Development of an Integrated Part and Tool Planning Heuristic

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II. Management Summary

In this Master Thesis a heuristic is developed for the inventory planning of service parts and tools for a company in the semiconductor industry. The company stocks service parts and tools in order to repair micro-lithography machines that are placed at customers at many different locations in the world. Since machine downtime results in high production losses for the customer, the company uses service contracts to agree upon the machine availability. Satisfying these service contracts is a top priority of the company.

The availability of service parts and tools has a major influence on the total downtime of machines. Therefore, the company has a world-wide network of warehouses in which the service parts and tools are stocked. These warehouses are situated close to the customers of the company. Since the demand rates of service parts and tools are low, stocking all service parts and tools in each location will result in very high service levels, but also in very high costs. Provisioning parts and tools over the network in a smart manner can thus result in high cost savings, while the service contracts are still satisfied.

Currently, the company uses a formal planning algorithm to determine the base stock levels of service parts for the warehouses in the network. However, for the planning of service tools no planning algorithm is used. This planning of service tools is based on the experience of the tool planners. Furthermore, the planning of tools and parts is separated. Since parts and tools are demanded in combinations, the possibility that a service order can be satisfied is dependent on both the availability of service parts and the availability of service tools. Planning parts and tools in an integrated way can thus result in a more efficient provisioning of the parts and tools. In this Master Thesis, we develop a heuristic for such an integrated planning.

Since a service order consists of a combination of parts and/or tools, the actual service is dependent on the delivery time of the complete service order. In this research a performance indicator on order level is used, called Down-Time-Waiting-Logistics (DTWL). DTWL is defined as the percentage of time a machine is down because it is waiting for a service order (parts and/or tools together). The research assignment is:

"Develop a heuristic planning algorithm which determines the base stock levels of all service parts and tools in all local warehouses in the service network. This planning algorithm should minimize total system costs subject to service requirements in terms of DTWL."

In total the planning algorithm to be developed should satisfy the following major requirements:

1. Efficiency with respect to the costs (cost efficiency)
2. Accuracy with respect to the service target (service accuracy)
3. Practicality with respect to the computation time
4. Understandability for the people that have to work with it
5. Ability to implement

The first two requirements are quantitative requirements, whereas the other three requirements are qualitative.

Four different heuristics will be assessed based on the requirements mentioned above. To compare the heuristics on the quantitative requirements, a detailed inventory model for parts and tools is developed. The detailed model includes all relevant process characteristics, such as coupling in tool demand, coupling in demand between parts and tools, lateral transshipments and demand substitution.
Using a simulation tool, the efficiency with respect to the costs and the accuracy with respect to the service target is evaluated.

The following four heuristics are developed:

- **Heuristic I**: This heuristic is based on the algorithm which the company currently uses for the planning of service parts. This heuristic does not take coupling in demand into account. Heuristic I is based on the continental model of Kranenburg (2006), which is a multi-location model that includes lateral transshipments. Unfortunately, Heuristic I cannot compute the base stock levels for a DTWL target. Instead a similar performance measure on item level is used, called DTWP. DTWP is defined as the percentage of time a machine is down because it is waiting on parts.

- **Heuristic II**: The second heuristic is an extension of Heuristic I and includes coupling in demand. This coupling in demand is included using an independent stock assumption. In this heuristic, coupling between tools as well as between parts and tools is included. Lateral transshipments are also included in this heuristic. The heuristic uses a starting solution generated by Heuristic I, in order to speed up the optimization.

- **Heuristic III**: In Heuristic III, the base stock levels of service tools are computed using a detailed single location model. This model is based on Vliegen and Van Houtum (2008) and includes coupling in demand and returns of tools in a detailed way. However, lateral transshipments are not included. In Heuristic III, the planning of parts and tools is done separately. This means that the coupling in demand between parts and tools is not included. The base stock levels of service parts are generated using Heuristic I.

- **US-Heuristic**: The US-Heuristic is based on a heuristic proposed by a project group of the company in the US. This heuristic uses simple decision rules to provision the service tools over the network. The heuristic proposed by the project group of the company proposes base stock levels for service tools only. In this research, the base stock levels of service parts are generated using Heuristic I. A drawback of the US-Heuristic is that no target is used for the computation of the base stock levels for service tools, resulting in a target-independent solution for the base stock levels of service tools.

The performance with respect to the quantitative requirements of the heuristics is assessed in different situations. For the comparison of the heuristics a test bed is constructed using data of the company. This data is collected out of the information systems of the company and is complemented by knowledge and experience of the employees of the company. Five different cases are constructed:

- Case I: US, with 13 local warehouses
- Case II: Korea, with 3 local warehouses
- Case III: Hong Kong, with 3 local warehouses and almost no lateral transshipment possibilities
- Case IV: As Case I, but with extra coupling in demand
- Case V: As Case I, but with higher demand rates per location

The US-Heuristic is only assessed in Case I. The other heuristics are compared in all five cases. The following research questions are answered using the results of the cases:

1. **Do the performances of the heuristics vary in different networks?**
   The results of Case I to III show that the Heuristic II is most efficient with respect to cost efficiency and service level accuracy. Heuristic I has equal results with respect to cost
efficiency, however, Heuristic I is less accurate with respect to the service target than Heuristic II. The comparison of the results for Case I to III further show that the performance of Heuristic III highly depends on the lateral transshipment possibilities in the network. Heuristic III performs equal to Heuristic I and II with respect to cost efficiency if the lateral transshipment possibilities are low, but worse when the network has many lateral transshipment possibilities. Finally, the results of the US-Heuristic in Case I show that the US-Heuristic results in considerable higher costs.

2. Do the performances of the heuristics vary for different levels of coupling in demand?

The result of the comparison between Case I and Case IV show that the relative cost benefits of Heuristic II compared to Heuristic I and III increase in case the coupling in demand increases. Furthermore, the results show that the effects of including lateral transshipments into a planning heuristic are more beneficial than including coupling in tool demand in an advanced way. The results further show that the service accuracy of Heuristic II increases in case the coupling in demand increases.

3. Do the performances of the heuristics vary for different demand rates per location?

For this research question the performance of the heuristics in Case I and V are compared. The performance with respect to cost efficiency does not vary considerably in case the demand rates per location are increased. The accuracy with respect to the service target of Heuristic II increases slightly in case the demand rates per location increase, whereas the accuracy of Heuristics I and III decreases slightly.

4. Do the performances of the heuristics vary for different target service levels?

Increasing or decreasing the service level in Case I does not have a major influence on the performance of Heuristics I and II with respect to cost efficiency. Increasing the service level has a positive effect on the service level accuracy of Heuristic II and a negative effect on the service accuracy of Heuristic I.

5. What are the effects on the performance if parts and tools are planned in an integrated way?

To answer this research question a comparison is made between planning parts and tools integrated using Heuristic II and planning parts and tools separately. In this separate planning, parts are planned using Heuristic I and tools are planned using Heuristic II. Planning parts and tools in an integrated way (by including coupling between parts and tools) results in considerable cost benefits compared to planning parts and tools separately. Furthermore, including coupling between parts and tools in a planning heuristic increases the accuracy with respect to the service target.

6. What are the benefits with respect to the performance of the heuristics if service measures are computed on order level?

The accuracy with respect to service is positively influenced by using a service target on order level. In the cases examined the differences between item and order service levels are about 10 percent. This difference increases if the coupling in demand increases.
A summary of the comparison based on the five requirements of a proper planning heuristic is given in Table II.1.

<table>
<thead>
<tr>
<th>Requirement</th>
<th>Heuristic I</th>
<th>Heuristic II</th>
<th>Heuristic III</th>
<th>US-Heuristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency with respect to the costs</td>
<td>+</td>
<td>++</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Accuracy with respect to the service target</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Practicality with respect to the computation time</td>
<td>++</td>
<td>+</td>
<td>-</td>
<td>++</td>
</tr>
<tr>
<td>Understandability for the people that have to work with it</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>++</td>
</tr>
<tr>
<td>Ability to implement</td>
<td>++</td>
<td>+</td>
<td>-</td>
<td>++</td>
</tr>
</tbody>
</table>

Table II.1: Comparison of the heuristics based on the five requirements

The following important conclusions can be drawn from the research:

- **Planning parts and tools in an integrated way results in considerable cost benefits.** By integrating the planning of parts and tools sub-optimization does not take place, resulting in a more beneficial base stock level provisioning. Taking the coupling between parts and tools into account, next to integrating the planning of parts and tools, increases the benefits further.

- **All experiments have shown that Heuristic II is most efficient with respect to cost difference and most accurate with respect to the service target.** Heuristic II also fits the qualitative requirements. The positive results of this heuristic are caused by the integration of the tool and part planning and the inclusion of the coupling between parts and tools. Heuristic II furthermore includes the coupling between tools and lateral transshipments.

- **Heuristic I also performs well in the qualitative comparison, however, since the coupling between parts and tools and the coupling in tool demand are not included in this heuristic, the quantitative results of Heuristic I are outperformed by the quantitative results of Heuristic II, especially with respect to service level accuracy.**

- **Heuristic III does not perform well at both the qualitative and quantitative requirements.** The main reason for this is that Heuristic III is a single location heuristic. Since most of the networks of the company do not fit the characteristics of a single location network, Heuristic III results in worse quantitative results. Finally, the complexity of Heuristic III leads to long computation times, difficulties to implement the heuristic and difficulties to understand the heuristic for the people that have to work with it.

- **The simple US-Heuristic is seriously outperformed by Heuristics I and II.** Next to the bad results with respect to cost efficiency, tuning the US-Heuristic is not possible. This is a serious drawback, since this makes it not possible to adapt the service of the solution generated by the US-Heuristic. The US-Heuristic only gives a target independent solution for the base stock levels of tools.

The following recommendations follow from the research:

- Since Heuristic II satisfies all requirements, we recommend to implement Heuristic II for the planning of parts and tools. To maximize the benefits of Heuristic II, the company should use a performance measure on service order level (DTWL) and the company should integrate the planning of parts and tools.

- The most important condition for a successful implementation of Heuristic II is that the data used in the heuristic is reliable. Without reliable input data, the heuristic will not result in the benefits described in this research. Specialists within the company should assess the input data for Heuristic II to make sure that the results obtained are reliable.
III. Preface

This Master Thesis report is the final result of a project conducted in the area of Service Logistics and at the same time the final report of my career as a student. My interest in the area of Service Logistics follows from the growing importance of this research area in business. Furthermore, the complexity of the topics in the area of Service Logistics makes it suitable for a challenging Master Thesis project. The opportunity to work in the company in the semiconductor industry motivated me even more to start the challenging project.

During the project I have learned a lot. First of all, I really enjoyed seeing that the complex algorithms developed in research are implemented at companies in business. The close relationship of the company with the university makes the company a perfect environment to apply scientific knowledge in a business context. Secondly, I have learned that simple issues in research can be hard to solve in business due to contrasting interests and that practicality of a solution is of high importance. Finally, I really enjoyed learning to work with a programming language, such as Delphi. The programming skills I have obtained during the project can be very beneficial in my further career.

I would like to thank Geert-Jan van Houtum for his supervision during the Master Thesis Project. His knowledge about the research area as well as the company really helped me during the project. The feedback I received in each meeting made me reflect on the project and kept me sharp at all times. I also would like to thank Ingrid Vliegen for the daily supervision. I really appreciate the time and effort she spent on programming the simulation model and helping me out with all kinds of questions.

From the company site I would like to thank Joris de Wit for giving me the opportunity to work at the company. His feedback ensured that the project contributes to the issues the company faces. I also would like to thank Baris Selcuk for his supervision. His background as a PhD at the university and his programming skills really helped me moving on, even during the hardest parts of the project. Further, I would like to thank Kurt Verborgt and Jorg Szlapka for helping me with practical issues and gathering data. The enthusiasm of all of the people mentioned above, make that I have enjoyed every bit of the project.

Finally, I would like to thank my family and friends for their support during my studies. They made the years as a student a wonderful time!

Ronny Buermans
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1. Introduction

This Master Thesis will contribute to the research field of spare parts logistics. In this Master Thesis several multi-item planning heuristics are developed and compared. Sherbrooke (1968) was the first to introduce such a multi-item heuristic in 1968. Since 1968, several adaptations on the model of Sherbrooke were made in order to fit specific business or research requirements. Many of these adaptations were focused on spare parts planning (Wong et al (2005), Wong et al (2006) and Kranenburg (2006)). Next to literature on spare parts, also, some interesting research is done regarding the planning of service tools (Vliegen and Van Houtum (2008)).

This Master Thesis contributes to both the spare parts and tool planning literature, since heuristics are developed for the planning of parts and tools together. This integration of part and tool planning has not yet been studied in literature. In order to integrate the planning of parts and tools, the inventory system is evaluated using order fill rates. Using order fill rates in the evaluation of a system follows from research on Assemble-To-Order systems (Song and Zipkin (2003) and Song et al. (1999)). Furthermore a system approach is used for the optimization of the base stock levels of both parts and tools. In Wong et al (2004) a similar system approach is used in a multi-location network for spare parts only. The performance of a complete inventory system is assessed instead of individual item performances. In a system approach, a lower service level of one item can be compensated by a higher service level of another item, as long as the system performance target is satisfied.

The research described in this Master Thesis is conducted at a company in industry. The company under consideration is a leading manufacturer of micro-lithography equipment for the semiconductor industry. The purchase of the machines used in this industry corresponds to a multi-million euro investment for the customers of the company. Since machine downtime results in high production losses for the customer, the company uses service contracts to agree upon the machine availability. Ensuring that the service levels in the contract are satisfied is a priority for the company. However it is still possible that a machine breaks down. In this case a service engineer identifies what repair action needs to be done and requests a service order consisting of a set of service parts and tools. Since service parts and service tools are regularly demanded in almost the same combinations, a certain level of demand coupling between the demand process of the various parts and tools exists. Next to coupling between tools, also coupling between parts and tools is common for the company under consideration.

The company has a global service network consisting of three regions with a central warehouse in each region. Next to the central warehouses the company has about 50 local warehouses at close distance of its customers. The company uses pooling of inventory to increase its service to the customer. Three types of deliveries are used; regular supply, lateral transshipments and emergency supply.

The main logistic performance indicator is Down-Time-Waiting-Parts (DTWP). DTWP is defined as the percentage of time a machine is down because it is waiting for parts. Currently the company has no performance indicators for the performance of the tool inventory.

The planning of service tools and parts is centralized. Due to this centralization, lateral and emergency shipments can be included in the planning. The planning of service parts is based on a formal planning algorithm; the continental model of Kranenburg (2006). The model includes lateral and emergency shipments and is able to evaluate service levels based on a system approach. The company uses this continental model to optimize the stock levels of parts and to provision the spare
parts over the warehouses in the service network. For the planning of service tools, the company does not have a proper planning algorithm. In this Master Thesis, heuristics are developed that plan the inventories of tools next to the planning of parts. Some of the heuristics integrate the planning of parts and tools.

In Section 2, the motivation of the research is described as well as the outline of the research. A detailed outline of the report is given at the end of Section 2.
2. Research Assignment & Approach

In this section the motivation of the research is discussed in detail followed by the formulation of the research assignment. Furthermore, six research questions are discussed as well as the approach to answer these questions. The research assignment is formulated in Section 2.1. Section 2.2 discusses the research approach and in Section 2.3 the research questions are formulated. Section 2 ends with an outline of the remainder of the report.

2.1. Research Assignment

Whereas the planning of service parts is based on a formal planning algorithm, no planning algorithm is used to determine the inventory levels of service tools and tool kits in the company. Currently, the decisions what tools to keep on stock and where to keep these tools on stock are based on 'common sense' and experience of the tool planners. When the installed base of machines changes, the inventory of tools is adapted and possibly shipped to another location. However, these decisions are also based on the tool planners' experiences only. The company would like to make these decisions in a more grounded way, preferably by using an algorithm similar to the method used for the determination of stock levels of service parts. Planning tools based on a proper planning algorithm should result in a more efficient distribution of the service tool inventory over the locations in the service network. To give an impression of the magnitude of the tool inventory of the company; the number of tools in inventory is about 50,000, representing an investment of tens of millions of euros.

Next to the need to plan the inventory of tools in a more formal way, the company also would like to integrate the planning of service tools with the planning of service parts. The main reason behind the need to integrate the planning of service parts and service tools is the integrated effect on down time. The total down time of a machine depends on many factors, such as diagnosing the problem, waiting on parts/tools and actual correcting of the failure. Since waiting on parts or tools is a major contributor to the downtime of a machine, efficient planning of parts and tools is important. The fraction of downtime which is caused by a delay in tool or part availability is dependent on the availability of both parts and tools. More explicitly, the downtime is dependent on the delivery time of the last tool or part delivered.

