Master’s degree thesis

LOG950 Logistics

Production planning in Glamox ASA

A hybrid approach for ML-CLSP under uncertainty

Jarle Drivdal Thomassen

David Behrens

Number of pages including this page: 91

Molde, 26.05.2015

Molde University College
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Acknowledgement

The master thesis represent the final work for us as master students at Molde University College – Specialized University in logistics. From December 2014, to May 2015, the research has been carry out in order to obtain Msc in logistics.

Firstly, we would like to express graduate to our supervisor Associate Professors Arild Hoff for always being available and willing to answer questions. We would also like to thank Glamox ASA for their hospitality, help and support during the last six months. In addition, we would like to specially thank Helge Ottar Heggemsli for providing information, data and helpful insight where needed.

Lastly, we really appreciated that Magne Sandvik plant manager at Glamox Molde let us choose direction of the research ourselves. This has been the most challenging and interesting problem for both of us.

Jarle Drivdal Thomassen and David Behrens

Molde, Norway

May 2015

Abstract

This thesis considers the real world production-planning problem in Glamox. When customers are faced with multiple configuration choices, it raises the need for a flexible manufacturing system in order to be able to quickly switch between production of several different stock keeping units. For this purpose, multiple work centers have been established that can be set up to perform production of multiple different stock keeping units. Furthermore, a multi-level product hierarchy requires production planning to also consider material requirements planning. Lastly, stochastic factors like variable production times, variable setup times and machine breakdowns will always be a factor in such production environments.

Therefore, a hybrid method has been developed in order to solve the multi-level capacitated lot sizing problem ML-CLSP under uncertainty. The model incorporates an analytical model to obtain a production plan and a simulation model to evaluate it. Solution is found through a looping procedure. Each time that a plan is found to be infeasible in the simulation model (Cannot meet demand on time), adjustments are made in the analytical model. This procedure is performed until number of infeasibilities are on a desirable level – robust production plan.

Due to complexity of the problem, it became necessary to develop two analytical models in order to ensure quality of the solution. Much effort was put into the development of a tabu search based heuristic to evaluate the solution of the exact method because of memory issues. It was found that the exact method gave sufficient results in our case.

Furthermore, results from applying the hybrid model to a case based on Glamox showed how crucial scheduling decisions are in a multi level product environment. On the other hand, it was still possible to increase robustness of the plan quite a lot with close to zero additional cost.

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Dictionary

External demand – Demand from customers.

Internal demand – Demand from higher level SKUs.

SKU – Stock keeping unit.

End-item – SKUs with external demand.

Intermediate – SKUs with internal demand.

Raw material – SKUs purchased from and delivered by external suppliers.

Time Bucket – A single period, normally days, weeks or months.

Net external demand- External demand including backorders and end-inventory from the previous time bucket.

Net internal demand- Internal demand including end-inventory from the previous time bucket.

Resource – A production unit that can be man or machine.

Requirement – Where not specifically stated otherwise, requirement means internal demand of intermediates and or raw materials.

ERP – Enterprise resource planning system

1.0 Introduction

Much research has been performed on topics regarding production planning. Recent years advances in computer technology and easy, cheap access to computer power has made it possible to solve more complex problems with the aid of personal computers. This thesis proposes a hybrid method to solve the multi-level, capacitated lot sizing problem (ML-CLSP) under uncertainty.

1.1 Problem Overview

Traditionally, the overall goal for any company is to meet customer needs while maintaining a more or less sustainable income. In order to support the corporate strategy, the production function ensures that demand is met by utilizing the means at their disposal. These can be available plants, machinery, equipment, labor and materials (Arnold, Chapman, and Clive 2011).

Further, production planning evolves around the development of a production plan that specifies what, when and how much that is going to be produced (Sule 2007, 1). The plan is developed a certain time prior to the actual production taking place. This time can be referred to as the "planning horizon" and is most commonly given in either days, weeks or months (Thomas and McClain).

Thus, the objectives of production planning includes deciding production quantities and inventory levels for all products in all time periods during the planning horizon as well as equipment, labor and material needs in the same time periods (Arnold, Chapman, and Clive 2011). Bad planning can lead to excess inventory, backorders/lost sales or overproduction.

How the actual production planning is performed will vary from company to company depending on how the manufacturing system is configured. Flexibility of the system is an important aspect. Production planning in an flow line environment where product types are few is less challenging than planning in a flexible manufacturing system where machines will have to be set up for batch production of many different products weekly (Sule 2007).

The manufacturing system can be more or less constrained, meaning that number of plants, equipment and labor can be fixed or somewhat flexible. Some companies have the option to lease equipment, outsource/subcontract production to other plants or work overtime during demand peaks. This flexibility gives additional options which needs to be considered in the production planning process as a last resort (Thomas and McClain).

The Bill of material (BOM) also referred to as Gozinto structure is an representation of the product hierarchy that shows dependencies between SKUs on the top level via intermediates to raw materials on the lowest level. How to ensure that we have the right amount of intermediates and raw materials available prior to production of a higher level product/intermediate is therefore essential and must be addressed in the production plan. This part of production planning is called material requirements planning (MRP) (Scott 1994).

In reality, production planning is highly stochastic because of many uncertain parameters like production times, unplanned machine downtime, demand, defect productions etc. How to cope with these uncertainties is therefore an important aspect of the planning process.

How demand is handled in a firm, highly affects the production planning process. Demand can fluctuate from period to period and these can be hard to predict with certainty. In order to cope with this, three main production strategies can be applied. In one end of the scale we have make-to-stock (MTS) strategy. Products are produced according to forecasts that attempts to predict future demand. Based on this forecast, products are then produced and stored, awaiting the arrival of actual orders. Because of stochastic elements, deviations in the forecasts can lead to excessive inventory due to overproduction or backorders/lost sales due to underproduction. The other extreme strategy is make-to-order (MTO) where production is postponed until an actual order arrives. This strategy allows a high degree of customer specifications, meaning that customers can decide the properties of the product. In between these two, assemble-to-order (ATO) is a mixed strategy. Subparts are produced and stored, while end products are assembled only when an actual order arrives. End-items consist of different configurations of intermediates/raw materials and thus allow a certain degree of customer choices. Forecasts are needed to predict future requirement for subparts. Lastly, engineer-to-order (ETO) configures and develops a new product based on customer configurations (Sule 2007).

1.2 Research Environment

"*The Glamox group is a group of companies that develops, manufactures and distributes professional lighting solutions for the global market*" (www.Glamox.com 2015). Customers are typically professional companies and municipalities that order total lightning solutions for a project such as office buildings, hospitals, schools, vessels and offshore installations. Orders received from customers can vary a lot in size, from big requests with long lead times to smaller orders that should be delivered as soon as possible. Maintaining a high service level is very important due to the nature of the customers. In the worst-case scenario, a project might be delayed due to the late arrival of an order.

The business strategy is based on differentiation with high focus on product quality. This focus is visualized as most of their quality systems are certificated according to ISO 9001. In addition, all products have a five year guarantee when it comes to production and material flaws. Therefore, in order to prevent defects and ensure top quality, a number of measures have been taken. Firstly, all new product types go through substantial testing to make sure that they work properly in the right environment. There are for instance special requirements for luminaires that operate in harsh environments like at sea. Secondly, every single unit in a production order is tested throughout for defects like earth faults, dysfunctions etc. before being shipped (www.Glamox.com 2015).

Glamox own a number of different plants and testing facilities. While some of them are located in other countries like Germany, Estonia and Kina, most are here in Norway. This thesis will solely focus on the production facility in Molde, which produce and deliver some of their products.

Products are categorized as A, B, C, M and E items based on degree of standardization and how demand is managed. A-items have no lead time and should be delivered immediately from inventory while B-items have a lead time of 10 days and C-items 5 weeks. M-items offer special configuration choices for the customer while still being defined as a product in the BOM. Lastly, E items are products that are not specified in BOM and a new product is engineered based on customer specifications. Glamox have more than 9000 products specified in their BOM. Note though that many of these are very similar and the only difference is due to small configuration choices from the customer's side. To offer many choices can be seen as a part of the business strategy and a way to differentiate oneself from competitors.

Sales are mostly performed by professional salespersons and orders to the plant are received from these. As mentioned above, A-items should have zero lead time and be delivered the same day as the customer order arrives. To make this possible, a safety stock is managed for each item. Safety stock level is calculated based on average demand for the last six months and should cover four weeks' worth of demand. When inventory falls below safety stock, a production order is released to the plant. This way of handling demand can be seen as a typical MTS strategy. B and C-items have a certain lead time which impose that production of the whole product or parts of the product isn't initiated before an actual order arrives. In addition to all raw materials, lower level SKUs that go into the production of B-items often have a safety stock due to the short lead time. A pure MTO strategy is only present when production of all SKUs that goes into a product is postponed until after an order has arrived. This means that the production strategy tends to have a higher degree of ATO for B-items than for C and M-items. Even though E-items are ETO, it might consist of multiple subparts specified in the BOM. Therefore, production and/or assembly of these will have to be performed when an order arrives. Similar to B, C and M-items, the production strategy can include more or less ATO or pure MTO, with the addition of some degree of ETO.

As mentioned earlier, Glamox present the customer with many choices when it comes to product configurations. Offering more choices means more SKUs which leads to a higher requirement on flexibility. To meet requirements to flexibility without possessing one machine for every single SKU, a specific system has been developed. This manufacturing system is referred to as cellular manufacturing in the literature (Curry and Feldman 2010) . The production floor has been divided into several work centers that consist of multiple resource types. Each resource types can perform several tasks where every task is related to the production of a specific SKU. Changing from production of a SKU to another one on the same resource will impose a setup time. Most of the production of intermediates have been automated with machines and robots, but there are still some work centers that utilize manual labor. This is especially the case when assembling and testing end-items. On another note, even though much of the production has been automated, it is still necessary to monitor the process so that defects, breakdowns etc. can be detected at an early stage. Setups are performed manually and include fetching necessary raw materials, reprogramming machines and in some instances running tests to ensure that, machines are programmed right.

If we exclude long-term investments like buying new equipment etc., there are several ways for Glamox to increase production capacity if needed. Firstly, production can be subcontracted to other plants in the Glamox group if they produce the same SKU. In some cases, there exist idle machines that are not used in the daily production. If necessary, these machines can be used to increase capacity when needed. Note though that using more machines in most cases will require more workers to operate them and can thereby reduce capacity other places. Lastly, it is also possible to use overtime to increase capacity for short periods – Working longer than you normally would have.

Production planning is currently performed manually in Glamox. The ERP system BAAN was implemented as a control system several years ago and still provides the production planners with necessary information. When an order arrive, information regarding quantity demanded, SKU number and delivery date is automatically stored in the ERP system. At the same time, future stock levels are updated for end-item(s) with associated intermediates. The task of a planner is to ensure that stock levels are always kept on a desirable level. To plan production manually, poses many challenges. For instance, it must be ensured that production is within capacity limits at all times. Even though the ERP system keeps track of available capacity, it is hard to make the best decisions. On another note, experience should never be underestimated.

1.3 Research Questions

Main purpose of this research is to develop a method that can be used for production planning in Glamox. This leaves us with the following research questions.

- How can we solve the production-planning problem in Glamox?
    1. What are the characteristics of the problem?
    2. Will an exact method suffice?
    3. How can uncertainty be handled?

2.0 Literature review

The next chapter is going to presents literature concerning the production-planning problem. The goal is to establish a good understanding of various problem types one can face in this field of study as well as methods that have previously been used to solve them. It is also desirable to look into different concerns and problematics associated with the different solution methods.

2.1 The lot sizing and scheduling problem

Lot sizing and scheduling problems is a term used in operation research to describe certain types of production planning problems. The key feature that is common to all of these is the introduction of a setup time when switching from production of a specific SKU to another SKU on the same machine. Due to limitations when it comes to available production time during a time bucket, frequent setups will consume a lot of capacity while few setups can lead to high inventory levels. Thus, because of this tradeoff between inventory and capacity consumption, it is difficult to decide the optimal quantity (lot size) to produce of each product every production run in order to meet demand in the best way possible (Brahimi et al. 2006).

2.1.1 Characteristics

The lot sizing problem (LSP) can include a number of different characteristics. Based on reviews on various types of LSPs and other sources, a number of different characteristics can be extracted (Karimi, Fatemi Ghomi, and Wilson 2003), (Amorim et al. 2013) and (Haase and Kimms 2000). Note that LSPs can include more or less of these and that most of the characteristics highly affect problem complexity.

2.1.1.1 Capacitated

The problem is capacitated when there are capacity restrictions associated with one or more resources. Examples of capacity restrictions in the manufacturing system can be limited machine capacity and manpower available or small inventories. In most cases, capacity constraints add complexity to the LSP.

2.1.1.2 Multi-Level structure

A multi-level product structure means that product dependencies are integrated in and considered by the model. As explained in chapter 1.1. *Problem overview*, these dependencies are represented in the BOM and can be pretty complex. Including a multi-level structure in the model increases complexity.

2.1.1.3 Period overlapping setups

Introducing period overlapping setups basically means that setups performed before the end of a time bucket is transferred to the next time bucket. More precisely, a machine does not have to be set up again for a specific SKU if that SKU was the last to be produced during the previous time bucket (Suerie 2006).

2.1.1.4 Sequence dependent setup times

Sequence dependent setup times include the logic that setup times can vary based on the previous product that was produced. An example can be that the setup time for product A on a specific machine is longer if product B was produced before than if product C was produced before. Both period overlapping setups and sequence dependent setup times adds to the complexity of a problem (Menezes, Clark, and Almada-Lobo 2011).

2.1.1.5 Big/small bucket formulation

A big bucket formulation allows the model to perform multiple setups within a time bucket while a small bucket formulation only allows one setup in each time bucket. Big bucket formulations are much more complex than small bucket formulations (Amorim et al. 2013).

2.1.1.6 Lot size restrictions

In many lot sizing problems, a minimum lot size is included. It ensures that, if production takes place, it must at least equal the quantity that is specified by the minimum lot size. Different products can have different minimum lot sizes and the size is typically that of one or several parcels. In addition, there can also be restrictions when it comes to production quantities that exceed minimum lot size. (Scott 1994) mentions a lot sizing technique with fixed increments above minimum lot size. These fixed increments are often equal to the size of a parcel.

2.1.1.7 Shortages

Allowing shortages means that the model includes the possibility of negative inventory represented in the form of either backorders or lost sales. Normally, it is not usual to plan for shortages, but due to fluctuations in demand, it can become necessary to make undesirable choices. Including this in the model also increase problem complexity.

2.1.1.8 Aggregation

That production planning is often performed on an aggregate level means that similar products and resources with similar properties are aggregated into groups in order to decrease the number of variables and thus also problem complexity. On the other hand, improper aggregation can reduce validity of the production plan. By validity we mean that the solution (plan) received from the model might not be feasible or optimal in reality – Solves a different problem than desired (Graves 1999).

2.2 **Solution Methods**

The next chapter is going to present different solution methods that can be used to solve the LSP. It starts out by presenting various analytical methods followed by a brief introduction to simulation.

2.2.1 Analytical Methods

Three different analytical methods have been considered. The chapter starts out by explaining what is meant with an exact method. Thereafter, two approximation methods, heuristic and metaheuristic are introduced. All methods have strengths and weaknesses and different methods can be favored in different settings.

2.2.1.1 Exact methods

Exact methods are methods that guarantee optimal solution and is therefore always preferable over any other solution method if the right circumstances are present. The main terminology is to examine all possible solutions to a problem in order to decide which solution(s) that is optimal. The downside to this is that the search can be very ineffective. The Branch-and-cut (Mitchell 2002) and branch-and-bound (Lawler and Wood 1966) is algorithms that are able to exclude parts of the solution space without affecting quality of the solution.

The problem by using exact methods arise when optimal solution is not possible to obtain within a scope set by the user. The main explanation for this is complexity. How much time and memory an algorithm use to obtain the optimal solution, indicates in a very simple way complexity of the problem (Ausiello 1999). Complexity issues related to exact methods causes the need for alternative approaches.

2.2.1.2 Heuristics

Heuristics can be applied as an alternative method to obtain solutions to problems where the exact method draws short. The common denominator for all heuristics are that, they do not guarantee an optimal solution. On the other hand, this does not necessarily mean that the solution obtained is bad. All heuristics follow a set of rules or ideas that guides the search towards the final solution. Some are simple minded while others can be more sophisticated (Hromkovic 2010).

Further, different heuristics can have different goals. Improvement based heuristics initialize its search from an already existing solution. We also have constructive heuristics that builds a solution piece by piece without a given starting point. Further, the library of different heuristics can be divided, based on the degree of randomness. A greedy heuristic always obtain the same solution when applied to a specific problem. This is because it always picks the most promising move based on its current position in the search. A move is performed when the search moves from one solution to another. At the other side of the scale, we have random heuristics. In contrast to a greedy heuristic, all moves are picked on a random basis. The advantage of this type of heuristic is that it is able to obtain several different solutions to the exact same problem (Talbi 2009).

