



# Master's degree thesis

**LOG950 Logistics**

**Decision support for production capacity planning  
under uncertainty: A case study of TINE SA**

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## **Preface**

Studying in a foreign country was a life-changing experience as well on a professional as on a personal level. The Master of Science in logistics has always caught my interest, challenged me throughout the whole time and helped me develop my logistical understanding and skills. I have enjoyed my stay in Molde and have met many people, who I hope to stay in contact with in the future.

I appreciate the chance to work with TINE on a practical topic, in which I could use my developed skills in modelling and the usage of quantitative methods. After getting in contact with the company, there were several optional topics for a master thesis. After discussing the opportunities, we agreed on the topic of developing and using a method for decision support in production capacity planning, which TINE was very interested in and which also reflected my personal interest in production planning.

I would particularly like to thank my supervisor Arild Hoff from Molde University College and my contact person Olga Sergeeva from TINE SA, who have both guided and supported me throughout the process of this Master Thesis. They were both always very helpful and gave me very good and detailed feedback whenever I needed it.

Furthermore my thanks go to Ketil Danielsen for the feedback and the discussions that helped me developing the simulation model and all employees of TINE, who provided me with information and answered my questions.

Last but not least I would like to thank my family and all my friends who supported me during the past two years.

Molde, 27<sup>th</sup> of May 2014

Dominik Schittenhelm

## **Abstract**

Due to the complex nature of capacity planning, sophisticated methods for decision support are used in order to handle challenges like uncertainties in demand, processes and capacity. Analytical and simulation models can help to understand a system's behavior and its reaction to demand, process and capacity changes and therefore build to basis to take decisions on when, how and to which extend to adjust capacity.

The research problem of this thesis was defined as a tactical capacity planning problem for a system operating in a Make-to-stock environment and producing two products, which leads to the necessity of changeovers and production is taking place in lot sizes. Lot sizes are variable in dependency of productive machine hours per day, as one product is always produced at least for one day. Furthermore demand and capacity are uncertain due to unplanned downtimes. The products are classified as fast-moving consumer products (FMCG) with complete standardization.

In this thesis there was developed and applied a methodology for decision support for capacity planning under uncertainty. The developed methodology is based on a system analysis, including process, demand and production capacity analysis and a discrete-event simulation model to test possible future scenarios, which are based on different demand levels and capacity configurations. Performance measures were defined based on the company's preferences.

The developed simulation model represents the production planning and production process of a packaging line and can build the basis for an evaluation of capacity alternatives. The driven tests within this thesis focus on the system's performance measured by fill rates (based on stock keeping units), overtime usage and utilization. The results show that fill rates decrease exponentially with an increasing utilization, and overtime increases exponentially when increasing demand. It was furthermore detected that the system would, without the usage of overtime, have fill rates just slightly below the ones with overtime, but the difference gets greater when demand increases. The developed model is set to be a tool for future capacity planning within the system at the case company and build the basis for similar problems.

*Key words: Capacity planning, Make-to-stock, Demand uncertainty, Capacity flexibility, Discrete-event simulation, Case study*

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## List of Abbreviations

<b>Abbreviation</b>	<b>Full Name</b>
ATO	Assemble-to-order
Chi <sup>2</sup> -test	Chi Square test – Statistical test to measure the goodness of fit of a probability distribution to a data set
CI	Confidence interval
CPOF	Capacity planning using overall factors
CRP	Capacity requirements planning
DES	Discrete-event simulation
DSS	Decision support system
FMCG	Fast-moving consumer goods
KS-test	Kolmogorov-Smirnoff Test – Statistical test to measure the goodness of fit of a probability distribution to a data set
MPC	Manufacturing planning and control
MPS	Master Production schedule
MRP	Material requirements planning
MTO	Make-to-order
MTS	Make-to-stock
OEE	Operating equipment effectiveness
RCCP	Rough-cut capacity planning
ROI	Return on investment
SD	System dynamics
SKU	Stock keeping units
SS	Safety stock
WIP	Work-in-progress

# 1 Introduction

## 1.1 Problem statement

While traditionally for many companies highly sophisticated capacity planning methods were not required as uncertainties could be handled through inventory and over-capacity (Bakke and Hellberg 1993), the increasing competition over the last decades has led to the necessity of putting more focus towards this problem. When making decisions on capacity to acquire and maintain, companies need to balance costs and benefits of over- or under-capacity. An inadequate capacity can lead to the loss of customers and slow service while excessive capacity on the other hand might lead to the need of reducing prices to stimulate demand, carry too much inventory or leave workforce and equipment idle (Yang, Haddad and Chow 2001). The decisions taken on a company's capacity configuration can affect several aspects of performance, which have been identified from Slack, Jones and Johnston (2013) as the following:

- Costs.
- Revenues.
- Working capital.
- Quality of goods and services.
- Dependability of supply.

As capacity changes are often connected to financial investments, the issue of evaluating possible investments arises and a financial analysis should be done in order to make good investment decisions.

The challenge in deciding on capacity levels is that the actual production capacity is often dependent on several factors which face uncertainty. Uncertainties to be considered when planning capacity can lie in the operations, such as stochastic breakdowns or variable processing times, in the supply, such as variable lead times and in the demand (Nyaga et al. 2007).

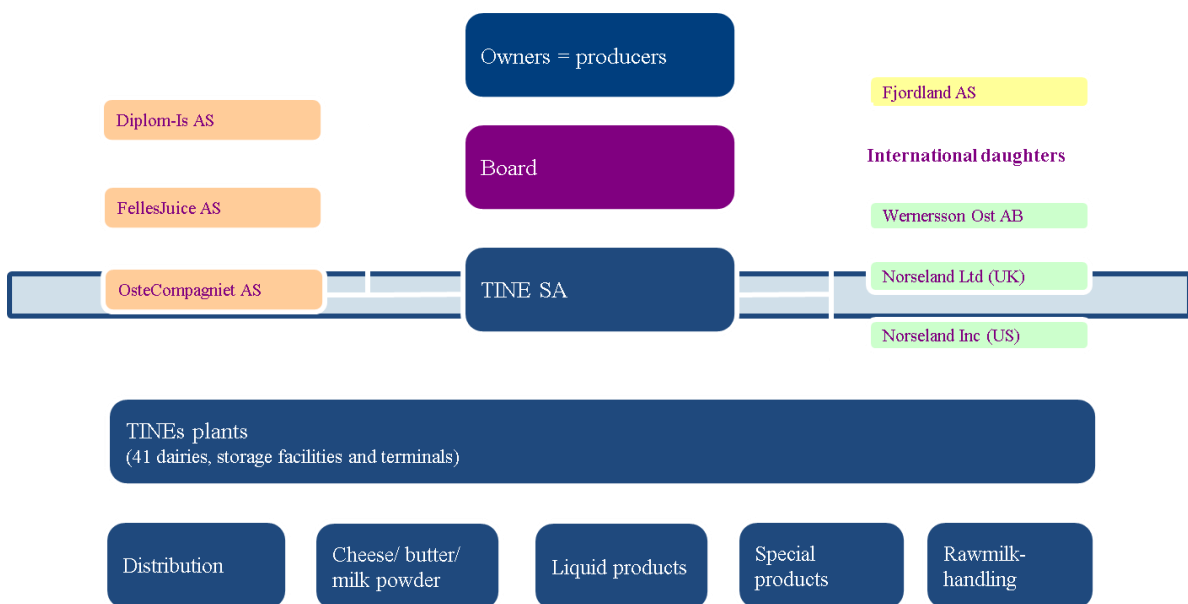
Furthermore there exists a variety of options to modify or use existing capacity which brings up the question of the impact on the performance when modifying the capacity with

different options. Also the timing in acquiring capacity needs to be considered (compare Heizer and Render 2006, Slack et al. 2013).

The complexity of the problem arising through uncertainties combined with the broad range of affected performance aspects makes the problem of capacity planning under uncertainty an important and complicated issue. Decision support systems (DSS) shall help decision makers to understand the impact of their choices and to determine capacity levels in a manner that helps the organization to achieve its goals.

## 1.2 Research environment

TINE is a food manufacturing group based in Norway, which aims to be a leading supplier of food and drink brands with a focus on dairy products. The company was founded in 1928 as “Norske Meieriers Eksportlag” with the main focus on exporting butter and cheese. Further on the company grew and had several name changes. In 1942 the company was renamed to “Norske Meieriers Salgssentral” and in 1984 to “Norske Meierier”. The name TINE was first registered as a trademark in 1992. In 2002 the TINE Group was formed out of “TINE Norske Meierier”, several dairy companies and other daughter organizations. In the same year “TINE Norske Meierier” was renamed to TINE BA. Later on in 2010 TINE BA merged with the dairy companies and was from then on named TINE SA (TINE 2013). The TINE Group organization and structure today is shown in figure 1.



**Figure 1: TINE Group organization**

In 2012 the TINE group consisted out of the parent company TINE SA and several fully and partly owned daughter companies. Fully owned daughter organizations are the “Diplom-Is AS”, “FellesJuice AS” and “OsteCompagniet AS”. TINE SA is owned by more than 14,000 dairy farmers, which are to be provided with the best possible milk price, and offers more than 1,300 product lines. In 2012 the TINE Group had more than 5,000 employees and revenue of NOK 19.8 billion. The primary market is Norway, but TINE is also growing internationally, with most of the international operations being based in the United States, Sweden, and the United Kingdom. The dairy industry in Norway has, in recent years, become more and more competitive through national and international actors entering the market (TINE 2012).

TINE’s supply chain begins with picking up the milk from the dairy farmers and transporting it to the 36 dairies within Norway, where the milk is processed into the different products. Afterwards the products can either be delivered directly to customers or shipped to either one of the three terminals or one of the two central warehouses, where the products are stored and delivered towards customer orders. For some products there are certain operations carried out at the warehouses, as for example cutting and/or packaging. The central warehouses store the full range of TINE’s products and can deliver mixed orders. Shipments also take place between the central warehouses, based on inventory and demand levels. The delivery to the customers is usually carried out by TINE itself rather than being picked up by the customer, which means that TINE is controlling their complete central supply chain. Other players only supply the processes with certain materials (packaging material, by-products).

This research will focus on an automated cheese-cutting and packaging line at TINE’s central warehouse in Heimdal. The production management and control system is based on demand forecasts and the system is operating in a Make-to-Stock (MTS) environment. As there are produced two products on the same production line, the production is taking place in lots and changeover times occur when switching the production from one product to another. Changeover times in the considered system are not sequence-dependent. The products can be classified as perishable, fast moving consumer goods (FMCG) with high volumes and a full standardization. There are several sources of uncertainty in the demand (fluctuations), capacity (unplanned downtimes) and forecasting accuracy.

### ***1.3 Research objectives and questions***

The main purpose of this research was to develop a methodology for decision support for capacity planning under uncertainty and demonstrate the application on a specific case. Therefore, two sub-problems were explored:

The first sub-problem focuses on the development of an appropriate method. To address this research problem, it is necessary to identify possible approaches of analyzing and evaluating different capacity plans. Consequently the thesis describes general methods and specific approaches and evaluates those towards the applicability on the specific case. In order to do that, the research environment needs to be considered. As the research is focusing on a specific case, it is important to identify the critical features of the system, especially those which are critical for capacity planning and the following questions need to be addressed:

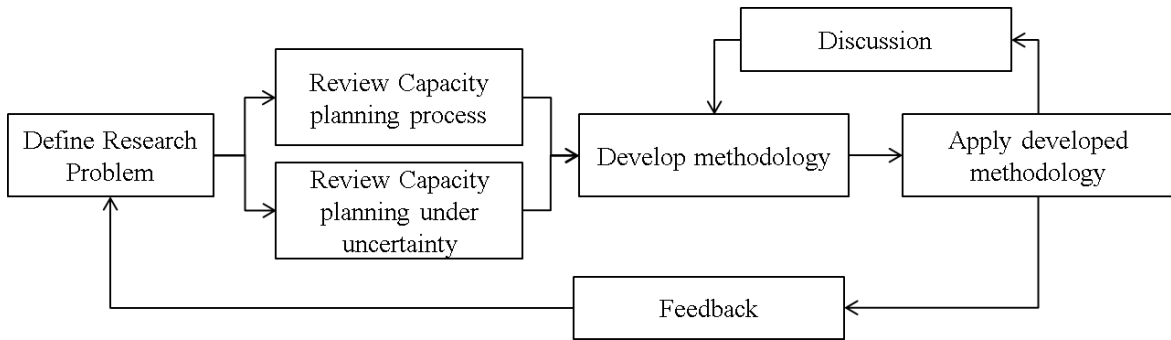
- Which approaches for capacity planning exist?
- How can capacity planning under uncertainty be approached?
- What is an appropriate method to address the case study problem?

The second sub-problem is an application of the methodology, developed within the first sub-problem. The application will contain an analysis of the system in the current state and the development of a DSS for future planning. The analysis of the current state includes quantitative methods in order to understand the current settings and identify future options, both of external and internal factors. The decision support system shall support the case company on capacity decisions in the future, build the basis for addressing similar problems on other systems and meet several requirements:

- Flexibility: The possibility to integrate future changes.
- Reusability: The possibility to use the model logic on similar cases.
- Support a broad range of capacity configurations and performance measures.

### ***1.4 Research process***

The general research process used to address the specific research sub-problems and questions in this research is presented in figure 2.



**Figure 2: Research process**

The research process started with the definition of the research problem, based on the research environment and the defined real-world problem by the case company, which was transferred into the stated research problem.

The theoretical background (chapter 2) will explore general capacity planning approaches, methods and specific applications under uncertainty. While the first part of the literature review examines capacity planning in general, the second part focuses on how to address the challenge of uncertainty. Sources of uncertainty as well as problem types are presented before investigating the possibilities of addressing such problems by means of quantitative models for decision support.

The literature review is followed by the presentation of the methodology (chapter 3), which will build the basis for the case study. The chapter presents the case study research model, applied research methods as well as data collection and analysis.

Afterwards, chapter 4 describes the application of the methodology, including executed steps as well as results.

Chapter 5 is discussing the methodology and the developed DSS, identifying strengths and weaknesses and critical factors as well as possible future developments and applications.

The thesis finalizes with conclusions and possible future research directions (chapter 6), which can focus on similar problems, developing the approach used to address the case and further usage of the developed model.

## 2 Literature review

### 2.1 General terms and concepts

The objective of capacity planning is “to ensure that the service provider has, at all times, sufficient capacity to meet the current and future demands of the customer’s business needs” (Dugmore and Lacy 2006). There are several definitions of capacity, as for example “the amount of output a system is capable of achieving over a specific period of time” (Yang, Haddad and Chow 2001) or “the maximum level of value-added activity over a period of time that the process can achieve under normal operating conditions” (Slack, Jones and Johnston 2013).

Production capacity planning is strongly interlinked with the according production planning tasks and the production system, which is why the Manufacturing Planning and Control (MPC) system has to be considered. Jacobs et al. (2011) present the capacity planning tasks in relation to the MPC System (Figure 3).

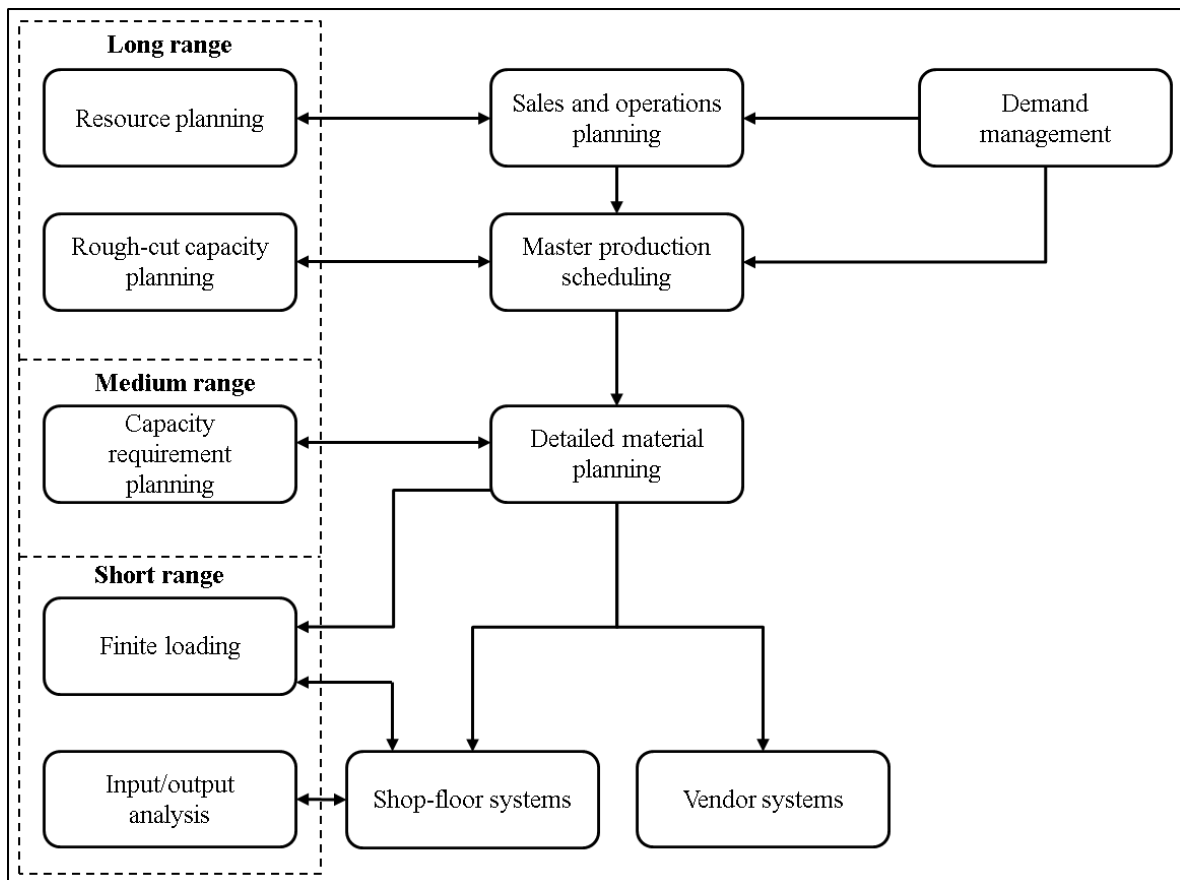


Figure 3: Capacity planning in the MPC System (Jacobs et al. 2011)



The hierarchy of capacity planning decisions puts the overall planning of resource needs on top and in interdependence with the sales and operations plan, which is affected by the demand management. In demand management one can differentiate between the main concepts of Make-to-Stock (MTS), Assemble-to-Order (ATO) and Make-to-Order (MTO) environment. In an MTS environment the demand management focuses on keeping the inventory of finished goods on a specified level or within a specified interval by producing the demand based on forecasts. Demand management in an ATO environment on the other hand is focusing on assembling the products from an inventory of components with the configuration defined by the customer. Whereas those two concepts are based on inventory (either finished goods or components), in the MTO concept, the products are produced towards specific customer orders. The resource planning is usually an aggregated and long-range planning problem. Rough-cut capacity planning (RCCP) is done towards a specific Master production schedule (MPS), which is “the disaggregated version of the sales and operation plan” (Jacobs et al. 2011). It shows which end items are to be produced in certain time intervals in the future. RCCP can be done by means of the following techniques as presented by several sources (for example Jacobs et al. 2011, Scott 1994): capacity planning using overall factors (CPOF), capacity bills and resource profiles. Scott (1994) describes resource planning and RCCP as two methods with a similar level of detail. In resource planning the main purpose is “to provide a statement of resources needed for achievement of the highest-level production plan, normally at product family level” (Scott 1994), while RCCP has the purpose of testing the feasibility of an MPS.

