected values when both factors are varied. However, it requires that the distribution of, in this case cycle times, is known.

Beyond introducing more uncertainty into the already established models, the linear programming model can be expanded to analyze multiple production facilities simultaneously. In this case, an additional production facility to choose from in the production plan could be considered another decision variable, for instance, s. Such a variable would be binary, as a production site is either used or not, turning the model into a mixed-integer linear programming model. Allowing an index $j \in \mathcal{J}$, to denote each production site ensures that this can be added to ingoing parameters. For instance, the maximum capacity in each production step and period, $\mathcal{Z}_{k,t}$, as well as, how much to produce of each product in each step and period, $p_{i,k,t}$ can be expanded to being site specific, denoted by $\mathcal{Z}_{j,k,t}$ and $p_{j,i,k,t}$. Naturally, adding production facilities would require further mathematical extensions. However, the idea illustrates how the same analytical tool can be expanded to cost-minimize not only in one facility, but across all factories relevant to the customer.

Moreover, the analytical tools that have been presented can be used on Ericsson's supply chain in a much wider case. For instance, it is possible to model the supply chain from a higher level. Instead of studying production steps, parts of the supply chain could be modeled. A distribution network consisting of component suppliers, component warehouses, production facilities, distribution hubs, and the transportation time between all aforementioned can be modeled using linear programming. Consequently, linear programming can be used to optimize where in the world a product should be produced, taking into account lead times, tariffs and production costs. The stochastic dimension can also be added to study the sensitivity of the system being able to deliver based on, for instance, variations in transportation time.

Furthermore, the objective of the linear programming model can be used to add a sustainability perspective to the analysis. If the model is used to determine what factories and distribution hubs to use for a certain customer, the minimizing factor can instead be the carbon emissions. Consequently, the same analytical tool can be adapted to ensure the least emitting option is selected. In addition, the sustainability perspective can be coupled with the cost perspective by penalizing emissions with a cost. However, this requires putting a cost on carbon emissions, which is a difficult thing to do accurately.

6.3 Statistical Tests

To be able to draw usable conclusions from the Monte Carlo simulations, statistical tests must be performed after using the models. As real data is not available when conducting this thesis, it is not insightful to conduct any statistical tests to validate that conclusions from the Monte Carlo simulations are statistically significant. However, in a situation where empirical data is available, it is vital to conduct tests to ensure statistically significant conclusions can be drawn. Additionally, it is important to establish that the number of iterations per simulation is satisfactory for significant results. To draw these conclusions, confidence intervals can be studied, as described in Section 3.4.2. The confidence intervals can be used to analyze whether the differences in production configuration costs between scenarios are actually statistically meaningful. If there is a substantial overlap between confidence intervals, it cannot be claimed that one scenario generates a larger cost than another.

6.4 Front-End and LLM Trial

Although front-end development and implementation of the models are left outside of the scope of this thesis, a trial of integrating the logic to a Large Language Model (LLM) was conducted in collaboration with another thesis student at Ericsson. It is recommended to further study and build upon the findings of this student's thesis whose findings provide a strong foundation for future development of the implementation.

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A THE LINEAR PROGRAMMING MODELS

Table 6. *Sets and indices*

Symbol	Description
$i \in \mathcal{I}$	Set of products
$k \in \mathcal{K}$	Set of production steps
$\mathcal{K}_i \subseteq \mathcal{K}$	Set of production steps in the route of product i
$\mathcal{K}_i^{wip} \subseteq \mathcal{K}_i$	Set of non-final production stages of product i
k_i^{final}	The final production stage of product i
$t \in \mathcal{T}$	Set of time periods