2.2.1.3 Metaheuristic

As mentioned above, heuristics are used to either construct solutions or further improve an already constructed solution. An improvement-based heuristic is often only performing a move if this results in an improved objective value. When all improvements are performed, the heuristic is stuck in local optimum. By a local optimum, it is meant that no single moves are available that directly improves the objective value. Further, the solution that is obtained can be either good or bad. Metaheuristics are special types of heuristics. By applying certain rules, it introduces the possibility to guide the search away from local optimum. This enables the heuristic to explore several regions in the solution space. Similar to heuristics, the number of different metaheuristics are huge. However, they can be divided into two main groups: local search and population based methods. A brief introduction to the most common concepts are given below (Talbi 2009).

Various types of local search

Several different local search (LS) techniques have been described in the literature. Examples are, variable neighborhood search (Mladenović and Hansen 1997), very large neighborhood search (Ahuja, Orlin, and Sharma 2000) and iterated local search (Lourenço, Martin, and Stutzle 2001). Isolated, LS can be seen as a heuristic but is rapidly used as a component in various metaheuristics. Common to all LS techniques is that they consist of four main steps. Firstly, it requires a starting solution to initialize its search from. Secondly, neighborhood of the search must be defined. More precise, this consist of defining close related solutions that can be reached through a move. The third component defines how to evaluate possible moves. A common way to differentiate between possible moves is to evaluate them based on what they add to the objective value. Lastly, the stopping criteria is met when there are no possible moves that directly improves the objective value. Consequently, the search finds itself in a local optimum. The downside with LS is that it can be stuck in an undesirable local optimum (Gendreau 2003) .

Tabu search (TS)

Fred Glover introduced tabu search (TS) with two papers (Glover 1989) and (Glover 1990) which is further described in (Glover and Laguna 1997).The fundamental idea is a guided search procedure based on local search in order to improve an already existing solution and further escaping local optima by using specific TS elements.

Simulated annealing (SA)

Simulated annealing is a randomized local search heuristic that was first introduced by (van Laarhoven and Aarts 1987). Following the same principles as TS, the basic idea is to improve an already existing solution. The local search procedure incorporates a random function which manipulates the acceptance criteria. Thus, LS does not necessarily pick the best possible move. Further, The acceptance criteria work as a control parameter while searching and is constantly changed during the search (Ribeiro and Hansen 2002). As the search progress, the acceptance criteria becomes stricter and stricter until only improving moves are accepted. Consequently, the search is finished when stuck in a local optimum.

Genetic Algorithms (GA)

Genetic algorithms are population-based algorithms and was first introduced by (Holland 1975). The method is derived from theory of evolution and introduces a logic based on "survival of the fittest". Firstly, it requires a population of different solutions. From these, new solutions are created by applying crossover or mutation. Crossover describes a way to combine components from different solutions. Mutation is randomly changing a component in a single solution. The survival of the fittest come into play when new solutions are created. Good mutations and crossovers have higher probability to survive into the next population of solutions made.

2.2.2 Simulation

There are a lot of literature regarding simulation. Below, a short discussion regarding some of the key aspects have been performed. All discussions are based on (Winston and Goldberg 2004) and (Render, Stair, and Hanna 2009).

“*Simulation may be defined as a technique that imitates the operation of a real-world system as it evolves over time*”(Winston and Goldberg 2004, p 1145). In other words, the goal of a simulation model is to mimic a real world system and apply changes to it in order to analyze the effects. Compared with an analytical model, you could say that the difference is that a simulation model does not make analytical decisions.

Simulation models utilize entities, attributes and state variables to manipulate and change the state of a system over time. Further, a system can be discrete or continuous which defines how system variables behave. In a discrete system, state variables change at certain points in time while in continuous systems, these are constantly changing.

Probability distributions are rapidly applied in simulation models in order to describe variations in values for state variables. For instance, number of defect occurrences in a production system can vary a lot from day to day. In order to generate these variations, a popular method is to fit historical data to a probability distribution that simulates these variations.

Another key aspect of simulation is that a model is usually solved a certain number of times in a row. This number is usually referred to as number of replications. The reason for this is to generate statistical representative values for system performance. If a model include probability distributions, system performance can vary a lot from replication to replication. Thereby, in order to generate a statistical significant number of observations, it is necessary to solve the model several times.

2.3 Previous Work

As described above, LSPs can include many different characteristics and there is a lot of literature regarding different problem types that consist of more or less of these. LSP in its simplest form was first introduced in the historical EOQ model (Harris 1990) which solves the un-capacitated, single-item, continuous time problem with constant demand. (Jans and Degraeve 2007) generalizes it by including discrete-time intervals to include variations in demand. Cost of production and inventory storage is minimized under the assumption that there is unlimited production and inventory capacity in every time bucket.(Drexl and Kimms 1997) further extend our knowledge when it comes to general problem types from the literature. Firstly, the capacitated lot sizing problem (CLSP) is described as a capacitated, single-level, big bucket model with multiple end-items. The discrete lot sizing problem (DLSP) is a small bucket model allowing only one product to be produced in a time bucket. In addition to this, it is also an “all or nothing” assumption, which means that production uses all available capacity to produce as much as possible of the scheduled product during that time bucket. A continuation of DLSP is the continuous setup lot sizing problem (CSLP) which removes the “all or nothing” assumption. This lets us specify the quantity to be produced but it is still assumed that only one product can be produced in a time bucket. The CSLP is further improved with the proportional lot sizing and scheduling problem (PLSP) which includes the possibility of scheduling a second item during the remaining production time in a time bucket. The model also makes sequencing decisions as to which product is produced first and second within the time bucket. The general lot sizing and scheduling problem (GLSP) incorporates sequencing decisions in a big bucket model. More precisely, the production sequence within time buckets is decided by the model. Lastly, neither of the above originally includes a multi-level product structure but it can be added at the cost of a substantial increase in computational effort depending on complexity of BOM.

Assumptions made in the models above have many shortcomings when dealing with real world problems. They can on the other hand serve as a general classification of problem types for the LSP. (Süral, Denizel, and Van Wassenhove 2009) developed a Lagrange relaxation based heuristic to address the capacitated, multi-item, single-level and single-machine LSP. Note that multi-item only means that the model can solve problems with several products. (Akartunalı and Miller 2009) generalizes the formulation by incorporating a multi-level product hierarchy. A heuristic procedure is tested on multiple datasets with different complexity, strictly developed to evaluate model performance. (Jans and Degraeve 2007) reviews metaheuristics used for the LSP which provides a lot of good references as well as an idea of the applicability of different types of metaheuristic on the LSP.

Sequence and period overlapping setups have been the cause of much research in the field of LSP. Adding sequence dependent setups in a big bucket model entails the introduction of sequencing decisions within time buckets. This is because production time now depend on the sequence that products are produced in. (Haase and Kimms 2000) have developed a linear MIP model for the purpose of solving the single-level, single-machine, multi-item big bucket LSP with sequence dependent setup times and costs. The branch and bound algorithm is applied to find optimal solution. (Meyr 2000) solves a problem with similar properties and specifies it as the general lot sizing and scheduling problem with sequence dependent setup times (GLSPST). Solution is found using a heuristic approach. (Meyr 2002) further generalizes the problem by adding multiple machines in their formulation. To simplify, products have also been aggregated into families if there is no significant setup time between them. Changing to production of a product from a different family triggers a significant setup time. Solution here, is also found with a heuristic. (Haase and Kimms 2000) and (Gupta and Magnusson 2005) have included period overlapping setup times with the possibility to preemptively setting up a machine for production in the next period.

Summed up, most LSPs are considered complex problems in the literature and because of this, heuristic methods dominates the area. (Bitran and Yanasse 1982) states that CLSP is NP-hard in most cases. By NP-hard we understand that no exact method exist that can solve large instances of the problem within polynomial time (Karimi, Fatemi Ghomi, and Wilson 2003). Further, (Talbi 2009) points at production and scheduling, logistics, routing and transportation as areas where metaheuristics have been applied with great success due to complexity of the problems.

3.0 Methodology

3.1 Research process

The research process presented below, describes how we want to approach the problem in order to answer the research questions. In other words, it describes how the analysis part of the thesis will be conducted. As mentioned earlier, the objective is to propose a method to perform production planning in Glamox. The thesis proposes a hybrid solution method which incorporates both optimization and simulation. Furthermore, the research process will constitute of three main parts.

- Process analysis
- Model development
- Computational experiments

3.1.1 Process analysis

Before development of necessary models can start, a process analysis describing the current manufacturing system in Glamox must be conducted. It is important to understand how it works in order to specify characteristics of the LSP and make necessary assumptions. The process analysis lay the foundation for subsequent steps when it comes to validation of the models physical structure – which aspects of the manufacturing system that must be covered by the models as well as data needs – which parameters that is needed. Data gathering is postponed until after the process analysis and model development in order to ensure that data needs are defined by the model and not the other way around. It is not desirable to change model functionalities because sufficient data is not available.

3.1.2 Model development

Based on the process analysis, the exact method is formulated mathematically. The mathematical formulation will serve as a framework for development of the analytical model(s). It defines the objective function that is going to be minimized or maximized as well as the constraints that the system operates under. Because many LSPs are considered to be NP-hard, a heuristic approach will be developed simultaneously with the exact approach.

A simulation model is also developed simultaneously with the analytical model(s). The idea is to address variations in stochastic parameters and describe how these can affect feasibility of the production plan. The simulation model attempts to mimic the current production process in the best way possible. Ideally, all aspects of the system would be included but, since reality is very complex, simplifications will have to be made. Therefore, a discussion regarding the level of detail in the model will be performed. This chapter will also explain the rules that will be applied when a production plan is found to be infeasible.

3.1.3 Computational experiments

Before the hybrid method can be applied, computational experiments for the analytical model(s) will be conducted. The objective is to make sure that the production plans generated are of acceptable quality. Several test instances will be generated and applied to both of the analytical models.

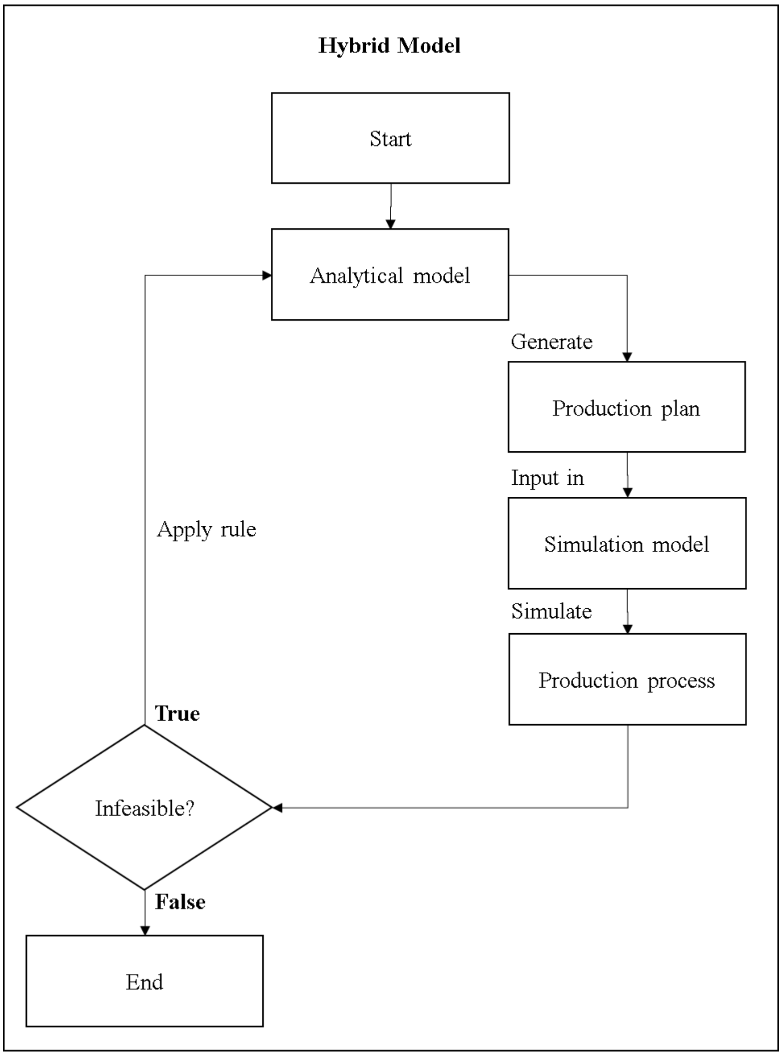

Figure 1: Hybrid model

Lastly, an example is presented, were the hybrid model is applied to a case based on Glamox. The production-planning problem is solved by a looping procedure that incorporates both the analytical and simulation model as illustrated in Figure 1. Firstly, the analytical model generates a production plan. Since this plan is solely based on deterministic data, deviations in these might affect feasibility of the plan. To address this issue, the next step would be to test robustness of the plan. A simulation model simulates the production process several times and stores information about infeasible occurrences. Thereafter, a specific rule is applied in the analytical model to try and generate a new plan where these infeasibilities won't occur again. New production plans will be generated and tested for several iterations, until probability of infeasibilities are on a desirable level – Robust plan.

4.0 Analysis

The next chapter is going to present the analysis part of the thesis. For the sake of clarity, this chapter has been divided into three subchapters. Firstly, the process analysis will be conducted followed by a detailed description of the models that has been developed and used. Lastly, computational results from testing the various models will be explained and presented.

4.1 Process analysis

The process analysis attempts to place Glamox in a theoretical context and thus lays the foundation for model development later on. What is the characteristics of the problem? Which assumptions needs to be made? Which parameters must be included? are questions that will be answered.

4.1.1 Characteristics

From chapter 1.2 *Research environment*, it is understood that Glamox faces a type of LSP in their production planning. In order to define the LSP at hand and establish its characteristics, several meetings have been conducted. Based on these meetings, characteristics of the LSP have been stated and discussed below.

4.1.1.1 Capacitated

From meetings, it appears that Glamox have a lot of available capacity at their disposal. Even so, the case is considered to be somewhat capacitated because all production planned during the planning horizon cannot be completed within a single time bucket. Consequently, production during the planning horizon must be distributed amongst the available time buckets as efficiently as possible. It is on the other hand expected that there will be enough available capacity during the planning horizon to cover internal and external demand without needing to backorder.

4.1.1.2 Aggregation

As mentioned in chapter 1.2 *Research environment*, the plant include a large number of different resources. There are automatic machines that only require supervision as well as workstations that utilize manual labor. For the continuation of this thesis, identical resources that perform the same tasks, will be aggregated and referred to as resource types.

4.1.1.3 Big Bucket formulation

The manufacturing system allows multiple SKUs to be produced on the same resource type during a single time bucket. Therefore, the model will be formulated as a big bucket model.

4.1.1.4 Multi-level structure

All end-items are unique and composed of different configurations of intermediates and raw materials. In turn, intermediates also have requirements associated with them and can consist of either raw materials, lower level intermediates or a combination of both. This implies that production of a single end-item can include several production steps in order to finalize all the required components. From this, it is understood that MRP is an essential task and must be considered by the models.

4.1.1.5 Sequence dependent and period overlapping setups

As mentioned earlier, including sequence dependent setup times or period overlapping setups in a big bucket model, means that the model has to make sequencing decisions within time buckets. Especially period overlapping setups can be of interest in the Glamox case. However, after an evaluation of how much effort it would require to implement this, it has been decided to exclude it from the analytical model. Regardless, the simulation model will allow for production of an SKU to be performed over several days if necessary to finish a commenced lot.

4.1.1.6 Lot size restrictions

Most of the lower level intermediates have minimum lot size restrictions associated with them. A lower bound dictates the quantity needed to be produced whenever a new production run is initiated. This implies that all lot sizes must be larger or equal to the minimum lot size restriction for that SKU. In addition, there are also restrictions associated with production quantities that exceed minimum lot size for some SKUs. In these cases, the quantity in excess must be separable into fixed increments – typically the size of a parcel. In the continuation of this thesis, fixed increments above minimum lot size will be referred to as batch sizes while lower bounds are described as minimum lot sizes. According to (Voß and Woodruff 2006), it is not very delicate to include constraints like this in a modelling situation and they should be removed if possible. Adding additional constraints narrows the solution space in which the optimal solution can be found and depending on the situation, this might worsen the optimal solution. On the other hand, if constraints are wrongly removed, it might reduce validity of the model. There can be many underlying reasons for Glamox to use minimum lot sizes and batch sizes in the production process. In order to ensure validity, the analytical model will therefore include the possibility to have both minimum lot size and batch size restrictions associated with a SKU.

4.1.1.7 Shortages

From the business strategy, it is clear that shortages should be avoided if possible. On the other hand, in some cases these are unavoidable. As a soft constraint, to let the model make decisions even though demand cannot be fulfilled for all end-items, backorders have been included.

4.1.1.8 Uncertainty

As it was described in chapter 1.2 *research environment,* maintaining a high service level is important for Glamox. Therefore, an extra focus have been put into developing a method that incorporates robustness into the production plan. Stochastic parameters can be many, and those considered in this thesis will be stated below.

4.1.2 Problem definition

It was not possible to find a problem in the literature with the exact same properties. The problem has therefore been formulated as the multi-level capacitated lot-sizing problem (ML-CLSP) even though it also includes lot size restrictions and lead time considerations. In addition, uncertainty will be included which leaves us with the final formulation of ML-CLSP under uncertainty.