When using material requirements planning (MRP) to achieve a detailed material plan, capacity requirements planning (CRP) can lead to a detailed plan of capacity requirements per planning horizon. The CRP techniques focus on machine centers and labor skills, typically for a time horizon from several weeks up to one year (Jacobs et al. 2011). Jonsson and Mattson (2002) compared the four capacity planning methods of CPOF, capacity bill procedures, resource profiles and CRP. They found that the applicability of those methods depends on the planning environment and horizon as well as the level of detail and can therefore lead to the necessity of combining two or more methods. Furthermore they conclude that CPOF and CRP are the most common methods, CPOF being used “in simple and stable environments and rough long-term planning”, while CRP is used “in more complex environments and for more detailed decisions”.

Finite loading is interrelated with production scheduling. The difference to CRP is that while CRP only calculates the capacity requirements, finite loading adjusts the plan to fit the finite loading constraints. The input/output analysis is concerned with monitoring the capacity utilization and is based on the actual shop-floor system.

## ***2.2 Capacity planning process***

### **2.2.1 Measurement of demand and capacity**

The first step in capacity planning is to measure demand and capacity of the system (Slack, Jones and Johnston 2013). As capacity decisions address the future, demand forecasts play an important role. In literature there is presented a broad range of forecasting techniques, but since forecasting is not the focus of this thesis, the following sections will only describe the requirements of demand forecasts in capacity planning as defined by Slack, Jones and Johnston (2013):

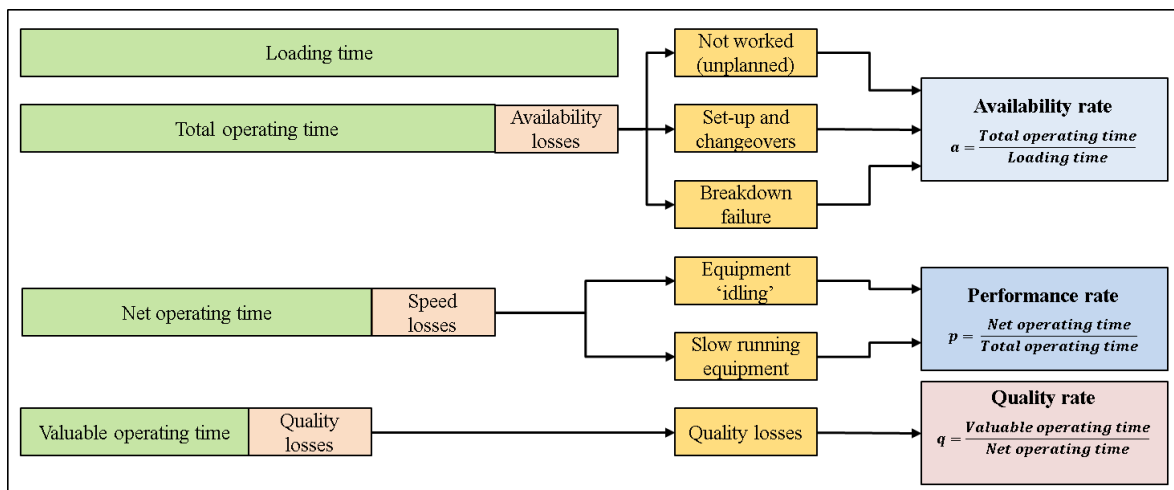
- **“It is expressed in terms which are useful for capacity management”**: It has to be expressed in the same units as the capacity.
- **“It is as accurate as possible”**: Whereas there exists a time between the decision to change capacity and its effect, the demand can change instantaneously. Therefore the decisions have to be taken in advance and lead to the necessity of good forecasts.
- **“It gives an indication of relative uncertainty”**: Demand is usually subject to fluctuations within certain time periods and often faces seasonality. To address the different demand levels with appropriate capacity changes, the relative uncertainty has to be represented in the forecast.

Capacity measures can be divided into input (i.e. Machine hours available) and output measures (i.e. Number of units per week). Whether capacity is measured in input or output capacity depends on the studied system. Krajewski, Ritzman and Malhotra (2013) state that output measures are “best utilized when applied to individual processes, or when the firm provides a relatively small number of standardized services and products” while input measures are “generally used for low-volume, flexible processes”. However output capacity measures may be inappropriate or insufficient in several situations:

- High product variety and process divergence.

- Changing product or service mix.
- Changing productivity rates.

When measuring capacity, it can be differentiated between certain terms. First one needs to distinguish between design capacity, e.g. the maximum output under optimal conditions, and effective capacity, which takes current operating constraints into consideration and accordingly represents the expectations on the actual capacity. Utilization is a fraction, calculated by dividing the actual output/input capacity of a system by its design capacity, while efficiency is the ratio of input/output to effective capacity (Heizer and Render 2006, Slack et al. 2013). Another measure is Operation equipment effectiveness (OEE) and according to that the availability rate, performance rate and quality rate, as shown in figure 4.



**Figure 4: Operating equipment effectiveness (Slack, Jones and Johnston 2013)**

The loading time is the time of scheduled hours. When subtracting time lost through set-ups, changeovers, breakdowns and time without scheduled work (unplanned), one gets the total operating time and the availability rate as a fraction of the loading time. In the next step, idle equipment time and a loss through slow running equipment sum up to speed losses and result in the net operating time and the performance rate. In the last step, quality losses, e.g. time “wasted” through producing products which do not pass the quality control, lead to the valuable operating time and the quality rate. The OEE is then calculated as the product of availability, performance and quality rate:

$$OEE = a * p * q = \frac{\text{Valuable operating time}}{\text{Loading time}}$$

## 2.2.2 Identification of alternative capacity plans

The second step proposed by Slack, Jones and Johnston (2013) is the identification of alternative capacity plans. In order to do that one first needs to understand options, plans and strategies for capacity planning. The general goal of the future planning is to match the capacity to the demand and there exist different strategies to approach that problem. The demand forecasts build the basis for the planning of future capacity, i.e. the decision on when to acquire extra capacity. Heizer and Render (2006) identified four strategies for capacity planning (Figures 5 (a) – (d)).

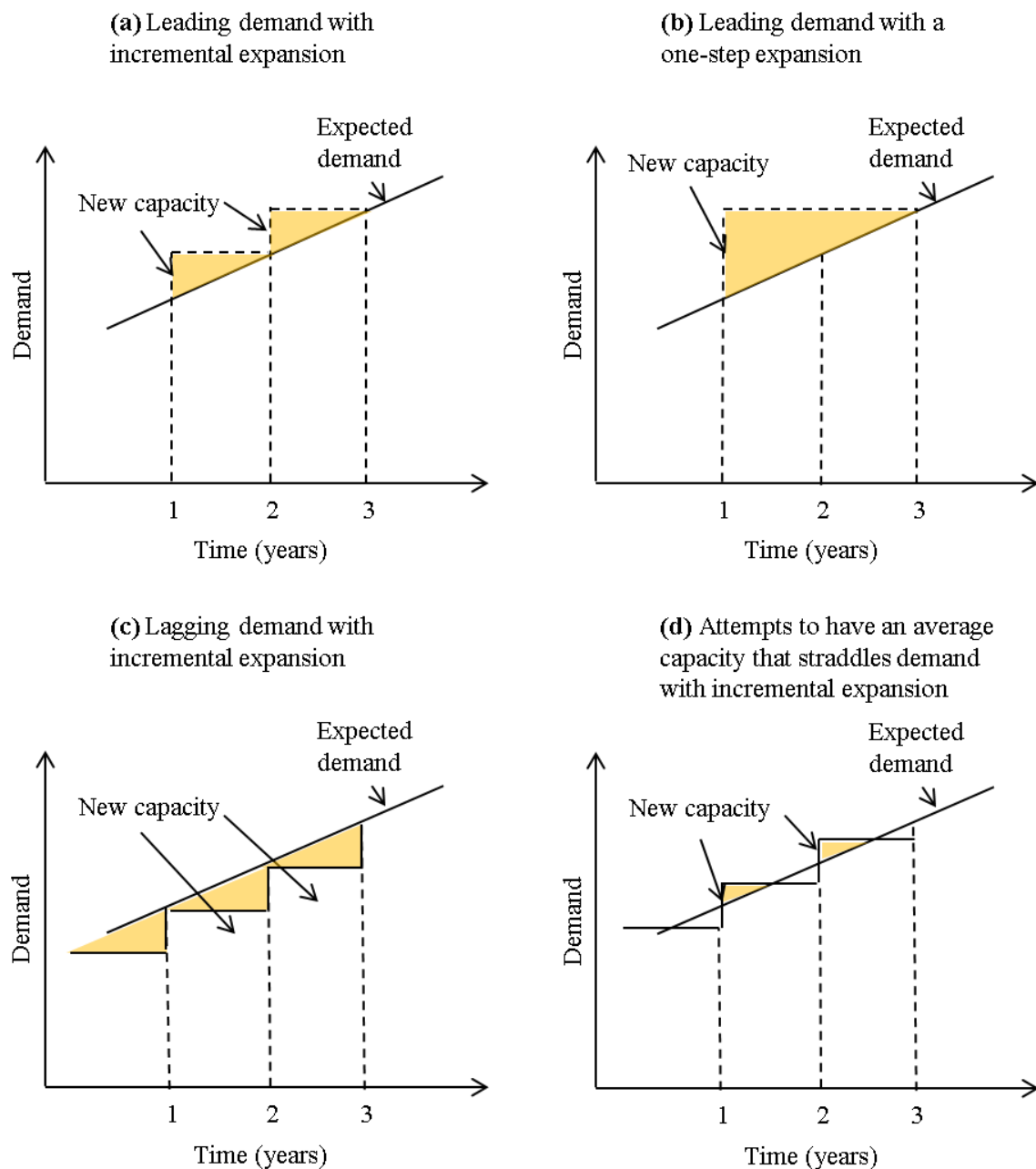


Figure 5: Capacity planning strategies (Heizer and Render 2006)

In strategies (a) and (b) the goal is to keep the capacity level above the demand level at any time by increasing the capacity when the demand approaches the capacity limit. Those strategies will lead to idle equipment or overproduction, but will result in high service levels. The difference between the two strategies is that (a) uses incremental capacity increases, while (b) has a larger expansion with one step. Strategy (c) on the other hand adds capacity whenever the demand exceeds the capacity in a manner that demand and capacity are matched. This strategy leads to lower service levels, but can result in high utilization levels. Strategy (d) is a combination of (a) and (c), using a middle ground between over- and under-capacity.

Furthermore, a company has to decide how to address demand fluctuations within the planning horizon. Slack, Jones and Johnston (2013) define the following capacity plans to do that:

- **Level capacity plan:** In this approach the capacity level is set to a defined level and kept on that level throughout the planning horizon, ignoring demand fluctuations.
- **Chase demand plan:** This is the opposite of the level capacity plan, trying to adjust the capacity constantly within the planning horizon to match the capacity to the demand as closely as possible.
- **Demand management:** Rather than adjusting the capacity, this approach focuses on influencing the demand. The most common technique to do that is to change the price, but also for example advertising can have an impact on demand levels.

The capacity plan has a strong impact on an organizations performance. A level capacity plan can help to achieve a stable employment pattern and high utilization levels, but on the other hand can lead to high inventory levels. A chase capacity plan “is much more difficult to achieve, as different numbers of staff, different working hours and different amounts of equipment may be necessary in each period”, but average inventory levels can be lower than with a level capacity plan (Slack, Jones and Johnston 2013). To achieve a chase capacity plan, methods of adjusting capacity on short term are required, which can be the following:

- Overtime and idle time.
- Varying the size of the workforce

- Using part-time staff.
- Subcontracting.

Besides deciding on capacity strategy and plan, one needs to define how to modify or use capacity. Heizer and Render (2006) present several methods for capacity configuration in dependence of the planning horizon. They characterize long-range planning with time horizons with more than one year, intermediate-range planning with a time horizon between three and 18 months and short-range planning with a horizon of up to three months. Table 1 gives an overview over which actions may be taken for the specified planning horizons:

**Table 1: Capacity configuration options per planning horizon (adapted from Heizer and Render 2006)**

	<b>Modify capacity</b>	<b>Use capacity</b>
<b>Long-range planning</b>	<ul style="list-style-type: none"> <li>• Add facilities</li> <li>• Add long lead time equipment</li> </ul>	<ul style="list-style-type: none"> <li>• Limited options exist</li> </ul>
<b>Intermediate-range planning</b>	<ul style="list-style-type: none"> <li>• Subcontract</li> <li>• Add equipment</li> <li>• Add shifts</li> </ul>	<ul style="list-style-type: none"> <li>• Add personnel</li> <li>• Build or use inventory</li> </ul>
<b>Short-range planning</b>	<ul style="list-style-type: none"> <li>• Limited options exist</li> </ul>	<ul style="list-style-type: none"> <li>• Schedule jobs</li> <li>• Schedule personnel</li> <li>• Allocate machinery</li> </ul>

Those options can be used to modify the capacity towards a desired level. In long-range planning there exist only limited options on using the capacity, while on the operational level capacity can hardly be modified. To take a decision on which methods to apply, one needs to consider several factors, such as costs and the impact on the system's performance. Mahadevan (2010) describes long-term planning with a time-horizon of two to five years with the planning premise of "augmenting capacity for projected growth", medium term planning for typically one year focusing on balancing demand and supply and short-term planning for a time horizon of one week to three months, targeting to maximize availability and efficient use of resources.

### **2.2.3 Evaluation of alternative capacity plans**

Capacity planning affects a broad range of performance aspects as was already indicated in the introduction to this thesis. As capacity decisions can affect all parts of a supply chain it is important to understand how performance measuring can be done in supply chains. There have been several approaches to develop frameworks for supply chain performance measuring:

Gunasekaran, Patel and McGaughey (2004) for example developed a framework for supply chain performance measurement and divided the performance measures according to the supply chain activities “plan”, “source”, “make/assemble” and “deliver/customer” and present a number of performance measures on a strategic, tactical and operational level for each of the activities. As the analyzed system within this research considers only the activities “make/assemble” and “deliver/customer”, the following will focus on those. For the “make/assemble” activity they present the following performance measures:

- Strategic: Range of products.
- Tactical and operational: Cost per operation hour and capacity utilization.
- Tactical: Utilization of economic order quantity.
- Operational: Human resource productivity index.

For the “deliver” activity they present a range of flexibility and effectiveness measures and also state the importance of delivery reliability performance on a tactical and operational level.

Beamon (1999) has investigated and evaluated which performance measures were used on supply chain modelling in previous studies. She found that in most cases either costs or a combination of costs and customer responsiveness have been used. Another approach presented is a combination of customer responsiveness and flexibility. On this basis she developed “an overview and evaluation of the performance measures used in supply chain models and [...] a framework for the selection of performance measurement systems for manufacturing supply chains” (Beamon 1999), dividing the performance measures into three types and defining goal and purpose of those types as listed in table 2:

**Table 2: Performance measure types (adapted from Beamon 1999)**

<b>Performance measure type</b>	<b>Goal</b>	<b>Purpose</b>
<b>Resources</b>	High level of efficiency	Efficient resource management is critical to profitability
<b>Output</b>	High level of customer service	Without acceptable output, customers will turn to other supply chains
<b>Flexibility</b>	Ability to respond to a changing environment	In an uncertain environment, supply chains must be able to respond to change

Resource performance measures include inventory levels, which can be measured per inventory group (Work-in-progress (WIP), raw materials and finished goods), personnel requirements, equipment utilization, energy usage and costs. The total costs may be divided by their source:

- Distribution costs.
- Manufacturing costs.
- Inventory holding costs.

Output measures focus on customer responsiveness, quality and quantity. Typical performance measures are for example sales, profit, fill rates (proportion of demand fulfilled from shelf), where one can differentiate between order fill rate, stock keeping unit (SKU) fill rate (from here on out referred to as fill rate) and case fill rate (Sople 2012), on-time deliveries, backorder or stock-out situations, customer response time, manufacturing lead time, shipping errors and customer complaints.

All those performance measures give indications on how a system is performing and can serve as decision support, when evaluating the impact of decisions on performance measures. However, when investing in capacity, there are several options to evaluate the investment, based on evaluating the costs of investment against the profit, such as for example a Break-even-analysis or Return on Investment (ROI) analysis. A break-even analysis focuses on determining the break-even point in which the revenue will cover the

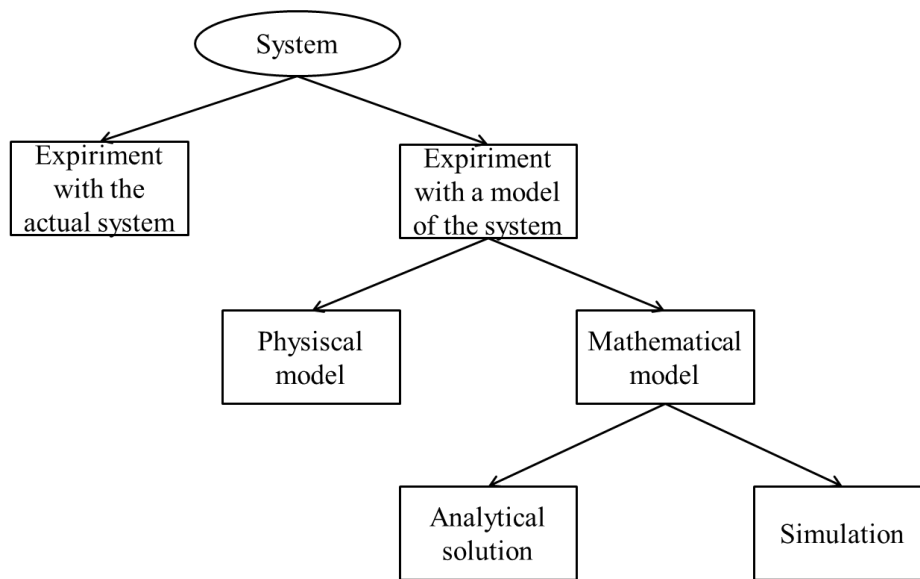


costs of an investment (Heizer and Render 2006). The ROI is calculating the efficiency of an investment by dividing the net profit through investment costs.