In case parts and tools are planned separately, using for example a system approach for parts and a separate system approach for tools, the part planning will result in relatively high service levels of the relatively less expensive parts and at the same time the tool planning will result in relatively high service levels of the relatively less expensive tools. The relatively expensive parts and tools will be stocked in lower amounts. In this separated approach, the coupling between parts and tools is not included in the planning. This means that in case a relatively inexpensive part is regularly demanded in combination with a relatively expensive tool, it is highly likely that the part will but the tool will not be in stock. By using an integrated instead of a separated approach, the coupling between parts and tools can be included in the planning, which is expected to result in an increase in service or a decrease in costs. So planning parts and tools in an integrated way does not lead to sub-optimization.

Since downtime is dependent on the availability of both service parts and tools, the planning should be assessed using a performance indicator on service order level. For this reason a new performance indicator is introduced called Down-Time-Waiting-Logistics (DTWL). DTWL is defined as the percentage of time a machine is down because it is waiting for a service order (parts and/or tools together). Using this performance indicator the delivery time of a complete service order is assessed.
This Master Thesis aims to develop a heuristic planning algorithm that plans service tools and parts together and evaluates the service network of the company based on performance indicators on service order level (DTWL). Therefore, the following research assignment is defined:

"Develop a heuristic planning algorithm which determines the base stock levels of all service parts and tools in all local warehouses in the service network. This planning algorithm should minimize total system costs subject to service requirements in terms of DTWL".

The heuristic planning algorithm to be developed should satisfy several requirements. First of all, the planning algorithm should result in a provisioning of parts and tools over the network that satisfies the DTWL target against as low as possible costs. Furthermore, the planning heuristic should be accurate with respect to the service target. This means that if a service target is used in the planning algorithm, the base stock levels of parts and tools provisioned by the planning algorithm should result in a service that is close to the service target. Finally, some qualitative requirements are important. The planning algorithm should be practical with respect to computation times; the planning algorithm should be able to compute the base stock levels of parts and tools in a short amount of time. The planning algorithm should also be understandable for the people that have to work with it and implementable. To summarize, the planning algorithms to be developed are assessed based on the following major requirements:

1. Efficiency with respect to the costs (cost efficiency)
2. Accuracy with respect to the service target (service accuracy)
3. Practicality with respect to the computation time
4. Understandability for the people that have to work with it
5. Ability to implement

2.2. Research Approach and Research Questions

In order to test whether the planning algorithm to be developed fits the requirements with respect to cost efficiency and service accuracy, a model is constructed which describes the ordering process of service tools and parts. In this detailed model all relevant characteristics of the inventory system are included. In this way, the model closely matches reality. Using simulation, the performance of the system in terms of DTWL, total system costs, and other performance indicators is evaluated for a given set of base stock levels (S-levels).

Once the detailed model is constructed, three heuristics are developed which determine the base stock levels for all service parts and tools in the inventory system under a target service level (DTWL_{target} or DTWP_{target}) and against as low as possible total system costs. Whether the target is a target on order level (DTWL_{target}) or a target on item level (DTWP_{target}) depends on the heuristic.

Since including all characteristics of the system in one heuristic is too complicated, the heuristics constructed simplify the planning process. Heuristic I is equal to the heuristic that is currently used at the company to determine base stock levels of spare parts. In this research this model is used for the planning of both parts and tools. This multi-location model takes lateral transshipments into account; however, coupling in demand is completely ignored. Heuristic I assumes that parts and tools are always demanded individually and therefore a target on item level (DTWP_{target}) is used. Since we know that this assumption is violated, coupling in demand is included in the other heuristics (Heuristics II and III). Heuristic II is a multi-location heuristic that includes lateral transshipments and that uses an independent stock assumption to include coupling in demand. In Heuristic II, next to coupling in demand between tools, also coupling between parts and tools is included. In Heuristic III
a single-location heuristic with coupled demands and returns included is used to provision the tools and the currently used heuristic for the determination of base stock levels of parts is used for the provisioning of parts (Heuristic I). This means that lateral transshipments are not included in the tool planning and that coupling between parts and tools is also not included. Heuristics I and II both plan parts and tools in an integrated way, whereas Heuristic III plans parts and tools separately. More detailed information about the heuristics developed is given in Section 4.

Next to the three heuristics, also a fourth heuristic (called the US-Heuristic), developed by a project group of the company in the US, is assessed using the simulation of the detailed model. In this US-Heuristic simple rules are used to determine the inventory levels for tools. For the planning of parts, the logic behind heuristic I is used. The US-Heuristic is only tested for the network of the US since it is developed for this network only.

In Figure 2.1, the approach is shown in a graphical way. A target service level ($DTWL_{\text{target}}$ or $DTWP_{\text{target}}$) is used as an input in the Heuristics I to III, whereas the US-Heuristic does not require a target service level as an input. Heuristic I uses a service target on item level ($DTWP$) and Heuristic II and III a service target on order level ($DTWL$). The stock levels proposed by all heuristics will feed the simulation of the detailed model, which then computes the resulting $DTWL$ and corresponding costs for all heuristics. To compare the performance of the four heuristics the total costs under a fixed $DTWL$-level (after simulation) are computed for all heuristics. This is done by tuning the target $DTWL$ in such a way that equal $DTWL$ levels are obtained after the simulation. The costs of the four heuristics under this $DTWL$ level are compared to assess the cost efficiency of the heuristics. The difference between the $DTWL$ and the target $DTWL$ for each heuristic are compared to assess the service accuracy of the heuristic.

### 2.3. Research Questions

The heuristics should satisfy both the qualitative and quantitative requirements. The comparison of the qualitative requirements is done based on the description of the heuristics. The heuristics can be compared on the qualitative requirements without conducting numerical experiments.
For the comparison of the heuristics with respect to the quantitative requirements, six research questions are defined:

1. Do the performances of the heuristics vary in different networks?
2. Do the performances of the heuristics vary for different levels of coupling in demand?
3. Do the performances of the heuristics vary for different demand rates per location?
4. Do the performances of the heuristics vary for different target service levels?
5. What are the effects on the performance if parts and tools are planned in an integrated way?
6. What are the benefits with respect to the performance of the heuristics if performance measures are computed on order level?

To answer the research questions, five different cases are constructed in which the heuristics are compared:

- Case I - United States (US)
- Case II - Korea
- Case III - Hong Kong
- Case IV - US extra coupling
- Case V - US higher demand rates per location

In the following subsections the research questions are discussed.

### 2.3.1. Do the performances of the heuristics vary in different networks?

To compare whether the performances of the heuristics vary in different networks, the heuristics are compared in different networks using the approach shown in Figure 2.1. The heuristics are compared in three networks of the company: the US, Korea and Hong Kong networks. For this comparison, Case I, II and III are used. The main differences between the cases/networks are the number of locations, number of lateral transshipment possibilities and the number of machines per location. The US network is characterized by a large number of warehouses (13) and as a result there are many lateral transshipment possibilities. The numbers of machines per location are close to the world-wide average. The Korea network (3 locations) is small compared to the US network, resulting in less lateral transshipment possibilities. Another characteristic of this network is the high number of machines per location. In the Hong Kong network, the lateral transshipment possibilities are extremely low, resulting in an almost completely decoupled network. The number of machines per location is average. For more details about the cases used we refer to Section 5.

Since the heuristics have differing characteristics, we expect the heuristics to perform differently in different networks. Heuristics I and II are multi-location heuristics which take lateral transshipments into account in planning. Therefore we expect these models to perform better in the US network (with many lateral transshipment possibilities). Since Heuristic III is a single location heuristic, we expect this heuristic to perform best in a network that matches the characteristics of a single location network. The Hong Kong network is almost a completely decoupled network and we therefore expect an improvement of the performance of Heuristic III in this network. For the company under consideration it is important to have a planning heuristic for both service parts and tools that performs well in all the networks of the company.

The US-heuristic is only examined in Case I. This heuristic is proposed by the company for the US network only. In this research, we therefore do not compare the US-Heuristic in other than the US network.
2.3.2. Do the performances of the heuristics vary for different levels of coupling in demand?

To identify what the effects of coupling in demand are, the performances of the heuristics are compared under cases with different levels of coupling in demand. The results of the heuristics in Case I and Case IV are compared to assess the effects of coupling in demand. In Case IV the coupling in demand is increased by assuming that individual tool or item demands are not possible. All other characteristics are equal to the characteristics of Case I. For more details about the data used in the cases we refer to Section 5.

Since Heuristic I assumes that service parts and tools are always demanded individually, we expect this heuristic to perform less in Case IV. Furthermore, we expect Heuristics II and III to perform relatively better in the case with higher coupling in demand, because these heuristics take the coupling in demand into account in the planning of tools.

This research question is particularly interesting since the coupling in demand is hard to identify exactly in the data of the company. In this research, cases are constructed from this data. For these relatively small cases, a considerable amount of time is spent to identify the exact coupling in demand. Since we do not exactly know the extent of coupling in demand of the complete data of the company, investigating the effects of varying the coupling in demand is important. The results with respect to cost efficiency and service accuracy of the heuristic to be implemented should be well in both Case I and Case IV. If Heuristic I, which does not take the coupling in demand into account, performs well in both Case I and Case IV, the company should not invest time and money in identifying the exact coupling in demand.

2.3.3. Do the performances of the heuristics vary under different demand rates per location?

The effects of increasing the demand rate per location are identified by comparing the performance of the heuristics of Case I and Case V. In Case V all characteristics are equal to Case I, only the aggregate demand rate per location is increased. We only examine increasing the demand rate, since the demand rates per location are higher in other networks than the US.

We do not expect that increasing the demand rate will have serious effects on the relative performance of the models. We expect that heuristics II and III to perform somewhat better, since by increasing the demand rate, also the absolute total number of coupled demand arrivals increases. Taking coupling in demand into account in the heuristic; thus becomes more beneficial. The heuristic to be implemented should perform well if the demand rates increase.

2.3.4. Do the performances of the heuristics vary for different target service levels?

The effects of increasing or decreasing the service levels are also examined. This is done by varying the service levels for Case I. We do not expect the heuristics to perform relatively better or worse under differing service targets, however, we would like to investigate this. The heuristic to be implemented should not only have good results under one target service level.

2.3.5. What are the effects on the performance if parts and tools are planned in an integrated way?

As described above, the benefits of planning service parts and tools in an integrated way versus in a separated way are assessed by comparing the results of Heuristics I and II with the results of the Heuristic III and the US-Heuristic. Heuristic III and the US-Heuristic both plan parts and tools separately and use the currently used method to compute the base stock levels of parts. We expect the
integrated heuristics to perform better with respect to cost efficiency and service level accuracy, since sub-optimization does not occur in these models.

Next to this comparison, also an extra experiment is done. In this experiment, Heuristic II is used in an integrated and separated approach. In the integrated approach, both parts and tools are planned using Heuristic II, whereas in the separated approach service tools are planned using Heuristic II and service parts using the currently used method. In this way, we can compare the effects of including coupling between parts and tools. In this extra experiment the data of Case I is used.

2.3.6. What are the benefits with respect to the performance of the heuristics if service measures are computed on order level?

The benefits of using performance measures on order level are assessed by comparing the results of Heuristic I and Heuristic II. The main difference between these two heuristics is that Heuristic II computes performance measures on order level (including coupling in demand), whereas Heuristic I does not. The performance measures on order and item level can be compared using the results of all cases. In case the difference between an order service level and an item service level is small, it might not be beneficial to plan based on an order service level. The results of the numerical experiments will show whether using a service level on order level results in a better performance with respect to cost efficiency and/or service accuracy. We expect that a significant difference occurs between the service measures on order and item level.

2.3.7. Effects of lateral transshipments

Next to varying the demand rate and coupling in demand, also a case could be constructed to assess the effects of varying the lateral transshipment possibilities. In this case the number of lateral transshipment possibilities could be increased or decreased. This means that taking lateral transshipments into account in a planning algorithm becomes less or more profitable compared to the US case. The effects of having more or less lateral transshipment possibilities are already researched by Kranenburg (2006). The effects of adding extra lateral transshipment possibilities to Case I could be researched. However, in reality a network with more lateral transshipment possibilities is not used by the company. Furthermore, Kranenburg (2006) showed that the relative benefits of adding one lateral transshipment possibility become less if the number of lateral transshipment possibilities increases. Kranenburg (2006) shows this for a case without coupling in demand; however, it is likely that the same holds for a case with coupling in demand. For the reasons mentioned above, a case with more lateral transshipment possibilities will not be examined. Further, the effects of lateral transshipments can be seen in the results of Case I to III, although these are not the single effects of lateral transshipments. In Case I to III also the demand rates per location vary.

2.4. Outline of the report

In Section 3 the detailed model including all process characteristics is discussed followed by a description of the simulation approach. Section 4 describes the four planning heuristics in detail and compares the models in a qualitative way. This is graphically shown in Figure 2.1. In Section 5, the test bed is constructed and the cases used for the numerical experiments are described in detail. In Section 6 the results of the numerical experiments are examined and the heuristics are compared on the quantitative criteria. Furthermore, the research questions are answered in this section. The report ends with conclusions and recommendations in Section 7.
3. Detailed Model

In this section, the detailed model of the ordering process is described. In this detailed model, all relevant process characteristics are included. A description of the detailed model is given in section 3.1. The relevant performance indicators are described in section 3.2. The detailed model is used to evaluate the performance of a network with a given set of base stock levels for service parts and tools. This is done by using simulation. In Section 3.3 the simulation approach is described as well as the analysis of the output of the simulation.

3.1. Detailed Model description

In this section, the model is described in detail. The declaration of variables is similar to the declaration in Vliegen and Van Houtum (2008) and Kranenburg and Van Houtum (2008).

3.1.1. Network, SKU-s and demand streams

Let $J = \{1, \ldots, |J|\}$ denote the non-empty set of local warehouses and $K = \{1, \ldots, |K|\}$ the set of main local warehouses. $K$ is a subset of $J (K \subseteq J)$. The difference between a main local warehouse and a regular local warehouse is that a main local warehouse can be the supplier of a lateral transshipment, whereas a regular local warehouse cannot. Lateral transshipments are discussed further in this section. To each local warehouse $j \in J$ a number of machines, $N_j$, is assigned. This means that local warehouse $j \in J$ is the first candidate to provide a spare part or tool in case a failure occurs at one of these machines. Let $Z = \{1, \ldots, |Z|\}$ denote the non-empty set of central warehouses. This is modeled explicitly since SKU-s are delivered by different warehouses resulting in different costs and different transportation times. It is assumed that the inventory of SKU-s is infinite in all central warehouses.

The local warehouses stock SKU-s, which can be service parts, service tools or tool kits. Let $I = \{1, \ldots, |I|\}$ denote the set of all SKU-s. Let $I_p = \{1, \ldots, |I_p|\}$ denote the set of all parts. Similarly, let $I_t = \{1, \ldots, |I_t|\}$ denote the (non-empty) set of all tools and let $I_{tk} = \{1, \ldots, |I_{tk}|\}$ denote the set of all tool kits. The sets of tools, parts and tool kits are a partition of the set of SKU-s. Each tool kit $i \in I_{tk}$ consists of a set of tools. The set of tools in a toolkit $i \in I_{tk}$ is denoted as $I_t(i)$, so $I_t(i) \subseteq I_t$.

For each type of defect, a different subset of SKU-s is required. Let $V = \{1, 2, \ldots, |V|\}$ denote the set of order streams, where $1 \leq |V| \leq 2^{|I|} - 1$. For each $v \in V$, the subset of SKU-s demanded is given by $I(v) \subseteq I (I(v) \neq \emptyset)$. $M_{v,j}$ is defined as the total demand rate per hour for order stream $v \in V$ at local warehouse $j \in J$. $M_J$ is defined as the total order demand rate per hour (over all order streams $v \in V$) at local warehouse $j \in J$ and can be calculated by taking the sum of the occurrence rates of all order streams $v \in V$ at local warehouse $j \in J$ and can be calculated by taking the sum of the occurrence rates of all order streams $v \in V$ at local warehouse $j \in J$. $M_{i,j}$ is defined as the total demand rate per hour for SKU $i \in I$ at local warehouse $j \in J$, where $M_{i,j} = \sum_{v \in V} 1_{\{i \in I(v)\}} M_{v,j}$. $M_J$ is defined as the total item demand rate per hour at local warehouse $j \in J$. $M_{j}$ is defined as the total part demand rate per hour at local warehouse $j \in J$. $M_{j}$ is defined as the total tool and tool kit demand rate per hour at local warehouse $j \in J$.