4.1.3 Assumptions and modeling choices

It has been necessary to make several assumptions due to complexity of the ML-CLSP.

4.1.3.1 Short term capacity increases

As mentioned in chapter 1.3 *Research Environment*, Glamox possess several means to increase production capacity during periods of need. Firstly, this thesis is only going to focus on the production facility in Molde, making the problem a single facility one. Secondly, neither of available options to increase capacity will be considered by the model. Thus, subcontracting to other plants, utilization of extra machines or working overtime is not considered. As mentioned in a meeting with Glamox, it is not desirable to plan for disaster. These means are rather ways to handle uncertainties in the production and not utilized unless things does not go as planned.

4.1.3.2 Scheduling

It is necessary to make a comment on scheduling. Some of the literature out there defines scheduling as being a part of production planning. The difference between the two is that production planning in itself does not make sequencing decisions within time buckets. A big bucket model without sequence dependent and period overlapping setups as presented in this thesis will not consider sequence decisions within time buckets.(Voß and Woodruff 2006) argues that sequencing is decisions performed on the operation level while production planning concerns planning on the tactical level. To clarify, this thesis will solely focus on production planning and scheduling will not be considered.

4.1.3.3 Planning horizon

Deciding length of the planning horizon is an important task that tells something about the level of detail that the model is going to analyze. A long planning horizon can for instance be one or several months with time buckets equal to a week while short planning horizons can be one or more weeks with time buckets equal to a day. As mentioned in chapter 1.2. *Research Environment*, Glamox receives different types of orders. Large orders with long lead times require a longer planning horizon than smaller orders with shorter lead times. If production of a large orders are postponed for too long, there might not be enough capacity available to finalize it in time. This implies that, for large orders, production must be scattered over the planning horizon to ensure that capacity will not become an issue. For this thesis, models will be tested on problems with short rather than long planning horizons. Thereby, capacity planning for large orders must be performed separately from the short term production planning. There are many reasons for choosing a short planning horizon. Firstly, time buckets can be shorter and more detailed without increasing computational effort drastically. Secondly, short time buckets makes scheduling a simpler task due to more detailed plans. Thirdly, a longer planning horizon requires the analytical model to include forecasting in order to predict future availability of capacity.

4.1.3.4 Raw materials

Ultimately, all SKUs are unique combinations of different raw materials. Thus, the lowest level component in any SKU is raw materials. Availability of most of these is ensured by the use of an order point system. When inventory falls below a certain level, the ERP-system automatically release a replenishment order of a certain size to the right supplier. After the duration of a certain lead-time, raw materials arrive at the plant and are stored, awaiting the arrival of production orders. Raw materials requirements will not be considered in this thesis. A possibility would be to include inventory policy and reorder decisions for raw materials in the simulation model to analyze the effect of stochastic lead times from suppliers. On the other hand, it is desirable to limit ourselves to only examine the actual production process and all raw materials is therefore assumed to always be available.

4.1.4 Parameters

This chapter is going to present the parameters used by the analytical and simulation models. The parameters have been divided into deterministic and stochastic. Note that parameters defined as deterministic might be stochastic in reality.

4.1.4.1 Deterministic parameters

Both the analytical and simulation model require deterministic parameters. These will be presented and explained in more detail later on but are.

- Demand during planning horizon
- Production costs
- Holding costs
- Backorder costs
- Production times
- Setup times
- Batch sizes
- Minimum lot sizes
- Resource capacities
- Inventory capacities

4.1.4.2 Stochastic parameters

As mentioned earlier, real production systems include several stochastic parameters. In order to limit ourselves, this thesis only focuses on those considered to have a high impact on system performance. The most important stochastic factors was found to be resource efficiency and defect probability.

Resource efficiency

Many different factors affect how efficient a resource is. In this thesis, resource efficiency have been defined as the total available production time after subtracting all time that is lost due to inefficiencies. There can be different reasons for the variations in resource efficiency and some of them are:

- Machine breakdowns
- Variable production times
- Variable setup times
- Production time lost due to handling of defect productions

Ideally, a model would like to address variations in each of these separately, but due to time limitations and data issues, these will be aggregated.

Defect probability

Defect probability has been excluded from the analysis for reasons that will be explained next. It is easy to imagine the implications that defect productions can have in a multi-level production environment. To illustrate this, imagine an extreme scenario where all production is performed just in time and no safety stock is kept for any of the SKUs specified in the BOM. Also, disregard lot size restrictions for the time being. In this extreme case of MTO, production will always be exactly equal to internal demand for intermediates and external demand for end items. Now, imagine that demand arrives for an end-item with a complex BOM structure. If defects occur in one of the production steps this may result in the disposal of intermediates, dependent on what can be salvaged. Since production quantities of all intermediates is equal to internal demand, new production must be performed if an intermediate has to be disposed. Further, this entails that new setups have to be performed which can be considered as inefficient time usage and thus, should be avoided if possible. Now, looking at the case of Glamox. Due to the sheer number of different SKUs, it is not possible to keep a safety stock for every single one of them. Further, internal and external demand for some SKUs vary a lot from time bucket to time bucket and in some cases, demand can be absent for several months. This implies that keeping a safety stock for these can become costly. In meetings, it was mentioned that most defects are associated with specific SKUs that are known to be troublesome. These are mostly intermediates on the lower levels. In addition, defects are few in the final assembly of end-items and in case it happens, most of the SKUs that goes into making it can be salvaged. Due to all of this, it has been decided to exclude defect occurrences because there are so many different uncertain factors associated with it.

4.2 Model Development

The next chapter introduces all three models that have been developed. Firstly, the exact formulation is introduced, followed by an explanation of the tabu search based heuristic. Lastly, the simulation model will be explained.

4.2.1 Exact method

Below, notation for sets, parameters and variables are presented followed by the general mathematical formulation to the ML-CSLP.

Sets:

P – Set of SKU's

R – Set of Resource types

T – Time buckets

Parameters:

M = Big number

c_p = Production cost for SKU p	$p \in P$
h_p = Holding cost for SKU p	$p \in P$
b_p = Backorder cost for SKU p	$p \in P$
d_{pt} = Demand for SKU p in time bucket t	$p \in P, t \in T$
q_{pr} = Production time for SKU p on resource type r	$p \in P, r \in R$
s_{pr} = Setup time for SKU p on resource type r	$p \in P, r \in R$
l_p = Leadtime for SKU p	$p \in P$
bz_p = batch size for SKU p	$p \in P$
mz_p = Minimum lot size for SKU p	$p \in P$
rc_{rt} = Capacity for resource type r in time bucket t	$r \in R, t \in T$
ic_p = Inventory capacity for SKU p	$p \in P$
BOM_{ps} = Number of SKU s needed to make one SKU p	$p \in P, s \in P$

Variables:

X_{pt} = Number of SKU p to be produced in time bucket t	$p \in P, t \in T$
Y_{pt} = Number of SKU p to be stored in time bucket t	$p \in P, t \in T$
Z_{pt} = Number of SKU p to be backordered in time bucket t	$p \in P, t \in T$
$\alpha_{pt} \begin{cases} 1 \text{ if SKU p is produced in time bucket t} \\ 0 \text{ otherwise} \end{cases}$	$p \in P, t \in T$
β_{pt} = How many Batches of SKU p to produce in time bucket t	$p \in P, t \in T$

Formulation:

(1) $$\text{Min} \sum_{p \in P} \sum_{t=T} (c_p X_{pt} + h_p Y_{pt} + b_p Z_{pt})$$

Subject to.

(2) $$\sum_{p \in P} (X_{pt} q_{pr} + \alpha_{pt} s_{pr}) \leq rc_{rt} \qquad \forall r \in R,\ \forall t = 1 \ldots T$$

(3) $$Y_{p(t-l_p)} \geq \sum_{s \in P} BOM_{ps} X_{st} + d_{pt} \qquad \forall p \in P_{l_{p>0}}, \forall t = 1 \ldots T$$

(4) $$X_{pt} + Y_{p(t-1)} - Z_{p(t-1)} = Y_{pt} - Z_{pt} + d_{pt} + \sum_{s \in P} BOM_{ps} X_{st} \qquad \forall p \in P,\ \forall t = 1 \ldots T$$

(5) $$X_{pt} \leq \alpha_{pt} M \qquad \forall p \in P,\ \forall t = 1 \ldots T$$

(6) $$Z_{pt} - Z_{p(t-1)} \leq d_{pt} \qquad \forall p \in P,\ \forall t = 1 \ldots T$$

(7) $$Y_{pt} \leq ic_p \qquad \forall p \in P,\ \forall t = 1 \ldots T$$

(8) $$X_{pt} = mz_p S_{pt} + bz_p \beta_{pt} \qquad \forall p \in P,\ \forall t = 1 \ldots T$$

(9) $$X_{p0} = 0 \qquad \forall p \in P,\ \forall t = 0 \ldots T$$

(10) $$Y_{p0} = 0 \qquad \forall p \in P,\ \forall t = 0 \ldots T$$

(11) $$Z_{p0} = 0 \qquad \forall p \in P,\ \forall t = 0 \ldots T$$

(12) $$X_{pt}, Y_{pt}, Z_{pt} \geq 0 \qquad \forall p \in P,\ \forall t = 0 \ldots T$$

(13) $$\beta_{pt} \geq 0 \qquad \forall p \in P,\ \forall t = 1 \ldots T$$

(14) $$\alpha_{pt} \in \{0,1\} \qquad \forall p \in P,\ \forall t = 1 \ldots T$$

Description:

The objective function (1) minimize total cost of production, inventory and backorders. The capacity constraints (2) makes sure that used production capacity does not exceed available capacity in each time bucket. Constraints (3) ensures that SKUs with lead-time above zero must be available on inventory lead-time before delivery. (4) Represent balance constraints that ensure that balance between production, inventory and backorder is present in all time buckets. Constraints (5) makes sure that no production is performed before necessary setup has been performed. Constraints (6) ensures that no intermediates can be backordered, which implies that, only SKU`s with external demand is allowed to be backordered. Constraints (8) ensures that production follow the lot and batch size restriction as explained in chapter 4.1 *Process analysis*. Constraints (7) comply with given inventory capacities and (9), (10) and (11) sets initial inventory, backorders and production levels. Lastly, constraints (12), (13) and (14) specifies variables as integer, binary and non-negative.

4.2.2 Approximation method

Due to complexity of the ML-CLSP, an algorithm based on properties of the tabu search heuristic (TS) has been developed as a supplement for the exact model. TS is an improvement-based heuristic that searches through the solution space of a problem. Due to the nature of TS, an initial solution is required before the search can start. TS includes two major phases. Firstly, a local search procedure that perform stepwise moves, guides the search towards better solutions. However, after a time, the local search procedure will reach a point where no candidate moves that directly improve the solution is available. The search is then stuck in a local optimum. This leads us to the second phase. In order to escape from the local optimum, TS allows moves that does not directly improve the solution. The idea behind this is to enable the search to move out of a local optimum so that new areas of the search space can be explored. When performing a move that leads to a worse solution, the reverse move will automatically become an improvement. To prevent the search from moving directly back into the same local optimum, a tabu list is established. In the tabu list, information concerning attribute values of the most resent non-improving moves are stored. Candidate moves that include these attribute values is considered to be tabu, which implies that they are not allowed to be performed. Further, the tabu tenure defines for how long a move is considered to be tabu and involves decisions regarding size and nature of the tabu list. Too few entries can lead to cycling which traps the search in a local optimum. Too many entries can skip good solutions since good moves are tabu.

4.2.2.1 Tabu search based heuristic

It is important to note that metaheuristics more so than exact models, have to be tailored to the problem at hand. This entails a lot of testing and tuning in order to ensure good performance. The overreaching goal of this thesis is to develop a heuristic to solve the ML-CLSP regardless of complexity. In order to do this, a TS based heuristic has been developed. By based, it is meant that some aspects of TS have been incorporated while others have been excluded. According to (Glover and Taillard 1993), many considerations have to be made when developing a TS heuristic. These considerations are concerned with: How to develop an initial solution, whether or not constraint violation should be allowed, defining the neighborhood structure(s), setting tabu tenure, deciding diversification strategies and aspiration criteria's. The continuation of this chapter evolves around the introduction of the TS based heuristic and a description of how it works. Firstly, an indepth discussion regarding the various aspects that have been included will be performed. Secondly, notation for and description of the heuristic is presented.

4.2.2.2 Initial solution

To our knowledge, there exist no studies that prove one procedure to be better than others and a bad initial solution do not necessarily lead to better performance of TS. Therefore, a simple constructive heuristic generates a feasible initial solution s_0 for the TS heuristic to initialize its search from.

Description of the constructive heuristic

For all time buckets 1…T do:

1. Randomly chose an end-item *p* with net external demand in time bucket *t*

While net external demand for end-item p is not fulfilled do:

i. If production quantity of end-item p = 0 in time bucket t
   1. Add one minimum lot size

   Else:
   2. Add one batch size

ii. Calculate internal requirement for intermediates

While net internal demand for intermediate s that is required to produce SKU p is not fulfilled do:

iii. If production quantity of intermediate s = 0 in time bucket t
   1. Add one minimum lot size

   Else:
   2. Add one batch size

End loop

iv. Update used capacity for resource types

While used capacity exceed available capacity for resource type r do:

i. If production quantity of end-item p = 0 in time bucket t
   1. Backorder one minimum lot size

   Else:
   2. Backorder one batch size

v. Remove unnecessary intermediates from production

End Loop

v. Perform step iv. until all resource types have been checked.

End loop

2. Update inventory for all SKU*s*
3. Perform step 1. until all end-items with net external demand is added to the solution.

End loop

4.2.2.3 Multi start

(Gendreau 2002) highlights that TS often requires a large number of iterations in order to find good solutions. This means that a particular starting point might find good solutions faster than another starting point. Since one starting point cannot be proven better than another, starting the search at multiple points might yield good solutions faster. In addition, modern processors normally consist of multiple cores that can run at the same time. The TS heuristic that will be described later on in this chapter only utilize the power of one core. Therefore, an idea is to start the heuristic multiple times for different initial solutions s_0, and compare the results gained from all the runs. The total number of starts should not exceed number of cores that is available in the computer since this will reduce performance. In order to generate different initial solutions s_0 that can be used in a multi start, a random segment have been included in the constructive heuristic described above. Because of this randomness, the variety of different initial solutions s_0 that can be generated from the constructive heuristic is very large.

4.2.2.4 Stopping criteria

The stopping criteria defines when to end the search. In theory, the search can continue infinitely due to the lack of a natural stopping criterion. In order to be able to stop the search at a given point in time, parameters α and β have been introduced. α keeps track of the current time while searching and β defines an upper bound on how long the search should last. Accordingly, the search continues as long as $\beta > \alpha$.

4.2.2.5 Constraint violation

Many TS approaches allow the search to move in infeasible space. Even though this have proved to be a viable method in many cases, the TS heuristic presented in the thesis, does not allow any violations of constraints. This means that constraints associated with capacity of resource types, requirement of intermediates and inventory capacity must be satisfied at all times.

4.2.2.6 Neighborhood structure

As mentioned above, TS heuristics perform stepwise moves when exploring the solution space. It is therefore essential to define a neighborhood of solutions that is reachable from the current solution in one move. In our case, the neighborhood N(s) is defined as all the neighboring solutions s that can be reached by moving production of an SKU p from current time bucket i to a new time bucket j. In other words, a move can be labeled with the attribute values (p, i, j). Note that time bucket i can either be prior to or following time bucket j, which means that a move attempts to either postpone or expedite production.

Before continuing, it is necessary to mention that the quantity of SKU p that the algorithm attempts to move from time bucket i to time bucket j can take on different values depending on the situation.

1. If quantity of SKU p produced in time bucket i > minimum lot size then try to remove quantity equal to a batch size and insert production in time bucket j.
    a. If quantity of SKU p produced in time bucket j = 0 then try to add a minimum lot size.
    b. If quantity of SKU p produced in time bucket j >= minimum lot size then try to add a batch size.
2. If quantity of SKU p produced in time bucket i = minimum lot size then try to remove quantity equal to a minimum lot size and insert production in time bucket j.
    a. If quantity of SKU p produced in time bucket j = 0 then try to add a minimum lot size.
    b. If quantity of SKU p produced in time bucket j >= minimum lot size then try to add quantity equal to net requirement for SKU p in time bucket i.
3. If time bucket i = time bucket j then Try to remove production.
4. If quantity of SKU p on inventory in time bucket i = quantity of SKU p produced in time bucket i and j = i + 1 then try to move all production from time bucket i to time bucket j. If move is rejected due to constraint violation or f(s') > f(s), perform step 1 or 2 depending on the situation.

Because of the multi-level product hierarchy, moving SKU p can also affect production of its intermediates. The algorithm handles this differently depending on the attribute values of the move. For simplicity, the explanation will not go into detail on this.

A candidate move can have three different outcomes. Below, these are explained.

- Improving move - A move that consist of attribute values (p, i, j) that yields f(s') < f(s).
- Non-improving move – A move that consist of attribute values (p, i, j) that yields f(s') > f(s). Solution of f(s)
- Best non-improving move – A move that consist of attribute values (p, i, j) that amongst all other attribute values in the neighborhood yields the best f(s') > f(s).