Harder to measure is the flexibility of a system. There are approaches to quantify a manufacturing or supply chain system's flexibility with measures such as volume flexibility, delivery flexibility, mix flexibility and new product flexibility. The flexibility is important when a system exists in an uncertain environment and has a broad range of advantages, as presented by Beamon (1999):

- “Reductions in the number of backorders.
- Reductions in the numbers of lost sales.
- Reductions in the number of late orders.
- Increased customer satisfaction.
- Ability to respond to and accommodate demand variations, such as seasonality.
- Ability to respond to and accommodate periods of poor manufacturing performance (machine breakdowns).
- Ability to respond to and accommodate periods of poor supplier performance.
- Ability to respond to and accommodate periods of poor delivery performance.
- Ability to respond to and accommodate new products, new markets, or new competitors.”

Besides the decision on which performance measures to use, one must decide how to evaluate the impact of alternative capacity plans and configurations on chosen performance measures and how the system will perform in uncertain conditions. Figure 6 shows different ways to study a system as proposed by Law and Kelton (2000). They categorize systems into discrete systems, in which state variables change instantaneously at certain times and continuous systems, in which state variables change steadily over time.



**Figure 6: Ways to study a system (Law and Kelton 2000)**

The experimentation with the actual system will have the advantage over experimentation with a model of the system as it will always be known to be valid. On the other hand experimentation with the actual system can be very costly and lead to disruptions. When deciding to experiment with a model of the system, there exist the options of using a physical or a mathematical model. Physical models have rarely been used in operations research and system analysis. A mathematical model is representing the system with logical and quantitative relationships and is used to study the system's behavior under different settings and can either be an analytical or a simulation model. Altiok and Melamed (2007) describe the difference between analytical and simulation modelling as follows:

- “An *analytical model* calls for the solution of a mathematical problem, and the derivation of mathematical formulas, or more generally, algorithmic procedures. The solution is then used to obtain performance measures of interest”
- “A *simulation model* calls for running (executing) a simulation program to produce sample histories. A set of statistics computed from these histories is then used to form performance measures of interest.”

If the system is simple enough to use an analytical approach, this should be done. However many systems are very complex and are facing many stochastic factors, which makes analytical solutions very complicated. Simulation models can help to study such systems (Law and Kelton 2000). Gokhale and Trivedi (1998) see the advantage of simulation over

analytical modelling “in the fact that very detailed system behavior can be captured”, while analytical models can be more cost effective than simulation.

### ***2.3 Uncertainties in capacity planning***

Uncertainties in capacity planning can appear throughout the whole supply chain. The main sources of uncertainty in a supply chain that may affect the performance and need to be considered when taking decisions are demand uncertainty, uncertainty in processes and uncertainty of lead-times (Peidro et al. 2009).

The challenge of demand uncertainty is not only an issue in capacity planning, but in general in supply chain management and production planning. Demand seasonality and fluctuations within shorter time horizons have to be considered (Slack, Jones and Johnston 2013). Within the production process there can be uncertainties, such as “operation yield uncertainty, production lead time uncertainty, and quality uncertainty, failure of production system and changes to product structure” (Mula et al. 2006). The uncertainty of lead-times appears within all parts of the supply chain. Each member of the supply chain faces the previous uncertainties and a company has to consider that lead-times for raw materials, components and other working materials may have a high variation.

Bakke and Hellberg (1993) have investigated challenges in capacity planning, focusing on “companies, producing fairly complex, and assembly intensive and customized products” and concluded that the challenge is the cumulated uncertainty of the following factors:

- MPS uncertainties towards composition and time.
- Capacity uncertainties due to unknown process or manpower qualifications.
- Load uncertainties through data collection problems, unknown process or a short planning horizon.
- Scheduling methodology uncertainties, for example a weak connection between work- and customer orders and the inability to simulate accurate work flow at work-center level.
- Pre-production uncertainties, e.g. failures in the capacity planning.
- Subcontracting uncertainties, especially the inability to identify items at an early stage.
- Capacity loss through idle bottleneck resources or the production of wrong items.

Even though these challenges focus on a different product type than considered in this thesis, many of those uncertainties can occur nevertheless.

Uncertainties are typically handled by “stochastic” or “probabilistic” approaches, what means that uncertainties are represented with probabilities. A stochastic model can be defined as “a model describing how the probability of a system being in different states changes over time” (Otto and Day 2007).

## ***2.4 Classification of capacity planning problems under uncertainty***

Within the research for this thesis no approach focusing exactly on the classification of capacity planning problems under uncertainty was found. However, within reviews there were developed taxonomies for supply chain planning (Peidro et al. 2009) and production planning (Mula et al. 2006) problems under uncertainty.

Peidro et al. (2009) based their taxonomy to classify supply chain planning problems on three dimensions:

- Source of uncertainty.
- Problem type.
- Modelling approach.

Sources of uncertainty which may affect capacity planning have been studied in detail in the previous chapter. The problem type is typically defined by the planning range, e.g. operational, tactical and strategic. As for the modelling approach, they distinguish between analytical models, models based on artificial intelligence, simulation models and hybrid models.

The study by Mula et al. (2006) focuses production planning models under uncertainty and their application to real-world problems. They did not differentiate by means of the source of uncertainty, but rather focused on the combination of the production planning area and the modelling approach. The research topics “Aggregate planning”, “Hierarchical production planning”, “Material requirement planning”, “Capacity planning”, “Manufacturing resource planning”, “Inventory management” and “Supply Chain planning” have been identified. Their classification of general types of uncertainty models in manufacturing systems distinguishes between conceptual models, analytical models,

artificial intelligence based models and simulation models. For the field of capacity planning, they only describe approaches with analytical models and simulation models. Those two approaches will be presented in the following chapters, including their advantages and disadvantages as well as applications within capacity planning. The two main approaches will be complemented by considering the possibility of combining analytical and simulation models in a recursive manner to study a system's behavior.

## ***2.5 Approaches to capacity planning under uncertainty***

### **2.5.1 Analytical modelling**

Mula et al. (2006) classified the following approaches as analytical modelling in production planning:

- Hierarchy process.
- Mathematical programming (Linear programming, Mixed-integer linear programming, Non-linear programming, Dynamic programming and Multi-objective programming).
- Stochastic programming.
- Deterministic approximations.
- Laplace transforms.
- Markov decision processes.

They have identified that especially deterministic approximation and stochastic programming have been used for production planning under uncertainty.

Chen, Li and Tirupati (2002) for example use a scenario-based stochastic programming approach in an uncertain environment with several products. They apply scenarios to capture the demand development and the programming approach to determine technology choices and capacity plans. They incorporate strategic (investment in new capacity) as well as tactical (allocation of the capacity) decisions in their model.

Alp and Tan (2008) consider a make-to-stock environment and include flexible capacity decisions in a finite-horizon dynamic programming approach to address the tactical capacity problem with a periodic review under non-stationary stochastic demand. The

model is used to investigate “the optimal capacity levels, the effect of operating on a suboptimal capacity level and the value of utilizing flexible capacity”.

Analytical models can have the goal of optimization, e.g. the objective of minimizing or maximizing a function subject to given constraints. In capacity planning, optimization models usually use a least cost objective under operational constraints (Ku 1995). Sahinidis (2004) found that the modelling philosophies when optimizing under uncertainty have a broad variety and included expectation minimization, minimization of deviation from goals, minimization of maximum costs and optimization over soft constraints. He states that main approaches to optimization under uncertainty are stochastic programming (resource models, robust stochastic programming and probabilistic models), fuzzy programming (flexible and possibilistic programming) and stochastic dynamic programming.

## **2.5.2 Simulation modelling**

“Simulation is the imitation of the operation of a real-world process or system over time. Simulation involves the generation of an artificial history of the system and the observation of that artificial history to draw inferences concerning the operating characteristics of the real system that is represented” (Banks 1998).

In comparison to the goal-seeking optimization, simulation is a more descriptive and exploratory approach. Rather than finding an optimal solution, simulation experiments with a system by using different values on input parameters. Mula et al. (2006) have classified the following approaches as Simulation modelling:

- Monte Carlo techniques.
- Probability distributions.
- Heuristic methods.
- Freezing parameters.
- Network modelling.
- Queuing theory.
- System dynamics.

Strengths and weaknesses of simulation modelling have been investigated by Banks (2000), who has identified several advantages and disadvantages (Table 3).

**Table 3: Advantages and disadvantages of simulation (based on Banks 2000)**

<b>Advantages</b>	<b>Disadvantages</b>
Understand “Why” to certain phenomena	Model building requires special training
Deal with complex systems	Simulation results can be difficult to interpret
Visualization	Time consuming and expensive
Consideration of “What-if” scenarios	Inappropriate usage

Two simulation modelling approaches commonly used as decision support tools in logistics and supply chain management are Discrete event simulation (DES) and system dynamics (SD) (Tako and Robinson 2012). While SD is mostly used for strategic problems, DES is used more frequently for operational and tactical planning problems and can be classified into two types, dependent on the simulation output data: steady state simulation and terminating simulation (Law and Kelton 2000).

- **Steady-state simulation:** The purpose of this simulation is to study the long-run and steady-state behavior of a system. For a steady-state simulation one needs to consider a warm-up period, in which performance measures achieve stability.
- **Terminating simulation:** In this case the simulation starts in a specific state and runs until a terminating event occurs or for finite planning horizon.

Umeda and Jain (2004) have studied “Modelling and Design Issues for Integrated Supply Chain Simulation Systems” and defined terminating simulation models to be specifically useful for supply chain problems, including capacity planning problems, if it is done for a defined time horizon.

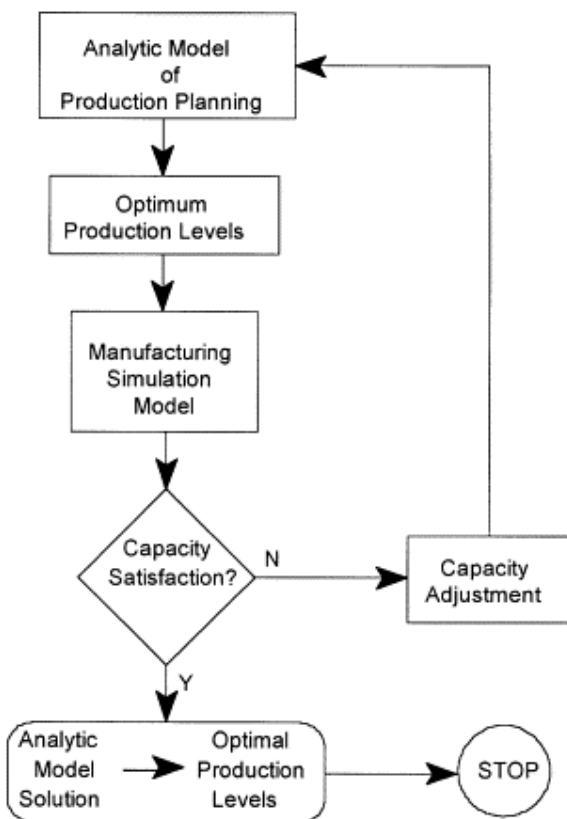
Nyaga et al. (2007) applied DES with ARENA to experiment with different capacity configurations in a configure-to-order environment under demand uncertainty. They investigate the effects on customer service performance measured by order fill rate, case fill rate and response time and found that the variables demand skew, demand variability and configuration capacity have a significant impact on the customer service.

Vlachos, Georgiadis and Iakovou (2007) applied the method of system dynamics to a long-term capacity planning problem in a reverse supply chain and used the total supply chain profit as performance indicator. DES usually tries to achieve a close match between the

model behavior and the real world behavior, they use SD to investigate the major dynamic patterns and focus on an approximation of profit development under certain conditions rather than trying to forecast profits.

### 2.5.3 Hybrid modelling

According to Byrne and Bakir (1999) traditional approaches like RCCP and CRP as well as mathematical solutions for capacity constrained MRP problems “have generally failed in realistically modelling the capacity” and analytical as well as simulation modelling have specific advantages and disadvantages. They focus on overcoming some of the disadvantages by using a combination of both approaches. They present an iterative approach, using a hybrid modelling procedure as shown figure 7:



**Figure 7: Hybrid modelling procedure (Byrne and Bakir 1999)**

In this hybrid approach an analytical model is used to determine optimal production levels, which are then tested with a simulation model for capacity satisfaction, which should be defined in accordance with the desired output or performance. Based on the simulation output, the analytical model is adjusted and new optimal production levels are determined. This is done repeatedly until capacity satisfaction is reached.



Nolan and Sovereign (1972) have done research on the advantages and disadvantages of analytical and simulation models and propose a recursive optimization and simulation approach, using optimization to take resource level decisions and determine optimal schedules, followed by testing the schedules with simulation and use the productivity measurement to start again on the resource level.

### **3 Methodology**

#### ***3.1 Problem classification***

The problem classification was done according to the classification procedure of supply chain planning problems used by Peidro et al. (2009) and in consequence based on the three subcategories “Source of uncertainty”, “Problem type” and “Modelling approach”.

The analyzed system faces several sources of uncertainty on the demand side as well as in the capacity and availability of raw material. In the processes the uncertainty lies mostly within unplanned downtimes, which can arise through breakdowns and failures of the machine or non-availability of raw-materials, which lead to fluctuations in the machine’s actual capacity. As due to the nature of the product (perishable) the goods shall not lay on inventory for a long time, the demand should be produced when it occurs, keeping the inventory levels within a certain range. The challenge is that all those uncertainties arise together, leading to changing capacity and demand levels and accordingly to periods with over- and periods with under-capacity.

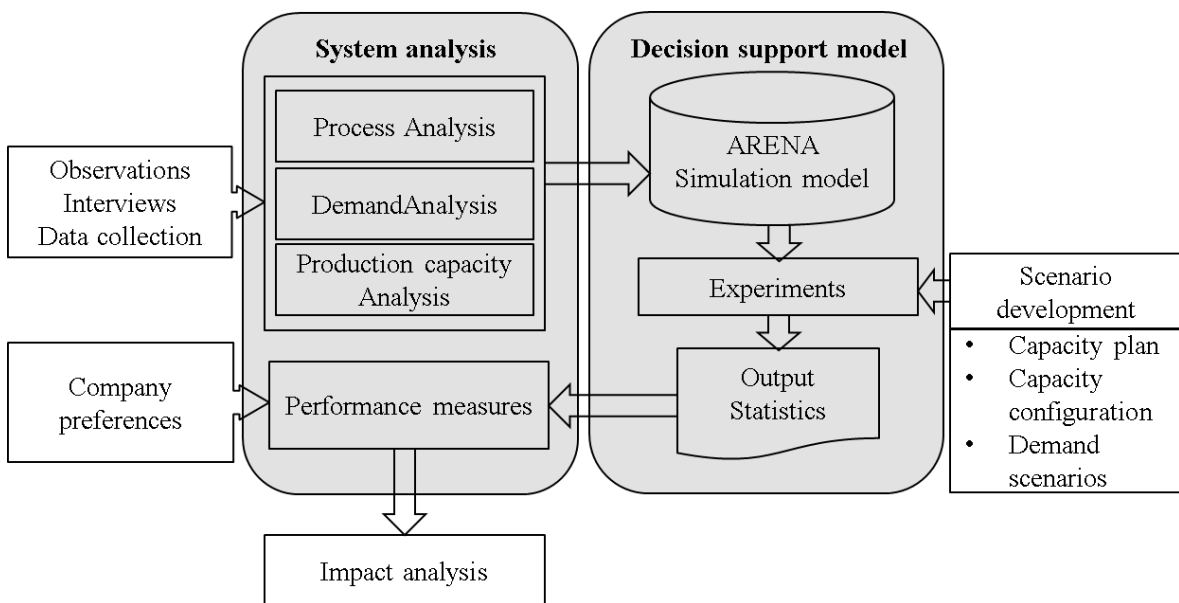
The approaches and methods to be used are dependent on the problem type and it is therefore important to decide which problem type (strategic, tactical or operational) is addressed before developing the methodology. Due to the decisions, which shall be supported (increased production speed, schedule changes etc.), the problem type can be classified as a tactical planning problem.

The modelling approach in this case study will be a discrete-event simulation with sensitivity analysis. It was decided to use this approach for several reasons. First of all, TINE has previously addressed similar problems with analytical models and wants to get an insight in opportunities to use simulation for this kind of problem. The uncertainty and complexity in the case leads to the conclusion that the problem is suitable to be addressed with simulation. As the problem type is a tactical capacity planning problem, it was decided to use the simulation method DES.

### 3.2 Case study research model

The case study research model (Figure 8) used to address the problem have four main steps:

1. System analysis.
2. Scenario development.
3. Decision support modelling.
4. Impact analysis.



**Figure 8: Case study research model**

Observations, interviews and provided data build the basis for the system analysis, which is divided into an analysis of processes, demand and production capacity. Those three analysis parts shall lead to a deep understanding of the system and are the foundation for the development of the DSS. Besides, performance measures were chosen on the basis of the company's preferences, literature review and system analysis. For the evaluation of the scenarios, consisting of demand scenarios and capacity configurations, the method of experimenting with a DES model was chosen. Whether to use a steady-state or terminating simulation model depends on the objective of the simulation, especially which performance measures shall be taken as output and whether the model is used for strategic (steady-state) or tactical (terminating simulation for a finite time horizon) planning. As the case study addresses a tactical planning problem with a finite time horizon, it was decided to use a terminating simulation.

### **3.3 Research methods**

#### **Interviews and observations**

Observations were taken in order to understand the physical process of the production and were important for accessing the different production steps and evaluating which steps are critical for capacity planning. The observations were taken at a visit at TINE's facilities.