The inventory of each SKU in all main and regular local warehouses is controlled by a base stock policy. The base stock level of SKU $i \in I$ in local warehouse $j \in J$ is denoted as $S_{i,j}$. Let $S(i) := (S_{i,1}, \ldots, S_{i,|I|})$, denote the vector of base stock levels for SKU $i \in I$, and let $S(v) := (S(i); i \in I)$. The base stock level is updated at the end of each period.
\(I(v)\) denote the vector of base stock levels for all SKU-s \(i\) which are part of order stream \(v\). The cost price of an SKU \(i \in I\) is given by \(C_i\). Since not all SKU-s are always available on stock, a variable \(Y_{i,j}\) is defined as the physical stock of SKU \(i \in I\) in local warehouse \(j \in J\).

A tool kit can be used as a substitute to satisfy demand of an individual tool, in case that tool is not available individually (\(Y_{i,j} = 0\), and if the tool is in this tool kit. Since a tool can be included in more than one tool kit, a set \(s_i\) is defined as all tool kits that can substitute tool \(i \in I\), so \(s_i = \{x \in I_{\text{it}} | i \in I(x)\}\).

In the network, pooling of inventory is used by lateral transshipments in case a local warehouse \(j \in J\) does not have inventory of an SKU \(i \in I\) (or a substitute) available (see Figure 3.1). For each local warehouse \(j \in J\) a pre-specified order exists in which the transshipment possibilities are checked. The following structure is used for the pre-specified order. Each regular local warehouse is assigned to one main. A main can have multiple regulars assigned to it. The main local warehouse \(k \in K\) to which a regular local warehouse \(j \in J \setminus K\) is assigned is denoted as \(k_j\). For each local warehouse \(j \in J\), a sequence is given for the mains to be checked. The pre-specified order can be based on increasing transportation time, but other orders are also possible. Vector \(\omega(j) := (\omega_1(j), ..., \omega_{|K|}(j))\) is defined as the permutation of main local warehouses \(K\) that represents this pre-specified order for local warehouse \(j\). In this permutation \(\omega_i(j)\) represents main local warehouse \(k_i\).

For demands observed at main local warehouse \(k \in K\), the first main local warehouse in the permutation is equal to \(k\) itself (\(\omega_1(k) = k\)). This pre-specified order is slightly different compared to the pre-specified order described in Kranenburg and Van Houtum (2008); the difference is that the order is defined for each local warehouse instead of for each main local warehouse.

Each SKU \(i \in I\) is linked to a central warehouse \(z_i (z_i \in Z)\) which will supply the SKU in case of an emergency supply. For spare parts this also means that spare part \(i \in I_{wp}\) is replenished from central warehouse \(z_i\).

3.1.2. Events

Three main events are modeled in the detailed model:

- Order arrival and delivery
- A tool (or set of tools) returns from the repair action
- A spare part is replenished from a central warehouse.

Events do not take place at the same time and time is assumed to be continuous.

Order arrival and delivery

In the detailed model, requests for order stream \(v \in V\) at local warehouse \(j \in J\) arrive following a Poisson process with a demand rate of \(M_{v,j}\). Order stream \(v \in V\) is split into demand for individual SKU-s \(i \in I(v)\). The SKU-s in this order stream can be delivered via several ways. A graphical representation of the network and supply possibilities is given in Figure 3.1. For each SKU \(i \in I(v)\), the delivery possibilities are checked in the following order:

Step 1 Local supply: It is checked whether \(Y_{i,j} > 0\). If the SKU is in stock, it is delivered from warehouse \(j\) and the physical stock of SKU \(i\) in warehouse \(j\) changes in the following way: \(Y_{i,j} = Y_{i,j} - 1\). This transaction is called local supply. For items delivered via local supply, the delivery time is denoted as \(t^{\text{loc}}\). This delivery time is equal for all SKU-s \(i \in I\) and all local warehouses \(j \in J\). The costs of local supply are assumed to be zero, since they
cannot be influenced by a planning tool. If SKU $i$ is not in stock and $i \in I_t$, step 2 is performed. If SKU $i$ is not in stock and $i \notin I_t$, step 3 is performed.

**Figure 3.1:** Three supply modes; regular supply (left), lateral supply (middle) and emergency supply (right)

**Step 2 Local supply by substitution:** It is checked whether $s_i \neq \emptyset$. If true, for each tool kit $x \in s_i$ it is checked whether $Y_{x,j} > 0$. If this is true for at least one $x \in s_i$, the tool kit is delivered via local supply by substitution. Since it is possible that two or more tools are substituted by one tool kit, the decision which tool kit to supply is made after it is known how all items in an order are delivered. This is done since delivering less tool kits results in less transportation costs and higher inventory availability. This is described in Section 3.1.3. $s_{i,j} = \{x \in s_i | i \in I_t(x), Y_{x,j} > 0, Y_{i,j} = 0\}$ is denoted as the set of tool kits that can be used to substitute tool $i \in I_t$ and that are in inventory in location $j$. If substitution is not possible, step 3 is performed.

**Step 3** If an item cannot be supplied by local warehouse $j$, either by regular supply or by substitution, it is checked whether the item can be shipped by a main local warehouse $k \in K$. The main local warehouses are checked in a predefined order, described in $\omega(j)$, until a main local warehouse is found that can supply the SKU or a substitute. This process will be described in more detail in step 3a and 3b. The following steps are done for $x = 1, \ldots, |K|$ until the SKU under consideration can be supplied. If the SKU cannot be supplied, step 4 is done. We start with $x = 1$.

**Step 3a Lateral supply:** It is checked whether $Y_{l,\omega_x(j)} > 0$. If this is true, SKU $i \in I_t$ is delivered by main local warehouse $\omega_x(j)$ and the physical stock of SKU $i$ in warehouse $\omega_x(j)$ changes in the following way: $Y_{l,\omega_x(j)} = Y_{l,\omega_x(j)} - 1$. This transaction is called lateral supply. The transportation time for a lateral transshipment from main $k \in K$ to local warehouse $j \in I$ is equal to $t_{j,k}^{lat}$ for all SKU-s $i \in I_t$. In the lateral transshipment time, the local delivery time is excluded. So, the actual lateral transshipment time is equal to $t_{j,k}^{lat} + t_{loc}$. The costs of a lateral transshipment do depend on the SKU and are equal to $C_{l,i,k}^{lat}$. Step 3b is performed if SKU $i$ is not available in main $\omega_x(j)$ and $i \in I_t$. If SKU $i$ is not available in main $\omega_x(j)$, $i \notin I_t$ and $x < |K|$, step 3a is performed again and $x = x + 1$. If SKU $i$ is not available in main $\omega_x(j)$, $i \notin I_t$ and $x = |K|$, step 4 is performed.
Step 3b Lateral supply by substitution: It is checked whether \( s_i \neq \emptyset \). If true, for all tool kits \( l \in s_i \) it is checked whether \( Y_{l, \omega_x(j)} > 0 \). If this is true for at least one tool kit, that tool kit is delivered via lateral supply by substitution. Since it is possible that two or more tools can be substituted by one tool kit, the decision which tool kit to supply is again made after it is known how all items in an order are delivered. This is described in Section 3.1.4.

\[
\mathcal{S}_{l, \omega_x(j)}(i) = \left\{ l \in s_i \mid i \in I_l, Y_{l, \omega_x(j)} > 0, \sum_{y=0}^{x-1} Y_{l, \omega_y(j)} = 0, \sum_{y=0}^{x} Y_{l, \omega_y(j)} = 0 \right\}
\]

is denoted as the set of tool kits that can be used to substitute tool \( i \) for delivery to local warehouse \( j \) and that are in inventory in location \( \omega_x(j) \). If substitution is not possible and \( x < |K| \), then step 3a is performed and \( x = x + 1 \). If \( x = |K| \), step 4 is performed.

Step 4 Emergency supply: SKU \( i \) is delivered by emergency supply by central warehouse \( z_i \in Z \).

The transportation time \( t_{z_i}^{em} \) of an emergency shipment is dependent on the central warehouse that supplies the SKU \( (z_i) \). The transportation cost of an emergency supply is defined as \( C_{i}^{em} \).

Return of tools or tool kits

After a repair action, the tools are not directly available in inventory again. The tools are returned after an exponentially distributed return time, denoted as \( t_{i}^{ret} \). Tools are returned to the local warehouse from which they were supplied. The costs of this return flow are included in the delivery costs of tools. Tools delivered in sets are also returned in the same sets (having the same return time). In case a tool or tool kit \( i \in (I_t \cup I_{tk}) \) is returned to local warehouse \( j \), the physical inventory of that warehouse changes according to the following formula: \( Y_{i,j} = Y_{i,j} + 1 \).

Replenishment of parts

Once a part is used to satisfy demand in a local warehouse, a new part is immediately requested from the central warehouse. This part will be delivered after an exponentially distributed replenishment lead time which is dependent on the replenishing central warehouse, denoted as \( t_i^{ret} \). A replenishment of SKU \( i \in I \) also results in costs, denoted as \( C_i^{ret} \). In case a part \( i \in I_p \) is returned to local warehouse \( j \), the physical inventory of that warehouse changes according to the following formula: \( Y_{i,j} = Y_{i,j} + 1 \).

3.1.3 Decision which tool kit to supply in case of local supply by substitution

For each order corresponding to order stream \( v \in V \), it is checked per location \( j \in J \) what tools \( i \in I_t \) are delivered via local supply by substitution. The set of tools which are delivered via local supply by substitution is denoted as \( I_{sub}(I_{sub} \subseteq I_t) \). The cost optimal possibility to deliver the substitutes is computed. This is done, since it is possible to substitute more than one tool by one tool kit at the same time. The set of tool kits that can be used to substitute one (or more) of the items \( i \in I_{sub} \) from local warehouse \( j \in J \) is denoted as \( \tilde{S}_{I_{sub}, I_t} \). All possible subsets of \( \tilde{S}_{I_{sub}, I_t} \) are defined as the power set of \( \tilde{S}_{I_{sub}, I_t} \), \( \tilde{S}_{I_{sub}, I_t}^{pos} = \emptyset(\tilde{S}_{I_{sub}, I_t}) \). All possible sets of tool kits that can be used to substitute all SKU-s in \( I_{sub} \) is a subset of \( \tilde{S}_{I_{sub}, I_t}^{pos} \) and is denoted as \( \tilde{S}_{I_{sub}, I_t}^{pos} \), so

\[
\tilde{S}_{I_{sub}, I_t}^{pos} = \left\{ x \mid x \in \tilde{S}_{I_{sub}, I_t}^{pow}, \forall \ell \in I_{sub} (\tilde{s}_{i,j} \cap x \neq \emptyset) \right\}.
\]
The cost optimal element of $\tilde{s}_{i_{\text{sub}}, j}^{\text{pos}}$ is defined using the cost price ($C_i$). For all elements of $\tilde{s}_{i_{\text{sub}}, j}^{\text{pos}}$, the sum of the costs prices is computed and the subset with the minimum sum is delivered. $\tilde{s}_{i_{\text{sub}}, j}^{\text{det}}$ is denoted as the set delivered, so

$$\tilde{s}_{i_{\text{sub}}, j}^{\text{det}} = \left\{ x \mid x \in \tilde{s}_{i_{\text{sub}}, j}^{\text{pos}}, \min_{x \in \tilde{s}_{i_{\text{sub}}, j}^{\text{pos}}} \left( \sum_{i \in X} C_i \right) \right\}.$$ 

The delivery time of $\tilde{s}_{i_{\text{sub}}, j}^{\text{det}}$ is equal to $t_{\text{loc}}$. The costs of local supply by substitution are assumed to be zero, since they cannot be influenced by a planning tool.

### 3.1.4 Decision which tool kit to supply in case of lateral supply by substitution

A similar approach is used for lateral supply by substitution. For each order corresponding to order stream $v \in V$, it is checked per main local $k \in K$ what tools $i \in I_v$ are delivered via lateral supply via substitution from main local warehouse $k \in K$ to local warehouse $j \in J$ is denoted as $\tilde{s}_{i_{\text{sub}}, j}^{\text{pos}}$. All possible subsets of $\tilde{s}_{i_{\text{sub}}, j}^{\text{pos}}$ are defined as the power set of $\tilde{s}_{i_{\text{sub}}, j}^{\text{pos}}$: $\tilde{s}_{i_{\text{sub}}, j}^{\text{pow}} = \mathcal{P}(\tilde{s}_{i_{\text{sub}}, j}^{\text{pos}})$. All possible sets of tool kits that can be used to substitute all SKU-s in $I_{\text{sub}}$ by lateral supply from main local warehouse $k \in K$ to local warehouse $j \in J$ is a subset of $\tilde{s}_{i_{\text{sub}}, j}^{\text{pow}}$ and is denoted as $\tilde{s}_{i_{\text{sub}}, j}^{\text{pos}}$. Computing $\tilde{s}_{i_{\text{sub}}, j}^{\text{pow}}$ is done in two steps:

$$\tilde{s}_{i_{\text{sub}}, j}^{\text{pow}} = \left\{ x \mid x \in \tilde{s}_{i_{\text{sub}}, j}^{\text{pow}}, \forall i \in I_{\text{sub}} (\tilde{s}_{i_{\text{sub}}, j}^{\text{pos}} \cap x) \neq \emptyset \right\}.$$ 

The cost optimal element of $\tilde{s}_{i_{\text{sub}}, j}^{\text{pow}}$ is defined using the delivery costs ($C_{i,j,k}^{\text{lat}}$) and the cost price ($C_i$). For all subsets of $\tilde{s}_{i_{\text{sub}}, j}^{\text{pow}}$ the total delivery costs are computed and the subset with the minimum delivery costs is delivered. If this minimum is equal for more than one element of $\tilde{s}_{i_{\text{sub}}, j}^{\text{pow}}$, the set with the lowest total cost price is delivered. $\tilde{s}_{i_{\text{sub}}, j}^{\text{det}}$ is denoted as the set delivered. Computing $\tilde{s}_{i_{\text{sub}}, j}^{\text{det}}$ is done in two steps:

$$\tilde{s}_{i_{\text{sub}}, j}^{\text{det}, 1} = \left\{ x \mid x \in \tilde{s}_{i_{\text{sub}}, j}^{\text{pow}}, \min_{x \in \tilde{s}_{i_{\text{sub}}, j}^{\text{pow}}} \left( \sum_{i \in X} C_{i,j,k}^{\text{lat}} \right) \right\}.$$ 

$$\tilde{s}_{i_{\text{sub}}, j}^{\text{det}} = \left\{ x \mid x \in \tilde{s}_{i_{\text{sub}}, j}^{\text{det}, 1}, \min_{x \in \tilde{s}_{i_{\text{sub}}, j}^{\text{det}, 1}} \left( \sum_{i \in X} C_i \right) \right\}.$$ 

The delivery time of $\tilde{s}_{i_{\text{sub}}, j}^{\text{det}}$ is equal to $t_{i,j,k}^{\text{lat}} + t_{\text{dir}}$. The costs of lateral supply by substitution are $\sum_{i \in \tilde{s}_{i_{\text{sub}}, j}^{\text{det}}} C_{i,j,k}^{\text{lat}}$. If two tools are substituted by one tool kit, the transportation costs are only computed for one tool kit, instead of two tools. The detailed model records for each order what the difference is between the cardinality of $I_{\text{sub}}$ and the cardinality of $\tilde{s}_{i_{\text{sub}}, j}^{\text{det}}$, which is equal to the number of items delivered without extra lateral transshipment costs. Using this difference, the fraction of items which are delivered by lateral supply via substitution without extra lateral transshipment costs can be computed.
3.2. Performance Measures

In this subsection, the performance measures used in this report are described. The detailed model computes some more performance measures that can be of interest for the company under consideration. A detailed description of the extra performance measures is given in Appendix II.