When going from current solution s to a new solution s’, a move is performed. The acceptance criteria specifies the requirements that must be met before a move is accepted. In our case, the objective function is to minimize f(s) = p(s) + i(s) + b(s) where p(s) is production cost, i(s) is inventory holding cost and b(s) is backorder cost of solution s. The first candidate move that gives a solution that yields f(s’) < f(s) will be performed as long as no constraints are violated. The algorithm checks attribute values (p, i, j) of candidate moves in a certain sequence. It is necessary to mention that when a move is performed, the search will not be restarted. Instead of having the sequence start all over again, the search continues by checking attribute (p, i, j) of the move that was just performed. To perform the search in this manner has proven to reduce the number of iterations needed to complete the local search.

Eventually, this procedure will be stuck in a local optimum and one or several moves that give solution that yield f(s’) > f(s) have to be performed. Normally, the acceptance criteria is to perform the best non-improving move once and put the attribute values for the reverse move of this on tabu list. On the other hand, for the problem described in this thesis, performing non-improving moves in this way often require a very large number of iterations in order to bring the search out of its local optimum. Therefore, an alternative way of performing non-improving moves have been introduced. Firstly, the best non-improving move is chosen and performed once. Thereafter, moves that include the same attribute values (p, i, j) is performed until either, a constraint is violated or, no SKUs p remains to be moved. For instance, if the best non-improving move received after a local search is (2, 1, 3) then the algorithm will try to move production of SKU 2 from time bucket 1 to time bucket 3 several times even if it is no longer the best non-improving move after the first iteration. By doing it this way, the search moves a longer distance away from the previously visited local optimum for every time that a non-improving move has to be performed. This lets us discover more local optima in a shorter amount of time but might cause the algorithm to overlook possible solutions. The attribute values (p, i, j) is stored for the move, and the reverse move of this is considered tabu for a certain number of iterations defined by the tabu tenure.

4.2.2.7 Tabu Tenure

The tabu tenure decides for how long a move is going to be tabu. Ideally, the tabu tenure should be large enough to avoid cycling and short enough to be able to explore all possible solution regions. On the other hand, (Glover and Taillard 1993) states that there does not exist any generalized rules when it comes to deciding the tabu tenure. Therefore, one of the bigger decisions in any TS heuristic is to decide this. Tabu tenure can be either dynamic or static (Løkketangen 2007). A dynamic tabu tenure changes the length at which a move is considered to be tabu as the search progresses. A static tenure applies a fixed tabu list that does not change during the search.

The TS heuristic presented in this thesis applies a dynamic tabu tenure. As mentioned above, when the search reaches a local optimum, moves that yield $f(s') > f(s)$ have to be performed. Attribute values (p, i, j) for all of these non-improving moves is stored in a tabu list of size. This list is updated until the search once again finds a move that yields $f(s') < f(s)$. When this happens, all entries in the tabu list is deleted. Having a tabu tenure that behaves in this way might lead to cycling in some instances. Therefore, in order to avoid this as well as diversify the search, a diversification strategy have been included.

4.2.2.8 Diversification

While searching, it is desirable to explore as many regions of the solution space as possible. This means that it we want to test a wide range of different moves instead of always performing the same ones just because they look more promising at first glance. To lead the search into new possible regions, different diversification strategies can be applied. For this case, a simple strategy has been implemented.

When searching though N(s), attribute values (p, i, j) are stored for candidate moves that yield $f(s') - \eta(p) > f(s)$ and $f(s') < \tau$. λ is attribute values for the best non-improving move found so far and τ is value of the candidate solution when λ was stored. Note that it is necessary to reset λ and τ at certain points during the search. Further, $\eta(p)$ is the sum of all penalty that is associated with an SKU p. This value is incremented by a fixed number each time SKU p is included in a worse move. Consequently, at the end of the local search, SKU p that belongs to attribute values of λ receives a fixed penalty that is added to $\eta(p)$. Note that $\eta(p)$ is never reset during the search. This is a diversification strategy because SKU p gets less and less attractive as a candidate to become best non-improving move for each time it is included in a worse move.

4.2.2.9 Aspiration Criteria

When searching, there may exist solutions that are better than best solution found s*, but the search is not able to find solution because attribute values of the move that needs to be performed is tabu γ. To try to avoid this, an aspiration criteria can be used to evaluate whether the tabu list should be ignored for a number of iterations. A normal way to do it, is to allow the search to perform tabu moves if it leads to a solution that is better than best solution found s*. The algorithm presented in this thesis, has not implemented any aspiration criteria's.

4.2.2.10 Template for the tabu search based heuristic

Notation

(p, i, j) – Attribute that specifies SKU p to be moved from time bucket i to time bucket j.
N(s) – Neighborhood of solution s.
M(s) – Subset of N(s) that include all non-tabu solutions s.
C(s) – Total cost of solution s, C(s) = p(s) + i(s) + b(s)
s* – Best solution found
s_0 – Initial solution
s – Current solution
Ø – Empty
η(p) – Penalty for SKU P counter
α – Time counter
β – Total search time available
γ – Tabu list consisting of attributes (p, i)
λ – Attribute values (p, i, j) for best non-improving move
τ – Value of solution for best non-improving move

Description of the Tabu search based heuristic

Obtain Initial solution s_0 from the constructive heuristic.
Set α, γ, η(p) = Ø
τ = High number
Set s* = s_0
Set s = s_0
While α < β do
    For All (p, i, j) ∈ M(s)
        Attempt Move as described above
        Calculate f(s')

        If f(s') - η(p) > f(s) and f(s') < τ then
            λ = record attribute values (p, i, j)
            τ = f(s')
        End if

        If f(s') < f(s) then
            s = s'
        End if

    End loop
    If s < s* then
        s = s*
    End if
    Update α timer
    Update η(p) = η(p) + Fixed penalty
    Perform attribute values (p, i, j) associated with λ until infeasible
    Update Tabu list γ by adding attribute values (p, j)
    Set τ = High number
End loop

4.2.3 Simulation

The objective of this simulation model is to evaluate which effect stochastic parameters have on the production system. As previously mentioned, the only stochastic parameter that will be included is resource efficiency. Further, discrete event simulation has been chosen as the method and implemented in ARENA, which is a module based simulation software (ArenaSimulation 2015). By module based, it is meant that the model consist of already programmed modules that is linked together in order to constitute the logic. This makes modeling easier for less experienced programmers as well as providing the user with an overview of which possibilities that exist. The model have been formulated generally which implies that you can increase the total number of SKUs and time buckets infinitely without having to spend time on changing the model logic.

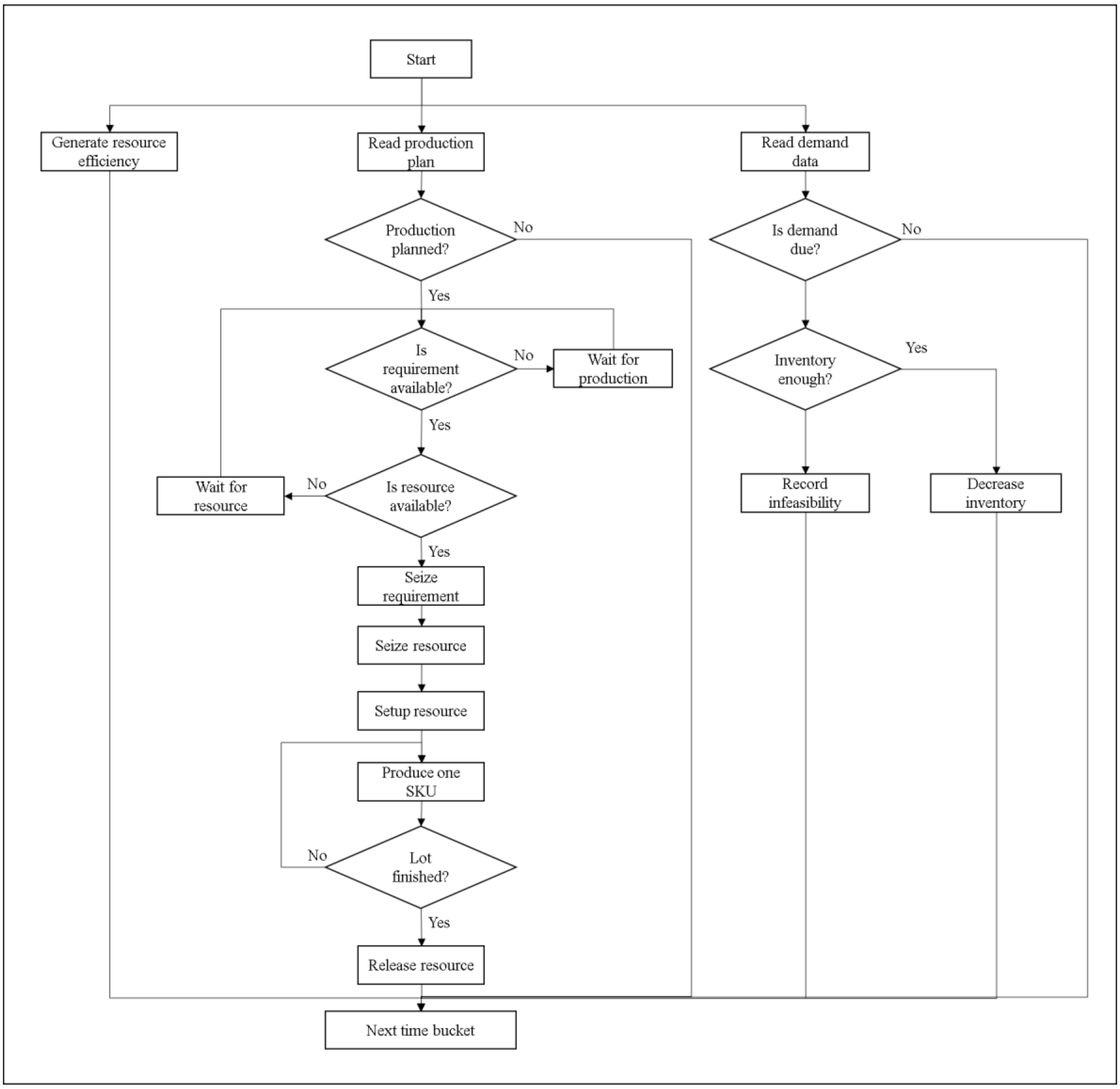

Figure 2: Conceptual model displaying logic of the simulation model

4.2.3.1 Assumptions and simplifications

As mentioned before, identical resources have been aggregated into resource types. Ideally, the simulation model should consider individual resources independently. However, that would require very specific data for resource efficiency and has therefore been disregarded.

In addition, no scheduling opportunities is included in the model, which implies that all sequencing is performed randomly. For instance, if production of two or more SKUs are planned to take place on the same resource type during a single time bucket, the first one to seize the resource will be scheduled first.

Before logic of the model will be explained, it is worth mentioning that the presentation below does not include a detailed description of modules, attributes and state variables that have been used in the ARENA model. The objective is not to explain how the model was programmed, but rather how it works. The explanation will be closely related to the conceptual model presented in Figure 2.

4.2.3.2 Model execution

Prior to each simulation run, data for deterministic parameters are read into the ARENA model from an excel file. This makes it easier to apply output data from the analytical model as input in the simulation. Further, the model has been separated into three parts that communicate with each other through system variables. Lastly, the entire planning horizon is simulated sequentially from first to last time bucket.

Generate resource efficiency

At the start of each time bucket, resource efficiency is generated according to a predefined probability distribution. Efficiency generated will affect production times in the production part of the model. This part of the model has been separated from the rest as it is only used to generate stochastic parameter data.

Simulate production

At the start of each time bucket, a single entity is created for every SKU specified in the BOM. Each entity is then assigned to a unique attribute value that specify which SKU it represent. Further, every entity reads the production plan and checks whether or not production is planned for their associated SKU during current time bucket. If production is planned, the entity proceed towards production, if not, it is disposed.

Before production can be initiated, two conditions must be fulfilled. Firstly, "*Is requirement available?*" Checks whether inventory of all required intermediates is large enough to produce the planned lot. If not, the entity waits for necessary production to finish. Secondly, "*Is resource available?*" Checks if the necessary resource type is seized or not. If not, the entity waits for the resource type to be released else, production can be initiated. As it appears in the conceptual model, an entity that is released from one of the wait modules is sent all the way back to check all the above conditions again. The reason for this is that conditions might have changed during the wait and are thus, not valid anymore.

When all the above conditions are met, a few operations are performed in sequence. Firstly, required intermediates are withdrawn from the inventory. Secondly, required resource type is seized. Thirdly, the entity is delayed for the duration that it takes to perform associated setup. After the setup is finished, production can start.

Production is performed in a looping procedure. For every SKU that is produced, the associated entity is checked for condition *"Lot finished?"*. As the name implies, this module checks whether total production is finished or not. If lot is finished, resource type is released and made available to be seized by other SKUs. If not, entity produce one more SKU. For every loop performed, inventory is incremented by one for the associated SKU. This means that all SKUs are available to be seized by its successors immediately after production.

Feasibility check

At the end of each time bucket, a single entity is created for all SKUs defined in the BOM. The entity is then checked for two conditions. Firstly, *"Is demand due?"* checks whether or not there is demand for the SKU in this time bucket. If no, the entity is disposed and if yes, it precedes. Secondly, *"Inventory enough?"* checks whether necessary SKUs is enough to cover external demand. If yes, amount equal to demand is withdrawn from inventory. If no, information concerning SKU-number, current time bucket and remaining production needed before demand can be met is registered.

4.2.3.3 Decision rule

As described above, the simulation model provides data concerning all end-items that did not meet external demand on time. For the hybrid model to work, it is necessary to define a decision rule that specifies how to act, when infeasibilities occur. Due to limited time for this thesis, only a simple technique has been applied. As described in chapter 4.1.2 *Exact method*, the possibility to add lead times to the delivery of SKUs have been included in the analytical models. To exemplify, if lead-time for a specific SKU is equal to one, it has to be finalized at least one time bucket before internal or external demand is due. Thus, the decision rule is to add one time bucket worth of lead-time to SKUs that is infeasible in more replications than the average of all SKUs infeasible. An example is provided to illustrate this.

End-item	**Percentage of the time infeasible**
1	40 %
2	10 %
3	100 %
4	50 %
5	20 %
6	70 %
7	100 %
Average	56 %

Table 1: Decision rule

Imagine that Table 1, display all end-items that were infeasible during a simulation run. Further, "*percentage of the time infeasible*" tells us in how many percent of total number of replications that the end-item was infeasible. The decision rule is to add lead-time to those with percentages larger than average, in this case end-items 3, 4, 6 and 7. However, if an end-item that already has lead-time restrictions associated with it is chosen, all its intermediates are picked instead. When a simulation run ends in the situation where no more SKUs without lead-times exist, the search is finished.

5.0 Computational experiments

The next part of the thesis will present all experiments that have been applied in order to test the models. These can be separated into two main parts. Firstly, the exact and tabu search based method is tested on different scenarios. Due to complexity of the ML-CLSP, it is necessary to evaluate whether or not the models can be used for the purpose of generating good production plans. Secondly, the hybrid model is applied to a case based on Glamox and results will be presented and discussed.

5.1 Testing the analytical models

As mentioned above, this chapter attempts to evaluate performance of the analytical models. The chapter starts out by explaining how different scenarios have been generated. Thereafter, parameters that is specific for the tabu search based heuristic is defined. When all scenarios and parameters have been defined, the next step is to test the models. Firstly, a performance analysis is conducted for the exact method. If the tests show good enough results, it will not be necessary to compare with the heuristic. On the other hand, if results are not desirable, a comparison with the tabu search based heuristic will be made.

The exact method was modeled in AMPL which is a programming language used to formulate mathematical models. Further, CPLEX 9.0.0 was used as the solver. Both the constructive and tabu search based heuristic is coded in visual basic application which is a modelling language in excel. For the exact method, a computer with Intel® Core™2 DUO CPU E8400 @ 3.00Ghz with 4.00 GB RAM was used. For the heuristic, a computer with Intel® Xeon® CPU E31270 @ 3.40GHz with of 16.00 GB RAM was used.

5.1.1 Generating test instances

In order to generate instances to test the analytical model on, different problem sizes have been combined with various scenarios. An explanation of how problem sizes and scenarios was generated will be presented below.

5.1.1.1 Generating problem sizes

Different values for number of time buckets T and number of SKUs P have been applied in order to make three unique combinations. T = 5, 10 number of time buckets t and P = 50, 100 number of SKUs p gives three unique combinations presented in Table 2.

Set	T	P	Problem size
1	5	50	5 X 50
2	5	100	5 X 100
3	10	50	10 X 50

Table 2: Problem sizes

5.1.1.2 Generating scenarios

Further, multiple scenarios is generated by combining different parameter values for external demand, capacity and lot size restrictions. Other parameter values are based on data received from Glamox and fixed in all test instances.

Variations in external demand frequency

Adjustments made to external demand frequency result in three different situations that are presented in Table 3. Outcomes describe the following situations: High, Medium and low external demand frequency. It is important to declare that it is not the quantity of demand that is adjusted but the frequency. In other words, demand frequency describes how often a end-item has external demand during the planning horizon. For instance, if total number of time buckets T = 10 and demand frequency is 80 percent, SKU p have external demand in eight out of the of ten time buckets.