Interviews with planners were another method used to study the system. Specialists who know the system can provide a research with essential information and help to understand the real-world decision making. Interviews were taken with a focus on production and capacity planning methods at TINE and were carried out with production planners and the contact person at TINE. Several questions arising throughout the project have been delivered to the contact person, who discussed the questions with relevant persons in order to give feedback.

#### **Experiments (simulation modelling)**

Another research method is experimentation in order to evaluate the impact of demand changes and capacity configurations on performance measures. The development of the simulation model was based on the methodology of discrete event simulation in logistics and supply chain research as proposed by Manuj, Mentzer and Bowers (2009) and was accordingly carried out with the following steps:

1. Problem formulation.
2. Specification of independent and dependent variables.
3. Development and validation of the conceptual model.
4. Data collection and analysis.
5. Development and verification of the computer-based model.
6. Validation of the model.
7. Performance of simulations.
8. Analysis and documentation of results.

For the development of the model, the general-purpose simulation software ARENA was chosen. The ARENA product family consists out of the ARENA Input Analyzer to determine probability distributions, the ARENA simulation software, which uses DES

based on simulation blocks, and the ARENA Process Analyzer for experimenting with different input parameters.

### ***3.4 Data collection and analysis***

Data collection and analysis is essential for both the understanding and analysis of the system, as well as for the development of the simulation model. Altiok and Melemed (2007) describe data collection in simulation modelling as necessary for estimating input parameters and model validation, which contains comparing the system's historical output statistics with those obtained from the model.

The data was provided from TINE SA and has been collected before through TINE's Enterprise Resource Planning-system MR3. The following data, all as observed in the year 2013 and separated per item, was provided by TINE:

- Daily demand.
- Amount and start dates of the production.
- Weekly production plans (including available and planned hours).
- Weekly production amount (including used hours).
- Lost sales.
- Daily machine downtimes, separated into planned, operational and unplanned downtimes.
- Daily scheduled machine hours.

The provided data was cleaned and prepared for further analysis using Microsoft Excel 2010. This step also included the matching of the measurement units (originally some data was provided in weights and amounts as well as in different time units). For the further analysis it was decided to measure in amounts of single stock keeping units (SKUs) and hours. Besides, Microsoft Excel 2010 was used for the general analysis of the system, for example for calculating performance measures, building graphs and bar charts etc. Furthermore the ARENA Input Analyzer, which has the functionality of fitting probability distributions to sample data sets and can recommend parameters which provide the best fit, was used for probability distribution analysis. For testing the "goodness of fit", the tool provides options of using a Chi-Square test ( $\chi^2$ -test) and Kolmogorov-Smirnoff test (KS-

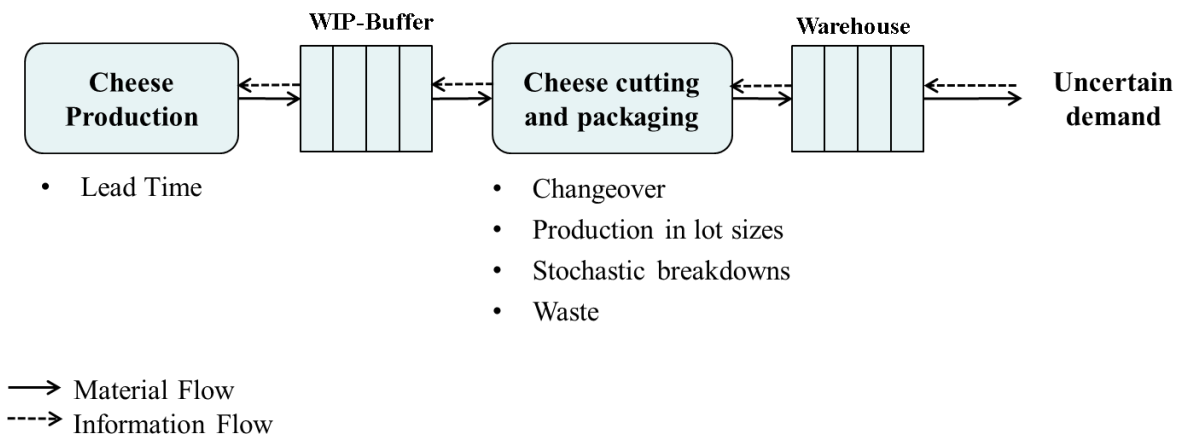
test) (Altiok and Melemed 2007), which will be described within the data analysis in the simulation modelling part.

## 4 Case Study

### 4.1 System analysis

#### 4.1.1 Process analysis

The considered system in this thesis (Figure 9) is a part of TINE’s cheese supply chain, with the main focus on an automated cheese-cutting and packaging line (from here on out called production or packaging line) at TINE’s central warehouse in Heimdal. On the production line, there are produced two products: Norvegia Cheese-0.83 kg (from here on out referred to as item 1) and Norvegia Cheese-1.0 kg (from here on out referred to as item 2). The system will besides the production line include the underlying inventory of finished goods, the incoming demand and the corresponding production planning and scheduling tasks.

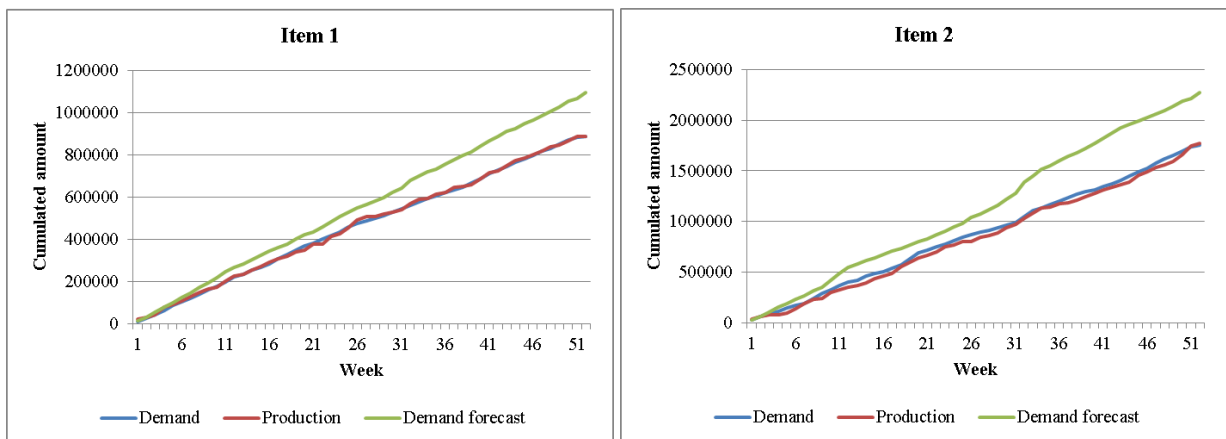


**Figure 9: System overview**

The figure above presents the analyzed system and its position within the supply chain. The system is supplied with Cheese-blocks from TINE’s production sites. The cheese production will only be considered in accordance to its impact on the considered packaging line, e.g. when stock-outs cause the machine to be idle. The packaging process consists out of the process steps “cutting”, “weight control”, “packaging” and “labelling”. The weight control checks whether the product’s weight lies within a predefined range and rejects the product if it does not. Even though rejected products may still be used as by-products on other production lines, it can still be considered as “waste” within the analyzed system.

As the production line is used for the production of two different products, changeovers, consisting out of a “clean-up”, “set-up” and “start-up” time, occur when switching from one item to the other. In this case the changeover times are not sequence-dependent, meaning that the changeover time will be the same for every changeover and the time is known to be half an hour. There might be small variations, but as these do not have a major impact on the performance, it is assumed that the time is constant. Furthermore the machines in the packaging process are subject to stochastic breakdowns. After a period of normal operation (uptime) a failure event takes place, leading to a stop of the operation for the duration of repairing (downtime). After the production, the end items are stored in a central warehouse, but are not supposed to be delivered before the end of a cool-down period.

Production planning is done based on demand forecasts for “the next few days”. This is hard to define, but it was indicated that usually the next three days are considered. The production will then be done to stock based on those forecasts. However the production plan is not strictly following the demand forecasts as shown in figure 10, which presents the cumulated demand, production and forecasts over one year.



**Figure 10: Cumulative comparison of demand, production and demand forecast**

A production order is only issued, if the forecasted demand would decrease the inventory to a lower value than the item’s safety stock (SS), which is 15,000 SKUs for item 1 and 36,000 SKUs for item 2. Besides the production plan may be adjusted on a daily level in order to address the problem of forecasting inaccuracy. The production time is subject to several constraints due to agreements with trade union and employment rights:



- From Monday to Thursday there are two shifts, with 6 hours in the early shift and 7.5 hours in the late shift.
- On Friday there is only one shift (6 hours).
- Optionally, after regular working hours, 3.5 hours of overtime can be used.
- If a production is started on a certain day, it will be produced until the end of the day. Thus if there is a production order that can be completed in less than a day, production still takes place for the complete day, leading to “Overproduction”. The same applies for the 3.5 hours of overtime.

Overtime is used whenever the total inventory (including inventory in cool-down) of the item currently in production is below its SS at the end of the regular production. Changeovers will occur if the produced item has fulfilled the production plan (based on demand forecasts for the next three days) or the inventory of the other product dropped below its SS.

The total throughput of the system depends on the product mix as the items have different throughput rates with a value of 1,695 per hour for item 1 and 2,439 per hour for item 2. The production cycle time (time between the completions of two subsequent units) is 0.00059 hours for item 1 and 0.00041 hours for item 2. The fill rates in 2013 were 99.49% (item 1) and 99.74% (item 2).

#### **4.1.2 Demand analysis**

The analysis of the demand was carried out on a weekly level. The first part focused on measuring the demand on a weekly basis to get an overview over volume, product mix and variation. Therefore the total demand, minimum and maximum weekly demand, weekly average as well as standard deviation (all measured in SKUs) and variation coefficient (standard deviation divided by average) have been calculated (Table 4). As the demand for item 2 is partly fulfilled from other locations, the following measures will all refer to the fraction of the demand which was actually fulfilled from the analyzed system. Because the amount of fulfilled demand from other production lines does not depend on the system’s performance, but on the performance of the other lines, this cannot be planned based on an analysis of the considered system.

**Table 4: Measurement of weekly demand**

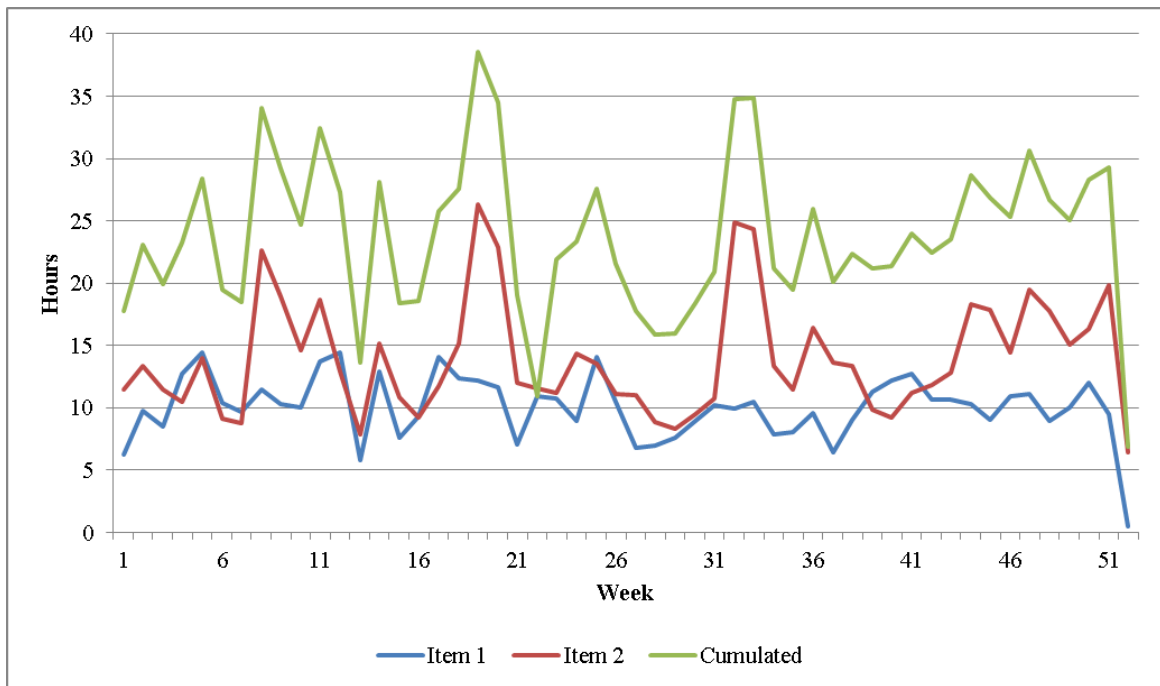
<b>Measure</b>	<b>Item 1</b>	<b>Item 2</b>
<b>Total demand</b>	886,056	1,755,544
<b>Minimum per week</b>	758	15,611
<b>Maximum per week</b>	24,480	63,716
<b>Weekly average</b>	17,039.54	33,760.47
<b>Standard deviation</b>	4,344.51	11,234.09
<b>Variation coefficient</b>	25.50%	33.28%

The measures show that the demand for item 2 is higher and has a higher variation than the one of item 1. However the coefficient of variation indicates that the demand of both products has a relatively low variance, as the values lay far below 100%.

As the product mix is varying between the weeks, it was decided to focus on input capacity measures in order to be able to compare the demand (measured in SKUs) to the capacity (measured in machine hours). Therefore the demand was transformed into necessary production hours based on cycle times. The fraction of the demand from item 1 is 33.54%; the one from item 2 is 66.46%. On this basis the average time for an aggregate unit can be calculated as follows:

$$33.54\% * 0.00059\text{hours} + 66.56\% * 0.00041\text{hours} \approx 0.00047\text{hours}$$

As for the analysis of the weekly development, not the yearly product mix was used as a basis but rather the product mix in the specific weeks. Figure 10 presents the development of weekly needed input capacity to fulfill the demand per item and cumulated.



**Figure 11: Weekly capacity demand**

The graph supports the hypothesis that the variation of product item 2 is mostly determining the variation of the cumulated demand. While item 1 has a quite constant demand, item 2 has several extreme peaks. As the two items are quite similar, it was necessary to check whether there exists a pattern of substitution between the two products, but no clear pattern can be identified based on the development of weekly demand levels. Another conclusion is that there are no clear seasonal patterns, but only fluctuations of the weekly demand levels.

#### **4.1.3 Production capacity analysis**

This part is separated into the analysis of the actual production, measured in terms of total production, average, minimum and maximum weekly production and standard deviation, all taken for each product and measured in SKUs, as well as the variation coefficient (Table 5).

**Table 5: Measurement of weekly production**

<b>Measure</b>	<b>Item 1</b>	<b>Item 2</b>
<b>Production</b>	886,664	1,790,617
<b>Minimum per week</b>	0	0
<b>Maximum per week</b>	40,168	95,520
<b>Weekly average</b>	17,051.23	34,424.90
<b>Standard deviation</b>	9,454.37	17,264.20
<b>Variation coefficient</b>	55.45%	50.15%

While the total production amounts are close to the total demand, the weekly production amounts per item have a higher variation than the weekly demand. This can be explained by the fact that only one product is produced at each time, while customer orders can come in for both products simultaneously and that there are weeks with over- and underproduction based on production plans. The variation coefficient is in consequence higher when considering the products separately. However the variation coefficient for the cumulated weekly production is lower with a value of 36.08%.

The second part of the production capacity analysis is focusing on the capacity measures, which were found to be appropriate for measuring capacity within the literature review. The following analysis will focus on the following measures:

- Design capacity.
- Effective capacity.
- Utilization.
- Efficiency.

For the measurement of the capacity, data on downtimes, scheduled and productive machine hours was provided. The data was already divided into planned downtime, such as planned meetings and breaks, operational downtime (shift change times, changeover times and preventive maintenance) and unplanned downtime (machine breakdowns, quality failure inspection and missing material). This division was taken as the basis for the further calculations. Furthermore important is the time without scheduled work. As not all days are used for production (if the complete forecasted demand has been produced),

the machine has idle time. The calculation of the efficient capacity and the actual output was done as follows:

$$\begin{aligned}
 & \textbf{Design Capacity} \\
 & - \text{Planned downtime} \\
 & - \text{Operational downtime} \\
 & \quad - \text{Idle time} \\
 & \quad + \text{Overtime} \\
 & = \textbf{Effective capacity} \\
 & - \text{Unplanned downtime} \\
 & = \textbf{Actual input capacity.}
 \end{aligned}$$

On this basis efficiency and utilization can be calculated following the description within the literature review. The system had, in the year 2013, a utilization of 47.0% and an efficiency of 74.6%. For utilization the minimum weekly value is as low as 8.9%, while the highest value is 122.9% in a week in which overtime was used. The differences mainly occur through time in which no production is scheduled (1,441.41 hours in 2013) or through unplanned downtimes (434.73 hours in 2013) because planned and operational downtimes (together 90.68 hours in 2013) are low in comparison. For the efficiency the value varies between 45.9% and 87.4%. The variation between the values shows the challenge of planning capacity accurately under the uncertainty of demand and unplanned downtimes.

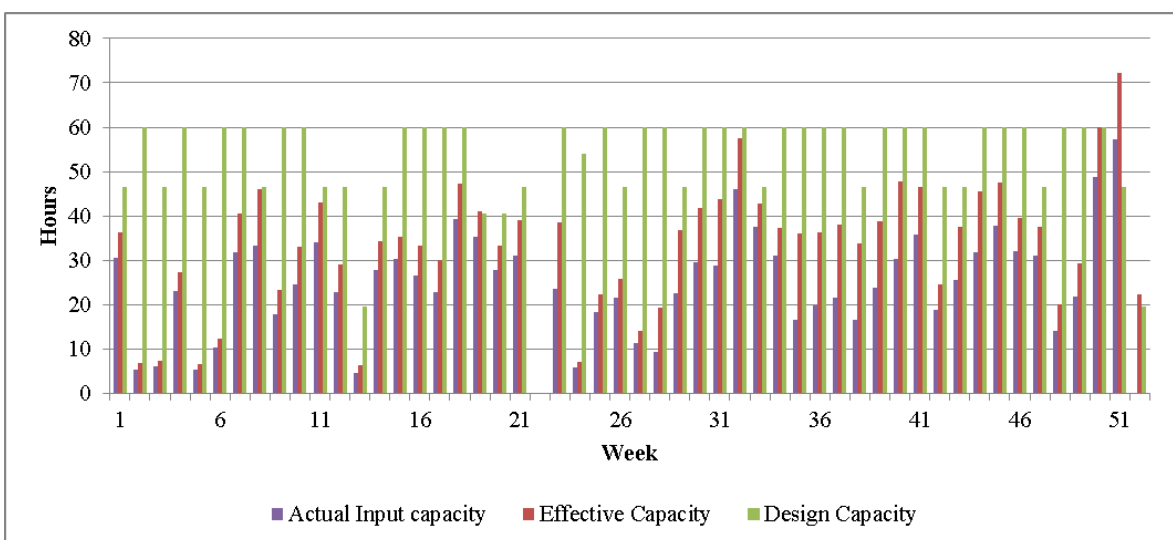


Figure 12: Output, design and effective capacity

Figure 12 illustrates the actual, effective and design input capacity per week. The differences in design capacity are based on holidays or other days without operations. The system mostly operates with idle time to adjust the capacity downwards, while overtime is not used extensively. However, even in weeks in which the effective capacity is below the design capacity, there can be overtime, as the decision on overtime usage is taken on a daily rather than a weekly basis. In 2013 there was used 28 hours of overtime out of 1,276.59 productive machine hours. As the utilization is, with less than 50%, quite low, it seems logical that idle time is used much more extensive than overtime. Besides the figure indicates that the unplanned downtime is dependent on the effective capacity and consequently might be modelled in relation to that.