3.2.1. Order delivery fractions

An order at local warehouse \( j \in J \) is assumed to be delivered from warehouse \( k \in K \), if the SKU with the longest delivery time of all SKU-s \( i \in I(v) \) is delivered from warehouse \( k \in K \). An order is said to be delivered via emergency shipment from central warehouse \( z \in Z \), if the SKU with the longest delivery time of all SKU-s \( i \in I(v) \) is delivered from central warehouse \( z \in Z \). The detailed model keeps track of the fraction of orders which is delivered via local supply, local supply by substitution, lateral transshipment, lateral transshipment by substitution, lateral transshipment by substitution without extra lateral transshipment costs and emergency supply. With respect to the fulfillment of demand for order stream \( v \in V \) at local warehouse \( j \in J \), the following notation is introduced:

- \( \beta_{v,j} \) for the fraction of demand for order stream \( v \in V \) at local warehouse \( j \in J \) that is delivered via local supply or via local supply by substitution. This performance indicator is called the order fill rate.
- \( \alpha_{v,j,k} \) for the fraction of the demand for order stream \( v \in V \) at local warehouse \( j \in J \) that is delivered from main local \( k \in K \) by means of lateral supply or lateral supply via substitution.
- \( \theta_{v,j,z} \) for the fraction of demand for order stream \( v \in V \) at local warehouse \( j \in J \) that is delivered from the central warehouse \( z \in Z \) as an emergency shipment.

3.2.2. Item delivery fractions

Next to the fractions above, similar fractions are computed on item level, so for each SKU \( i \in I \). With respect to the fulfillment of demand for SKU \( i \in I \) at local warehouse \( j \in J \), the following notation is introduced:

- \( \beta_{i,j} \) for the fraction of demand for SKU \( i \in I \) at local warehouse \( j \in J \) that is delivered via local supply or via local supply by substitution. This performance indicator is called the item fill rate.
- \( \alpha_{i,j,k} \) for the fraction of the demand for SKU \( i \in I \) at local warehouse \( j \in J \) that is delivered from main local \( k \in K \) by means of lateral supply or lateral supply via substitution.
- \( \alpha_{i,j,k}^{\text{no cost}} \) for the fraction of the demand for SKU \( i \in I \) at local warehouse \( j \in J \) that is delivered from main local \( k \in K \) by means of lateral supply by substitution, which does not result in extra lateral transshipment costs.
- \( \theta_{i,j} \) for the fraction of demand for SKU \( i \in I \) at local warehouse \( j \in J \) that is delivered via emergency supply from the central warehouse. This fraction is always delivered from central warehouse \( z \).

3.2.3. Down-Time-Waiting-Logistics

The Down-Time-Waiting-Logistics can be computed for each local warehouse in the network \( DTWL_j \) as well as for the network as a whole \( DTWL \). \( DTWL \) is defined as the percentage of time a machine is down because it is waiting for a service order (parts and/or tools together). \( DTWL \) is a service measure on order level. In formula;
3.2.4. Down-Time-Waiting-Parts, Down-Time-Waiting-Tools and Down-Time-Waiting-Items

Down-Time-Waiting-Part (DTWP), Down-Time-Waiting-Tool (DTWT) and Down-Time-Waiting-Item (DTWI) are similar to DTWL. The main difference is that DTWP, DTWT and DTWI are computed on item level and DTWL on order level. DTWT is defined as the percentage of time a machine is down because it is waiting for tools, whereas DTWI is the percentage of time a machine is down because it is waiting on either a part or a tool. In formula:

\[
DTWP_j = \frac{100}{N_j} \sum_{i \in \mathcal{I}_j} \left[ M_{i,j} \left( t^{loc} + \sum_{k \in \mathcal{K}} t^{lat}_{j,k} \alpha_{i,j,k} + \theta_{i,j} t^{em}_{i} \right) \right]
\]

\[
DTWT = \frac{\sum_{j \in \mathcal{J}} [M_j \cdot DTWT_j]}{\sum_{j \in \mathcal{J}} M_j}
\]

\[
DTWI_j = \frac{100}{N_j} \sum_{i \in \mathcal{I}_j} \left[ M_{i,j} \left( t^{loc} + \sum_{k \in \mathcal{K}} t^{lat}_{j,k} \alpha_{i,j,k} + \theta_{i,j} t^{em}_{i} \right) \right]
\]

\[
DTWI = \frac{\sum_{j \in \mathcal{J}} [M_j \cdot DTWI_j]}{\sum_{j \in \mathcal{J}} M_j}
\]

3.2.5. (Order) Waiting Time

The Waiting Time is defined as the average waiting time between an item request and the delivery of the item. This performance measure is computed per location for parts (WT\textsubscript{P}), tools (WT\textsubscript{T}) and items (WT\textsubscript{I}) and for the network as a whole for parts (WT\textsubscript{P}), tools (WT\textsubscript{T}) and items (WT\textsubscript{I}). In formula,

\[
WT\textsubscript{P} = \frac{\sum_{i \in \mathcal{I}} \left[ M_{i,j} \left( t^{loc} + \sum_{k \in \mathcal{K}} t^{lat}_{j,k} \alpha_{i,j,k} + \theta_{i,j} t^{em}_{i} \right) \right]}{n_j}
\]
The order waiting time (OWT) is defined similarly and is equal to the average time between an order request and the complete delivery of that order. In formula:

\[ W_{T} = \frac{\sum_{i \in l} M_{i,j} \cdot (t_{loc} + \sum_{k \in K} t_{lat}^{i} \cdot \alpha_{i,j,k} + \theta_{i,j} \cdot t_{cm}^{e})}{\sum_{i \in l} M_{i,j}} \]

\[ W_{T}^{j} = \frac{\sum_{i \in l} M_{i,j} \cdot (t_{loc} + \sum_{k \in K} t_{lat}^{i} \cdot \alpha_{i,j,k} + \theta_{i,j} \cdot t_{cm}^{e})}{M_{j}} \]

\[ W_{T}^{j} = \frac{\sum_{j \in J} M_{j} \cdot (t_{loc} + \sum_{k \in K} t_{lat}^{j} \cdot \alpha_{i,j,k} + \theta_{i,j} \cdot t_{cm}^{e})}{\sum_{j \in J} M_{j}} \]

The customer service degree is defined as the percentage of items that is delivered directly out of inventory by the local warehouse to which the broken down machine is assigned to. In general this service measure is called the item fill rate. The customer service degree can be computed for the entire network (CSD) as well as for each local warehouse \( j \) (CSD\( _{j} \)). In formula;

\[ CSD_{j} = \frac{\sum_{i \in l} M_{i,j} \cdot \beta_{i,j}}{M_{j}} \]

\[ CSD = \frac{\sum_{j \in J} M_{j} \cdot CSD_{j}}{\sum_{j \in J} M_{j}} \]

 Similarly, a similar service measure is computed on order level called Order Customer Service Degree (OCSD). This performance indicator is also computed for the entire network as well as for the local warehouses separately. In formula;

\[ OCSD_{j} = \frac{\sum_{v \in V} M_{v,j} \cdot \beta_{v,j}}{M_{j}} \]

\[ OCSD = \frac{\sum_{j \in J} M_{j} \cdot OCSD_{j}}{\sum_{j \in J} M_{j}} \]
3.2.7. Total Relevant Costs

Total relevant costs per year are equal to the yearly costs of holding inventory plus the yearly costs of transport, which includes lateral supply, emergency supply and replenishment costs. Costs for regular supply are excluded, since these costs cannot be influenced by the planning models.

The cost for holding one unit of SKU \( i \in I \) in stock for one year is equal to a holding cost factor \( h \) times the cost price \( (C_i) \) of the SKU \( i \). It is assumed that holding costs are incurred as well for parts/tools in the replenishment/return and transshipment pipelines. This is a logical assumption, since the whole service supply network is the property of the company. Total relevant costs \( (TRC) \) are defined as:

\[
TRC = 24 \times 365 \times \sum_{i \in I} \sum_{j \in J} \left( M_{i,j} \times \left[ \sum_{k \in K} c_{i,j,k}^{lat} \times (\alpha_{i,j,k} - \alpha_{i,j,k}^{no\_cost}) + C_{i,j,k}^{em} \times \theta_{i,j} + C_{i,j,k}^{et} \right] + h \times \sum_{i \in I} \sum_{j \in J} (C_i \times S_{i,j}) \right)
\]

3.3. Simulation Approach

The detailed model as described in Section 3.1 will be used to evaluate the performance of a network for a given set of base stock levels. This is done by using a simulation tool. In this simulation tool the performance in terms of the performance measures defined in Section 3.2 is evaluated for a defined number of order arrivals. To ensure that the results of the simulation are reliable, a proper warm-up period, run length and number of runs are identified. In this research the terms run and batch are used interchangeably.

3.3.1. Warm-up period, run length and number of runs

The simulation outputs in terms of the performance measures defined in Section 3.2 are generated using a batch-means method (Law and Kelton, 1991). In this method, the mean values of the performance indicators are computed using the mean values of the performance indicators of a number of independent batches. The batches are independent in case the warm-up period has expired and the outputs are in a steady state. To investigate what a proper warm-up period for the simulation of the detailed model is, the simulation is run with different warm-up periods for a realistic case. This realistic case is similar to the test bed used in Case I (US case). For details of this test bed is referred to Section 6. After the warm-up period has expired, 100 runs of three different run lengths were started. The run lengths are varied between 1,000, 2,500 and 5,000 order arrivals.

The outcomes of these experiments were checked for independence using the rank version of the von Neumann’s Ratio Test for randomness (Bartels, 1982). In this test the means of the performance indicators are ranked (the smallest batch mean has rank 1, the largest batch mean has rank 100) before the rank version of von Neumann’s ratio (RVN) is computed using the following formula;

\[
RVN = \frac{\sum_{i=1}^{T-1} (R_i - R_{i+1})^2}{\sum_{i=1}^{T}(R_i - \bar{R})^2}
\]

\( R_i \) is defined as the rank of the i-th observation in a sequence of T observations and \( \bar{R} \) is defined as the average rank. A significant value for the RVN-test means that the runs of the simulation are dependent on each other. This can mean that the length of a run is too short or the warm-up period has not expired yet. For a significance level of 95%, the RVN-test statistic must be between 1.67 and 2.33 to be insignificant.
The RVN-test statistics for the different warm-up periods and run lengths were computed. For a warm-up period of 150,000 order arrivals, all three run lengths give insignificant RVN-test statistics for all performance indicators in all locations. This long warm-up period is required to ensure that the locations with a small installed base are in a steady state. If a network is used with only warehouses with a large installed base, the warm-up period can be decreased. However, we will always use a warm-up period of 150,000 order arrivals in this research.

The results of the RVN-tests further show that the runs are independent for all three run lengths. For all numerical experiments in this research a run length of 5,000 order arrivals is used. The reason to choose for the longest run length is that longer runs give more reliable outcomes. Since using a run length of 5,000 order arrivals does not result in a considerable increase in computation time, using a run length of 5,000 order arrivals is practical. Next to the RVN test one can visually see that the system is in steady state in case a warm-up period is used of 150,000 order arrivals and a run length of 5,000 order arrivals. Figure 3.2 shows that the mean DTWL for each run is in steady state. Of course, the runs start after the warm-up period.

![Figure 3.2: Mean DTWL for each run in steady state](image)

For all experiments in this research the independence of runs is checked using the RVN-ratio. In case the RVN-value is significant (95% significance level), the simulation runs are repeated with a longer warm-up period and/or a longer run length.

### 3.3.2. Construction of confidence intervals

Confidence intervals are constructed for the performance indicator outcomes of the simulation of the detailed model. This is done using the batch mean values of the 100 runs or batches. The mean and standard deviation of these 100 runs/batches are computed. Using the following formula, the confidence intervals are constructed:

\[
CI = \bar{X} \pm t_{df,\alpha} \times \frac{s}{\sqrt{T}}
\]

In this formula, \(CI\) is defined as the confidence interval, \(\bar{X}\) is the mean value of all batch means of the performance indicator under consideration and \(s\) is the standard deviation of all batch means of the performance indicator under consideration. \(T\) is defined as the number of runs. \(t_{df,\alpha}\) is the student t-value for \(df\) degrees of freedom and a significance level of \(\alpha\). The degrees of freedom are equal to \(T - 1\). In this research, the confidence intervals are constructed using an \(\alpha\) of 0.05.
4. Description of heuristics

In this section, the four different heuristics that will be compared are described in detail. The heuristics simplify the detailed model of Section 3 and compute the base stock levels of parts and tool. Heuristic I and II compute the base stock levels of both parts and tools using one method. In Heuristic III and the US-Heuristic the base stock levels of parts are computed using Heuristic I, whereas the base stock levels of tools are computed using a different method. In Sections 4.1 to 4.4, the four heuristics are described in detail. Section 4 ends with a qualitative comparison of the heuristics in Section 4.5.


The first heuristic used to determine the base stock levels of service parts and tools is the continental model of Kranenburg (2006). The continental model of Kranenburg (2006) is used by the company to determine the base stock levels of the service parts in each continent. The continental model assumes that items are only demanded individually and thus that the stocks of items are independent. A detailed description of the continental model is given in the literature review [A] and Kranenburg (2006). In Heuristic I, both parts and tools are planned using the continental model of Kranenburg (2006).

In Heuristic I two extra adaptations are made in the continental model to fit the situation of the company better. The first one is that the replenishment times are dependent on the item, so not all items have the same replenishment time. This is done since service parts have different replenishment times compared to service tools. For service replenishment time is called return time. The second adaptation is that the emergency shipment times are dependent on the central warehouse that delivers the part or tool in case of an emergency shipment. The company has multiple central warehouses and each part or tool is delivered by one of the central warehouses in case of an emergency shipment. Since the emergency shipment times and costs are different for each item, taking this difference into account in the heuristic is important. The items are thus linked to a specific central warehouse.

The continental model computes three fractions; the fraction of demand that is satisfied directly by the local warehouse to which the machine is assigned \( \beta_{i,j} \), the fraction of demand satisfied by lateral transshipment from each main local warehouse \( \alpha_{i,j,k} \) and the fraction of demand satisfied by emergency shipment \( \theta_{i,j} \). These fractions are computed for all individual items (parts, tools and tool kits). The notation of these fractions is equal to the notation given in the simulation description in Section 3.2. Using these fractions, the continental model computes the item level performance indicators, such as DTWP, DTWT, DTWI and CSD.

In the demand process of service parts and tools together, the independent stock assumption is seriously violated, since tools are demanded in combinations and parts are demanded in combination with tools. However, to test the effect of this violation, we will use the continental model to determine the base stock levels of both parts and tool. Since the continental model is not able to optimize for a DTWL target, a DTWI target is used to determine the base stock levels. Using the simulation, the corresponding DTWL is determined. By increasing or decreasing the DTWI target in Heuristic I, the DTWL after simulation can be tuned to a defined service level.

4.2. Heuristic II: Continental Model with demand coupling included

Unfortunately Heuristic I is not able to determine base stock levels for a DTWL target. In Heuristic II, the continental model is extended to make it suitable to optimize for a DTWL target. This
means that Heuristic II will take coupling in demand into account. To make this possible we assume that stock levels of items are independent. Using this independent stock assumption the order fill rate \( \beta_{v,j}(S^Y(v)) \), the order lateral transshipment rates \( \alpha_{v,j,k}(S^Y(v)) \) and the order emergency shipment rates \( \theta_{v,j,z}(S^Y(v)) \) are computed. These rates are computed by using the item rates computed by Heuristic I. The order rates can thus be computed for a given set of base stock levels. This evaluation is optimized using a greedy procedure. In this way the base stock levels can be computed for a given DTWL target and against (near) minimal costs. Since a greedy procedure is used, the exact minimal costs will most probably not be obtained. Heuristic II is given graphically in Figure 4.1. In the following paragraphs the computation of the order service levels as well as the greedy procedure are described in more detail.

![Diagram of Heuristic II](image)

**Figure 4.1: Heuristic II**

### 4.2.1. Calculation of Order Fill Rates

As described in Section 4.1, Heuristic I calculates, for a given set of base stock levels, the fraction of demand delivered by local supply, the fraction of demand delivered by lateral transshipment from each main local warehouse and the fraction of demand delivered by emergency shipment. This is done for each item (part or tool). Heuristic I uses these fractions to determine the performance measures on item level.

To compute the performance measures on order level, similar fractions are computed, however on order level. Since the waiting time of an order is dependent on the item with the longest delivery time, an order is only delivered by local supply if all items in an order are delivered by local supply. An order is assumed to be delivered by lateral supply from warehouse \( k \in K \), if the item with the longest delivery time of all items \( i \in I(v) \) is delivered by lateral supply from warehouse \( k \in K \). An order is delivered by emergency shipment from central warehouse \( z \in Z \), if the item with the longest delivery time is delivered from central warehouse \( z \in Z \).