Situation	
High	80 %
Medium	40 % - 50 %
Low	20 %

Table 3 Demand frequence situations

Variations in production capacity

Two different capacity situations are presented in Table 4. These are two extreme cases that might be more or less present in the case of Glamox. Firstly, a capacitated situation entails that total available production time on resource type r is limited during the planning horizon. The idea is to analyze how the models behave in situations where some end-items needs to be backordered. Secondly, the opposite situation "*un-capacitated*" is also generated. This situation does not mean that capacity is unlimited on all resource types, but rather that capacity is sufficient to prevent backorders easily.

Situation	
1	Uncapacitated
2	Capacitated

Table 4: Capacity situations

Variations in lot size restrictions

Thirdly, changes in lot size restrictions are introduced. These are defined as the total number of SKUs that have minimum lot size and batch size restrictions associated with them. The idea is to analyze how lot sizes affect performance of the analytical models. Table 5 presents 11 different situations from 0% to 100% lot size restrictions.

Situation	
1	0 %
2	10 %
3	20 %
4	30 %
5	40 %
6	50 %
7	60 %
8	70 %
9	80 %
10	90 %
11	100 %

Table 5: Lot Size situations

5.1.1.3 Introducing scenarios

Ideally, it would be desirable to test as many scenarios as possible. However, due to limited time, only the most important ones have been included. All scenarios 1-26 are presented in table 6. As you can see, each scenario include a unique combinations of lot size restrictions, demand frequency and production capacity.

Scenario	lot size restrictions	demand frequency	production capacity
Scenario 1	60 %	High	Capacitated
Scenario 2	60 %	High	Uncapacitated
Scenario 3	60 %	Medium	Capacitated
Scenario 4	60 %	Medium	Uncapacitated
Scenario 5	60 %	Low	Capacitated
Scenario 6	60 %	Low	Uncapacitated
Scenario 7	0 %	High	Uncapacitated
Scenario 8	10 %	High	Uncapacitated
Scenario 9	20 %	High	Uncapacitated
Scenario 10	30 %	High	Uncapacitated
Scenario 11	40 %	High	Uncapacitated
Scenario 12	50 %	High	Uncapacitated
Scenario 13	70 %	High	Uncapacitated
Scenario 14	80 %	High	Uncapacitated
Scenario 15	90 %	High	Uncapacitated
Scenario 16	100 %	High	Uncapacitated
Scenario 17	0 %	High	Capacitated
Scenario 18	10 %	High	Capacitated
Scenario 19	20 %	High	Capacitated
Scenario 20	30 %	High	Capacitated
Scenario 21	40 %	High	Capacitated
Scenario 22	50 %	High	Capacitated
Scenario 23	70 %	High	Capacitated
Scenario 24	80 %	High	Capacitated
Scenario 25	90 %	High	Capacitated
Scenario 26	100 %	High	Capacitated

Table 6: Scenarios generated

5.1.2 Deciding parameter values for the heuristic

In order to achieve good performance from the TS based heuristic, parameter values concerning the diversification strategy, tabu list and stopping criteria needs to be tuned properly. The goal is to avoid unnecessary cycling and be able to explore as many local optimums as possible. The next chapter will include a discussion regarding how these parameters have been tuned for different test instances.

5.1.2.1 Diversification

As mentioned before, in order to create diversity in the search and avoid cycling, a penalty parameter is used. From test runs, we have found that diversification is much more important when faced with a capacitated situation. Therefore, a smaller penalty will be implemented for un-capacitated than capacitated scenarios. The two different penalties have been presented in Table 7.

Penelty	Situation
1	Uncapacitated
10	Capacitated

Table 7: Diversification parameters

5.1.2.2 Size of tabu list

Size of the tabu list also affect effectiveness of the search. Too many entries can make the search overlook good moves because they are still on tabu list. Based on testing, size of tabu list have been set to 4 percent of total problem size. Different tabu list sizes for each of the four problem sizes introduced above are presented in Table 8.

Size of tabu list	Problem size
10	5 X 50
20	10 X 50
20	5 X 100

Table 8: Tabu List parameters

5.1.2.3 Stopping criteria

As mentioned earlier, the stopping criteria defines how long the search should go on. In a production planning setting, it might not always be important to generate a plan very quickly. For instance, when planning horizon is long, the search can go on for several days before a new plan is needed. On the other hand, due to limited time to run tests for this thesis, the stopping criteria has been set to four hours (14400 seconds). Thereby, the search is stopped after four hours regardless of how bad the solution is.

5.1.3 Testing the exact method

In total, the exact method was tested on 46 different instances in order to evaluate performance. Further, problems associated with the method was not related to long computational time but rather memory issues. In all instances where optimal solution was not found, CPLEX ran out of memory. Therefore, performance is defined as deviation from lower bound for the best solution obtained so far. The lower bound is received from CPLEX and the difference between this and the best solution obtained is called the MIP GAP.

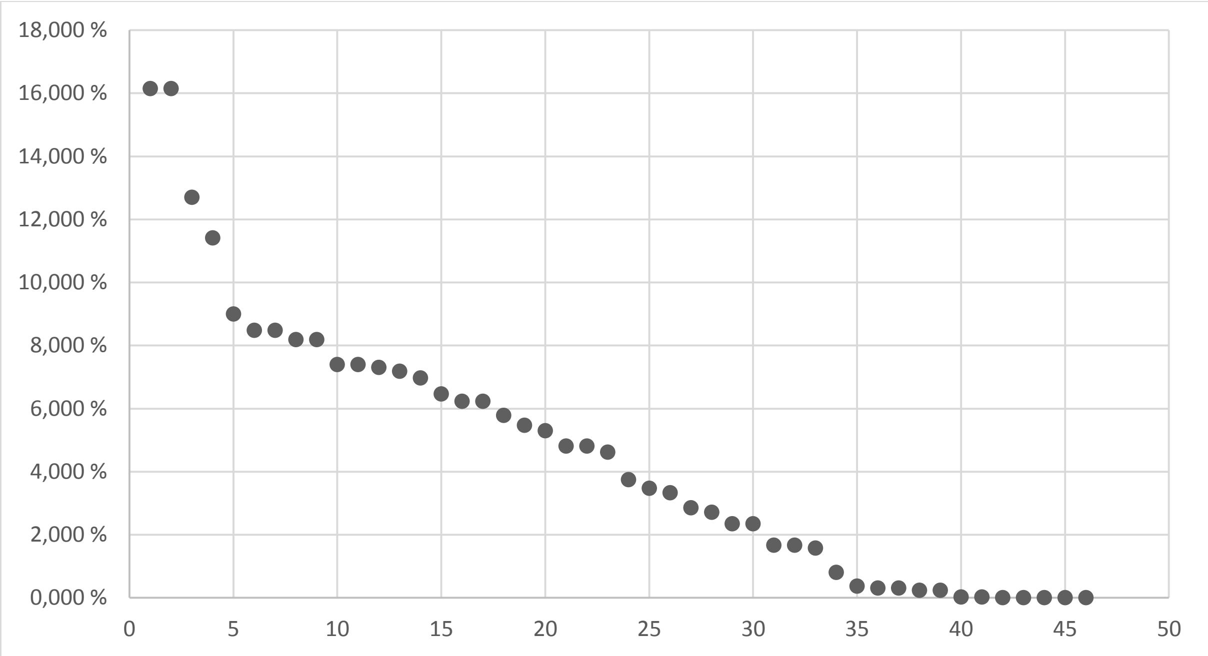

Figure 3: MIP GAPs obtained with exact method

Results from the tests are illustrated in Figure 3. Values for the MIP GAP is presented on the Y-axis, and instance number on the X-axis. Further, each dot represent the MIP GAP obtained from solving a specific instance. Average MIP GAP from all instances was 4.623 percent, varying from 16.145 percent in instance 35 to 0 percent in instance 40, 37 and 25. When obtaining a MIP GAP that is larger than zero percent, this raises a question concerning how good the solution really is. For instances with relatively large MIP GAPs, it is nearly impossible to clarify whether the solution is good, bad or excellent without comparing it with solutions obtained from alternative methods.

Lot situation	Average
Under 50 %	0,41 %
Above 50 %	8 %

Table 9: Average MIP GAPS and lot situations

Table 9 presents average MIP GAP received for all instances that include lot size situations above and below 50%. As you can see, lot size restrictions have big impact and more restrictions equals larger MIP GAPs. On the other hand, due to the limited number of instances that were generated, this effect might not be as big in reality.

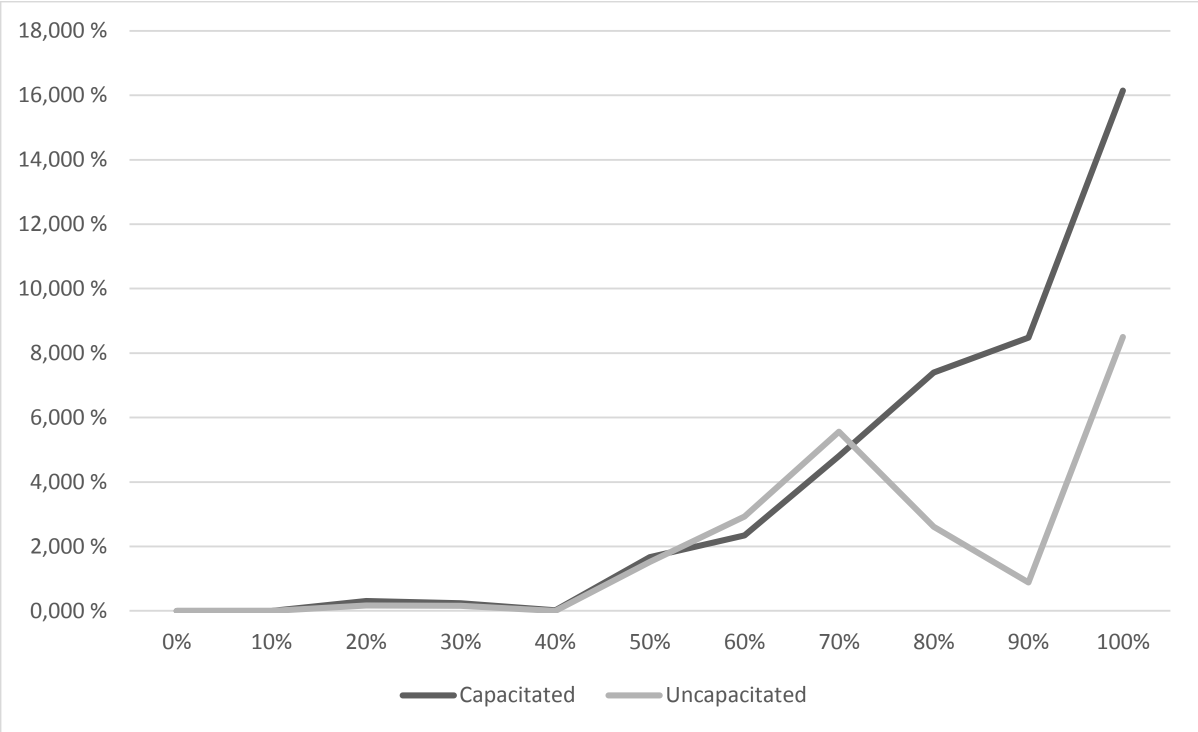

Figure 4: Comparison of MIP GAPs and lot situations

Further, Figure 4 shows how the MIP GAP evolves for the capacitated and un-capacitated situations when lot size restrictions are increased. The X-axis represent percentages for different situations of lot size restriction and the Y-axis shows size of the MIP GAP. From the figure you can see that, a shift occur when the lot restriction increases to 40 percent. Even if the sample size is too small for us to make any conclusions, a tendency towards higher MIP GAPs when faced with more lot size restrictions can be noted. On the other hand, it is important to understand that this tendency does not mean that the optimal solution is not reached. It might be that the exact method did find the optimal solution in all instances, but we cannot be certain.

From the performance analysis above, it appears to exist big differences in MIP GAPs obtained for different problem instances. For starters, there may exist a relationship between lot size situation and MIP GAP obtained. In addition, since so many instances have large MIP GAPs, it is impossible to indicate whether the solution obtained is decent or good. To further analyze the results received from the exact approach, a tabu search based heuristic has been developed.

5.1.4 Exact vs heuristic method

In this section, a comparison will be made between the exact and tabu search based method. Instances that have been tested are presented in Table 13. The table consist of instance name, which scenario the instance was tested on, problem size of the instance and result, which display the MIP GAP for both the exact and heuristic method. On the right hand side of the table, difference between the two solutions are compared. Accordingly, a negative percentage indicates that the exact method performed best.

Instance	Scenario	Problem Size	Exact Method	TS based heuristic	DIFF
Instance_1	Scenario_1	50 X 5	0,00 %	0,00 %	-0,0000719 %
Instance_2	Scenario_2	50 X 5	1,58 %	1,58 %	-0,0001840 %
Instance_3	Scenario_3	50 X 5	0,36 %	0,37 %	-0,0025921 %
Instance_4	Scenario_4	50 X 5	6,97 %	6,97 %	-0,0000796 %
Instance_5	Scenario_5	50 X 5	0,81 %	18,04 %	-17,2295695 %
Instance_6	Scenario_6	50 X 5	11,41 %	11,41 %	-0,0007840 %
Instance_7	Scenario_7	50 X 5	0,000 %	0,000 %	0,0000000 %
Instance_8	Scenario_8	50 X 5	0,000 %	0,000 %	0,0000000 %
Instance_9	Scenario_9	50 X 5	0,307 %	0,307 %	0,0000000 %
Instance_10	Scenario_10	50 X 5	0,237 %	0,237 %	-0,0000204 %
Instance_11	Scenario_11	50 X 5	0,020 %	0,020 %	0,0000000 %
Instance_12	Scenario_12	50 X 5	1,665 %	1,665 %	-0,0000004 %
Instance_13	Scenario_2	50 X 5	2,340 %	2,340 %	0,0000000 %
Instance_14	Scenario_13	50 X 5	4,809 %	4,810 %	-0,0007025 %
Instance_15	Scenario_14	50 X 5	7,393 %	7,393 %	0,0000002 %
Instance_16	Scenario_15	50 X 5	8,482 %	8,482 %	-0,0000221 %
Instance_17	Scenario_16	50 X 5	16,149 %	16,148 %	0,0004209 %
Instance_18	Scenario_1	50 X 10	2,85 %	2,85 %	-0,0001662 %
Instance_19	Scenario_2	50 X 10	4,62 %	4,62 %	0,0000000 %
Instance_20	Scenario_3	50 X 10	3,47 %	3,47 %	-0,0008688 %
Instance_21	Scenario_4	50 X 10	6,22 %	6,22 %	0,0000621 %
Instance_22	Scenario_6	50 X 10	9,00 %	9,00 %	-0,0008302 %
Instance_23	Scenario_1	100 X 5	3,32 %	3,32 %	0,0015679 %
Instance_24	Scenario_2	100 X 5	5,78 %	5,78 %	-0,0000390 %
Instance_25	Scenario_3	100 X 5	3,74 %	3,74 %	0,0010013 %
Instance_26	Scenario_4	100 X 5	8,19 %	8,19 %	-0,0035498 %
Instance_27	Scenario_5	100 X 5	7,19 %	7,19 %	0,0002391 %
Instance_28	Scenario_6	100 X 5	12,70 %	12,71 %	-0,0025427 %
Instance_29	Scenario_17	50 X 5	0,000 %	4,265 %	-4,2647805 %
Instance_30	Scenario_25	50 X 5	0,887 %	24,437 %	-23,5499395 %
Instance_31	Scenario_26	50 X 5	8,498 %	24,018 %	-15,5201194 %
Avereage			**4,48 %**	**6,44 %**	**-1,95 %**

Table 10: Results from exact versus heuristic method

In total, 31 instances were tested. The limited number of instances that was possible to test makes it impossible for us to conclude anything with certainty. On the other hand, it is still possible to make some interesting remarks about possible tendencies. On average, the exact method perform 1.95 % better than the heuristic. Average solving time for the CPLEX solver was 957.5. In contrast, the heuristic, have the possibility to search for infinity due to little to no memory usage but is interrupted after 14400 seconds.

Firstly, an interesting observation is that, in 87 % of all instances tested, both methods yield very similar solutions when comparing total costs. Even in instances with rather large MIP GAPs, solutions are almost equal. This could indicate that the solution obtained in these instances are close to optimum. However, we cannot be certain of this.

Another good indication regarding quality of the heuristic is that it obtains optimal solution in two of the instances. This could mean that it has the possibility to also obtain optimal solution in larger problem instances.

In instances 5, 29, 30 and 31 you can see that the heuristic shows signs of bad performance. These performance issues are related to capacitated cases where backorders are hard to eliminate. Thus, it can be stated that the heuristic struggle in capacitated instances.

Further, it is necessary to state that the exact method perform better than the heuristic in most instances. In addition, when this is not the case, difference is very small. In the best-case scenario, this could mean that the exact method performs good.