Table 7. *Parameters*

Parameter	Description	Indexes	Unit
$\delta_{i,t}$	Demand	$i \in \mathcal{I},\ t \in \mathcal{T}$	pieces
$\mathcal{Z}_{k,t}$	Total production capacity	$k \in \mathcal{K},\ t \in \mathcal{T}$	hours
$\zeta_{k,t}$	Occupied production capacity	$k \in \mathcal{K},\ t \in \mathcal{T}$	hours
$\mathcal{E}_{i,k,t}$	Total fixture capacity	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	hours
$\epsilon_{i,k,t}$	Occupied fixture capacity	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	hours
$\tau_{i,k}$	Processing time	$i \in \mathcal{I},\ k \in \mathcal{K}_i$	hours
γ_i	Production cost	$i \in \mathcal{I}$	cost/piece
β_i	Backlog cost	$i \in \mathcal{I}$	cost/piece
η	Holding cost rate	–	%
ψ	Capacity utilization factor	–	%
Q	Sufficiently large constant	–	–

Table 8. *Decision variables*

Variable	Description	Indexes	Unit
$x_{i,k,t}$	Production time allocated	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	hours
$p_{i,k,t}$	Production quantity	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	pieces
$w_{i,k,t}$	WIP inventory after step k	$i \in \mathcal{I},\ k \in \mathcal{K}_i^{wip},\ t \in \mathcal{T}$	pieces
$f_{i,t}$	Finished goods inventory	$i \in \mathcal{I},\ t \in \mathcal{T}$	pieces
$b_{i,t}$	Backlog	$i \in \mathcal{I},\ t \in \mathcal{T}$	pieces
$a_{k,t}$	Production capacity investment requirement	$k \in \mathcal{K},\ t \in \mathcal{T}$	hours
$q_{i,k,t}$	Fixture capacity investment requirement	$i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$	hours

The Linear Programming Model: Backlog Allowed

$$\min \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} \Big(\gamma_i \, p_{i,k_i^{final},t} + \beta_i \, b_{i,t} + \gamma_i \, \eta \, f_{i,t}\Big) + \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i^{wip}} \sum_{t\in\mathcal{T}} \frac{|\mathcal{K}_i^{\leq k}|}{|\mathcal{K}_i|} \gamma_i \, \eta \, w_{i,k,t}$$

$$\sum_{i\in\mathcal{I}} x_{i,k,t} + \zeta_{k,t} \leq \mathcal{Z}_{k,t} \, \psi \quad \forall\, k \in \mathcal{K}_i,\ t \in \mathcal{T}$$

$$x_{i,k,t} + \epsilon_{i,k,t} \leq \mathcal{E}_{i,k,t} \, \psi \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$$

$$p_{i,k,t} = \frac{x_{i,k,t}}{\tau_{i,k}} \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$$

$$w_{i,k,t} = w_{i,k,t-1} + p_{i,k,t} - p_{i,k',t} \quad \forall\, i \in \mathcal{I},\ t \in \mathcal{T}$$

$$f_{i,t} - b_{i,t} = f_{i,t-1} - b_{i,t-1} + p_{i,k_i^{final},t} - \delta_{i,t} \quad \forall\, i \in \mathcal{I},\ t \in \mathcal{T}$$

$$w_{i,k,t\,=\,\text{(-1)}} = 0 \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i^{wip}$$

$$f_{i,t\,=\,\text{(-1)}} = 0 \quad \forall\, i \in \mathcal{I}$$

$$x_{i,k,t},\ p_{i,k,t},\ w_{i,k,t},\ f_{i,t},\ b_{i,t} \geq 0 \quad \forall\, i \in \mathcal{I},\ k \in \mathcal{K}_i,\ t \in \mathcal{T}$$