For the computation of order fill rates \( \beta_{v,j}(S^Y(v)), \alpha_{v,j,k}(S^Y(v)) \) and \( \theta_{v,j,z}(S^Y(v)) \) an independent stock assumption is made. This means that the fill rate of an item is independent of the fill rate of the other items in a network. Using this assumption, the order fill rates can be computed using probability theory. To compute the fraction of orders \( v \in V \) delivered by local supply in location \( j \in J \), the item fill rates of the items \( i \in I(v) \) in location \( j \in J \) are multiplied. In formula:

\[
\beta_{v,j}(S^Y(v)) = \prod_{i \in I(v)} \beta_{i,j}(S_{i})
\]

The computation of the order lateral transshipment fraction is slightly more difficult. The lateral transshipment fraction of order \( v \in V \) in location \( j \in J \) which is delivered from main local \( k \in K \), is computed by subtracting the probability that an order is delivered by local supply or a faster
lateral supply than lateral supply from main local $k \in K$, from the probability that the order is delivered from main local warehouse $k \in K$ or via a faster way. In formula,

$$\alpha_{v,k}^Y(S^Y(v)) = \prod_{i \in \mathcal{O}} \left( \beta_{l,j}(S_i) + \sum_{r \in \mathcal{R}} 1_{\{t_{r,j,k}^{lat} < t_{r,j,k}^{lat}\}} \alpha_{l,j,r}(S_i) \right) - \left( \beta_{v,j}(S^Y(v)) + \sum_{r \in \mathcal{R}} 1_{\{t_{v,j,k}^{lat} < t_{v,j,k}^{lat}\}} \alpha_{v,j,r}(S^Y(v)) \right)$$

The order lateral transshipment fractions need to be computed in a predefined order. This order is based on increasing lateral transshipment times. This requires to be done, since the order lateral transshipment fractions from all main local warehouses with a shorter lateral transshipment time than the lateral transshipment time from main local warehouse $k \in K$ are required to compute the order lateral transshipment fraction from main local $k \in K$. It has to be noticed that $\alpha_{l,j,k}(S_i) = 0$, if $j = k$.

Similar computations are required to compute the order emergency shipment fractions from central warehouse $z \in Z$. In formula,

$$\theta_{v,j,z}(S^Y(v)) = \prod_{i \in \mathcal{O}} \left( \beta_{l,j}(S_i) + \sum_{k \in \mathcal{K}} \alpha_{l,j,k}(S_i) + 1_{\{t_{z,j}^{em} < t_{z,j}^{em}\}} \theta_{l,j}(S_i) \right)$$

$$- \left( \beta_{v,j}(S^Y(v)) + \sum_{k \in \mathcal{K}} \alpha_{v,j,k}(S^Y(v)) + \sum_{z \in \mathcal{Z}} 1_{\{t_{z,j}^{em} < t_{z,j}^{em}\}} \theta_{v,j,z}(S^Y(v)) \right)$$

Again, the order emergency shipment fractions need to be computed in a predefined order based on increasing emergency shipment times.

The same performance indicators as used in the detailed model are computed in Heuristic II. For the formulae we refer to Section 4.2 and Appendix II. Only the formula which computes the total relevant costs has changed to

$$TRC = h \times \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \left( c_{l,i} \times S_{l,i} \right) + 24 \times 365 \times \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \left( M_{i,j} \times \left( \sum_{k \in \mathcal{K}} c_{l,j,k}^{lat} \times \alpha_{l,j,k}(S_i) + c_{e,i}^{em} \times \theta_{l,j}(S_i) + c_{e,i}^{ret} \right) \right)$$

Since Heuristic II does not take demand substitution into account, the fraction of items delivered via lateral transshipment by substitution without extra transshipment costs is not included in the total cost function.

### 4.2.2. Greedy approach

Using Heuristic I and the formulas to compute the order service levels, the total costs and performance on order level can be computed for a given set of base stock levels. To optimize the base stock levels for a given target service level, an optimization approach is developed. This approach is similar to the greedy approach described in Kranenburg (2006). In this approach all base stock levels in each location are set to zero and the base stock level of the item with the highest service increase per euro is increased by one. This procedure is repeated until the target service level is reached for each location.

The main difference between the approach of Kranenburg (2006) and the approach used in Heuristic II is the dependence between stock levels in Heuristic II. In the approach of Kranenburg (2006) the assumption is made that stock levels are independent. Since this assumption is seriously violated (parts and tools are demanded in combinations), adaptations on the greedy approach of
Kranenburg (2006) are necessary. In the greedy approach of Kranenburg (2006), increasing the base stock level of item \( i \), only influences the performance of item \( i \) itself. In the approach used in this research, increasing the base stock level of item \( i \), influences the performance of each order that includes item \( i \).

Since items are demanded in combinations, increasing the base stock level of only one item can be less beneficial compared to increasing the base stock levels of two or more items that are regularly demanded in combination. This is logical since the order level performance is dependent on the item performance of all items in that order. In the greedy procedure used in Heuristic II not only increasing the base stock levels by individual items is considered, increasing a combination of items is also considered. The greedy procedure will thus evaluate the relative benefits of increasing the base stock levels of individual items as well as increasing the base stock levels of combinations of items. An option list is used, which defines the options that the greedy procedure will evaluate for each greedy step. The options can consist of a single item or a combination of items. More details about the different option lists are given later (Section 4.2.3).

The greedy procedure builds up inventory for all SKU-s in all locations in three steps. The first step is the initialization, in which the base stock levels of all items are set to zero. The second step is increasing the base stock levels (and thus service) that result in a cost decrease. If no increase in base stock level(s) decrease(s) the costs of the system, step 3 is started. In step 3 the base stock levels that result in the largest service increase per euro cost increase, are increased.

The following notation is introduced to describe the greedy method in a formal way. Let \( O = \{1, \ldots, |O|\} \) denote the non-empty set of options in the option list. Each option \( o \in O \) consists of a set of items called \( I_o(o) \). Let \( e(o,j) \) denote a matrix of size \( |I| \times |J| \). In this matrix all elements in all columns are equal to zero except for the elements of the \( j \)-th column. In this column all elements are equal to zero except for the elements in \( I_o(o) \). These elements are equal to 1.

\[ S \] is defined as a matrix of size \( |I| \times |J| \) with row \( i \) equal to vector \( S(i) \), so \( S = \{S(i) ; i \in I\} \).

Using the evaluation model of Heuristic II, the DTWL for each location and the total costs can be computed for a given set of base stock levels \( S \). The total cost for a given set of base stock levels \( S \) is defined as \( TRC(S) \). The DTWL for location \( j \in J \) and for a given set of base stock levels \( S \) is equal to \( DTWL_j(S) \). The target DTWL for location \( j \in J \) is equal to \( DTWL_j^{\text{target}} \).

Define \( \Delta TRC(o,j) := TC(S + e(o,j)) - TC(S) \), as the cost difference if the base stock levels of the SKU-s in option \( o \in O \) are increased in location \( j \in J \). The service difference, if the base stock levels of the SKU-s in option \( o \in O \) are increased in location \( j \in J \), is defined as \( \Delta DTWL(o,j) \). This difference is dependent on the current DTWL in each location, the DTWL in each location if option \( o \in O \) is implemented in location \( j \in J \), and the target DTWL in each location. In case the DTWL after implementation of an option is smaller than the target DTWL, the service increase is only measured up till the target DTWL. This means that service above the target is considered as unnecessary and thus this service increase is not included in the computation of \( \Delta DTWL(o,j) \). In formula;

\[
\Delta DTWL(o,j) = \sum_{j \in J} \left[ DTWL_j(S) - DTWL_j^{\text{target}} \right]^+ - \sum_{j \in J} \left[ DTWL_j(S + e(o,j)) - DTWL_j^{\text{target}} \right]^+
\]
Finally, define product $P(o,j), o \in O, j \in J$, as $P(o,j) := \Delta DTWL(o,j) \times -\Delta TRC(o,j)$ and ratio $R(o,j), o \in O, j \in J$, as $R(o,j) := \frac{\Delta DTWL(o,j)}{\Delta TRC(o,j)}$.

The greedy procedure is formally described in Algorithm 4.1.

Algorithm 4.1

Step 1 Set $S_{i,j} := 0, i \in I, j \in J$.

Step 2-a Calculate $\Delta TC(o,j), o \in O, j \in J$.

Step 2-b While $\min\{\Delta TC(o,j)\} \leq 0$:
  1. Calculate $P(o,j), o \in O, j \in J$
  2. Determine $\delta$ and $j$ such that $(\delta, j) = \text{argmax}\{P(o,j), o \in O, j \in J\}$
  3. Set $S_{i,j} := S_{i,j} + 1, i \in I_\delta(\delta)$
  4. Calculate $\Delta TC(o,j), o \in O, j \in J$.

Step 3-a Calculate $R(o,j), o \in O, j \in J$.

Step 3-b While $\max\{R(o,j)\} > 0$:
  1. Determine $\delta$ and $j$ such that $(\delta, j) = \text{argmax}\{R(o,j), o \in O, j \in J\}$
  2. Set $S_{i,j} := S_{i,j} + 1, i \in I_\delta(\delta)$
  3. Calculate $R(o,j), o \in O, j \in J$.

Computation times of the greedy algorithm can be limited by only updating the variables that are affected by the last greedy step made. If the base stock levels of the items in option $o \in O$ are increased, the relative benefits of increasing the base stock levels change for all options including one or more of the items included in option $o \in O$. Furthermore, also the relative benefits change for all options that include an item that is demanded in an order in which one or more of the items of option $o \in O$ are included. The relative benefits of all other options do not change and thus do not need to be updated in the optimization approach.

For example, we have three items (A, B, and C) and these items are demanded in three different combinations (A, AB, and BC), called orders. Assume the base stock levels of all three items are equal to zero. Suppose the option list consists of four options; A, AB, BC, and C (note that this option list can be longer or shorter). If option A is implemented, the base stock level of A is increased to 1. This means that only order A can be fulfilled in most cases. Furthermore, the relative benefits of increasing the items in option AB decrease. Before the implementation of option A, implementing option AB would increase the order fill rate of order A and order AB. After the implementation of option A, the order fill rate of order A is already increased, which makes the implementation of option AB relatively less beneficial. The opposite is true for option BC. Before the implementation of option A, implementing option BC would only increase the order fill rate of order BC. After the implementation of option A, implementing option BC also increases the order fill rate of order AB. This makes the implementation of option BC more beneficial. By implementing option A, the relative benefits change for all options including the items in option A (thus option A and option AB). Furthermore, also the relative benefits change for all options that include an item that is demanded in an order in which one or more of the items of option x are included (thus option BC). The relative benefits of all other options do not change. Thus the relative benefits of option C remain the same. The logic of the example does not only hold for the case with base stock levels of zero.
4.2.3. Option Lists

As mentioned in the previous section, different option lists can be used in the optimization approach. Of course, the length of the option list influences the computation time of the optimization approach. Furthermore, including more options in an intelligent way will improve the solution of the optimization approach. The option list used should thus be small enough to result in a practical computation time and long enough to generate a proper solution. In order to decide which option list to use in the optimization several option lists are tested in a realistic situation.

In total, 4 different option lists will be tested:
- Item list
- Order list
- Item + order list
- Item + order extra list

The item list consists of all individual items included in the test bed. Combinations of items are not included in the list. The order list consists of all combinations of items that are included in the data set. This list is most likely longer than the item list, since items are demanded in a large number of different combinations. The order + item list is a combination of the order and item list, all options of the item list and order list are included in this list. Since the item and order list can overlap, the item + order list will be shorter than (or equal to) the sum of the lengths of the item and order list. Finally, the item + order extra list will be tested. This list is equal to the item + order list; however, a number of smart extra options are included in the option list. These smart extra options are determined by examining the difference between options in the item + order list. By implementing a certain option in the greedy procedure, a combination of items that is not included in the option list can lead to a very beneficial base stock level increase.

For example, assume that we only have two different orders that can occur; ABC and CD. In this example, the item list consists of A, B, C and D, the order list consists of ABC and CD. The item + order list then consists of A, B, C, D, ABC and CD. Assume we have base stock levels of zero for all items and option CD is the most cost effective option to implement. After implementation of option CD, order CD can be fulfilled. It is now possible that option ABC is the next most effective option to implement. By implementing this option both order ABC and CD can be fulfilled, and the base stock level of item C will be 2. In case of low demand rates, it will not be very likely that both order ABC and CD will occur shortly after each other. Having only one item of C on inventory will thus be a smarter and more cost effective solution. This can be achieved by adding option AB to the option list. After implementing all the options, other combinations that do not occur in the item + order list can become more effective than the options in the item + order list. These options are included in the item + option extra list. This is done by examining the difference between the options in the item + order list. By comparing the difference between option ABC and CD, options AB and D should be added. Since D is already in the option list only AB is added to the item + option extra lists. By comparing all items in the item + order list in this way the following item + option extra list is obtained of A, B, C, D, ABC, CD, BC, AC and AB.

The item list is the shortest list and therefore the one that results in the shortest computation time. The item + order extra list is the longest one and will result in the longest computation time. Since the item + order extra list includes all options of the other lists, we expect the item + order extra list to result in the best solution. In Section 4.2.5 we will examine the differences in the solution if different option lists are implemented.
4.2.4. Starting Solution

Since the computation time of the optimization can be very long for large networks with a large number of items and combinations, using a starting solution in the optimization of Heuristic II can be beneficial. A drawback of a starting solution is that the part of the base stock levels provisioned by the starting solution will most likely be less optimal than if the stock levels determined by the greedy method of Heuristic II. However, in case a smart starting solution is used, the loss in optimality can be compensated by the decrease in computation time.

By implementing a starting solution, step 1 of Algorithm 4.1 is changed. In step 1 the base stock levels are not set to zero, but to the base stock levels of the starting solution. The remaining part of Algorithm 4.1 is the same.

The starting solution used is generated by Heuristic I. The target DTWP (or DTWI) is equal to the DTWL target times the average number of items in an order. Since Heuristic I does not include coupling in demand, it can be proven that the proposed starting solution generated by Heuristic I will result in a DTWL larger than the target DTWL. The optimization model of Heuristic II will thus have to increase the base stock levels to reach the target DTWL. The average number of items in an order is equal to \( n \). The formal proof is given below;

\[
\begin{align*}
E[OWT_j] & \geq E[WT'_j] \\
\frac{100}{N_j} \cdot M'_j \cdot E[OWT_j] & \geq \frac{100}{N_j} \cdot M'_j \cdot E[WT'_j] \\
DTWL_j & \geq \frac{100}{N_j} \cdot M'_j \cdot E[WT'_j] \\
DTWL_j & \geq \frac{100}{N_j} \cdot \frac{M_j}{n} \cdot E[WT'_j] \\
DTWL_j & \geq \frac{DTWI_j}{n}
\end{align*}
\]

The waiting time of an order is always larger or equal to the average waiting time of the individual items in an order. The average order waiting time in a location is thus always equal or larger than the average item waiting time in the same location. If the average order waiting time in a location is multiplied by the total order demand rate of the location and divided by the number of machines, the DTWL fraction for a location is obtained. Multiplying this by 100 gives the DTWL of a location. If we multiply and divide the average item waiting time in a location with the same numbers, the third equation is obtained. Since the total order demand rate in a location is equal to the total item demand rate divided by the average number of items in an order, the fifth equation is true. This means that if we use a DTWI target in Heuristic I of \( n \) times the DTWL target, the corresponding DTWL will always be larger than the DTWL target. The optimization model will thus need to increase the base stock levels to achieve the DTWL target.

The performance of the optimization model with and without the starting solution and for different option lists will be discussed in the next paragraph.