5.1.5 Summary

The objective of this chapter was to evaluate performance of the analytical models. Due to limited time, it has not been possible to perform as many tests as we would like. On the other hand, some observations have been made. Firstly, due to memory issues, it is impossible to know if the exact method finds good solutions in most instances. In order to evaluate quality of the solution regardless of this, a tabu search based heuristic was developed. By comparing results received from running these models on the same problem instances, it was discovered that they perform equally in most instances. The only deviation was for capacitated instances where backorders are hard to eliminate. From chapter 4.1 *Process analysis*, we remember that this is mostly not the case in Glamox. Therefore, the solution that is obtained from the exact model is considered to be sufficient and can be used to generate production plans for the hybrid model.

5.2 Application of hybrid model

The next chapter is going to exemplify an application of the hybrid model. The idea is to apply the model to a case based on Glamox and analyze the results. As explained in chapter 3.0 *Methodology*, both models will run sequentially for several iterations until a robust production plan is obtained.

5.2.1 Case description

Before results from running the hybrid model can be presented and discussed, it is necessary to introduce the case.

5.2.1.1 Planning horizon

The planning horizon have been set to two weeks and time buckets are specified as days. Further, no production is allowed during weekends, which leaves us with a total number of ten time buckets. The reason behind this choice is that it is desirable to plan production for the most frequent end-items with short lead times (A and B).

5.2.1.2 Parameters

All deterministic data concerning production costs, holding costs, production times, setup times, resource capacities, minimum lot sizes and batch sizes was gathered from the ERP system in Glamox. It is necessary to point out that holding cost relative to production cost is very small and that backorder cost has been given a large value due to the business strategy.

Unfortunately, sufficient historical data for daily resource efficiency was not obtainable. This parameter has therefore been generated from a triangular distribution defined by us. It is especially interesting to analyze how the production plan behaves when production takes longer than expected. Thus, the distribution is slightly pessimistic which means that there is a higher chance that resource efficiency is lower rather than higher. Number of replications have been set to fifty in order to ensure statistical representative results.

5.2.1.3 Bill of material

External demand for end-items can vary a lot and items in demand during one week may be entirely different the next week. From a modeling perspective, it means that only part of the entire BOM needs to be extracted when solving a problem. More specific, size of BOM corresponds to which end-items that are demanded during the planning horizon.

Unfortunately, it was not possible to separate a work center or resource type entirely from rest of the plant as it is all connected through SKU dependencies. In addition, A, B, C, M and E-items can consist of SKUs that is common to all of them. This implies that all product types must be included in the model to ensure a valid production plan.

For this case, BOM have been extracted from the ERP system in Glamox. Due to the vastness of different SKUs that is produced and the lack of possibilities when it comes to separating one part of the plant from others, simplifications had to be made. BOM constitutes of those end-items that were produced during a single week on a specific resource type. Thus, all end-items in the case is produced on the same resource type and intermediates are only those that goes into the production of these. A weakness is that validation cannot be ensured because intermediates also have internal demand elsewhere that wont be considered. The case is therefore only "based" on the situation in Glamox and not nearly as complex as the actual system.

5.2.1.4 Demand

As mentioned in chapter 4.1. *Process analysis*, capacity is mostly high enough to finish production of all required SKUs during the planning horizon. On the other hand, it was also stated that capacity is not high enough to produce everything within a single time bucket. Therefore, external demand has been generated randomly in order to obtain the situation described above.

5.2.2 Analysis

Results received from running the hybrid model will be presented below including a discussion of the findings. Note that, due to the assumptions made above, it is not possible for us to draw any certain conclusions as to whether or not the method can be used to improve production planning in Glamox. Instead, the case can serve as an example of how to apply the method.

5.2.2.1 Importance of scheduling

Firstly, an initial production plan was generated with all lead times equal to zero Appendix 1. This plan is then simulated two times for different scenarios. Scenario2 only include deterministic values while scenario1 incorporate stochastic resource efficiency. Table 11 and Table 12 present results from the simulation and shows which end-items that did not meet their due date. The percentage indicates how many times out of the fifty replications that the end-item was delayed.

Scenario1	
End-item	**Percentage of the time infeasible**
10	100 %
14	8 %
16	100 %
18	100 %
2	100 %
20	48 %
22	8 %
29	100 %
3	2 %
30	100 %
5	100 %
Average	**70 %**

Table 11: Scenario 1. Percentage of the time infeasible

Scenario2	
End-item	**Percentage of the time infeasible**
10	100 %
16	100 %
18	100 %
2	100 %
29	100 %
30	100 %
5	100 %
Average	100 %

Table 12: Scenario 2. Percentage of the time infeasible

Even though scenario2 includes no stochastic parameters, there are still infeasibilities. This can be explained as the effect of not performing scheduling and highlights the importance of this in a multi-level product environment.

5.2.2.2 Generating robust production plan

Including scheduling in the hybrid model might cause the production plan to become feasible in scenario2. It is on the other hand still value in applying the hybrid approach. A new scenario3 is presented in Table 13 that introduce another extreme case where lead-times are equal to one for all SKUs. You can see that applying this scenario causes a drastic decrease in number of infeasibilities. In scenario1, 32.4 % of all end-items was infeasible while in scenario3, only 2.9 % was infeasible. In addition, comparing total cost of the two solutions show a very small cost difference. From this, it is understood that number of infeasibilities can be reduced without increasing cost noteworthy. In addition, the last 2.9 % can probably be eliminated by applying scheduling. On the other hand, it is rather extreme to include lead-times between every single level in the BOM. Therefore, the hybrid approach has been applied in order to find a solution that require less lead times.

	Percentage of end-items infeasible stochastic	Percentage of end-items infeasible deterministic	Total cost of solution	Lead time added to SKUs
Scenario3	2,9 %	2,9 %	718375	
Scenario1	32,4 %	20,6 %	718143	10, 16, 18, 2, 29, 30, 5
Iteration1	32,4 %	17,6 %	718169	54, 56, 13, 38, 39, 40, 42, 27, 32, 33, 4
Iteration2	32,4 %	8,8 %	718202	11, 12, 41, 67, 68, 48, 49, 50
Iteration3	17,6 %	2,9 %	718213	88, 14
Iteration4	14,7 %	5,9 %	718217	69, 70
Iteration5	29,4 %	11,8 %	718572	22, 24
Iteration6	11,8 %	2,9 %	718236	47, 62, 63, 3
Iteration7	8,8 %	2,9 %	718249	45, 46
Iteration8	5,9 %	2,9 %	718249	83, 84, 86
Iteration9	5,9 %	2,9 %	718250	**No more options**

Table 13: Scenario and iterations

Starting from the initial solution found in scenario1, the hybrid approach was applied stepwise as explained in chapter 4.2.3 *Simulation.* Nine iterations were performed before the approach was stuck. Table 13 present all iterations with corresponding percentages for end-items that were infeasible. In addition, each iteration was simulated with and without uncertain resource efficiency to examine the effect of scheduling. Furthermore, SKUs that received a lead-time in each iteration have also been presented. Production plans from the analytical model for each iteration can be found in Appendices 1 – 11.

As you can see from the results above, the tendency is decreasing except from iteration5 where both total cost and number of infeasibilities suddenly increases. From iteration5 to iteration6, total cost decreases again which indicates that the production plan received in iteration5 is not as good as it could be. The reason for this is that the analytical model does not necessarily provide the optimal solution as stated in chapter 5.1. *Testing the analytical models*.

Figure 5: Percentage Infeasibilities in each iteration. Stochastic and deterministic

Figure 5 compares number of infeasible observations in each iteration for the deterministic and stochastic case. You can see that the effect of uncertain resource efficiency have high impact on robustness of the production plan. Even after nine iterations, the stochastic case does not perform as good as the deterministic case. On the other hand, the tendency is decreasing which implies that the plan has become more robust. Further, if we exclude iteration5, the difference in total cost between the highest and lowest iteration is only 0. 0015 % which is so small that it can be disregarded entirely as a factor.

5.2.2.3 Summary

Based on the data received and assumptions made for this case, we can say that it is desirable to buffer against uncertainties if possible. Applying the hybrid model to generate more robust production plans cause little to no extra cost. As an additional point, it is also necessary to highlight the importance of scheduling. It would be interesting to examine the effect when including scheduling decisions in the hybrid model to see if all infeasibilities can be prevented.

6.0 Conclusion

The main purpose of this thesis was to develop a method that could be used to perform production planning in Glamox. Firstly, we analyzed the production-planning problem and categorized it as ML-CLSP under uncertainty. Further, it was decided to develop a hybrid model that incorporates both analytical and simulation methods. The analytical model is used to generate a production plan. This plan is then simulated multiple times with a simulation model that incorporates stochastic parameters. All infeasible occurrences are registered and based on these, necessary adjustments are made in the analytical model. This procedure is looped until number of infeasibilities have been reduced to a desirable level.

Due to complexity of the ML-CLSP, it became necessary to develop two analytical models. These were an exact model and a tabu search based heuristic. Models were tested on several different instances in order to ensure acceptable solution quality. Even though instances were few, the results implies that the exact method finds acceptable solutions within reasonable time for instances tested.

Next, the hybrid model was tested on a case based on Glamox with stochastic resource efficiency. The first observation was related to scheduling. Infeasibilities occurred even in the deterministic case due to the lack of scheduling in the hybrid model. This effect was surprisingly high and neither of the iterations performed during the looping procedure was able to eliminate all infeasibilities in the deterministic case. However, despite the lack of scheduling, it was possible to reduce number of infeasibilities substantially by applying the hybrid method. In addition, difference in total cost between all iterations is very small. Due to this, it is considered to be desirable to buffer against uncertainties. Note though, that due to many assumptions and limited data, these results might be misleading.

7.0 Further research

Concerning the Glamox case, several additions can be incorporated into the models that have been developed.

- Add period overlapping setups and/or sequence dependent set up times to the analytical models.
- Include short-term capacity increases like overtime in the simulation model.
- Develop a method for scheduling in the hybrid model. It can either be connected to the analytical model, separate or part of the simulation.
- Apply a more sophisticated decision rule than simple lead-time additions between the simulation and analytical-model.
- Introduce more stochastic parameters.
- Especially interesting in a multi-level product hierarchy is defect occurrences.
- Disaggregate resource types in the simulation model so that it is possible to make plans for each of them separately. Will require scheduling to be performed.
- Apply another objective function that obtain more robust initial solutions.

A lot of time was spent on development of the tabu search based heuristic and many choices have been made. When looking back, we see that some things could have been done differently. For further research, it is suggested to:

- Implement aspiration criteria in the search.
- Include more sophisticated diversification strategies.
- Develop more sophisticated and advanced move strategies.
- Code the algorithm in another language will most likely speed up the search,
- TS might not be the best option for ML-CLSP. Try to apply another heuristic to the problem.

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9.0 Appendices

Appendix 1. All SKUs Lead-time = 0:
SKU p and corresponding production in each time bucket t over the planning horizon T

	Production All_Lead_Time = 0									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	0	49
SKU3	0	0	0	0	0	0	0	0	75	0
SKU4	0	0	0	0	0	50	0	0	0	0
SKU5	0	0	0	0	0	18	12	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	0	144	0	0	0
SKU10	0	0	0	0	0	0	0	0	0	102
SKU11	0	0	0	0	0	0	0	0	68	0
SKU12	0	0	0	0	0	0	75	0	0	0
SKU13	0	0	0	0	0	0	0	25	0	0
SKU14	0	0	0	0	0	13	0	67	0	0
SKU15	0	0	0	0	0	22	43	0	0	0
SKU16	0	0	0	0	0	0	0	69	0	71
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	0	60	0	0	0	0	46	11
SKU19	0	0	0	0	0	0	0	55	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	0	100
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	0	27	0	33	0
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	0	0	150	0	0	0	35	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	0	192	0	0	0
SKU30	0	0	0	100	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	0	144
SKU32	0	0	0	0	55	0	0	0	35	0
SKU33	0	0	0	0	0	0	0	0	160	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	0	270	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	0	0	500
SKU39	0	0	0	0	0	0	0	0	0	1000
SKU40	0	0	0	0	0	0	0	0	0	120
SKU41	0	0	0	0	0	0	0	0	0	120
SKU42	0	0	0	0	0	0	0	0	0	180
SKU43	0	0	0	0	0	0	120	0	120	0
SKU44	0	0	0	0	0	0	0	0	180	0
SKU45	0	0	0	0	0	75	0	0	0	0
SKU46	0	0	0	0	400	0	0	0	0	0
SKU47	0	0	0	360	0	0	0	0	0	0
SKU48	0	0	0	0	0	18	12	0	0	0
SKU49	0	0	0	0	0	36	24	0	0	0
SKU50	0	0	0	0	0	18	12	0	0	0

SKU51	0	756	0	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	0	360	0	0
SKU53	0	0	0	0	0	0	150	0	0	0
SKU54	0	0	0	0	0	0	0	55	41	61
SKU55	0	0	0	0	0	0	0	55	41	61
SKU56	0	0	0	0	0	0	0	0	0	120
SKU57	0	0	0	0	0	0	0	0	0	120
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	360	0	0	0
SKU60	0	0	0	0	0	68	0	0	0	0
SKU61	0	0	0	0	0	0	180	0	0	0
SKU62	0	0	0	0	0	0	100	0	0	0
SKU63	0	0	0	0	0	0	0	500	0	0
SKU64	0	0	0	200	0	0	0	0	0	0
SKU65	0	0	0	0	0	900	0	0	0	0
SKU66	0	0	0	0	0	146	0	0	0	0
SKU67	0	0	0	0	0	22	65	0	138	0
SKU68	0	0	0	0	0	22	43	0	160	0
SKU69	0	0	0	0	0	0	0	69	0	71
SKU70	0	0	0	0	0	0	47	22	0	71
SKU71	0	0	100	80	0	120	0	0	46	11
SKU72	0	0	0	120	0	0	0	0	92	22
SKU73	0	0	0	0	0	0	0	180	0	0
SKU74	0	0	0	0	0	0	0	0	0	100
SKU75	0	0	0	0	0	180	180	0	0	0
SKU76	0	0	0	0	0	151	287	0	66	0
SKU77	0	0	0	0	150	0	0	0	50	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	0	100	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	0	500	0	0	0	0	0	0
SKU82	0	0	0	0	329	0	0	0	0	0
SKU83	0	0	0	0	100	0	0	0	0	0
SKU84	0	0	0	0	150	0	0	0	0	0
SKU85	0	0	0	0	150	0	0	0	0	0
SKU86	0	0	0	0	55	0	0	0	35	0
SKU87	0	0	0	0	1260	0	0	0	0	0
SKU88	0	0	0	1800	0	0	0	0	0	0
SKU89	0	0	0	0	0	1080	0	0	0	0
SKU90	0	0	0	0	0	0	720	0	0	0
SKU91	0	0	0	0	0	0	0	180	0	0
SKU92	0	0	0	0	0	0	0	0	0	100
SKU93	0	0	0	0	0	0	0	0	0	100
SKU94	0	0	0	540	0	0	0	0	0	0
SKU95	0	0	0	0	180	0	0	0	0	0

Appendix 2. Instance 1:
SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_1									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	0	75	0
SKU4	0	0	0	0	0	50	0	0	0	0
SKU5	0	0	0	0	0	30	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	0	144	0	0	0
SKU10	0	0	0	0	0	0	0	58	44	0
SKU11	0	0	0	0	0	0	0	0	0	68
SKU12	0	0	0	0	0	0	75	0	0	0
SKU13	0	0	0	0	0	0	0	25	0	0
SKU14	0	0	0	0	0	13	0	67	0	0
SKU15	0	0	0	0	0	18	47	0	0	0
SKU16	0	0	0	0	0	0	0	65	75	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	0	52	3	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	0	100
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	0	27	0	0	33
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	0	0	100	0	0	0	0	85
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	144	0	0
SKU32	0	0	0	0	55	0	0	0	35	0
SKU33	0	0	0	0	0	0	0	0	0	160
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	0	270	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	0	500	0
SKU39	0	0	0	0	0	0	0	0	1000	0
SKU40	0	0	0	0	0	0	0	120	0	0
SKU41	0	0	0	0	0	0	0	120	0	0
SKU42	0	0	0	0	0	0	0	0	180	0
SKU43	0	0	0	0	0	120	0	0	120	0
SKU44	0	0	0	0	0	0	0	0	180	0
SKU45	0	0	0	0	0	75	0	0	0	0
SKU46	0	0	0	0	0	400	0	0	0	0
SKU47	0	0	360	0	0	0	0	0	0	0
SKU48	0	0	0	0	0	30	0	0	0	0
SKU49	0	0	0	0	0	60	0	0	0	0
SKU50	0	0	0	0	0	30	0	0	0	0