#### 4.1.4 Comparison of production capacity and demand

The last part of the system analysis focused on comparing production capacity and demand. In a first step it was checked how the capacity usage corresponds with the input, which would have been necessary to fulfill the demand. Figure 13 shows the necessary, design and actual input capacity per week.

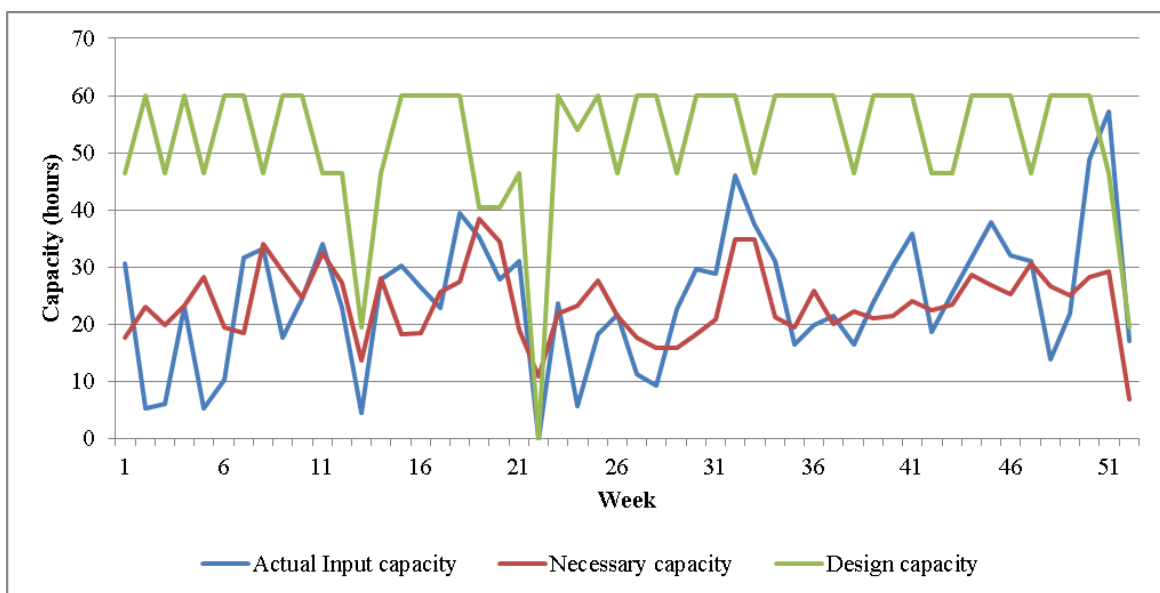


Figure 13: Actual, necessary and design input capacity

The graph shows that the capacity usage (actual input capacity) is chasing the demand, but due to demand variation, forecasting inaccuracy, lot production and uncertainty uses more or less capacity when comparing on a weekly basis. Measured in design capacity, there are only two weeks with a capacity lag, which proves the importance of considering unplanned downtimes as those can lead to capacity lags.

## ***4.2 Scenario development***

The following section will focus on defining possible scenarios and options as a basis for future capacity planning. The presented options will not all be tested and used within this thesis, but shall give an indication on how the system can be configured and will also build the basis for defining the goal of the decision support model. For the development of scenarios the following points were investigated.

- Capacity plan.
- Possible capacity configurations.

Capacity strategies are not included here, since the case study is focusing on a tactical planning problem, but should be considered for strategic planning.

As described within the literature review, there exist the three options of “Level capacity plan”, “Chase capacity plan” and “Demand management”, which can be combined. The system follows a chase capacity plan, using the method of overtime (limited) and idle time. There are several options to explore impacts of using a different capacity plan. For example it could be explored how the system reacts if the capacity can only be adjusted downwards (idle time), but not upwards (overtime). As overtime is rather costly, it is interesting to explore the impact on the system’s performance without using overtime. Also different rules for when and how to apply overtime (for example only if the demand on the following day could not be fulfilled) and when to leave the system idle are options that could be investigated.

There exist several options for modifying the system’s capacity, which will either increase/decrease the capacity by increasing/decreasing the scheduled time (number and length of shifts), increasing/decreasing the throughput rate (adding of personnel, process optimization or change of production speed) or by increasing/decreasing the efficiency (more or less downtime). The last factor is however not fully controllable, but can only be influenced. The non-availability of the raw-material on the one hand is an external factor as it is delivered to the system from a supplier<sup>1</sup>, but can be partly controlled through high inventory levels. The breakdowns and failures of the machine are in general not

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<sup>1</sup> The supplier in this case is TINE itself, but it can still be considered as an external supplier to the system.

controllable, but it might be possible to adjust the length and probability of breakdowns by for example purchasing new equipment.

Furthermore the future demand will be considered. When talking about alternative future demand scenarios, the total demand as well its variation might be changed. As in the current case there are two products with different throughput rates, also the product mix plays an important role.

The actual scenarios to be tested with the simulation model have been developed in cooperation with the contact person at TINE. The previously described options have been presented and scenarios to be tested have been agreed upon with the company. They are particularly interested in the following alternatives:

- Increase in demand: This means an increase of the total demand without a change in the variation or the product mix, e.g. the distribution is kept and both products are increased simultaneously. The demand increases are to be tested in combination with different capacity configurations.
- Higher production speed: Increasing the system's throughput rate by increasing the production speed.
- Schedule changes: This category focuses on the possible capacity modifications "adding shifts" or increasing/decreasing the length of shifts
- Reduce unplanned downtimes: This can be tested in the simulation model, but only be controlled partly in real life. It must also be distinguished between a lower probability for breakdowns or shorter durations of repair times.
- Overtime Usage: Testing how the system would perform without overtime or different rules for overtime usage.

Within each of those factors an unlimited number of scenarios can be developed by adjusting the measures on different levels. Furthermore all factors can be combined in many different ways, as for example through increasing demand combined with a higher production speed. To limit the number of experiments it was decided to use increases and decreases in steps of 10%. Based on discussions it was decided to test the following three test classes within this research:

- **Test class 1:** Current capacity settings with increasing demand



- **Test class 2:** No usage of overtime with increasing demand.
- **Test class 3:** Higher production speed with increasing demand.

Those tests shall give an indication on how simulation can be used and explore how the system will react to certain changes. However, the model shall support all defined options, which can be tested in the future.

For the evaluation of capacity plans, performance measures were defined based on the performance measures, which have previously been applied by TINE, and the literature review. For TINE, the output performance measures are the most important ones, focusing on fill rate levels close to 100%. The output performance is dependent on the resource performance, which will be measured by terms of utilization and efficiency, and the flexibility of the system, which will just be explored by how much the previously mentioned performance measures are affected by changing input values.

The tests will focus on the impact on the performance measures fill rate (as only daily demand data was available, order fill rates could not be measured), machine utilization and overtime and compare the results of test classes 2 and 3 to the results obtained with the current settings. The decision support model however shall support further measures such as inventory levels, productive machine hours and efficiency as a basis for a monetary analysis and investment evaluation.

### ***4.3 Decision support model***

#### **4.3.1 Problem formulation**

The objective is to develop a simulation model that can estimate the effects of changes within the previously described factors, e.g. it should be possible to make adjustments for the values of those factors. The model shall be constructed in a way that makes it reusable for similar systems as TINE has several similar packaging lines. Especially the process and the model logic shall be identifiable for the purpose of using the model logic for simulating similar production lines.

It was agreed that the focus shall lie on the utilization of the machine, the amount of overtime used to adjust the capacity on short term and fill rates. The model shall also support the calculation of monetary performance measures. As the occurring costs can be

calculated on the basis of costs per operating machine hour, cost per non-operating machine hour and cost per hour on overtime, the actual used hours in those three categories should be calculable. Furthermore inventory levels and stock-out situations shall be given as output.

The system faces the problem that capacity (downtimes), demand and planning accuracy are uncertain, which means that there exist the possibility that demand peaks occur in weeks with low capacity or the opposite. The model shall represent the range of those combinations of different capacity, demand and forecasting accuracy levels with a stochastic approach.

#### **4.3.2 Definition of dependent and independent variables**

The next step presented by Manuj, Mentzer and Bowers (2009) is the definition of dependent and independent variables. The independent variables can be seen as parameters of the system, which are affecting the performance measures, represented by the dependent variables. The independent variables can be defined on the basis of the scenario development to be the following:

- Demand.
- Scheduled machine hours.
- Cycle time (for example for testing production speed changes).
- Length and probability of unplanned downtimes.
- Overtime rule.

The dependent variables are defined, based on the performance measures, which are to be investigated as the following:

- Efficiency.
- Utilization.
- Overtime hours.
- Fill rates.
- Production, downtime and idle time hours.
- Inventory levels.
- Stock-out situations.

### **4.3.3 Development and validation of conceptual model**

Manuj, Mentzer and Bowers (2009) define the tasks within this step to be the specification of assumptions, algorithms and model components for the development of the conceptual model and suggest performing a structured walk-through with experts for the validation of the model. The conceptual model was developed based on interviews and regular discussions with employees from TINE and validated through a structured walk-through with several process experts from TINE.

Several assumptions were taken prior to the development of the simulation model:

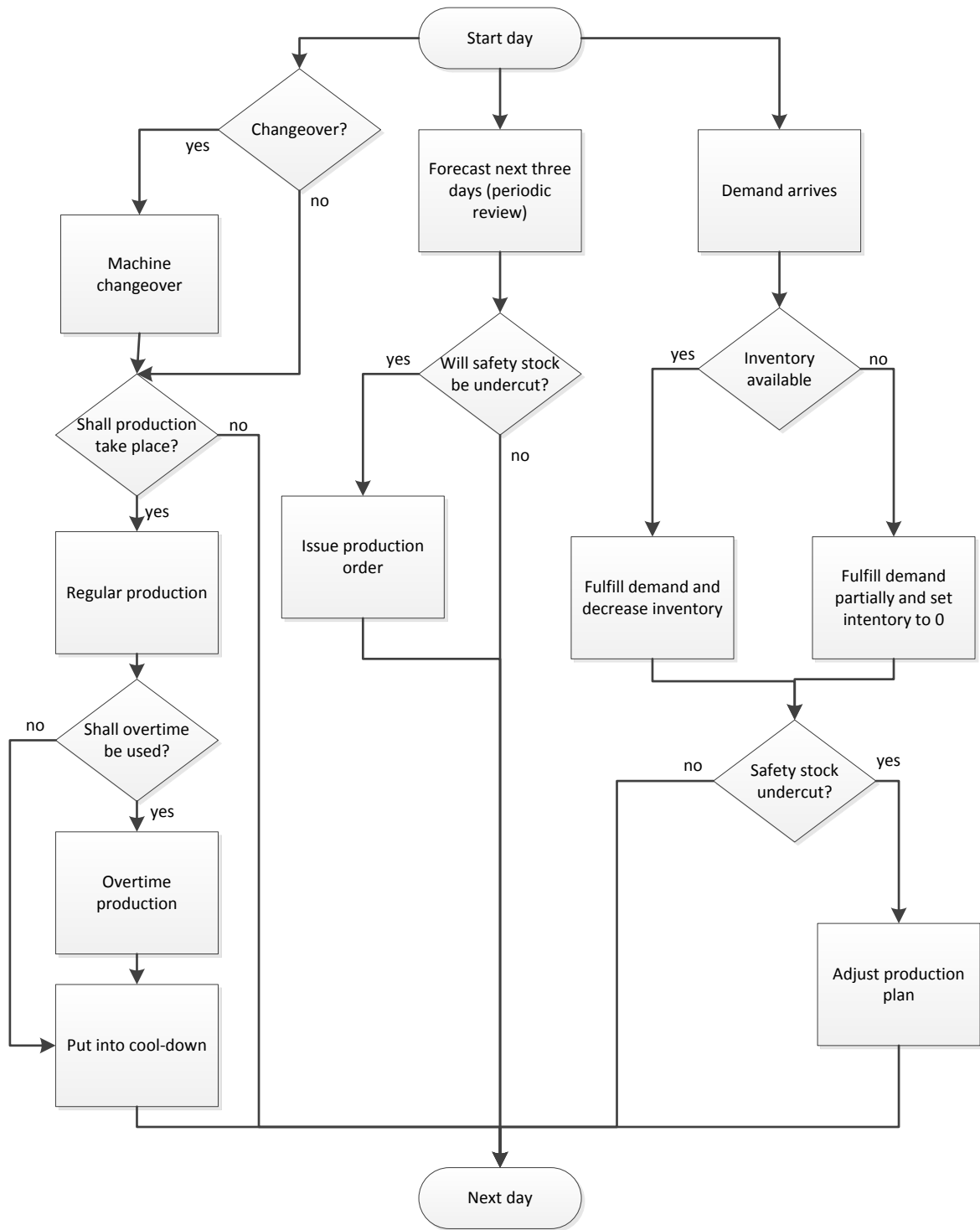
In practice finished products have to go into cool-down storage for 24 hours before getting available for delivery. In the model the products will be made available at the beginning of the next day and the daily demand arrives after the products are made available, assuming that the products are available for delivery the next day. This seems like a reasonable assumption as early orders can usually be fulfilled from inventory or with the products produced early on the previous day. Furthermore the following assumptions were taken:

- The model will focus on the machine capacity and it is assumed that there are no capacity limitations on inventory, personnel or other related resources.
- Stock-outs of raw and working-materials have the same probability when increasing the demand. In practice a higher demand might lead to delivery problems on raw and working-materials and consequently a higher probability of stock-outs, leading to machine idling.

The conceptual flow diagram (Figure 14) consists out of three main parts:

- Scheduling and production.
- Production planning.
- Demand and inventory management.

The demand and inventory management is driving the production planning, which then builds the basis for the production and scheduling. The scheduling is also dependent on inventory levels as changeovers and overtime usage are decided upon based SS.



**Figure 14: Conceptual flow diagram**

#### 4.3.4 Data analysis

While the previous analysis has focused on getting a deep understanding of the system's behavior and real-world decision making, the following data analysis will target the necessary simulation input. In the first step it was specified what was needed as input to the model:

- Probability distributions for the daily demand per item.
- Probability distribution for the daily downtime.
- Probability distribution for the forecasting accuracy in dependency of the demand.
- Daily schedule.
- Cycle time per batch (one pallet with 96 SKUs for item 1 or 84 SKUs for item 2).
- SS per item.

It was decided to use probability distributions rather than historical data for demand, forecasting accuracy and downtimes for two main reasons: Firstly, probability distributions make future testing easier as not only the total value but as well different levels of variation can be tested without changing the complete data set. The second reason is that this will allow the different combinations of demand, capacity and forecasting accuracy levels. The demand distributions are based on the daily values as no data on customer orders was available. Because the production planning is based on forecasts, which do not represent the actual demand, it was decided to include the forecasting accuracy into the model by fitting a probability distribution on the forecasting accuracy, measured as the ratio of forecasts to actual demand. The probability distribution for the unplanned downtime was determined on a daily basis and in relation to the scheduled time on a certain day, because no appropriate data for fitting probability distributions for length of downtime per occurrence and inter-arrival times of occurrences was available.

For the daily schedule there were taken the actual values instead of a probability distribution since this is a planned input, which can be subject to capacity configurations. The model uses a daily schedule (scheduled machine hours), which was obtained by subtracting the daily planned and operational downtimes. Rather than using the actual planned and operational downtimes from the data, it was decided to use fixed subtractions, which are used at TINE, as this will make future planning easier and because planned and

operational downtimes do not have a large impact on the output. Changeover times were excluded from those subtractions as they will be considered within the model.

The probability distributions were determined using the ARENA Input Analyzer and the statistical methods Chi<sup>2</sup>-test and KS-test were applied to test the goodness of fit. As the statistical methods for fitting the distributions are not the focus of this thesis and have been done using the ARENA Input Analyzer, the methods will not be described in detail, but the focus will rather be on how to interpret the test results. First there are two hypothesis stated:

- H<sub>0</sub>: The fitted distribution does represent the data set on an appropriate level.
- H<sub>1</sub>: The fitted distribution does not represent the data set on an appropriate level.

The H<sub>0</sub>-hypothesis represents the taken assumption and it is tested whether this assumption can be accepted or has to be rejected on a certain significance level, which is to be chosen by the researcher.

The ARENA Input Analyzer provides the option of fitting all probability distributions, which are supported by the tool<sup>2</sup>, and provides output measures for all distributions as well as suggesting a best fit distribution with parameters. Both mentioned tests will give a so-called p-value and their test statistic as an output. If the p-value is higher than the chosen significance level, the test indicates that the H<sub>0</sub>-hypothesis cannot be rejected on the current significance level, leading to the assumption that the fitted distribution represents the sample data appropriately. In general it can be stated, that a higher p-value indicates a better fit. Table 6 gives an overview over the fitted distributions, their parameters and the results from the goodness-of-fit tests<sup>3</sup>.

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<sup>2</sup> Probability distributions supported by the ARENA Input Analyzer are listed in Appendix A.

<sup>3</sup> Extended probability distribution analysis results are shown in appendix B.