4.2.5. Performance of the different optimization approaches

For realistic test beds, the performance of the optimization with different option lists and with and without a starting solution is examined. The optimization approaches are compared based on three important criteria; efficiency with respect to costs, accuracy with respect to the service level and
computation time. The test beds used are similar to Cases I to III. For a detailed description of the construction of the test beds is referred to Section 5. The different optimization approaches are thus compared for three different networks; the Korea, Hong Kong and US network. Six different optimization approaches are compared:

- Item list, starting solution
- Item list, no starting solution
- Order list, starting solution
- Order list, no starting solution
- Item + order list, starting solution
- Item + order extra list, starting solution

The item + order list and item + order extra list are not compared without a starting solution. The reason for this is that the computation times become too long for these optimization approaches. The results of the optimization approaches for the Korea-network are displayed in Figure 4.2. In this graph, the total costs of the approaches are compared with the item-start approach, which is the fastest approach. The graph shows that only including orders in the option list results in a large difference compared to the item-start approach. Furthermore, in this approach the difference seems to grow when the target DTWL decreases, which means that the service increases. Using an item option list without a starting solution also results in large difference with the item option list with a starting solution. A possible explanation why these two approaches result in higher costs is that the smart extra options included in the item + order extra list are not included, resulting in less efficient greedy steps. One can see that the solution of the item - no start and order - no start approaches generate worse solutions if the target DTWL decreases. This supports the explanation of less efficient greedy steps for the item and order approach without a starting solution.

**Figure 4.2:** Percentage cost difference compared to the Item-Start approach for varying DTWL in the Korea Network (the figure below is an enlargement of the figure above around 0 % percentage cost difference)

Furthermore, the item - no start generates worse results since combinations that are always demanded together and not in combination with other items are never increased in Heuristic II. Increasing the item fill rate of only one item does not increase the order fill rate. The reason why the
item + start approach generates good results is that the starting solution already has provisioned a considerable part of the items. Since a considerable amount of parts and tools are already provisioned by the starting solution, adding individual items can result in smart base stock level increases.

The same results are obtained for the Hong Kong network. For the graphs corresponding to the Hong Kong network, see Appendix III. In both the Hong Kong and Korea network all approaches with a starting solution result in similar outcomes. For the US-network, the approaches without a starting solution were not compared, since this results in very long computation times. Furthermore, the item + order extra – start approach could also not be compared with the other approaches since the computation times are too high. The results for the US-network are similar to the results of the Hong Kong and Korea network. No large differences occur between the item, order and item + order approach with a starting solution. The graphs corresponding to the US network can be seen in Appendix III.

Figure 4.3 shows the difference between the DTWL target used in Heuristic II and the corresponding DTWL of the simulation. One can see that we underestimate the service of the Heuristic. This means that the actual service is higher than the proposed service by Heuristic II. This can be explained by the fact that Heuristic II does not include coupling between tool demands in a detailed way. Furthermore, Heuristic II does not include substitution in demand. Both effects are included in the detailed model and therefore the service of the simulation of the detailed model is higher than the service estimated by Heuristic II. We can further see that the difference between the target and the simulation output is almost equal for the optimization approaches with a starting solution. Figure 4.3 shows that the difference between the target DTWL and the simulation DTWL becomes smaller if the target DTWL decreases. Similar results are obtained for the Hong Kong and US network, however, the percentage difference varies somewhat between the networks. The graphs corresponding to the Hong Kong and US networks are given in Appendix III.

![Figure 4.3: Percentage service difference between DTWL target and simulation DTWL in the Korea-network](image)

In section 4.2.4 a proof is given that the starting solution results in a DTWL that is higher than the DTWL target, which means that base stock levels have to be increased to make sure that the service target is realized. Figure 4.4 shows the difference between the DTWL target and the DTWL corresponding to the starting solution. In this graph one can see that the starting solution results in a DTWL that is at least 10 percent higher than the target DTWL. This difference varies between the networks, and can also vary if the coupling in demand changes. However, in this research, the DTWL of the starting solution will be at least 10 percent higher than the target DTWL.
In this section, the performance of 6 different optimization approaches was assessed. The results show that using a starting solution generated by Heuristic I does not seriously decrease the performance of the solution, however it does decrease the computation time considerably. Furthermore, using the item list, the item + order list or the item + order extra list all give similar results with respect to cost efficiency and service level accuracy. The main difference between the performances of the option lists is the difference in computation time. In the remainder of this research, the item optimization approach with a starting solution is used in Heuristic II. This is the optimization approach which fits the criteria with respect to cost efficiency, service level accuracy and computation times best.

4.3. Heuristic III: Single-location model including coupled demands and returns

Heuristic III is a single location model with coupled demand and returns included. Heuristic III also consists of an evaluation model that is optimized using a greedy procedure. The evaluation model is discussed in detail in Vliegen and Van Houtum (2008) and the Literature Review [A]. The evaluation model approximates the order performance for a demand process with coupled demands and returns. Vliegen and Van Houtum (2008) show that this approximation is accurate for a test bed constructed on the basis of realistic data. The model of Vliegen and Van Houtum only computes the base stock levels of service tools. The base stock levels of parts are computed using Heuristic I.

The optimization method used in the tool planning part of Heuristic III is similar to the optimization heuristic discussed in Section 4.2.2 and is based on Vliegen et al (2008). In this working paper a greedy heuristic is used to optimize the base stock levels for the evaluation model of Vliegen and Van Houtum (2008).

A drawback of Heuristic III is that the computation times are very long for the tool planning part of the optimization. Especially in cases with a large number of items and item combinations included. For this reason a starting solution is used. This starting solution really decreases the computation time of the tool planning part of Heuristic III. The method to obtain the starting solution is equal to the method described in Section 4.2.4 and is thus generated by Heuristic I. This method ensures that the DTWL corresponding to the starting solution is lower than the target DTWL.

Another drawback of Heuristic III is the fact that tool and part planning are separated. The coupling between parts and tools is not included in this model. Since both the tool planning part and the part planning part of Heuristic III compute base stock levels with a system approach, sub-optimization can lead to less beneficial results.
4.4. US-Heuristic

The US-Heuristic is a heuristic proposed by a project group of the company in the US. The heuristic uses clear and simple decision rules to decide in which location the service tools should be stocked. Three decision variables are identified. The first is the cost price of a service tool, the second is the usage (demand rate) of a service tool and the third is the installed base of machines in a location.

Service tools with a cost price lower than €2,500 are called low-cost tools, tools with a cost price between €2,500 and €10,000 are called medium-cost tools and tools with a value of over €10,000 are called high-cost tools.

Service tools that are demanded less than 1/6 times a month per machine are called low-usage tools, tools that are demanded between 1/6 and ones a month are called medium-usage tools and tools that are demanded more than ones a month are called high-usage tools.

The installed base of machines is equal to the number of machines per location. Five ranges are defined for the installed base; less than 3 machines, between 3 and 5 machines, between 5 and 10 machines, between 10 and 20 machines and more than 20 machines. The BOM-structure of service tools defines which tools are used on which machines. Using this BOM-structure, the installed base of machines for each specific tool can be determined.

The combination of the three variables defines whether a service tool requires to be stocked continentally, in the zone or in the office. This is similar to at one main local in the whole continent, in all main locals and in all local warehouses. Figure 4.5 illustrates the heuristic in a diagram. The number of items to stock per location is always 1 in the US-Heuristic, so each tool is stocked at most ones per location.

In the US-Heuristic, the planning of parts and tools is done separately. The part planning of the US-Heuristic is done by Heuristic I. Since the tool planning part of the US-Heuristic is not dependent on the service level, the US-Heuristic can only be tuned by the part planning. The DTWP target in Heuristic I can be used to tune the performance of the US-Heuristic to a defined DTWL level.

![Figure 4.5: US-Heuristic](image-url)
4.5. Qualitative comparison of heuristics

A qualitative comparison of the heuristics is given in Table 4.1 and 4.2. In Table 4.1 a comparison is made based on the characteristics of the heuristics. In Table 4.2, the heuristics are compared on the qualitative criteria defined in Section 2.1. In these tables the advantages of a heuristic are illustrated by plusses, whereas the disadvantages are given by minuses. A quantitative comparison between the heuristics will be given in Section 6, in which the heuristics are compared on the efficiency with respect to costs and the accuracy with respect to the service target.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Heuristic I</th>
<th>Heuristic II</th>
<th>Heuristic III</th>
<th>US-Heuristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Includes lateral transshipments in tool planning</td>
<td>++</td>
<td>++</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Includes lateral transshipments in part planning</td>
<td>++</td>
<td>++</td>
<td>++</td>
<td>++</td>
</tr>
<tr>
<td>Includes demand substitution</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Includes coupling in tool demand</td>
<td>-</td>
<td>+</td>
<td>++</td>
<td>-</td>
</tr>
<tr>
<td>Includes coupling between parts and tools</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Integrates part and tool planning (in one heuristic)</td>
<td>++</td>
<td>++</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Possibility of tuning</td>
<td>++</td>
<td>++</td>
<td>+</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 4.1: Characteristics of the four heuristics

Heuristics I and II both include lateral transshipments in the planning of parts and tools. The effects of lateral transshipments are included in the planning of parts in Heuristic III and the US-Heuristic, because in these two heuristics Heuristic I is used for the planning of parts. Since the tool planning part of Heuristic III is a single location model, the effects of lateral transshipments for tools are completely ignored. In the tool planning part of the US-Heuristic, the effects of lateral transshipments are included partly, since the US-Heuristic can decide to stock a tool in only the main local warehouses. However, the US-Heuristic does not take the lateral transshipments into account in detail, like Heuristics I and II do.

None of the heuristics includes the effects of substitution of service tools and parts into account. In case the possibilities of substitution are high, this is a serious drawback of the heuristics.

The US-heuristic does not take the coupling in tool demand into account. The decisions in this heuristic are based on the demand rate, standard price and installed base only. In Heuristic I the assumption is made that parts and tools are always demanded individually. This means that Heuristic I does also not include coupling in demand. Coupling in tool demand is included in the other heuristics, Heuristics II and III. Heuristic III does include coupling in tool demand in a more detailed way, compared to Heuristic II. In Heuristic III also the coupling in returns is included.

Coupling between parts and tools is only included in Heuristic II. Heuristic II also integrates the planning of parts and tools into one heuristic. Since Heuristic III and the US-Heuristic both plan parts and tools separately, coupling between parts and tools is not included. As already mentioned, Heuristic I assumes that parts and tools are demanded individually. This means that Heuristic I does not include the coupling between parts and tools. However, Heuristic I does integrate the planning of parts and tools into one model.

To compare the quantitative results of the heuristics, the possibility of tuning is important. Heuristics I and II both integrate the planning of parts and tools into one model and both use one service target. In this way the heuristics are relatively easy to tune. Heuristic III separates the planning of parts and tools and used two different targets for the part and tool planning. This makes tuning of Heuristic III relatively more difficult. One has to decide which of two targets to adapt in Heuristic III or to adapt both of the targets. This makes the tuning process more complicated. The US-Heuristics is
even more difficult to tune. The US-Heuristic has only one solution for the base stock levels of tools, so no tuning in tool planning is possible in the US-Heuristic. The US-Heuristic can only be tuned by changing the target of the tool planning part.

<table>
<thead>
<tr>
<th>Practicality with respect to the computation time</th>
<th>Heuristic I</th>
<th>Heuristic II</th>
<th>Heuristic III</th>
<th>US-Heuristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Understandability for the people that have to work with it</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>++</td>
</tr>
<tr>
<td>Ability to implement</td>
<td>++</td>
<td>+</td>
<td>-</td>
<td>++</td>
</tr>
</tbody>
</table>

*Table 4.2: Comparison of the four heuristics based on qualitative criteria*

The computation times of the US-Heuristic and Heuristic I are both very low. A solution for a complete network with all parts and tools included can be computed in a few minutes. The computation times of Heuristic II are higher, however, still a solution can be computed in a practical amount of time. The tool planning part of Heuristic III is very slow and for a complete network including all parts and tools, it may even be impossible to compute the base stock levels for tools.

The main advantage of the US-Heuristic is the simplicity of the decision rules. Therefore the US-Heuristic is easy to understand. Furthermore, implementing the US-Heuristic will not result in major problems. Heuristic I and II are both relatively easy to understand. Heuristic I is already implemented and the people working with it are able to understand the logic behind Heuristic I. Implementing Heuristic I for both parts and tools will thus be possible without major problems. Heuristic II is somewhat more complicated than Heuristic I, however those who understand Heuristic I will also be able to understand the logic behind the inclusion of coupling in demand in Heuristic II. Implementing Heuristic II will not be difficult with respect to programming, however, the company has to ensure that this heuristic is fed with the right data. Especially the data about coupling in demand is difficult to obtain. However, using the knowledge and experience of the people within the company in combination with the data in the information systems, will make it possible to obtain the right data with respect to coupling in demand. The same problem holds for Heuristic III. This heuristic also requires information about the coupling in demand. Furthermore, this heuristic will be more difficult to program. Finally, the tool planning part of Heuristic III will be very difficult to explain to the people working with it. Implementing Heuristic III is not impossible; however it will be a real challenge.

The quantitative criteria will be compared for the heuristics by examining the results of the numerical experiments. The criteria cost efficiency and service level accuracy will be discussed in Section 6.
5 Data collection

In this section the construction of the test bed is discussed. This test bed is used in the numerical experiments. To ensure that the test bed is as realistic as possible, the data used is collected out of the information systems of the company. In Section 5.1, the scope of the test bed is discussed, followed by a discussion of the data requirements of the detailed model and heuristics in Section 5.2. Finally, details about the construction of the cases used for the numerical experiments are discussed in Section 5.3.

5.1 Scope of the test bed

The number of service parts and tools that are used to service the machines in the field is large. Including all service parts and tools in a test bed will result in computation times for Heuristic II and Heuristic III that will be too large for testing purposes. The number of parts and tools included in the test bed is thus downsized. This is done by using the practical knowledge of the tool planners of the company. In the test bed, only machines of one specific range are included. This machine range has a large installed base and is not recently introduced. This is very important, since the reliability of the consumption data is dependent on the time a machine is in the field. The longer a machine is running in the field, the more reliable the consumption data are.

Figure 6.1 shows that the commonality of the chosen machine range (machine types 1 and 2) is low compared to other machine types. This means that service tools or parts that are used on machine type 1 or 2 are not regularly used on the other machine types. Furthermore, one can see that the internal commonality between machine type 1 and 2 is high. This means that the service tools and parts used on machine type 1 are also regularly used on machine type 2. Figure 5.1 shows thus that the parts and tools used on machine type 1 and 2 are a relatively independent set of parts and tools. Only including machine type 1 and 2 is thus a proper way to decrease the size of the test bed. In the remainder of the research we will assume that all machines of the company are of these machine types and that all machines are equal with respect to their consumption of service parts and tools in case of a machine breakdown. This assumption simplifies the network of the company; however, for the purpose of the research this will not harm the results. In case one of the heuristics will be implemented by the company, including different machine types is possible without adapting the heuristics.

![Figure 5.1: Service tool and part commonality between machine types 1 to 5](image)

In the test bed, only parts and tools that are used during corrective maintenance actions are included in the experiments. This means that no stock levels for calibration tools, installation tools,
etcetera are included in the test bed. This is done since these tools have other characteristics than corrective maintenance tools; for example less variability in demand and more coupling. Furthermore, the planning heuristics developed are not suitable for the planning of these other tools.

5.2 Data requirements for the test bed

The test bed includes three types of data; data to define the network under consideration, demand and return data about service parts and tools and data required for the computation of performance indicators. Three types of information systems were used to gather the required data for the test bed. The first is the SAP-system of the company. In this system information is stored about the network, the BOM structure of machines, parts and tools, current base stock levels, etcetera. In the second information system, detailed information about inventory transactions is stored. The third system is a system in which the procedures regarding repair actions are stored. In this system one can find which service parts and service tools are required for which repair action.

5.2.1 Network data

To define the structure of a network, information is required about the number of warehouses in a network and the number of main and regular local warehouses. Furthermore, the installed base per location is required as well as the service parts, tools and tool kits that can be used to repair possible failures on this installed base. Finally, the set of substitution possibilities corresponding to this set of parts and tools is required.

Information about the number of warehouses and whether a warehouse is a main or regular local warehouse is easily obtained using the SAP system. The possibilities of lateral transshipments follow from the number of main local warehouses.

Since we assume that all machines are of the same machine type, obtaining the number of machines of this type per location is also easy. Using the BOM-structure, the parts and tools used on the machine type under consideration is known. The company has also defined for each tool and part, the type of part/tool. In the test bed only the corrective maintenance tools are included.

Two types of substitution possibilities exist. The first is substitution by a predecessor of the tool or part, and the second type is substitution of a tool by a tool kit. In the test bed, only the newest version of parts and tools is included, since this is the actual version of a tool/part that will be ordered by a service engineer in case of a machine breakdown. By including only the newest version, substitution by a predecessor is excluded from the test bed. The SAP system of the company stores successor/predecessor information for each part or tool. The SAP system also stores the composition of tool kits. Using this composition, the substitution possibilities for each tool are easily obtained.