SKU51	56	0	0	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	0	360	0	0
SKU53	0	0	0	0	0	0	150	0	0	0
SKU54	0	0	0	0	0	0	52	61	44	0
SKU55	0	0	0	0	0	0	52	61	44	0
SKU56	0	0	0	0	0	0	0	120	0	0
SKU57	0	0	0	0	0	0	0	120	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	360	0	0	0
SKU60	0	0	0	0	0	68	0	0	0	0
SKU61	0	0	0	0	0	0	180	0	0	0
SKU62	0	0	0	0	0	0	100	0	0	0
SKU63	0	0	0	0	0	0	0	500	0	0
SKU64	0	0	0	0	200	0	0	0	0	0
SKU65	0	0	0	0	900	0	0	0	0	0
SKU66	0	0	0	0	0	146	0	0	0	0
SKU67	0	0	0	0	0	18	117	0	0	90
SKU68	0	0	0	0	0	18	47	0	0	160
SKU69	0	0	0	0	0	0	0	65	75	0
SKU70	0	0	0	0	0	0	0	65	75	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	0	180	0	0	0
SKU74	0	0	0	0	0	0	0	0	0	100
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	0	384	54	0	0	66
SKU77	0	0	0	50	50	0	0	0	0	100
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	0	0	500	0	0	0	0	0
SKU82	0	0	0	0	329	0	0	0	0	0
SKU83	0	0	0	0	100	0	0	0	0	0
SKU84	0	0	0	0	150	0	0	0	0	0
SKU85	0	0	0	0	150	0	0	0	0	0
SKU86	0	0	0	0	55	0	0	0	35	0
SKU87	0	0	0	0	1260	0	0	0	0	0
SKU88	0	0	1800	0	0	0	0	0	0	0
SKU89	0	0	0	0	0	1080	0	0	0	0
SKU90	0	0	0	0	0	0	720	0	0	0
SKU91	0	0	0	0	0	0	180	0	0	0
SKU92	0	0	0	0	0	0	0	0	0	100
SKU93	0	0	0	0	0	0	0	0	0	100
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	0	0	0	180	0	0	0	0	0

Appendix 3. Instance 2:
SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_2									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	0	75	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	24	6	0	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	144	0	0	0	0
SKU10	0	0	0	0	0	0	0	0	102	0
SKU11	0	0	0	0	0	0	0	0	0	68
SKU12	0	0	0	0	0	0	75	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	0	13	0	67	0	0
SKU15	0	0	0	0	0	65	0	0	0	0
SKU16	0	0	0	0	28	0	32	71	9	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	0	0	55	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	0	100
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	0	27	0	0	33
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	0	100	0	0	85	0	0	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	0	144
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	0	0	0	160	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	0	270	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	0	120	0	0
SKU41	0	0	0	0	0	0	0	120	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	0	0	120	0	120	0
SKU44	0	0	0	0	0	0	0	0	180	0
SKU45	0	0	75	0	0	0	0	0	0	0
SKU46	0	0	0	0	400	0	0	0	0	0
SKU47	0	0	360	0	0	0	0	0	0	0
SKU48	0	0	0	24	6	0	0	0	0	0
SKU49	0	0	0	48	12	0	0	0	0	0
SKU50	0	0	0	24	6	0	0	0	0	0

SKU51	0	756	0	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	360	0	0	0
SKU53	0	0	0	0	0	150	0	0	0	0
SKU54	0	0	0	0	0	52	44	61	0	0
SKU55	0	0	0	0	0	52	44	61	0	0
SKU56	0	0	0	0	0	0	0	120	0	0
SKU57	0	0	0	0	0	0	0	120	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	0	360	0	0
SKU60	0	0	0	0	0	68	0	0	0	0
SKU61	0	0	0	0	0	0	180	0	0	0
SKU62	0	0	0	0	100	0	0	0	0	0
SKU63	0	0	0	0	0	0	500	0	0	0
SKU64	0	0	0	0	0	200	0	0	0	0
SKU65	0	0	0	0	0	900	0	0	0	0
SKU66	0	0	0	0	0	146	0	0	0	0
SKU67	0	0	0	0	0	65	0	0	160	0
SKU68	0	0	0	0	0	65	0	0	160	0
SKU69	0	0	0	0	28	0	32	71	9	0
SKU70	0	0	0	0	28	10	22	71	9	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	0	0	180	0	0
SKU74	0	0	0	0	0	0	0	0	0	100
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	0	384	54	0	0	66
SKU77	0	0	0	100	0	0	100	0	0	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	500	0	0	0	0	0	0	0
SKU82	0	0	0	329	0	0	0	0	0	0
SKU83	0	0	0	100	0	0	0	0	0	0
SKU84	0	0	0	150	0	0	0	0	0	0
SKU85	0	0	0	150	0	0	0	0	0	0
SKU86	0	0	0	55	0	0	0	35	0	0
SKU87	0	0	0	0	1260	0	0	0	0	0
SKU88	0	0	1800	0	0	0	0	0	0	0
SKU89	0	0	0	0	0	1080	0	0	0	0
SKU90	0	0	0	0	0	0	720	0	0	0
SKU91	0	0	0	0	0	0	0	180	0	0
SKU92	0	0	0	0	0	0	0	0	0	100
SKU93	0	0	0	0	0	0	0	0	0	100
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	0	0	180	0	0	0	0	0	0

Appendix 4. Instance 3:
SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_3									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	0	75	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	0	0	30	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	144	0	0	0	0
SKU10	0	0	0	0	0	0	0	12	90	0
SKU11	0	0	0	0	0	0	0	0	68	0
SKU12	0	0	0	0	0	75	0	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	0	13	0	67	0	0
SKU15	0	0	0	0	0	0	65	0	0	0
SKU16	0	0	0	0	0	0	65	0	75	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	0	0	55	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	0	100
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	0	27	0	0	33
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	0	150	0	0	0	35	0	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	144	0
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	0	0	20	140	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	0	270	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	120	0	0	0
SKU41	0	0	0	0	0	120	0	0	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	0	120	0	0	120	0
SKU44	0	0	0	0	0	0	0	0	180	0
SKU45	0	0	0	75	0	0	0	0	0	0
SKU46	0	0	0	0	400	0	0	0	0	0
SKU47	0	0	360	0	0	0	0	0	0	0
SKU48	0	0	0	0	30	0	0	0	0	0
SKU49	0	0	0	0	60	0	0	0	0	0
SKU50	0	0	0	0	30	0	0	0	0	0

SKU51	0	756	0	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	360	0	0	0
SKU53	0	0	0	0	0	150	0	0	0	0
SKU54	0	0	0	0	0	30	37	90	0	0
SKU55	0	0	0	0	0	30	37	90	0	0
SKU56	0	0	0	0	0	0	120	0	0	0
SKU57	0	0	0	0	0	0	120	0	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	0	360	0	0
SKU60	0	0	0	0	0	68	0	0	0	0
SKU61	0	0	0	0	0	180	0	0	0	0
SKU62	0	0	0	0	0	100	0	0	0	0
SKU63	0	0	0	0	0	0	500	0	0	0
SKU64	0	0	0	0	200	0	0	0	0	0
SKU65	0	0	0	0	0	900	0	0	0	0
SKU66	0	0	0	0	0	122	24	0	0	0
SKU67	0	0	0	0	0	83	4	138	0	0
SKU68	0	0	0	0	0	65	38	122	0	0
SKU69	0	0	0	0	0	0	65	0	75	0
SKU70	0	0	0	0	0	0	65	0	75	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	0	0	180	0	0
SKU74	0	0	0	0	0	0	0	0	0	100
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	384	0	54	0	0	66
SKU77	0	0	50	100	0	0	0	50	0	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	500	0	0	0	0	0	0	0
SKU82	0	0	0	329	0	0	0	0	0	0
SKU83	0	0	0	100	0	0	0	0	0	0
SKU84	0	0	0	150	0	0	0	0	0	0
SKU85	0	0	0	150	0	0	0	0	0	0
SKU86	0	0	0	55	0	0	0	35	0	0
SKU87	0	0	0	0	1260	0	0	0	0	0
SKU88	0	0	1800	0	0	0	0	0	0	0
SKU89	0	0	0	0	0	1080	0	0	0	0
SKU90	0	0	0	0	0	720	0	0	0	0
SKU91	0	0	0	0	0	0	0	180	0	0
SKU92	0	0	0	0	0	0	0	0	0	100
SKU93	0	0	0	0	0	0	0	0	0	100
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	0	0	180	0	0	0	0	0	0

Appendix 5. Instance 4:
SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_4									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	0	75	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	0	0	30	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	0	144	0	0	0
SKU10	0	0	0	0	0	0	0	12	90	0
SKU11	0	0	0	0	0	0	0	0	68	0
SKU12	0	0	0	0	0	75	0	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	0	13	0	67	0	0
SKU15	0	0	0	0	0	20	45	0	0	0
SKU16	0	0	0	0	0	0	65	0	75	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	0	0	55	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	0	100
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	0	27	0	0	33
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	0	150	0	0	0	35	0	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	144	0
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	0	0	20	140	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	270	0	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	0	120	0	0
SKU41	0	0	0	0	0	0	120	0	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	0	120	0	0	120	0
SKU44	0	0	0	0	0	0	0	0	180	0
SKU45	0	0	75	0	0	0	0	0	0	0
SKU46	0	0	0	0	400	0	0	0	0	0
SKU47	0	0	360	0	0	0	0	0	0	0
SKU48	0	0	0	0	30	0	0	0	0	0
SKU49	0	0	0	0	60	0	0	0	0	0
SKU50	0	0	0	0	30	0	0	0	0	0

SKU51	0	756	0	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	360	0	0	0
SKU53	0	0	0	0	0	0	150	0	0	0
SKU54	0	0	0	0	0	30	37	90	0	0
SKU55	0	0	0	0	0	30	37	90	0	0
SKU56	0	0	0	0	0	0	120	0	0	0
SKU57	0	0	0	0	0	0	120	0	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	0	360	0	0
SKU60	0	0	0	0	0	68	0	0	0	0
SKU61	0	0	0	0	0	180	0	0	0	0
SKU62	0	0	0	0	100	0	0	0	0	0
SKU63	0	0	0	0	0	0	500	0	0	0
SKU64	0	0	0	0	0	200	0	0	0	0
SKU65	0	0	0	0	0	900	0	0	0	0
SKU66	0	0	0	0	0	122	24	0	0	0
SKU67	0	0	0	0	20	67	0	138	0	0
SKU68	0	0	0	0	20	45	38	122	0	0
SKU69	0	0	0	0	0	0	65	0	75	0
SKU70	0	0	0	0	0	0	65	0	75	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	0	0	180	0	0
SKU74	0	0	0	0	0	0	0	0	0	100
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	384	0	54	0	0	66
SKU77	0	0	0	150	0	0	0	50	0	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	500	0	0	0	0	0	0	0
SKU82	0	0	0	329	0	0	0	0	0	0
SKU83	0	0	0	100	0	0	0	0	0	0
SKU84	0	0	0	150	0	0	0	0	0	0
SKU85	0	0	0	150	0	0	0	0	0	0
SKU86	0	0	0	55	0	0	0	35	0	0
SKU87	0	0	0	1260	0	0	0	0	0	0
SKU88	0	1800	0	0	0	0	0	0	0	0
SKU89	0	0	0	0	0	1080	0	0	0	0
SKU90	0	0	0	0	0	720	0	0	0	0
SKU91	0	0	0	0	0	0	0	180	0	0
SKU92	0	0	0	0	0	0	0	0	0	100
SKU93	0	0	0	0	0	0	0	0	0	100
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	0	0	180	0	0	0	0	0	0

Appendix 6. Instance 5:
SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_5									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	0	75	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	0	19	11	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	0	144	0	0	0
SKU10	0	0	0	0	0	0	0	12	90	0
SKU11	0	0	0	0	0	0	0	0	68	0
SKU12	0	0	0	0	0	75	0	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	13	0	67	0	0	0
SKU15	0	0	0	0	0	18	47	0	0	0
SKU16	0	0	0	0	0	0	65	0	75	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	0	0	55	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	0	100
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	0	27	0	0	33
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	0	100	0	0	0	85	0	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	144	0
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	0	0	40	120	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	0	270	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	0	120	0	0
SKU41	0	0	0	0	0	0	120	0	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	0	120	0	0	120	0
SKU44	0	0	0	0	0	0	0	0	180	0
SKU45	0	0	75	0	0	0	0	0	0	0
SKU46	0	0	0	400	0	0	0	0	0	0
SKU47	0	0	360	0	0	0	0	0	0	0
SKU48	0	0	0	19	11	0	0	0	0	0
SKU49	0	0	0	38	22	0	0	0	0	0
SKU50	0	0	0	19	11	0	0	0	0	0

SKU51	0	0	0	432	0	0	0	0	0	432
SKU52	0	0	0	0	0	0	360	0	0	0
SKU53	0	0	0	0	0	0	150	0	0	0
SKU54	0	0	0	0	0	30	37	90	0	0
SKU55	0	0	0	0	0	30	37	90	0	0
SKU56	0	0	0	0	0	0	120	0	0	0
SKU57	0	0	0	0	0	0	120	0	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	0	360	0	0
SKU60	0	0	0	68	0	0	0	0	0	0
SKU61	0	0	0	0	0	180	0	0	0	0
SKU62	0	0	0	0	0	100	0	0	0	0
SKU63	0	0	0	0	0	0	500	0	0	0
SKU64	0	0	0	0	200	0	0	0	0	0
SKU65	0	0	0	0	900	0	0	0	0	0
SKU66	0	0	0	146	0	0	0	0	0	0
SKU67	0	0	0	0	18	117	0	90	0	0
SKU68	0	0	0	0	18	47	40	120	0	0
SKU69	0	0	0	0	0	0	65	0	75	0
SKU70	0	0	0	0	0	0	65	0	75	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	0	0	180	0	0
SKU74	0	0	0	0	0	0	0	0	0	100
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	97	287	54	0	0	66
SKU77	0	0	0	100	0	0	0	100	0	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	0	500	0	0	0	0	0	0
SKU82	0	0	329	0	0	0	0	0	0	0
SKU83	0	0	0	100	0	0	0	0	0	0
SKU84	0	0	0	150	0	0	0	0	0	0
SKU85	0	0	0	150	0	0	0	0	0	0
SKU86	0	0	0	55	0	0	0	35	0	0
SKU87	0	0	0	0	1260	0	0	0	0	0
SKU88	0	1800	0	0	0	0	0	0	0	0
SKU89	0	0	0	1080	0	0	0	0	0	0
SKU90	0	0	0	0	0	720	0	0	0	0
SKU91	0	0	0	0	0	0	0	180	0	0
SKU92	0	0	0	0	0	0	0	0	0	100
SKU93	0	0	0	0	0	0	0	0	0	100
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	0	0	180	0	0	0	0	0	0

Appendix 7. Instance 6:

SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_6									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	0	75	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	2	28	0	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	0	144	0	0	0
SKU10	0	0	0	0	0	0	0	12	90	0
SKU11	0	0	0	0	0	0	0	0	68	0
SKU12	0	0	0	0	0	75	0	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	13	0	67	0	0	0
SKU15	0	0	0	0	0	65	0	0	0	0
SKU16	0	0	0	0	18	0	42	71	9	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	0	0	55	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	100	0
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	27	0	0	33	0
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	50	50	0	0	0	0	85	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	144	0
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	0	0	0	160	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	0	270	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	0	120	0	0
SKU41	0	0	0	0	0	0	120	0	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	0	120	0	0	120	0
SKU44	0	0	0	0	0	0	0	0	180	0
SKU45	0	0	75	0	0	0	0	0	0	0
SKU46	0	0	0	400	0	0	0	0	0	0
SKU47	0	0	360	0	0	0	0	0	0	0
SKU48	0	0	2	28	0	0	0	0	0	0
SKU49	0	0	4	56	0	0	0	0	0	0
SKU50	0	0	2	28	0	0	0	0	0	0

SKU51	0	756	0	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	360	0	0	0
SKU53	0	0	0	0	0	0	150	0	0	0
SKU54	0	0	0	0	0	30	37	90	0	0
SKU55	0	0	0	0	0	30	37	90	0	0
SKU56	0	0	0	0	0	0	120	0	0	0
SKU57	0	0	0	0	0	0	120	0	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	0	360	0	0
SKU60	0	0	0	68	0	0	0	0	0	0
SKU61	0	0	0	0	0	180	0	0	0	0
SKU62	0	0	0	0	0	100	0	0	0	0
SKU63	0	0	0	0	0	0	500	0	0	0
SKU64	0	0	0	0	200	0	0	0	0	0
SKU65	0	0	0	0	900	0	0	0	0	0
SKU66	0	0	0	146	0	0	0	0	0	0
SKU67	0	0	0	0	65	0	0	160	0	0
SKU68	0	0	0	0	65	6	42	112	0	0
SKU69	0	0	0	18	0	42	71	9	0	0
SKU70	0	0	0	18	0	42	71	9	0	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	0	0	180	0	0
SKU74	0	0	0	0	0	0	0	100	0	0
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	151	287	0	0	66	0
SKU77	0	0	50	50	0	0	0	0	100	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	500	0	0	0	0	0	0	0
SKU82	0	0	329	0	0	0	0	0	0	0
SKU83	0	0	0	100	0	0	0	0	0	0
SKU84	0	0	0	150	0	0	0	0	0	0
SKU85	0	0	0	150	0	0	0	0	0	0
SKU86	0	0	0	55	0	0	0	35	0	0
SKU87	0	0	0	0	1260	0	0	0	0	0
SKU88	0	1800	0	0	0	0	0	0	0	0
SKU89	0	0	0	1080	0	0	0	0	0	0
SKU90	0	0	0	0	0	720	0	0	0	0
SKU91	0	0	0	0	0	0	0	180	0	0
SKU92	0	0	0	0	0	0	0	100	0	0
SKU93	0	0	0	0	0	0	0	100	0	0
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	0	0	180	0	0	0	0	0	0