**Table 6: Fitted probability distributions**

<b>Data set</b>	<b>Best-fit distribution</b>	<b>p-value Chi<sup>2</sup>- test</b>	<b>KS-test statistic</b>	<b>p-value KS-test</b>	<b>Square error</b>
<b>Daily Demand item 1</b>	Beta	0.338	0.058	> 0.15	0.00385
<b>Daily Demand item 2</b>	Erlang	0.495	0.0613	> 0.15	0.00190
<b>Forecasting Accuracy item 1</b>	Normal	0.0587	0.0761	> 0.15	0.00735
<b>Forecasting Accuracy item 2</b>	Erlang	< 0.05	0.0848	> 0.15	0.01050
<b>Unplanned downtimes</b>	Lognormal	0.0624	0.0792	> 0.15	0.01077

The data indicates that the fitted probability distributions represent the data set on an appropriate level. For the two demand distributions both tests indicate that the fitted distributions are appropriate on very high significance levels. As for the unplanned downtimes and accuracy measures, the Chi<sup>2</sup>-test only accepts the H<sub>0</sub>-hypothesis on a lower significance level. But according to Altıok and Melemed (2007) “the chi-square test requires a considerable amount of data (to set up a reasonably “smooth” histogram) [...] the K-S test can get away with smaller samples, since it does not require a histogram.” Since all distributions have a rather low KS-test statistic, which also indicates a good fit, and the p-value of the KS-test indicates that the distributions can be accepted, the H<sub>0</sub> – hypothesis was accepted for all fitted distributions.

Cycle times per pallet were chosen on the basis of the planning values, which already take “waste” due to the quality control into consideration by calculating with more time to include defined percentage of “waste”.

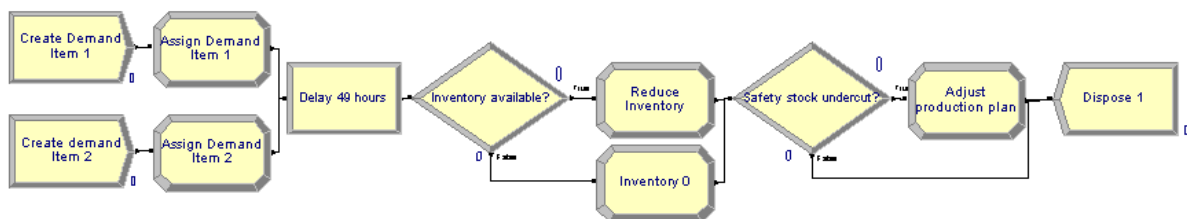
#### **4.3.5 Model development and verification**

The model was developed using the ARENA simulation software package and is accordingly based on general simulation blocks, which build a logical flow of entities through the system. The computer-based model consists out of three main blocks, which interact through global variables. The three simultaneously running model segments are

the “demand and inventory management segment”, the “production planning segment” and the “scheduling and production segment”, based on the developed conceptual model. The global variables connecting the three segments are demand, inventory and production plans.

In the following paragraphs the logic of the three segments will be presented separately. Variables, attributes and expressions, which are part of the model, are written in *italic*<sup>4</sup>. Also are all variables and expressions, which are focusing on amounts (*demand*, *production* and *inventory*) dependent on the product, which is defined by its *item number* and therefore have, at any time, two separate values. Variables representing *time* are not dependent on this and in consequence have only one value at each time. The time variables are set to represent one day, starting at time zero (representing the start of the operation) and up to 24 (end of the day). Furthermore there is applied a variable for *used time*, which measures how much time was used within the production process.

### **Part 1: Demand and inventory management segment**



**Figure 15: ARENA Model Part 1: Demand and inventory management segment**

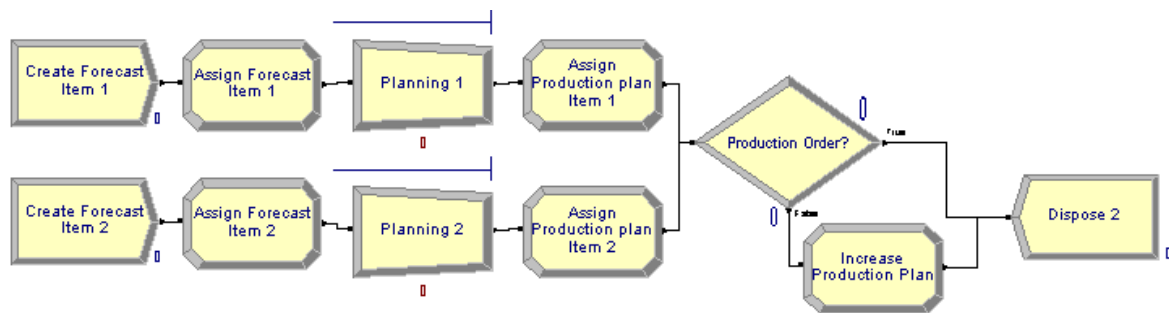
The demand and inventory management segment (Figure 15) starts with the creation of the daily demand. Per *item* one entity is created every day with the first creation taking place at time zero. After assigning the *demand* value, the entity is delayed for three days. This is done because the *production plans* are created for the next 49 hours. Since the model defines the *production plan* in dependency of the *demand*, the first plan will be created at beginning of day two (when three *daily forecasts* have been created). As a specified assumption is that the produced amount from the previous day can be used to fulfill the *demand*, it has to come in shortly after the production starts and consequently needs to be delayed for more than two days. Afterwards it is checked whether the complete *demand*

<sup>4</sup> The variables, attributes and expressions will not be written with the actual names used in the simulation model for the purpose of better reading, but will clearly indicate them.



can be fulfilled, either leading to a reduction of the *inventory* or setting the *inventory* to zero. At the same time *fulfilled* and *non-fulfilled amount* variables are updated. In the case of lost sales, the *production plan* is decreased by that amount as the lost amount no longer needs to be produced. The new *inventory* level is then compared to the *SS* and the *production plan* increased by the difference of *SS* and *inventory* level, if it is below, in order to react to forecasting inaccuracy.

## **Part 2: Production planning segment**



**Figure 16: ARENA Model Part 2: Production planning segment**

The production planning segment (Figure 16) starts with the creation of one *forecast per item* and day at time zero. Three daily *forecasts*, based on the *demand* and the probability distribution on forecasting accuracy, get batched to represent the *forecasted demand* for the next three days. In the following step, it is checked, whether the *forecasted demand* will cause the *inventory* to fall below its *SS* and issue a production order with the value of the *forecasted demand* and becomes a *production plan*.

### Part 3: Scheduling and production segment

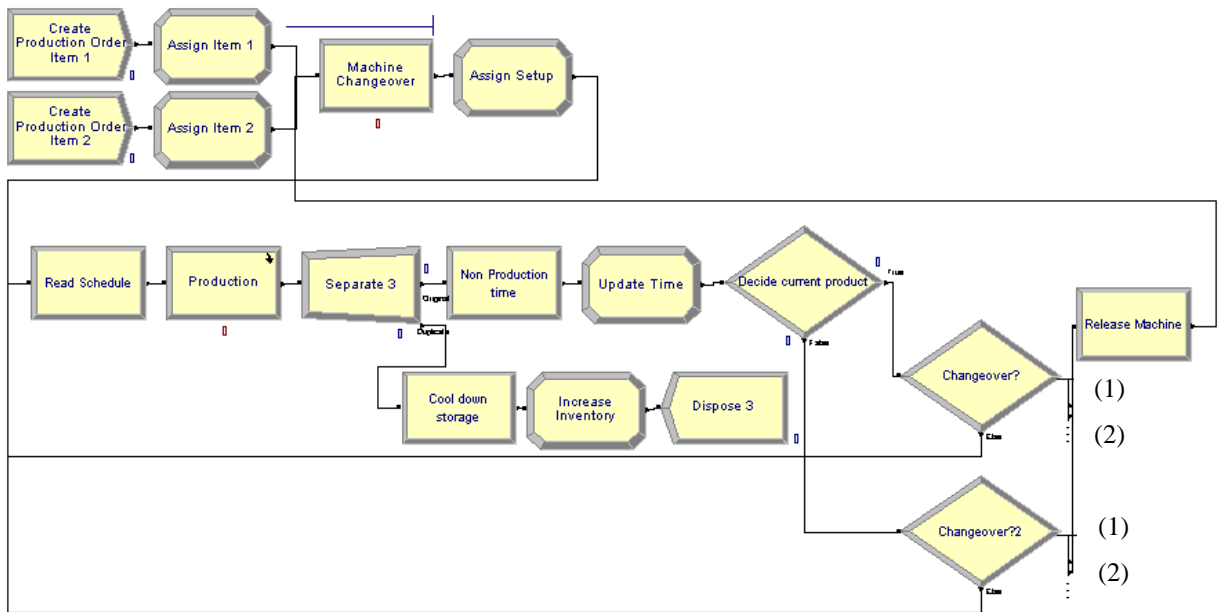


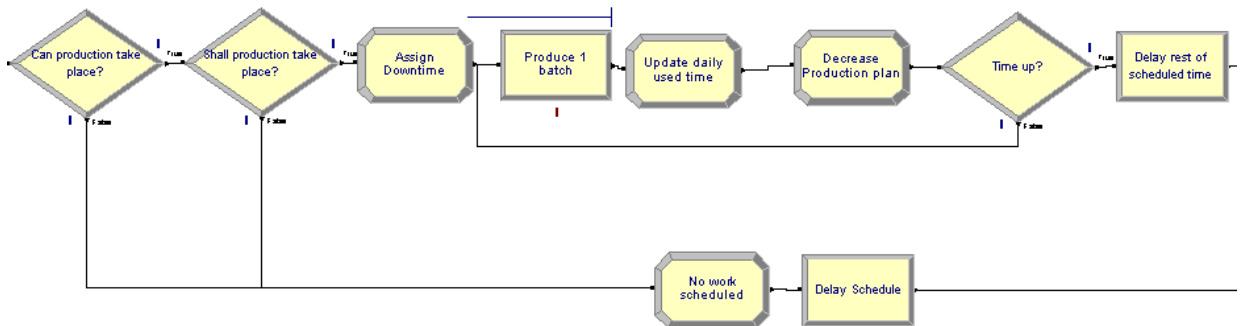
Figure 17: ARENA Model Part 3: Scheduling and production segment

Figure 17 represents the overall scheduling simulation with the production, represented by a sub-model, which will be described separately afterwards. In this segment only one entity per *item* is created at time two (first time a *production plan* is available). Those entities represent PO's, which will get assigned values based on the production planning. The following machine changeover process seizes the resources machine and system and will choose the *item* based on a First Come First Serve rule, which is why the first item to be produced is chosen randomly. Afterwards the variable *changeover time* is set to 0.5, indicating that the machine is set-up for the product. In the following step the *scheduled machine hours* for regular production (based on the schedule calculation described in the data analysis) are read from a data file and the entity enters the production sub-model, consisting out of regular and overtime production. At the end of the production day, the entity will carry information about the *daily produced amount* and will then simultaneously (the entity is separated) enter the non-production time in the schedule and the cool-down period, which will always take as much time as there is left on the day ("24 hours – *productive machine hours* – *overtime* – *changeover time*"). After that time the *inventory* is increased and the next day starts, setting the *time* variables back to zero.

The model then checks which item was produced and based on that, the two options which will lead to a changeover are explored: Either the other *item's inventory* will have fallen

below its *SS* (1) or the current item has a *production plan* equal to zero (2). If this is the case the resource *system* is released, causing the entity of the other *item* to seize the *system* instantaneously as it is queued in front of the seize-module. If not, the same product will be produced another day and starts again with reading the *scheduled machine hours* for the next day.

### **Sub-model “Production”**



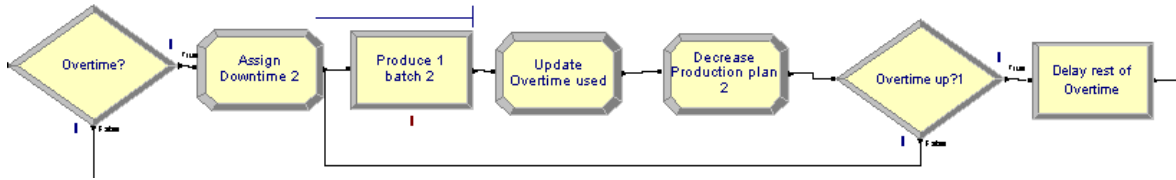
**Figure 18: ARENA Sub-model “Production” (regular production)**

The first part of the production sub-model (Figure 18) starts with checking whether it actually can be produced (if *scheduled machine hours* > 0) and whether it should be produced (if *production plan* > 0). If one of those tests is not true the machine will be idle the following day and the entity is delayed for the *scheduled machine hours*. If however production can and shall take place, the *daily downtime* is assigned according to the probability distribution in dependence on the *scheduled machine hours* and the production starts.

The production process itself is represented by a circle taking place for the length of the available productive machine hours (*scheduled machine hours* – *daily downtime* – *changeover time*). There is produced one *batch* at a time with a *cycle time* delay. Afterwards the variable *used time* is updated and the *production plan* decreased by the produced amount. The next step is to check whether there is enough *time* left for the production of another *batch* or not, comparing the *used time* to the total available productive machine hours:

$$\text{Used Time} + \text{cycle time per batch} > \text{scheduled machine hours} - \text{daily downtime} - \text{changeover time}$$

Therefore, whenever the production of the next *batch* would lead to exceeding the available *time*, the regular production is over. The final step is delaying the entity for the length of the *daily downtime* and the entity enters the overtime section (Figure 19).



**Figure 19: ARENA Sub-model “Production” (overtime production)**

In the beginning it is checked whether *overtime* should be used or not. This will be the case whenever the sum of *inventory* will be below the *SS* at the beginning of the next day:

$$Inventory + daily\ produced\ amount < SS$$

If *overtime* will be used, the following process is a copy of the regular production using 3.5 hours instead of the *scheduled machine hours*. At the end the entity will always be assigned the value of the *daily produced amount* and leave the sub-model.

Model verification was done constantly during the process of model development. As the model was developed, starting with simple models and adding complexity subsequently, the model development was accompanied by discussions with stakeholders. Besides, some parts of the model were tested by comparing the simulation output to manually calculated values. The final model was checked with several persons who have experience with the use of ARENA as a simulation tool in order to verify rather the model works as intended. Averages and standard deviations of the probability distributions were compared to the actual data. As the demand was simulated on a daily level, it was checked whether this also represents the weekly fluctuations of the demand by measuring the values every five days and comparing the standard deviation to historical data. Another method of verification used, was to check the reasonability of the effects of changing input parameters on the model output. For example was the demand increased and the cycle times decreased and the effect on overtime, fill rate and utilization was checked. A higher demand should lead to more overtime, a higher utilization and/or lower fill rates, while a lower cycle time per batch should have the opposite effect. In both cases the measures reacted in a logical way.

### 4.3.6 Model validation

For the model validation, there was done a structured walk-through with several employees from TINE in order to validate whether the model represents the real-world decision making process and logical relations. Also an input-output model validation was done by comparing the output of the model (30 replications) with the data from 2013 and calculating their relative difference (Table 7).

**Table 7: Model validation**

<b>Measure</b>	<b>Model Output</b>	<b>Historical Data</b>	<b>Relative difference</b>
<b>Demand item 1 (SKUs)</b>	894,976.27	886,056	-1.01%
<b>Demand item 2 (SKUs)</b>	1,740,934.50	1,755,544	-0.83%
<b>Production item 1 (SKUs)</b>	902,601.50	886,664	+1.80%
<b>Production item 2 (SKUs)</b>	1,749,952.50	1,790,617	-2.27%
<b>Productive machine hours</b>	1,254.36	1,276.59	-1.74%
<b>Unplanned downtime (hours)</b>	415.88	434.73	-4.34%
<b>Utilization</b>	46.15%	46.97%	-1.75%
<b>Fill rate item 1</b>	99.62%	99.49%	+0.13%
<b>Fill rate item 2</b>	99.64%	99.74%	-0.10%

As the relative differences for all performance measures are below 5%, the model was accepted to represent the reality in appropriate detail. Overtime was not used in this validation because there was only one value available, which is highly dependent on the sources of uncertainty. Furthermore in week 51, excessive overtime was used, when there was no need according to the rule and in consequence the overtime usage of 28 hours in year 2013 was not considered representative. The model output on overtime was 21.12 hours with a 95% confidence interval (CI) between 18.24 and 24 hours.

### 4.3.7 Performance of simulations

The main dimensions, which have to be determined for the performance of the simulation, are the number of independent model replications (sample size), the run length and the warm-up period (Manuj, Mentzer and Bowers 2009). However, the factors of run-length and warm-up period are only critical for steady-state simulation models, while for terminating simulation models, the number of replications is the only critical factor (Altiock

and Melemed 2007). As it was defined to use a terminating simulation model, the important factor to determine was the number of replications.

Manuj, Mentzer and Bowers (2009) write that “increasing the number of runs reduces the standard deviation of the sampling distribution, and therefore, for a given level of confidence, the half-width of the confidence interval decreases”. However it is very complicated to decide on an appropriate number of replications since the time and money to perform additional simulations has to be weighed against the value of additional runs. A common method to decide of the amount of replications is to gradually increase the number of simulations, until either an absolute or relative degree of precision, measured by the half-width was obtained (Bienstock 1996). For this case study it was chosen to use the relative precision method with a 5% desired relative precision level for all continuous variables. However, for overtime, as a discrete variable which can only take multiple values of 3.5, it was decided to use the absolute precision approach to get a half-width below 3.5 (one occurrence). The specified precision values were achieved with twelve replications, but as a large number of replications increase accuracy and confidence in the results and the computing time was quite short, the number of replications was set to 30.

The length of the simulation was determined based on the defined planning horizon. As the model is focusing on output data on a yearly basis (time horizon for tactical capacity planning), the run-length was set to represent one year. As no operations take place at weekends, only five days per week are simulated.