The Linear Programming Model: Investments Allowed

$$\begin{aligned}
\min \sum_{i\in\mathcal{I}}\sum_{t\in\mathcal{T}} &\Big(\gamma_i\, p_{i,k_i^{final},t} + \gamma_i\,\eta\, f_{i,t}\Big)\\
&+ \sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i^{wip}}\sum_{t\in\mathcal{T}} \frac{|\mathcal{K}_i^{\le k}|}{|\mathcal{K}_i|}\,\gamma_i\,\eta\, w_{i,k,t}\\
&+ \sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} M\, a_{k,t}\\
&+ \sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\sum_{t\in\mathcal{T}} M\, q_{i,k,t}
\end{aligned}$$

$$\begin{aligned}
\sum_{i\in\mathcal{I}} x_{i,k,t} + \zeta_{k,t} \le \psi\left(\mathcal{Z}_{k,t} + \sum_{\hat{t}\in\mathcal{T}_{\le t}} a_{k,\hat{t}}\right) &\quad \forall\, k\in\mathcal{K}_i,\ t\in\mathcal{T}\\
x_{i,k,t} + \epsilon_{i,k,t} \le \psi\left(\mathcal{E}_{i,k,t} + \sum_{\hat{t}\in\mathcal{T}_{\le t}} q_{i,k,\hat{t}}\right) &\quad \forall\, i\in\mathcal{I},\ k\in\mathcal{K}_i,\ t\in\mathcal{T}\\
p_{i,k,t} = \frac{x_{i,k,t}}{\tau_{i,k}} &\quad \forall\, i\in\mathcal{I},\ k\in\mathcal{K}_i,\ t\in\mathcal{T}\\
w_{i,k,t} = w_{i,k,t-1} + p_{i,k,t} - p_{i,k',t} &\quad \forall\, i\in\mathcal{I},\ t\in\mathcal{T}\\
f_{i,t} = f_{i,t-1} + p_{i,k_i^{final},t} - \delta_{i,t} &\quad \forall\, i\in\mathcal{I},\ t\in\mathcal{T}\\
w_{i,k,t\,=\,(-1)} = 0 &\quad \forall\, i\in\mathcal{I},\ k\in\mathcal{K}_i^{wip}\\
f_{i,t\,=\,(-1)} = 0 &\quad \forall\, i\in\mathcal{I}\\
x_{i,k,t},\ p_{i,k,t},\ w_{i,k,t},\ f_{i,t},\ a_{k,t},\ q_{i,k,t} \ge 0 &\quad \forall\, i\in\mathcal{I},\ k\in\mathcal{K}_i,\ t\in\mathcal{T}
\end{aligned}$$

B INTERVIEW GUIDE FOR CURRENT-STATE ANALYSIS

Scenario Planning Process

How do you define a scenario?

How do you work with scenarios?

Which factors and parameters do you vary in your scenarios?

What outputs do you study in your scenarios?

How can the way scenarios are handled be improved?

S&OP

In which phase of the S&OP cycle do you participate?

What information, data, or input do you present in S&OP?

What action points do you get from S&OP?

IBP

What is IBP going to change for you?

Simulation

What do you simulate?

What is the output of your simulation?

What kind of simulation do you perform?

What factors and parameters do you consider?

What assumptions do you make?

What tools do you use?

C INTERVIEW GUIDE FOR BENCHMARKING WITH VOLVO

Scenario Planning Process

How do you work with scenarios?

How do you define a scenario?

When is a scenario initiated?

What factors/parameters do you vary in your scenarios?

Who is involved in constructing scenarios?

What decisions are scenarios used to support?

How are scenario results presented in S&OP?

How can the way scenarios are handled be improved?

Scenario Planning Data

What data is required to perform scenario analysis?

What outputs/KPIs do you study in your scenarios?

Do you have any software that supports scenario planning?

Simulation in S&OP and Scenarios Analysis

Do you use simulation/analytical models for scenario analysis?

What kind of simulation do you perform?

What factors/parameters do you consider?

How do you determine ranges for ingoing parameters?

What is the output of your simulation?

What assumptions do you make?

What tools/software/mathematical models do you use?

Rational Decision-Making in S&OP

Do you have a standardized set of business rules for replanning decisions in the S&OP process?

How do you use data to make informed decisions?

When do you override model/analytical outputs?