5.2.2 Demand and return data

Reliable demand data is more difficult to obtain. To define the characteristics of the demand streams, the combinations in which parts and tools are demanded are determined, as well as the demand rate for each of these combinations. The system that records inventory transactions is used to define the set of combinations. About 2.5 years of historical data is available in this system. Using this information system, all service orders for corrective maintenance and on the machine type under consideration are analyzed to define combinations of items that are demanded together. Predecessors of tools/parts in the list of tools/parts used in the test bed are replaced by the successor. By doing this,
we assume that the demand rate of a successor of a part/tool is equal to the demand rate of the predecessor.

After all historical service transactions are defined, a Microsoft-Excel Macro was developed to define the number of times a specific combination of tools/parts was demanded in the historical data. By using information about the total time a machine is in the field, the number of hours a machine was running during the 2.5 years of data was defined for all machines in the network. We assume that machines are running the complete year (24 hours a day, 7 days a week). The demand rate for each transaction is computed by dividing the number of times a specific transaction was demanded by the number of machine hours.

Unreliable elements in the list with order combinations were deleted in consultation with employees of the company and by using the information system in which the procedures for specific repair actions are stored. In this information system, no procedures for corrective maintenance actions in which more than 10 items (parts or tools) are demanded could be found. The tool and part planners of the company have confirmed that transactions of more than 10 items at ones can hardly occur for corrective maintenance actions. For this reason all transactions with more than 10 items were deleted from the list with order combinations. Furthermore, in the information system with the procedures of corrective maintenance actions, no procedures were found in which multiple items of the same item type are used for one transaction. In the list with order combinations, several combinations were found in which more than one item of the same item type are demanded for one corrective maintenance action. Employees of the company have confirmed that in case a part or tool is regularly demanded multiple times for one transaction, the part or tool is stocked in sets as one SKU. So, we assume that demand for multiple items of the same type cannot occur in one transaction. All multiple items were thus deleted out of the list with order combinations.

Next to demand data, also return data of parts and tools is used as an input in the simulation of the detailed model and in the heuristics. A distinction is made between the return time of parts and the return time of tools. The return time of parts is equal to the replenishment lead time. In the already implemented planning heuristic for parts in the company, a replenishment lead time of 14 days is used and employees of the company have confirmed that this is a reliable lead time.

![Figure 5.2: Return time frequencies in days](image-url)

The return time of tools is not known exactly. However, the information system with historical transactions stores information about the time a tool is delivered to the service engineer and the time a tool returns. When analyzing the individual return times for each transaction, several
transactions with a return time of a few minutes were found as well as transactions with a return time of more than 50 days. For both is a plausible explanation. The very small return times are due to administrative errors, in which tools are shipped to an engineer by mistake and then returned back. This means that no real transaction has taken place. These transactions were thus not used to compute the average return time of tools. The return times of over 50 days are caused by customers who would like to have tools permanently available at their machine location. These tools do thus not return in a regular way and have to be excluded in the determination of the return time of tools. In Figure 5.2, a histogram is given in which the return time frequencies are given. In this figure one can see that the assumption of an exponentially distributed return time seems reliable.

Figure 5.3 shows a box-plot, which is used to define what return times to exclude in the computation of the average return time. The stars in this figure correspond to the outliers in the list with return times. One can see that a considerable number of return times are outliers. For the computation of the average return time, these outliers were deleted from the list with return times. The resulting average return time of tools is equal to 7 days. Specialists of the company have confirmed that this is a proper return time to use in the heuristics and the detailed model.

![Figure 5.3: Box-plot of return times](image)

### 5.2.3 Performance indicator data

For the computation of performance indicators several transshipment times and transshipment costs are identified as well as the costs of holding inventory and the cost price of tools. The average transshipment times (local, lateral and emergency) are stored in the SAP system of the company and are thus downloaded directly. The same is done for the cost price of parts and tools.

Next to the transshipment times, also the costs of transshipments are required. These costs are defined using information from logistic service providers of the company. In the determination of the transshipment costs, no distinction is made between individual parts and tools, so an average is taken over the cost of all transactions. The costs are defined per continent, so the emergency costs vary between continents.

Finally, the holding cost parameter is taken as 25 percent. This percentage is determined by financial specialists of the company.
5.3 Details about the data used in the cases

In the numerical experiments, five cases are used to compare the heuristics. In these cases the number of item types is equal. In total, 493 item types are included of which 100 are tools and 393 are parts. The parts and tools are demanded in 1177 combinations which vary between combinations of 1 to combinations of 9 items. The cost price of the items varies between less than one Euro and a few hundred thousand Euros. In the remainder of the report, this number of items, parts, tools and combinations is used. It will be explicitly mentioned if an experiment uses other numbers. More details about the items and combinations are given in Appendix IV. This appendix can be used in case one would like to replicate the experiments. In the following subsections, the details of the five different cases are described.

5.3.1. Case I: US

In Case I, the heuristics are compared for the US-network. This network consists of 13 locations of which 7 are main local warehouses. In fact, the company has more than 13 warehouses in the US, however, some warehouses do not have an installed base of the machine type under considerations and are thus not included in the test bed. The US-network is shown in Figure 5.4. The US network is characterized by the high number of lateral transshipment possibilities (7 for each regular local warehouse). The number of machines per location varies between 1 and 27 of the machine type considered. The coupling in demand included in this case is the coupling defined at the beginning of Section 5.3.

5.3.2. Case II: Korea

The Korea network consists of three main local warehouses with 122, 49 and 10 machines. The average number of machines per warehouse is thus higher than in Case I (US), whereas the number of lateral transshipment possibilities is lower. The Korea network is shown in Figure 5.5. The coupling in demand is equal to the coupling in the Case I (US).

5.3.3. Case III: Hong Kong

The Hong Kong network is similar to the Korea network, however, the number of machines per location is lower (2, 16 and 33). The lateral transshipment possibilities are equal to the possibilities in Case II (Korea), however, since the lateral transshipment times are very high the benefits of lateral transshipments are almost completely lost. This means that the network is almost equal to a network with three independent warehouses. The coupling in demand is equal to the coupling in Case I (US) and Case II (Korea). The Hong Kong network is shown in Figure 5.5.
5.3.4. Case IV: US extra coupling

In Case IV, the coupling in demand is increased by removing the individual item demands out of the order combination data. This means that items are always demanded in a combination. Since the total order demand rate decreases due to the removal of orders including only one item, a lower target DTWL is used for the comparison of the heuristics. The DTWL target is decreased with the same ratio as the order demand rate decreases (compared to Case I). The number of warehouses, the structure regarding lateral transshipments and the number of machines per location are also equal to Case I.

5.3.5. Case V: US Higher demand rates per location

In Case V, the demand rate per location is increased, by increasing the number of machines per location of Case I. This is done by increasing the number of machines to 8, 18 or 27. The number of machines in a location with less than 8 machines is increased to 8 machines, the number of machines in a location with 9 to 17 machines is increased to 18 machines, and the number of machines in a location with 19 to 26 machines is increased to 27. The coupling in demand and lateral transshipment possibilities are equal to the ones used in Case I.
6. Results

In this section the results of the quantitative comparison between the four planning heuristics is discussed. The heuristics are compared on two criteria; cost efficiency and service accuracy. The results with respect to the cost efficiency of the models are compared using the costs of Heuristic I. The total relevant costs of Heuristic I are set to 100 percent. The costs of the other heuristics are expressed in percentage of the costs of Heuristic I. The service accuracy is measured with the percentage service difference from the target used in the heuristics;

\[
\text{percentage service difference from target} = \frac{\text{DTWL after simulation}}{\text{Target DTWL}} \times 100\%
\]

A small value of the percentage difference from target corresponds to a high accuracy.

The sections 6.1 to 6.6 all answer one of the research questions. In these sections the results of Heuristics I to III are compared. The results of the US-Heuristic will only be assessed for Case I, since the US-Heuristic is developed for the US-network only. This is done in Section 6.7. Section 6.8 gives an overview of the quantitative comparison between the heuristics.

6.1. Do the performances of the heuristics vary in different networks?

6.1.1. Comparison of performance with respect to cost efficiency

In Cases I to III the heuristics are compared in three different networks (US, Korea and Hong Kong). The DTWL after simulation of Heuristic III is used as a tuning target for Heuristics I and II. This means that the target DTWL in Heuristics I and II will be tuned until the DTWL after simulation is equal to the tuning target. Due to its long computation time and its difficulty of tuning, Heuristic III will be used to generate the tuning target. The yearly total costs for each heuristic are compared.

The results for the different networks are shown in Figure 6.1. In this figure, the yearly costs of Heuristic I are set to 100 percent. One can see that the yearly costs of Heuristic II are smaller in all three cases, however, the difference is relatively small. The performance of Heuristic III varies considerably among the networks. In Case I, which has many lateral transshipment possibilities, the performance of Heuristic III is really inferior to the results of the other two models. The total costs are about two times as high as the total yearly costs of Heuristics I and II. This can be explained by the characteristics of the heuristic. Heuristic III uses a single location model for the computation of the base stock levels of tools, whereas the other two heuristics are multi-location heuristics that take sharing of inventory by lateral transshipments into account. In a network with many lateral transshipment possibilities, using a model that does not include lateral transshipments is less beneficial. This can clearly be seen in the results of Figure 6.1.

For the other two cases, which consist of only three warehouses, the total yearly costs of Heuristic III are more in range with the results of Heuristics I and II. This supports the statement that the number of lateral transshipment possibilities has a significant impact on the performance of Heuristic III. Furthermore, one can see that in the Hong Kong case, the results of Heuristic III are really close to those of Heuristics I and II. In the Hong Kong case three main local warehouses are included; however, since the lateral transshipment times are almost as high as the emergency shipment times, the benefits of lateral transshipments are almost completely lost. This means that the Hong Kong network is similar to a network with three single locations. In this case, the characteristics of Heuristic III do better fit the network, resulting in better results. This can also be seen in Figure 6.1.
The performance of Heuristics I and II are quite close to one another in Cases I to III. This is logical since a starting solution is used in Heuristic II that is generated by Heuristic I. This means that up till the service level generated by the starting solution, the models propose the same base stock levels. After this service level, the heuristics start to provision stocks differently. The percentage cost difference after the starting solution is shown in Figure 6.2. One can see that the difference between Heuristic I and Heuristic II is larger for the base stock level provisioning after the starting solution. In Case I, Heuristic II even saves up to 16 percent in total yearly costs. For the Korea and Hong Kong cases, the savings are 7 percent. For Heuristic III one can see that the difference with Heuristic I is larger for the part of the base stock levels provisioned after the starting solution in Cases I and II.

We can conclude that the starting solution has an impact on the relative performance of Heuristic II compared to Heuristic I. The results show that the cost benefits of Heuristic II are obtained after the starting solution. Further research about the height of the starting solution is recommended. Decreasing the height of the starting solution may seriously increase the performance of Heuristic II compared to Heuristic I.

**Finding 1:** Heuristics II outperforms Heuristic I slightly in all networks with respect to cost efficiency

**Finding 2:** Heuristic III performs less compared to Heuristics I and II with respect to cost efficiency in networks with many lateral transshipment possibilities

**Finding 3:** The height of the starting solution may have a significant effect on the cost benefits of Heuristic II compared to Heuristic I
6.1.2. Comparison of performance with respect to service level accuracy

Next to the costs corresponding to a specific service level, also the difference between the service target and the resulting service in the simulation is important. In Figure 6.3, the difference between the target used in the heuristics and the resulting DTWL in the simulation is compared. In Heuristic I the target used is a DTWI target on item level. Heuristic II uses a DTWL target and Heuristic III uses a DTWL target for the tool planning and a DTWP target for the part planning. For the comparison the DTWL target and DTWP target of Heuristic III are summed. In Figure 6.3 one can see that Heuristic I underestimates the service with more than 50 percent in all three cases. Heuristic II is most accurate and varies between 12 and only 7 percent difference. This means that Heuristic II describes the current tool and part planning process in a more valid way. The differences in service levels seem to decrease for Heuristic I and II in case the number of lateral transshipment possibilities of the network decreases. The results of Heuristic III are relatively constant and vary between 39 and 48 percent. Furthermore the results show that all three heuristics underestimate the service. This means that the actual service (after simulation) is higher than the service target.

![Figure 6.3: Percentage difference between the DTWL target used and the DTWL after simulation in Case I to III](image)

**Finding 4:** Heuristic II is most accurate with respect to the difference between the target service and the service after simulation

6.2. Do the performances of the heuristics vary for different levels of coupling in demand?

To answer the second research question, the results of Case I are compared with the results of Case IV. In Case IV the coupling in demand is increased and no individual item demand is included in this case. All order combinations consist of at least 2 items.

6.2.1. Comparison of performance with respect to cost efficiency

In Figure 6.4, one can see that if demand includes more coupling, Heuristic II performs better compared to Heuristic I and III. This is logical, since this heuristic includes coupling in demand in the tool planning part as well as the coupling between parts and tools. One would expect that Heuristic III will perform better compared to Heuristic I in case more coupling is included in demand. However, the results show the opposite. A possible explanation is that, relatively, the coupling between tools is increased less compared to the coupling between parts and tools in Case IV. Since parts and tools are planned separately in Heuristic III, the relative performance of Heuristic III decreases.

Figure 6.4 further shows that the effects of including lateral transshipments in planning are higher than the effects of including coupling in tool demand. This means that Heuristic III still
performs less compared to Heuristics I and II (these include lateral transshipments). Also in this case Heuristic II performs best, with a cost decrease of about 10 percent compared to Heuristic I.

Finding 5: The relative cost benefits of Heuristic II compared to Heuristic I and III increase in case the coupling in demand increases

Finding 6: Including lateral transshipments in a planning heuristic is more beneficial with respect to costs than including coupling in tool demand

6.2.2. Comparison of performance with respect to service level accuracy

In Figure 6.5, the difference between the target service level and the DTWL after simulation for Case I and Case IV is shown. From this figure is concluded that Heuristic II is most accurate in both cases. One can further conclude that the accuracy of Heuristic II increases in case the coupling in demand increases. The accuracy of the other two heuristics decreases in case the coupling in demand increases. The reason of this is that by increasing the coupling in demand, both the coupling between tools and the coupling between parts and tools increases. Since Heuristic I does not include any coupling, the accuracy of this heuristic decreases most. The accuracy of Heuristic II decreases less, since the coupling between tools is included.

Finding 7: Heuristic II is also most accurate with respect to the difference between the target service and the service after simulation in case the coupling in demand increases. The accuracy of Heuristic II increases in case the coupling in demand increases
6.3. Do the performances of the heuristics vary for different demand rates per location?

To answer the third research question, the results of Case I are compared with the results of Case V. In Case V the demand rates per location are increased.

6.3.1. Comparison of performance with respect to cost efficiency

In Figure 6.6, the results with respect to costs of Cases I and V are shown. One can see that no considerable differences exist between the results of Cases I and V. Only, the relative performance of Heuristic III increases with a few percent. Still, the performance with respect to costs of Heuristic III is inferior to the results of Heuristics I and II.

Finding 8: The performance of the heuristics does not vary considerably in case the demand rates per location are increased.

![Figure 6.6: Costs of the heuristics compared to the costs of Heuristic I for Case I and V](image)

6.3.2. Comparison of performance with respect to service level accuracy

Also with respect to the accuracy of the service level, no major differences occur between Cases I and V. In Figure 6.7, one can see that the accuracy decreases slightly for Heuristics I and III, whereas the accuracy increases for Heuristic II. A plausible explanation is that by increasing the demand rate, also the absolute number of coupled demands increases, which has a negative effect on the accuracy of Heuristics I and III and a positive effect on the accuracy of Heuristic II. These are smaller than the effects of increasing the coupling in demand in a relative way.

![Figure 6.7: Percentage difference between the DTWL target used and the DTWL after simulation in Case I and V](image)

Finding 9: The accuracy of Heuristic II increases slightly in case the demand rates per location increase, whereas the accuracy of Heuristic I and III decreases slightly.
6.4. Do the performances of the heuristics vary for different target service levels?

To answer the fourth research question, the results of Case I are compared for different DTWL targets in Heuristic II. Due to the long computation times Heuristic III is not included in this comparison. The DTWL after simulation of Heuristic II is used as a tuning target for Heuristic I. The target DTWL will be varied between 0.5% and 0.3%. This corresponds to a CSD (or fill rate) of between 85% and 95%.