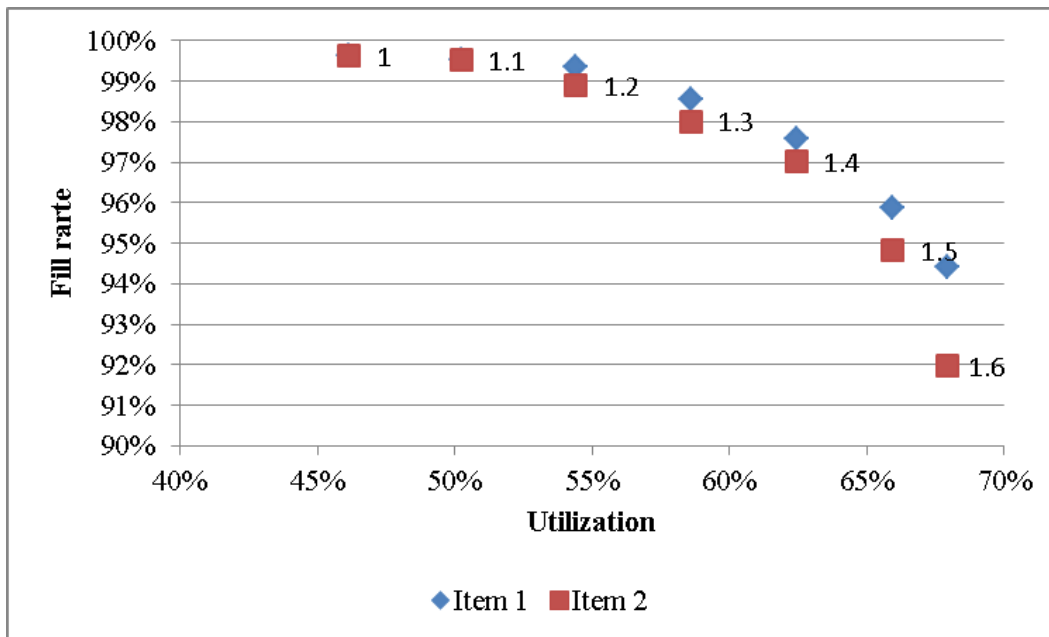
#### **4.3.8 Impact analysis**

##### **Test class 1: Increase in demand with current settings**

For this test class six scenarios were considered, each with a demand increase of 10% for both products. The analysis of the results focuses on the fill rate per item, the utilization and overtime<sup>5</sup>. As it can be expected that a higher demand leads to a higher utilization and decreasing fill rates, the relation between those three factors was investigated (Figure 20).

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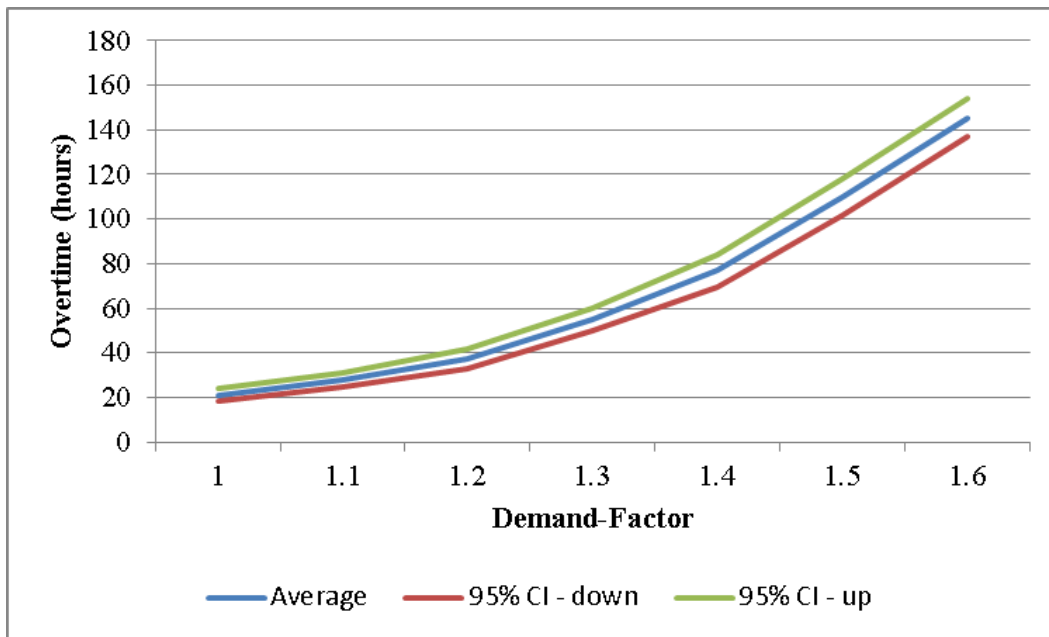
<sup>5</sup> The simulation output values per test class are listed in appendix C.



**Figure 20: Relation between utilization and fill rate**

The data labels indicate the factor of the demand (1.1 standing for a 10% demand increase for both products etc.). The graph shows that an increasing demand and consequently a higher utilization will lead to an exponential decrease in the fill rate. For increases of 10% and 20% the fill rates are expected to still be above 98.5%. It is interesting to see that on very high demand levels (50% and 60%) the difference in the fill rates between items 1 and item 2 increases. Increases of 50% and 60% might seem extreme, but this must not necessarily be an increase of the external demand, but can also come into existence through a different allocation to production lines.

At this point another effect has to be considered: As the used overtime depends on the demand, an increased demand level will probably lead to more overtime. This effect was investigated and the results are shown in figure 21.



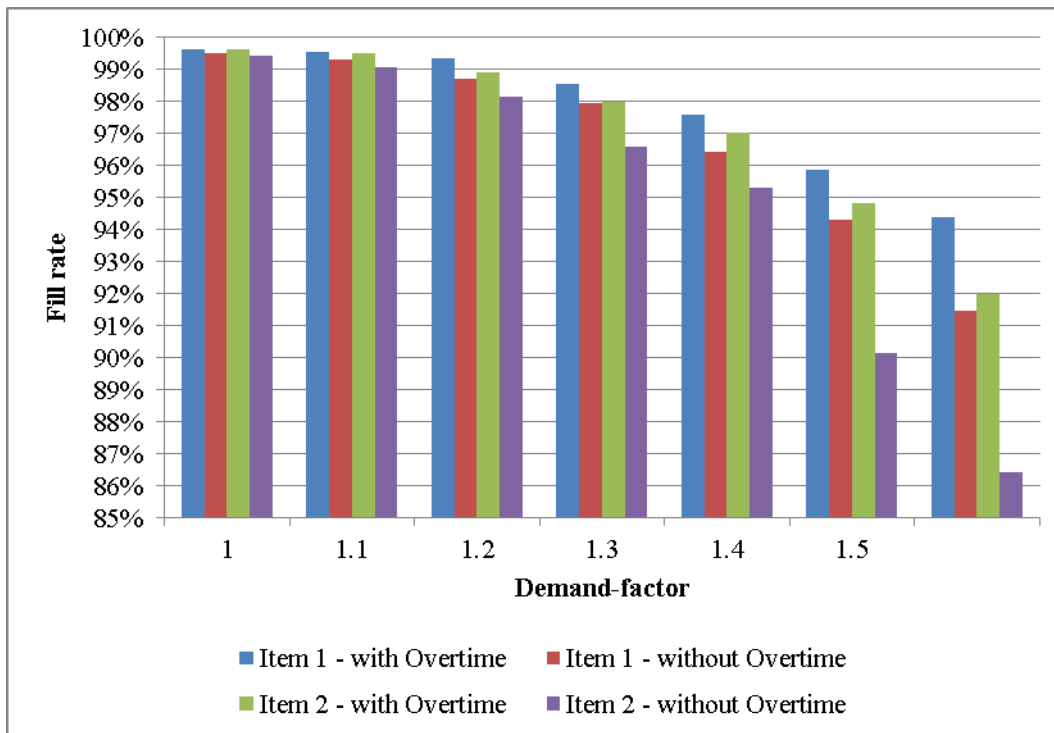
**Figure 21: Effect of increasing demand on overtime**

The graph shows the different levels of overtime, including 95% CIs, calculated based on the half-width. Overtime increases exponentially with a linear increase in demand. When looking at both previous figures together, one can conclude that 10% and 20% demand increases have a relatively small impact, as the system is operating on a low utilization. The increase in overtime is counteracting the decrease in fill rate and it can be expected that without using overtime the fill rates would decrease faster. Test 2 was driven in order to examine how well the system would perform in terms of fill rate without any overtime allowance.

**Test class 2: Increase in demand without overtime**

This test class is checking the impact of using overtime on the fill rates. The previous results are compared to the results obtained when disabling the model to use overtime (Figure 22). To test that, the decide-module within the model was set to a zero percent chance, when deciding on overtime.



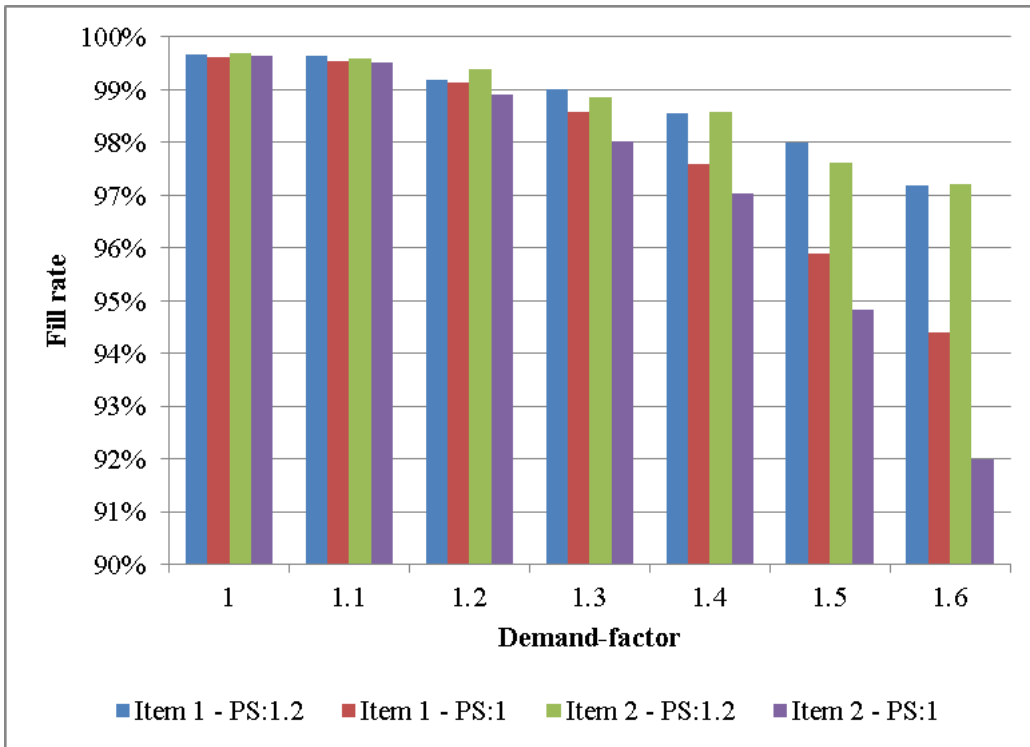


**Figure 22: Effect of overtime prohibition on fill rates**

The results show the expected effect that overtime is counteracting the decrease of the fill rate with an increasing demand. While with lower demand factors, the fill rates are just slightly smaller, the fill rate is decreasing in bigger steps without overtime, leading to larger differences with demand factors of 1.2 or higher. Those test results are very relevant when deciding on whether or not to use overtime. As the overtime production is cost intensive, there should be done a monetary analysis comparing the negative impact on the income (lost sales) with the positive effect of lower costs (no overtime) in order to decide whether overtime is desirable or not. However, also strategic goals should be considered.

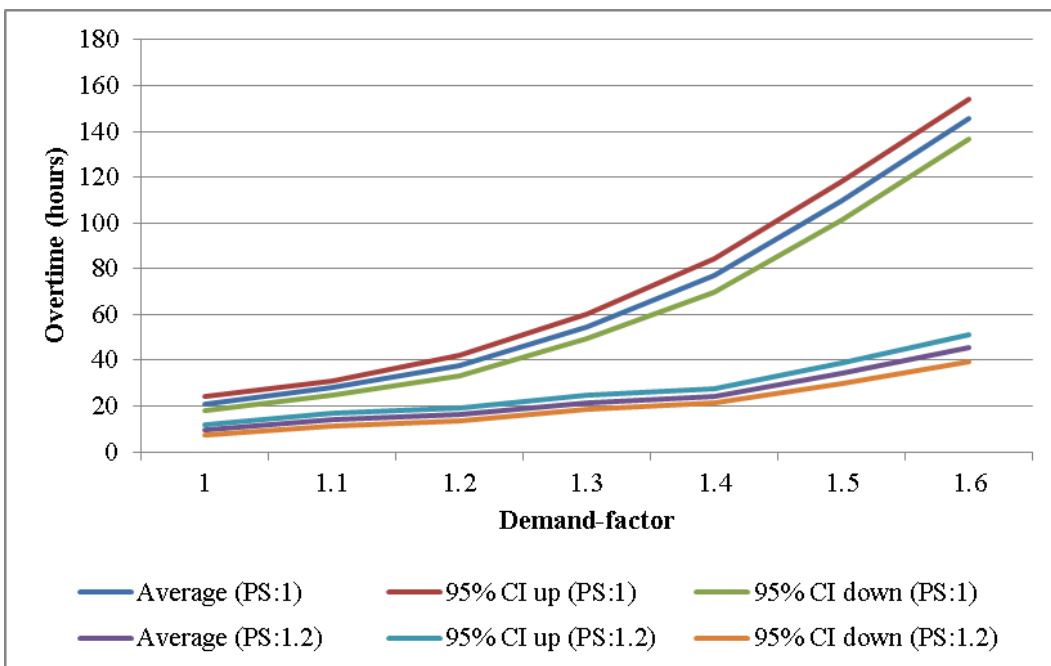
### **Test class 3: Increase in demand with a higher production speed**

For the last test the cycle time per batch was decreased by 20% (production speed factor PS: 1.2) and the results compared to the actual output with the actual production speed. In a first step the fill rates in both cases with increasing demand were compared (Figure 23). The production speed is a method to increase the throughput rate. For the testing the cycle time per batch and item was decreased by 20%.



**Figure 23: Effect of increased production speed on fill rates**

With the higher production speed the fill rates decrease in smaller steps. The graph indicates that especially from demand increases of 30% or more, the higher production speed has a significant impact on the fill rate. At the same time less overtime is used and reacts with smaller increases to higher demand levels, as shown in figure 24.



**Figure 24: Effect of increased production speed on overtime**

In the current state an increased production speed would not have a strong impact on fill rates and overtime, but from demand increases of 30% or more, the impact gets more significant. One must also consider that while fill rates are higher and less overtime is used, the utilization of the machine will be lower (between 9.28% and 11.54% lower in the tested scenarios).

The previous tests have all shown that at the utilization level the system is operating right now, capacity configurations have a rather small impact on the performance measured by fill rates and overtime. The tests have demonstrated that the system has very high fill rates without using overtime and that the usage of overtime or increasing the production speed will have major impacts only when high demand increases take place. However, production time and overtime will affect costs and utilization of flexible resources (staff), who can be appointed to other tasks, are affected.

## 5 Discussion

This section will focus on advantages and disadvantages of the simulation model and the general methodology as well as discuss opportunities to develop the model and use the model for further capacity planning and analysis.

I believe that the developed methodology builds a good basis for a structured approach to capacity planning. The classification is an important factor for the development of methodology, as the modelling approach depends on the problem type and the uncertainty within the system. The problem type is furthermore important to decide on appropriate system analysis methods. As the development of simulation models is rather time-consuming, a suggestion for the future is to focus first on systems, which do not meet the goals, are operating on high utilization levels or have a capacity lag in several weeks, which can be found based on the system analysis as presented.

As a disadvantage it can be seen that the simulation model could in this case not consider the effect of the deliveries from other plants as they are not dependent on the production in Heimdal, but instead on the production of the other plants. This was addressed by a relative decrease of the demand over the whole year, while in practice the relative decrease may vary between weeks. Another issue on demand modelling was the data availability and purity, as demand values were only available on a daily level and on many days throughout the year were not registered at all. Furthermore the developed simulation model is (like models in general) not usable for all kind of capacity decisions, but was developed towards a special purpose. Besides it must be stated, that the model is a representation of reality and uses logical relations to simulate choices the way they are usually taken and planned. However, in reality some decisions might be taken in a different manner due to subjectivity.

Nevertheless an advantage is that a broad range of capacity configurations can be tested within the model and yearly performance measures can be estimated under different capacity configurations and demand scenarios, which can help to understand the impact of decisions. The model has been found to represent the system accurately and in appropriate detail and includes the possibility of getting output measures on regular production hours, overtime production hours and idle time hours, which based on machine hour costs helps estimating operating costs. Also total sales and average inventory levels are supported and

can be monetized. With those measures a monetary analysis can be driven to further support decisions. The model also helps to understand the system with its logical mathematical relations and rules. The reusability of many parts of the model for similar problems is considered another positive aspect as the general ideas and approaches can be applied within TINE.

The data collection and analysis for the simulation model was very difficult since necessary data often was not available or only available on aggregate levels that did not fit the simulation. The model was changed several times in order to react to those factors. Those are of course “real world” issues that have to be dealt with, either actively by intruding measurements of the data or passive by making assumptions and adjusting the model.

The model so far represents a system without sequence dependent changeovers, which might be the case in other systems. For such systems, the scheduling will be more difficult to model. The opportunities for the further development of the simulation model can be divided into three parts:

- Horizontal integration
- Vertical integration
- Level of detail.

Horizontal integration means that several production lines will be simulated and run simultaneously, which will on the one hand allow to take out biases such as the relative decrease of the demand over the whole time, as the other line which supplies Heimdal would be simulated as well, and on the other hand give a better decision support as limited resources should be used in an optimal manner. This means that even though increasing the capacity on one machine would lead to better results, the resources might be better used on other production lines.

Vertical integration refers to a simulation of other parts of the addressed supply chain with the goal of simulating the complete supply chain starting from the milk production and ending with the delivery to the customer. So far the model works with a set of assumptions, basically focusing on assuming that the capacity on other parts of the supply chain will not be an issue even when demand increases. Especially when considering

horizontal and vertical integration, the problem of limited capacity should be considered. If for example the demand for all cheese products would increase and the model tests the possibility to fulfill the demand on the packaging lines, the cheese production will at some point not be able to deliver everything, leading to “starving” of the machines. The same might apply downstream of the supply chain as for example in the transportation capacity. The vertical integration will allow a bottleneck analysis on a supply chain level.

As for the level of detail it can be said that the simulation on the current level of detail gave appropriate results and is in consequence considered to be detailed enough. Furthermore the development of a more detailed simulation would use more resources. However a more detailed simulation could be achieved for example by separating the downtime distribution by occurrence whether than taking the daily downtime and then used in combination with the uptime distribution between the occurrences. Also the demand distribution could be found for customer orders with inter-arrival times instead of using the daily demand, when the data is made available.