Appendix 8. Instance 7:
SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_7									
	T1	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**	**T9**	**T10**
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	75	0	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	30	0	0	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	0	144	0	0	0
SKU10	0	0	0	0	0	0	0	58	44	0
SKU11	0	0	0	0	0	0	0	0	68	0
SKU12	0	0	0	0	0	75	0	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	13	0	67	0	0	0
SKU15	0	0	0	0	65	0	0	0	0	0
SKU16	0	0	0	1	0	0	37	75	27	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	30	25	0	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	100	0
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	27	0	0	33	0
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	50	50	0	0	0	0	85	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	144	0
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	30	10	10	110	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	0	270	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	120	0	0	0
SKU41	0	0	0	0	0	120	0	0	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	0	120	0	120	0	0
SKU44	0	0	0	0	0	0	0	180	0	0
SKU45	0	0	0	0	75	0	0	0	0	0
SKU46	0	0	0	400	0	0	0	0	0	0
SKU47	0	360	0	0	0	0	0	0	0	0
SKU48	0	0	30	0	0	0	0	0	0	0
SKU49	0	0	60	0	0	0	0	0	0	0
SKU50	0	0	30	0	0	0	0	0	0	0

SKU51	756	0	0	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	360	0	0	0
SKU53	0	0	0	0	0	150	0	0	0	0
SKU54	0	0	0	0	30	30	53	44	0	0
SKU55	0	0	0	0	30	30	53	44	0	0
SKU56	0	0	0	0	0	0	120	0	0	0
SKU57	0	0	0	0	0	0	120	0	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	0	360	0	0
SKU60	0	0	0	68	0	0	0	0	0	0
SKU61	0	0	0	0	0	180	0	0	0	0
SKU62	0	0	0	0	0	100	0	0	0	0
SKU63	0	0	0	0	0	500	0	0	0	0
SKU64	0	0	0	0	200	0	0	0	0	0
SKU65	0	0	0	0	900	0	0	0	0	0
SKU66	0	0	0	146	0	0	0	0	0	0
SKU67	0	0	0	115	0	0	0	110	0	0
SKU68	0	0	0	65	30	13	39	78	0	0
SKU69	0	0	1	0	0	37	75	27	0	0
SKU70	0	0	1	0	0	37	75	27	0	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	180	0	0	0	0
SKU74	0	0	0	0	0	0	0	100	0	0
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	151	287	0	0	66	0
SKU77	0	0	50	50	0	0	0	0	100	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	500	0	0	0	0	0	0	0	0
SKU82	0	0	329	0	0	0	0	0	0	0
SKU83	0	0	0	100	0	0	0	0	0	0
SKU84	0	0	0	150	0	0	0	0	0	0
SKU85	0	0	0	150	0	0	0	0	0	0
SKU86	0	0	0	55	0	0	0	35	0	0
SKU87	0	0	0	0	1260	0	0	0	0	0
SKU88	1800	0	0	0	0	0	0	0	0	0
SKU89	0	0	0	1080	0	0	0	0	0	0
SKU90	0	0	0	0	0	720	0	0	0	0
SKU91	0	0	0	0	0	180	0	0	0	0
SKU92	0	0	0	0	0	0	0	100	0	0
SKU93	0	0	0	0	0	0	0	100	0	0
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	0	0	180	0	0	0	0	0	0

Appendix 9. Instance 8:
SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_8									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	75	0	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	29	0	1	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	0	144	0	0	0
SKU10	0	0	0	0	0	0	30	28	44	0
SKU11	0	0	0	0	0	0	0	0	68	0
SKU12	0	0	0	0	0	75	0	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	13	0	67	0	0	0
SKU15	0	0	0	0	0	65	0	0	0	0
SKU16	0	0	0	0	18	0	42	71	9	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	0	0	55	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	100	0
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	27	0	0	33	0
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	0	100	0	0	0	0	85	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	144	0
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	0	0	0	160	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	0	270	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	0	120	0	0
SKU41	0	0	0	0	0	0	120	0	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	0	120	0	120	0	0
SKU44	0	0	0	0	0	0	0	180	0	0
SKU45	0	75	0	0	0	0	0	0	0	0
SKU46	0	0	0	400	0	0	0	0	0	0
SKU47	0	180	180	0	0	0	0	0	0	0
SKU48	0	0	30	0	0	0	0	0	0	0
SKU49	0	0	58	0	2	0	0	0	0	0
SKU50	0	0	29	0	1	0	0	0	0	0

SKU51	0	0	0	756	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	360	0	0	0
SKU53	0	0	0	0	0	150	0	0	0	0
SKU54	0	0	0	0	0	30	83	44	0	0
SKU55	0	0	0	0	0	30	83	44	0	0
SKU56	0	0	0	0	120	0	0	0	0	0
SKU57	0	0	0	0	120	0	0	0	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	0	360	0	0
SKU60	0	0	0	67	1	0	0	0	0	0
SKU61	0	0	0	0	0	180	0	0	0	0
SKU62	0	0	0	0	0	100	0	0	0	0
SKU63	0	0	0	0	0	500	0	0	0	0
SKU64	0	0	0	0	200	0	0	0	0	0
SKU65	0	0	0	0	900	0	0	0	0	0
SKU66	0	0	0	30	116	0	0	0	0	0
SKU67	0	0	0	0	65	0	0	160	0	0
SKU68	0	0	0	0	65	153	0	7	0	0
SKU69	0	0	0	18	0	42	71	9	0	0
SKU70	0	0	0	18	0	42	71	9	0	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	0	0	180	0	0
SKU74	0	0	0	0	0	0	0	100	0	0
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	151	287	0	0	66	0
SKU77	0	0	0	100	0	0	0	0	100	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	500	0	0	0	0	0	0	0
SKU82	0	0	329	0	0	0	0	0	0	0
SKU83	0	0	0	100	0	0	0	0	0	0
SKU84	0	0	0	150	0	0	0	0	0	0
SKU85	0	0	0	150	0	0	0	0	0	0
SKU86	0	0	0	55	0	0	0	35	0	0
SKU87	0	0	0	0	1260	0	0	0	0	0
SKU88	1800	0	0	0	0	0	0	0	0	0
SKU89	0	0	0	1080	0	0	0	0	0	0
SKU90	0	0	0	0	0	720	0	0	0	0
SKU91	0	0	0	0	0	0	0	180	0	0
SKU92	0	0	0	0	0	0	0	100	0	0
SKU93	0	0	0	0	0	0	0	100	0	0
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	0	0	180	0	0	0	0	0	0

Appendix 10. Instance 9:
SKU p and corresponding production in each period time bucket over T planning horizon

	Instance_9									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
SKU1	0	0	0	0	80	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	75	0	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	9	21	0	0	0	0	0
SKU6	0	0	0	55	0	0	0	0	0	550
SKU7	0	0	0	0	0	0	0	80	0	0
SKU8	0	0	0	0	0	76	0	50	0	0
SKU9	0	0	0	0	0	0	144	0	0	0
SKU10	0	0	0	0	0	0	0	58	44	0
SKU11	0	0	0	0	0	0	0	0	68	0
SKU12	0	0	0	0	0	75	0	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	13	0	67	0	0	0
SKU15	0	0	0	0	0	65	0	0	0	0
SKU16	0	0	0	0	18	0	42	71	9	0
SKU17	0	0	0	0	0	0	0	0	55	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	30	25	0	0	0
SKU20	0	0	0	0	100	0	0	0	0	40
SKU21	0	0	0	0	0	0	0	77	0	0
SKU22	0	0	0	0	0	0	0	0	100	0
SKU23	0	0	0	0	0	23	0	0	47	0
SKU24	0	0	0	0	0	27	0	0	33	0
SKU25	0	0	0	0	0	0	0	0	140	0
SKU26	0	0	0	120	0	120	0	0	0	0
SKU27	0	0	100	0	0	0	0	0	85	0
SKU28	0	0	0	0	0	0	0	0	100	0
SKU29	0	0	0	0	0	192	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	0	144	0
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	0	0	0	160	0
SKU34	0	0	0	0	0	0	66	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	0	270	0	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	0	120	0	0
SKU41	0	0	0	0	0	0	120	0	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	0	120	0	120	0	0
SKU44	0	0	0	0	0	0	0	180	0	0
SKU45	0	0	0	75	0	0	0	0	0	0
SKU46	0	0	0	400	0	0	0	0	0	0
SKU47	0	360	0	0	0	0	0	0	0	0
SKU48	0	0	9	21	0	0	0	0	0	0
SKU49	0	0	18	42	0	0	0	0	0	0
SKU50	0	0	9	21	0	0	0	0	0	0

SKU51	0	0	756	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	0	360	0	0	0
SKU53	0	0	0	0	0	150	0	0	0	0
SKU54	0	0	0	0	30	30	53	44	0	0
SKU55	0	0	0	0	30	30	53	44	0	0
SKU56	0	0	0	0	0	0	120	0	0	0
SKU57	0	0	0	0	0	0	120	0	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	0	0	0	360	0	0
SKU60	0	0	0	0	68	0	0	0	0	0
SKU61	0	0	0	0	0	180	0	0	0	0
SKU62	0	0	0	0	0	100	0	0	0	0
SKU63	0	0	0	0	0	500	0	0	0	0
SKU64	0	0	0	0	200	0	0	0	0	0
SKU65	0	0	0	0	900	0	0	0	0	0
SKU66	0	0	0	0	146	0	0	0	0	0
SKU67	0	0	0	0	65	0	0	160	0	0
SKU68	0	0	0	0	65	24	18	118	0	0
SKU69	0	0	0	18	0	42	71	9	0	0
SKU70	0	0	0	18	0	42	71	9	0	0
SKU71	0	0	60	120	0	120	0	0	57	0
SKU72	0	0	120	0	0	0	0	0	114	0
SKU73	0	0	0	0	0	180	0	0	0	0
SKU74	0	0	0	0	0	0	0	100	0	0
SKU75	0	0	0	0	180	180	0	0	0	0
SKU76	0	0	0	0	151	287	0	0	66	0
SKU77	0	0	100	0	0	0	0	0	100	0
SKU78	0	0	0	0	0	0	0	0	700	0
SKU79	0	0	100	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	0	0	432	0
SKU81	0	0	500	0	0	0	0	0	0	0
SKU82	0	0	329	0	0	0	0	0	0	0
SKU83	0	0	100	0	0	0	0	0	0	0
SKU84	0	0	150	0	0	0	0	0	0	0
SKU85	0	0	150	0	0	0	0	0	0	0
SKU86	0	0	55	0	0	0	35	0	0	0
SKU87	0	0	0	1260	0	0	0	0	0	0
SKU88	1800	0	0	0	0	0	0	0	0	0
SKU89	0	0	0	0	1080	0	0	0	0	0
SKU90	0	0	0	0	0	720	0	0	0	0
SKU91	0	0	0	0	0	180	0	0	0	0
SKU92	0	0	0	0	0	0	0	100	0	0
SKU93	0	0	0	0	0	0	0	100	0	0
SKU94	0	0	540	0	0	0	0	0	0	0
SKU95	0	180	0	0	0	0	0	0	0	0

Appendix 11. All SKUs Lead-time = 1:
SKU p and corresponding production in each period time bucket over T planning horizon

	All_Lead_Time=1									
	T1	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**	**T9**	**T10**
SKU1	0	0	0	80	0	0	0	0	0	0
SKU2	0	0	0	0	0	0	0	0	49	0
SKU3	0	0	0	0	0	0	0	75	0	0
SKU4	0	0	0	0	50	0	0	0	0	0
SKU5	0	0	0	29	1	0	0	0	0	0
SKU6	0	0	55	0	0	0	0	0	550	0
SKU7	0	0	0	0	0	0	80	0	0	0
SKU8	0	0	0	0	76	0	50	0	0	0
SKU9	0	0	0	0	0	144	0	0	0	0
SKU10	0	0	0	0	0	0	0	0	102	0
SKU11	0	0	0	0	0	0	0	12	56	0
SKU12	0	0	0	0	0	75	0	0	0	0
SKU13	0	0	0	0	0	0	25	0	0	0
SKU14	0	0	0	0	13	0	67	0	0	0
SKU15	0	0	0	0	53	12	0	0	0	0
SKU16	0	0	0	0	0	28	32	5	75	0
SKU17	0	0	0	0	0	0	0	55	0	0
SKU18	0	0	60	0	0	0	0	0	57	0
SKU19	0	0	0	0	0	0	55	0	0	0
SKU20	0	0	0	100	0	0	0	0	40	0
SKU21	0	0	0	0	0	0	77	0	0	0
SKU22	0	0	0	0	0	0	0	0	100	0
SKU23	0	0	0	0	23	0	0	47	0	0
SKU24	0	0	0	0	0	27	0	33	0	0
SKU25	0	0	0	0	0	0	0	140	0	0
SKU26	0	0	120	0	120	0	0	0	0	0
SKU27	0	0	0	100	0	0	85	0	0	0
SKU28	0	0	0	0	0	0	0	100	0	0
SKU29	0	0	0	0	64	128	0	0	0	0
SKU30	0	0	100	0	0	0	0	0	0	0
SKU31	0	0	0	0	0	0	0	144	0	0
SKU32	0	0	0	55	0	0	0	35	0	0
SKU33	0	0	0	0	0	0	0	160	0	0
SKU34	0	0	0	0	0	66	0	0	0	0
SKU35	0	0	0	0	0	0	0	0	0	0
SKU36	0	0	270	0	0	0	0	0	0	0
SKU37	0	0	0	0	0	0	0	0	0	0
SKU38	0	0	0	0	0	0	0	500	0	0
SKU39	0	0	0	0	0	0	0	1000	0	0
SKU40	0	0	0	0	0	0	0	120	0	0
SKU41	0	0	0	0	0	0	120	0	0	0
SKU42	0	0	0	0	0	0	0	180	0	0
SKU43	0	0	0	0	120	0	120	0	0	0
SKU44	0	0	0	0	0	0	180	0	0	0
SKU45	0	75	0	0	0	0	0	0	0	0
SKU46	0	0	400	0	0	0	0	0	0	0
SKU47	0	360	0	0	0	0	0	0	0	0
SKU48	0	0	30	0	0	0	0	0	0	0
SKU49	0	0	60	0	0	0	0	0	0	0
SKU50	0	0	29	1	0	0	0	0	0	0

SKU51	756	0	0	0	0	0	0	0	0	0
SKU52	0	0	0	0	0	360	0	0	0	0
SKU53	0	0	0	150	0	0	0	0	0	0
SKU54	0	0	0	0	0	55	41	61	0	0
SKU55	0	0	0	0	55	41	61	0	0	0
SKU56	0	0	0	0	0	0	0	120	0	0
SKU57	0	0	0	0	0	0	120	0	0	0
SKU58	0	0	0	0	0	0	0	0	0	0
SKU59	0	0	0	0	360	0	0	0	0	0
SKU60	0	0	0	68	0	0	0	0	0	0
SKU61	0	0	0	0	180	0	0	0	0	0
SKU62	0	0	0	0	100	0	0	0	0	0
SKU63	0	0	0	0	0	500	0	0	0	0
SKU64	0	0	0	200	0	0	0	0	0	0
SKU65	0	0	0	900	0	0	0	0	0	0
SKU66	0	0	0	122	24	0	0	0	0	0
SKU67	0	0	0	53	13	0	159	0	0	0
SKU68	0	0	0	53	12	0	160	0	0	0
SKU69	0	0	0	0	28	32	5	75	0	0
SKU70	0	0	0	0	38	22	5	75	0	0
SKU71	1	179	0	120	0	0	0	57	0	0
SKU72	99	21	0	0	0	0	0	114	0	0
SKU73	0	0	0	0	0	180	0	0	0	0
SKU74	0	0	0	0	0	0	100	0	0	0
SKU75	0	0	0	180	180	0	0	0	0	0
SKU76	0	0	128	0	310	0	66	0	0	0
SKU77	0	0	100	0	0	100	0	0	0	0
SKU78	0	0	0	0	0	0	700	0	0	0
SKU79	0	100	0	0	0	0	0	0	0	0
SKU80	0	0	0	0	0	0	432	0	0	0
SKU81	0	500	0	0	0	0	0	0	0	0
SKU82	0	0	329	0	0	0	0	0	0	0
SKU83	0	0	100	0	0	0	0	0	0	0
SKU84	0	0	150	0	0	0	0	0	0	0
SKU85	0	150	0	0	0	0	0	0	0	0
SKU86	0	0	55	0	0	0	35	0	0	0
SKU87	0	1260	0	0	0	0	0	0	0	0
SKU88	1800	0	0	0	0	0	0	0	0	0
SKU89	0	0	1080	0	0	0	0	0	0	0
SKU90	0	0	0	720	0	0	0	0	0	0
SKU91	0	0	0	0	180	0	0	0	0	0
SKU92	0	0	0	0	0	100	0	0	0	0
SKU93	0	0	0	0	0	100	0	0	0	0
SKU94	540	0	0	0	0	0	0	0	0	0
SKU95	0	180	0	0	0	0	0	0	0	0