For a further analysis and to accomplish a more sophisticated decision support, other performance measures should be calculated. The model can support several other performance measures, also including monetary measures, which will support decisions better by means of a financial investment analysis (Break-even-analysis or ROI). The model was built with the intention of making this possible, but for the testing in this work it was decided to focus on some measures rather than doing a complete analysis.

## **6 Conclusions and further research**

### ***6.1 Conclusions***

The first research objective was to develop a methodology to address the problem of decision support for capacity planning when facing uncertainties. Based on the literature review and earlier applications of modelling approaches under uncertainty, it was established a research methodology, consisting out of a system analysis, the definition of appropriate performance measures, analysis of opportunities to define alternative capacity plans and the development of a simulation model to analyze the impact of capacity decisions, which uses probability distributions to capture uncertainties. Performance measures were defined based on the case company's preferences and the opportunities for alternative capacity plans are based on investigating capacity plans and configurations as well as demand scenarios.

The second sub-problem was to apply the developed methodology on a real-life case study. Following the defined steps, a deep understanding of the system was acquired and a simulation model was developed, which can help estimating effects of a broad range of capacity configurations on several defined performance measures. The impact analysis within this thesis has shown the development of utilization, fill rate and overtime usage under different capacity settings (increased production speed and no overtime allowance) and found that the impact on the current demand levels and with small increases is rather small as the system is operating on a low utilization level, but gets more significant with higher demand levels. The model supports more capacity decisions and performance measures than were actually used and can build the basis for future planning within the analyzed system, including a financial analysis.

It can be stated that with the simulation model a tool was developed which can support TINE on future capacity planning. Several parts of the model, and especially the simulation logic, can be used to model similar production lines. Furthermore the methodology can help to address similar problems with a structured approach.

## **6.2 Further research**

After this exploratory approach to the problem, there could be found determined several possibilities for future research. The first group of future research options focuses on the development of the model and the general methodology:

- Apply downtimes by occurrence and inter-arrival times rather than on a daily level, when data is made available.
- Apply demand in terms of customer orders and inter-arrival time of orders when data is made available. This would allow measuring order fill rates instead of SKU fill rates.
- Develop the model towards the use on production lines with more than two items, which might need more sophisticated rules for changeover assignment.
- Develop the model to support production lines with sequence-dependent changeovers.
- Adjust the model for the purpose of studying the system's long-term behavior with a steady-state simulation. On that basis also strategic decisions could be approached.

A second group of future research is the application of the model for more detailed and sophisticated decision support and analysis:

- Usage of the model for monetary analysis: As the model can give output on regular production hours, overtime production hours and downtime hours, these could be monetized by terms of a machine-hour rate, considering costs of driving the machine, personnel costs etc. Furthermore inventory levels can be measured by holding costs and the total sales by income per sold item. On this basis an investment analysis, as for example by calculating the ROI, could be done.
- Horizontal integration by simulating several production lines to support capacity planning on an aggregate level.
- Vertical integration by simulation operations down- and up-stream the supply chain for a bottleneck analysis.
- The developed model could be used in combination with an analytical model for production planning in order to test the capacity satisfaction of optimum production levels in a hybrid modelling approach.



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## Appendices

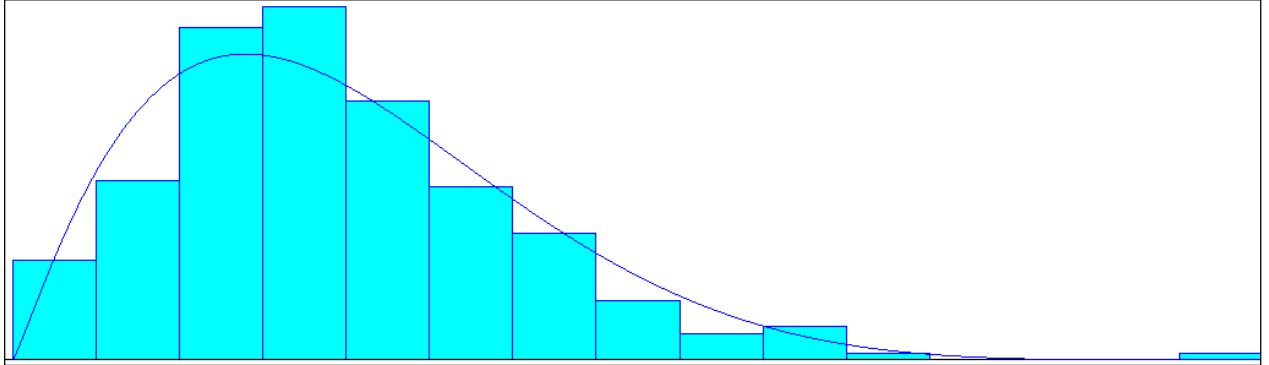
### *Appendix A: Probability distributions supported by the ARENA Input Analyzer*

Beta distribution	Lognormal distribution
Empirical distribution	Normal distribution
Erlang distribution	Poisson distribution
Exponential distribution	Triangular distribution
Gamma distribution	Uniform distribution
Johnson distribution	Weibull distribution

## Appendix B: Probability distribution analysis

### Daily demand item 1:

#### Histogram:

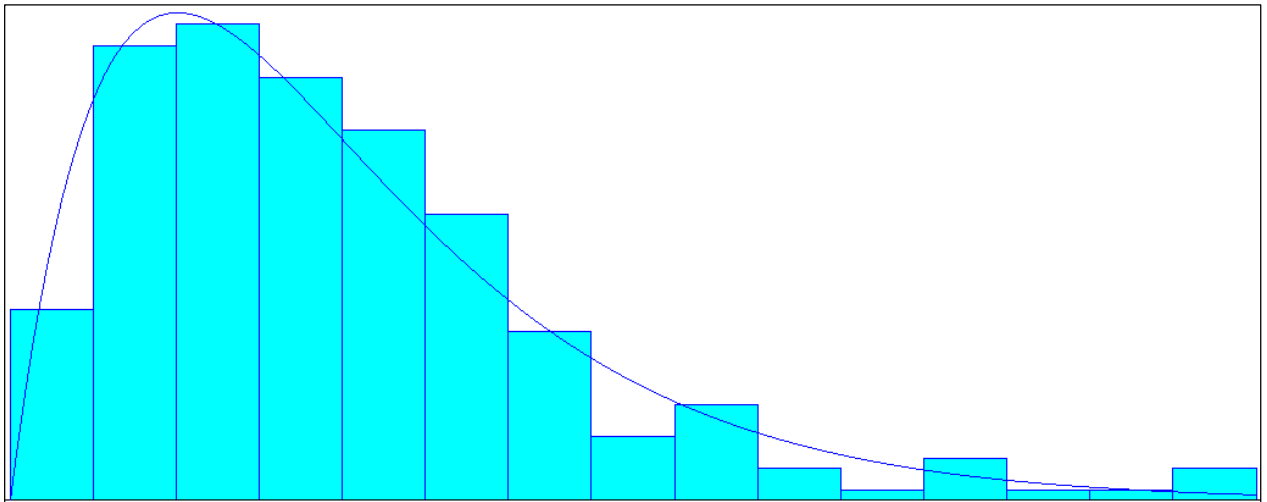


#### Distribution summary:

Distribution:	Beta
Expression:	$384 + 1.2e+004 * \text{BETA}(2.14, 5.97)$
Square Error:	0.003850
Chi Square Test	
Number of intervals	= 9
Degrees of freedom	= 6
Test Statistic	= 6.97
Corresponding p-value	= 0.338
Kolmogorov-Smirnov Test	
Test Statistic	= 0.058
Corresponding p-value	> 0.15
Data Summary	
Number of Data Points	= 249
Min Data Value	= 384
Max Data Value	= 1.24e+004
Sample Mean	= 3.55e+003
Sample Std Dev	= 1.75e+003
Histogram Summary	
Histogram Range	= 384 to 1.24e+004
Number of Intervals	= 15

## Daily demand item 2:

Histogram:

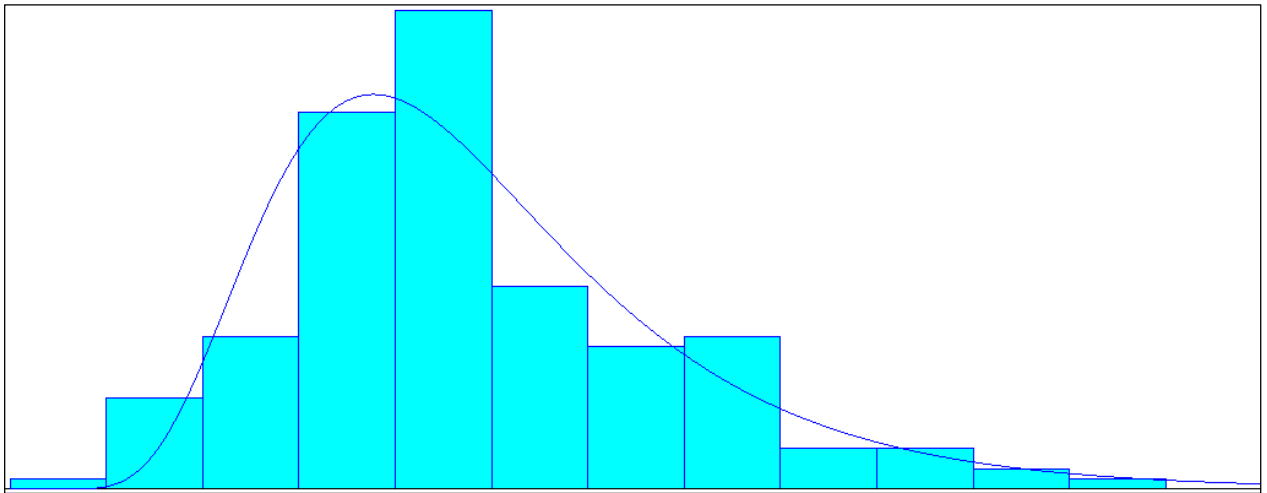


Distribution summary:

Distribution:	Erlang
Expression:	536 + ERLA(3.21e+003, 2)
Square Error:	0.001908
Chi Square Test	
Number of intervals	= 9
Degrees of freedom	= 6
Test Statistic	= 5.4
Corresponding p-value	= 0.495
Kolmogorov-Smirnov Test	
Test Statistic	= 0.0613
Corresponding p-value	> 0.15
Data Summary	
Number of Data Points	= 252
Min Data Value	= 536
Max Data Value	= 2.45e+004
Sample Mean	= 6.96e+003
Sample Std Dev	= 4.37e+003
Histogram Summary	
Histogram Range	= 536 to 2.45e+004

## Daily downtime as a fraction of scheduled hours:

Histogram:



Distribution summary:

```
Distribution:      Lognormal
Expression:       LOGN(0.246, 0.109)
Square Error:    0.010774

Chi Square Test
Number of intervals = 7
Degrees of freedom  = 4
Test Statistic     = 9.07
Corresponding p-value = 0.0624

Kolmogorov-Smirnov Test
Test Statistic     = 0.0792
Corresponding p-value > 0.15

      Data Summary

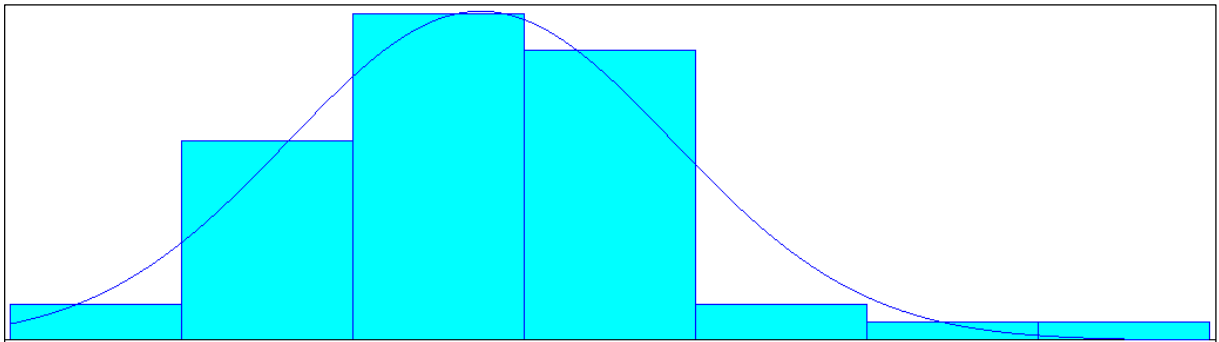
Number of Data Points = 169
Min Data Value        = 0.05
Max Data Value        = 0.59
Sample Mean           = 0.245
Sample Std Dev        = 0.0978

      Histogram Summary

Histogram Range       = 0 to 0.65
```

## Forecasting accuracy item 1:

Histogram:



Distribution summary:

```
Distribution:      Normal
Expression:       NORM(1.24, 0.277)
Square Error:    0.007356

Chi Square Test
Number of intervals = 4
Degrees of freedom  = 1
Test Statistic     = 3.64
Corresponding p-value = 0.0587

Kolmogorov-Smirnov Test
Test Statistic     = 0.0761
Corresponding p-value > 0.15

      Data Summary

Number of Data Points = 51
Min Data Value       = 0.71
Max Data Value       = 2.14
Sample Mean          = 1.24
Sample Std Dev       = 0.279

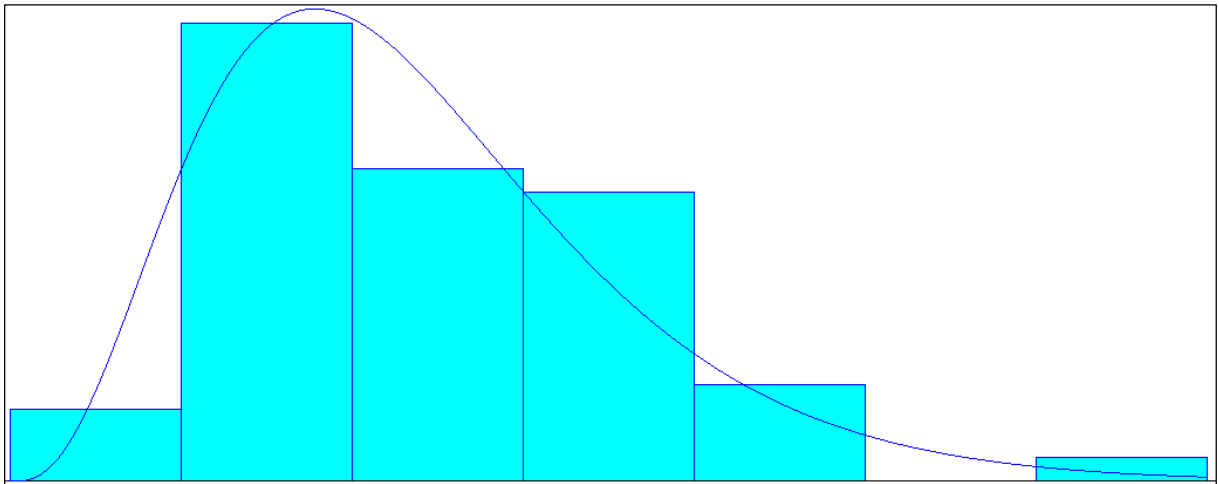
      Histogram Summary

Histogram Range      = 0.56 to 2.29
Number of Intervals = 7
```



## Forecasting accuracy item 2:

### Histogram:



### Distribution summary:

```
Distribution: Erlang
Expression: 0.15 + ERLA(0.242, 4)
Square Error: 0.010503

Chi Square Test
Number of intervals = 3
Degrees of freedom = 0
Test Statistic = 3.18
Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
Test Statistic = 0.0848
Corresponding p-value > 0.15

Data Summary

Number of Data Points = 52
Min Data Value = 0.4
Max Data Value = 2.9
Sample Mean = 1.12
Sample Std Dev = 0.479

Histogram Summary

Histogram Range = 0.15 to 3
```

## ***Appendix C: Simulation output***

### **Baseline (30 replications):**

<b>Performance measure</b>	<b>Value</b>	<b>Half-width</b>
<b>Demand Item 1 (SKUs)</b>	894,976.27	8,538.45
<b>Demand Item 2 (SKUs)</b>	1,740,934.50	30,874.37
<b>Production item 1 (SKUs)</b>	902,601.50	9,238.76
<b>Production item 2 (SKUs)</b>	1,749,952.50	32,312.42
<b>Productive machine hours</b>	1,254.36	14.43
<b>Unplanned downtime (hours)</b>	415.88	10.39
<b>Utilization</b>	0.4615	0.01
<b>Fill rate item 1</b>	0.9962	0.00
<b>Fill rate item 2</b>	0.9964	0.00

### **Test class 1 (30 replications):**

<b>Demand-factor</b>	<b>Fill rate item 1</b>	<b>Fill rate item 2</b>	<b>Utilization</b>	<b>Overtime (hours)</b>	<b>95% CI down</b>	<b>95% CI up</b>
1	99.62%	99.64%	46.15%	21.12	18.24	24
1.1	99.54%	99.52%	50.22%	28.12	25	31.24
1.2	99.14%	98.90%	54.40%	37.57	33.09	42.05
1.3	98.57%	98.01%	58.60%	54.83	49.67	59.99
1.4	97.58%	97.02%	62.42%	76.88	69.58	84.18
1.5	95.89%	94.82%	65.94%	109.78	101.48	118.08
1.6	94.40%	91.99%	67.93%	145.48	136.92	154.04

**Test class 2 (30 replications):**

<b>Demand-factor</b>	<b>Fill rate item 1</b>	<b>Fill rate item 2</b>	<b>Utilization</b>
1	99.53%	99.43%	45.71%
1.1	99.32%	99.09%	50.19%
1.2	98.73%	98.16%	54.20%
1.3	97.94%	96.59%	57.72%
1.4	96.42%	95.30%	61.43%
1.5	94.33%	90.14%	63.51%
1.6	91.46%	86.42%	64.46%

**Test class 3 (30 replications):**

<b>Demand-factor</b>	<b>Fill rate item 1</b>	<b>Fill rate item 2</b>	<b>Utilization</b>	<b>Overtime (hours)</b>	<b>95% CI down</b>	<b>95% CI up</b>
1	99.68%	99.70%	36.87%	9.57	7.46	11.68
1.1	99.64%	99.58%	40.32%	14.23	11.5	16.96
1.2	99.19%	99.38%	43.90%	16.57	13.74	19.4
1.3	99.00%	98.85%	47.91%	21.47	18.35	24.59
1.4	98.55%	98.57%	50.87%	24.5	21.57	27.43
1.5	97.99%	97.61%	54.40%	34.42	30.08	38.76
1.6	97.18%	97.22%	57.41%	45.38	39.4	51.36