6.4.1. Comparison of performance with respect to cost efficiency

In Figure 6.8 one can see that the performance with respect to cost efficiency of Heuristics I and II do not vary considerably. The difference between the costs of the heuristics becomes smaller in case the service level increases. A plausible explanation for this could be that the difference between an item and an order service level decreases in case the service increases. However, since the differences are very small, further research is required to explain this in a reliable way.

![Figure 6.8](image_url)

**Figure 6.8:** Costs of the heuristics compared to the costs of Heuristic I for different DTWL targets in Case I

**Finding 10:** Increasing or decreasing the service level has no major influence on the performance of Heuristics I and II with respect to cost efficiency

6.4.2. Comparison of performance with respect to service level accuracy

Figure 6.9 shows that the accuracy of Heuristic I decreases if the service level is increased, whereas the accuracy of Heuristic II increases if the service level is increased. The results of Heuristic I can be explained by the fact that an absolute service difference increases relatively if the DTWL changes. In case the absolute difference is equal, the relative difference increases. This can be the reason for the decreasing accuracy of Heuristic I.

![Figure 6.9](image_url)

**Figure 6.9:** Percentage difference between the DTWL target used and the DTWL after simulation for different DTWL targets in Case I
The increasing accuracy of Heuristic II can be explained by the number of greedy steps that have to be made to satisfy the service level. If more greedy steps are made in Heuristic II, the effects of coupling in demand are included more. This increases the accuracy of Heuristic II.

Finding 11: Increasing the service level has a positive effect on the accuracy of Heuristic II and a negative effect on the accuracy of Heuristic I

6.5. What are the effects on the performance if parts and tools are planned in an integrated way?

To show the effects on the performance if parts and tools are planned in an integrated way, a extra experiment is done. In this experiment Heuristic II is compared with a heuristic in which parts are planned using Heuristic I and tools are planned separately using the logic behind Heuristic II. This heuristic in which parts and tools are planned separately is called ‘Heuristic II decoupled’. The coupling between parts and tools is thus not included in this heuristic. The effects of including coupling between parts and tools can be identified by this experiment.

6.5.1. Comparison of performance with respect to cost efficiency

In Figure 6.10 (left), one can see that the costs of Heuristic II which includes the coupling between parts and tools is 40 percent lower compared to the costs of the heuristic in which parts and tools are planned separately. This means that planning tools and parts in one heuristic results in considerable cost benefits. The main reason for the higher cost in the decoupled approach is that the coupling between parts and tools is not included in the ‘Heuristic II decoupled’. By planning parts and tools separately (and both using a system approach), it is likely that base stock levels of relatively inexpensive parts and tools are higher compared to the base stock levels of relatively expensive parts and tools. In case an inexpensive part is always demanded in combination with an expensive tool, it is highly likely that the part will be on stock and the tool will not. By integrating the part and tool planning, the coupling will be taken into account. And parts and tools that are regularly demand together will be stocked together.

A similar result is obtained in Cases I to V. In these cases one can see that the performance of Heuristic III (which plans parts and tools separately) is outperformed by the heuristics that have integrated the planning of parts and tools. It has to be noticed, that this difference is not only caused by the separation of part and tool planning, but also by the characteristics of the model.

Finding 12: Planning parts and tools in an integrated way (by including coupling between parts and tools) results in considerable cost benefits compared to planning parts and tools separately

Figure 6.10: Cost comparison of the heuristics (left) and percentage difference between the DTWL target used and the DTWL after simulation (right) between Heuristic II and Heuristic II decoupled
6.5.2. Comparison of performance with respect to service level accuracy

In Figure 6.10 (right) one can see that integrating the service part and tool planning also results in a more accurate heuristic. This is also caused by the fact that the coupling between parts and tools is included in Heuristic II.

Finding 13: **Planning parts and tools in an integrated way (by including coupling between parts and tools) results in a more accurate planning heuristic, since the coupling between parts and tools can be taken into account**

6.6. What are the benefits with respect to the performance of the heuristics if service measures are computed on order level?

In Figure 6.11, the difference between the order fill rate (OCSD) and item fill rate (CSD) are graphically shown for the results of the simulation of Heuristics I and II. One can see that the difference between OCSD and CSD is around 10 percent in all cases. This shows that planning based on an item fill rate will result in a service that is about 10 percent lower than expected. Since the DTWP and DTWL are computed using the CSD and OCSD measures, this difference is passed on to the DTWP and DTWL service levels. This means that planning based on an order service measure will positively influence the accuracy of the heuristic. This is also shown in Figures 6.5, 6.7, 6.9 and 6.10, in which Heuristic II is most accurate with respect to the service target. Furthermore, this difference between OCSD and CSD increases if the coupling in demand increases (Case IV).

![Figure 6.11: Percentage difference between OCSD and CSD for the five cases for Heuristics I and II](image)

Finding 14: **The accuracy with respect to service is positively influenced by using a service target on order level**

6.7. Results of the US-Heuristic

To compare the results of the US-Heuristic, a separate experiment is done, in which the US-Heuristic is compared to Heuristics I and II. A project group of the company in the US has proposed to use the US-Heuristic for the planning of tools next to the planning of parts by Heuristic I. In the experiment, the US-Heuristic is used to determine the base stock levels of tools. The planning of parts in the experiment is done by using Heuristic I. The target used in Heuristic I is a CSD of 95%. This target is equal to the target currently used by the company.

The comparison between Heuristics I and II and the US-Heuristic is done in Case I, however, for a larger test bed. The test bed used consists of 1,082 parts and 431 tools, which are demanded in 2,192 combinations.
To compare the results of the two heuristics, the target DTWL of Heuristics I and II are varied to tune to the DTWL after simulation of the US-Heuristic. The results of the comparison are shown in Figure 6.12. In this figure one can see that the yearly costs of the US-Heuristic are 75% higher than the costs of Heuristic I and even more compared to the costs of Heuristic II. This shows again, that planning parts and tools in an integrated way results in lower costs.

Since in the tool planning part of the US-Heuristic no service target is used, no results for the service accuracy of the US-Heuristic are obtained.

Finding 15: Planning parts and tools using the US-Heuristic results in higher costs than planning parts and tools with Heuristic I and II

6.8. Quantitative comparison of heuristics

In this subsection, the heuristics are compared on the quantitative criteria discussed in section 2.1. This quantitative comparison is based on the results discussed in section 6.1 to 6.7.

In all experiments, Heuristic II results in the lowest costs. This shows that Heuristic II is the most efficient with respect to costs. This is caused by the fact that parts and tools are planned in an integrated way, so the coupling between parts and tools is taken into account. Furthermore, the coupling between tools is including as well as lateral transshipment possibilities. Only in the case with high coupling, Heuristic I is seriously outperformed by Heuristic II.

The two heuristics that plan parts and tools separately are outperformed in all cases by Heuristics I and II. This shows that an integrated planning of parts and tools is really beneficial. This is also shown by the results of Section 6.5. The results further show that Heuristic III plans parts and tools properly in a network that closely matches the characteristics of a single location network. In the Hong Kong network (Case III), this heuristic performed equal compared to Heuristics I and II.

Next to cost efficiency, also accuracy of the heuristics with respect to the service level is important. The experiments have shown that Heuristic II is also most accurate. In all experiments, Heuristic II outperforms all other heuristics. The main reason for this is that Heuristic II uses a DTWL target and integrates the planning of parts and tools. Heuristic I has worse results with respect to accuracy, since it does use a target on item level. Furthermore it does not take coupling in demand into account. Heuristic III is less accurate since it is a single-location model and it does not take lateral transshipments into account. This seriously affects the accuracy of the heuristic.

<table>
<thead>
<tr>
<th>Efficiency with respect to the costs</th>
<th>Heuristic I</th>
<th>Heuristic II</th>
<th>Heuristic III</th>
<th>US-Heuristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy with respect to the service target</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 6.2: Quantitative comparison of the four heuristics
7. Conclusions and Recommendations

In this section, a summary of the most important conclusions resulting from the qualitative (section 4.5) and quantitative comparison (section 6.8) of the heuristics is given. Furthermore, recommendations for the implementation of one of the models are given as well as recommendations for further research.

7.1. Conclusions

• **Planning parts and tools in an integrated way has a positive effect on the quantitative results of a planning heuristic.** By integrating the planning of parts and tools no sub-optimization takes place. This results in a more beneficial base stock level provisioning. Taking the coupling in demand between parts and tools into account, next to integrating the planning of parts and tools, increases the benefits further.

• **Using an order service level has positive effects on the accuracy of the heuristics.** The difference between an item and an order service level is considerable. This means that using an item service level results in an overestimation of the service. In the experiments done, this over-estimation of service is about 10 percent.

• All experiments have shown that **Heuristic II is most efficient with respect to cost difference and accuracy.** This means that Heuristic II is the most suitable heuristic to implement if we only consider the quantitative requirements of the heuristics defined in Section 2.1. Next to the quantitative requirements of the heuristics, the heuristic to be implemented should satisfy the qualitative requirements described in Section 2.1. These requirements are that the heuristic should be practical with respect to computation times, easy to understand for the people that work with it and implementable without major differences. In the qualitative comparison of the heuristic (Section 4.5), we show that **Heuristic II also fits the qualitative requirements.** The positive results of this heuristic are caused by the integration of the tool and part planning and the inclusion of the coupling between parts and tools. Heuristic II furthermore includes the coupling between tools and lateral transshipments.

• Heuristic I also performs well in the qualitative comparison; however, since the coupling in demand between parts and tools and the coupling in tool demand are not included in this heuristic, **Heuristic I is outperformed by Heuristic II based on the quantitative criteria, especially with respect to service level accuracy.**

• **Heuristic III does not perform well at both the qualitative and quantitative requirements.** The main reason for this is that Heuristic III is a single location heuristic. Since most of the networks of the company, do not fit the characteristics of a single location network, Heuristic III performs worse with respect to cost efficiency and service accuracy. The results have shown that including lateral transshipments into a planning heuristic has a more positive effect on the quantitative results of the heuristics than including coupling in tool demand. Finally, the complexity of Heuristic III makes that the heuristic has long computation times, is difficult to implement and difficult to understand for the people that have to work with it.

• **The simple US-Heuristic is also seriously outperformed by Heuristics I and II.** Next to the worse results with respect to cost efficiency, tuning the US-Heuristic is not possible. This is a
serious drawback, since this makes it not possible to adapt the service of the solution generated by the US-Heuristic. The US-Heuristic only gives one solution for the planning of tools.

7.2. Recommendations

- The conclusions have shown that Heuristic II will be the best heuristic to implement. This heuristic satisfies all five requirements defined in Section 2.1. The heuristic has the best results with respect to cost efficiency and cost accuracy. Furthermore it is understandable for the people that have to work with it, since the heuristic is an extension of the already implemented planning algorithm for service parts (Heuristic I). Since a large part of Heuristic II is already implemented, implementing the remainder of Heuristic II will not result in major difficulties. The requirement with respect to the computation times is also satisfied. Heuristic II is able to compute a solution for the complete network of the company, including all parts and tools. To maximize the benefits of Heuristic II, the company has to use a performance measure on service order level (DTWL) and has to integrate the planning of parts and tools.

- The most important condition for a successful implementation of Heuristic II is that the data used in the heuristic is reliable. Without reliable input data, the heuristic will not result in the benefits described in this research. Especially, the data about the combinations of parts and tools used has a large impact on the solution generated by Heuristic II. The test bed used in the research is based on historical data, and many manual actions were required in order to get a suitable input file. It should be researched what the most reliable way is to obtain the information about what combinations are demanded together and in what frequency. Using the information system that stores information about all service transactions is a good starting point, however, we noticed that the information stored in this information system is not always 100 percent in line with reality. Service transactions with more than 10 and even up to 100 parts and tools were found. Service transactions with a return time of less than a minute were found and tools and parts were demanded multiple times for one transaction (and even up to 10 times in one transaction). This is not in line with the procedures stored and the reliability of these transactions should thus be researched. Specialists of within the company should assess the input data for Heuristic II to make sure that the results obtained are reliable.

- During the construction of the test bed used in the experiments, many order transactions that include multiple of the same items, were found in the transaction database. It should be researched whether these transactions are reliable. If this is the case, Heuristic II should be adapted in order to make the results of Heuristic II reliable for a test bed including multiple of the same items per order. It should not be difficult to adapt Heuristic II in this way, however, some additional programming requires to be done.

- Next to the reliability of the input data, further research should be done regarding the starting solution of Heuristic II. In the results of Section 6, one can see that the benefits of Heuristic II are obtained in the base stock level increases that are implemented after the starting solution. The number of items provisioned by the starting solution does thus have a large impact on the solution. Research should be done to assess what the most practical (with regard to computation time) and effective (with regard to the quality of the solution) starting solution is.
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Wong, H., G.J. van Houtum, D. Cattrysse, and D. van Oudheusden (2004), A system approach for multi-location spare parts systems with lateral transshipments and waiting time constraints, Beta working paper, vol. 108


Other Sources

[A] Preparation Master Thesis 1 – Literature Review; Buermans, R.J.G.
Appendix I List of Variables

- $C_i$ := the cost price of SKU $i \in I$
- $C_{i}^{em}$ := emergency shipment cost of SKU $i \in I$
- $C_{i,j,k}^{lat}$ := lateral transshipment cost for SKU $i \in I$ from main local warehouse $k \in K$ to local warehouse $j \in J$
- $C_{i}^{ret}$ := replenishment cost for item $i \in I$
- $CSD_j$ := Customer Service Degree for local warehouse $j \in J$
- $CSD$ := Customer Service Degree for the complete network
- $DTWI_{j}$ := Down-Time-Waiting-Items (parts and tools) for local warehouse $j \in J$
- $DTWI$ := Down-Time-Waiting-Items (parts and tools) for a complete network
- $DTWL_{j}$ := Down-Time-Waiting-Logistics for local warehouse $j \in J$
- $DTWL_{j}^{target}$ := Down-Time-Waiting-Logistics target for local warehouse $j \in J$
- $DTWL$ := Down-Time-Waiting-Logistics for a complete network
- $\Delta DTWL(o,j)$ := Difference in DTWL if the base stock levels of the SKU-s in option $o \in O$ are increased in location $j \in J$
- $DTWP_{j}$ := Down-Time-Waiting-Parts for local warehouse $j \in J$
- $DTWP$ := Down-Time-Waiting-Parts for a complete network
- $DTWT_{j}$ := Down-Time-Waiting-Tools for local warehouse $j \in J$
- $DTWT$ := Down-Time-Waiting-Tools for a complete network
- $h$ := holding cost factor
- $I = \{1, \ldots, |I|\}$ := the (non-empty) set of all SKU-s
- $I_{p} = \{1, \ldots, |I_{p}|\}$ := the (non-empty) set of all service parts
- $I_{t} = \{1, \ldots, |I_{t}|\}$ := the (non-empty) set of all service tools
- $I_{tk} = \{1, \ldots, |I_{tk}|\}$ := the (non-empty) set of all tool kits
- $I(v)$ := the set of items in order $v \in V$
- $I_{o}(o)$ := the (non-empty) set of items including in option $o \in O$
- $I_{sub}$ := the set of tools that are delivered via local supply by substitution
- $I_{t}(i)$ := the (non-empty) set of tools in toolkit $i \in I_{tk}$
- $J = \{1, \ldots, |J|\}$ := the (non-empty) set of local warehouses
- $K = \{1, \ldots, |K|\}$ := the set of main local warehouses
- $k_{j}$ := the main local warehouse $k \in K$ to which a regular local $j \in J$ is assigned
- $M_{i,j}^{I}$ := the demand rate per hour for SKU $i \in I$ at local warehouse $j \in J$
- $M_{j}^{I}$ := the total item demand rate per hour at local warehouse $j \in J$
- $M_{j}^{p}$ := the total part demand rate per hour at local warehouse $j \in J$
- $M_{j}^{T}$ := the total tool demand rate per hour at local warehouse $j \in J$
- $M_{v,j}^{o'}$ := the demand rate per hour for demand stream $v \in V$ at local warehouse $j \in J$
- $M_{j}^{0'}$ := the total order demand rate per hour at local warehouse $j \in J$
- $LD_j$ := Average number of long downs per machine per year for local warehouse $j \in J$ on item level
- **LD** := Average number of long downs per machine per year for the complete network on item level
- **N_j** := the number of machines assigned to local warehouse \( j \in J \)
- **n** := average number of items in a service order
- **O = \{1, \ldots, |O|\}** := the (non-empty) set of options in the option list
- **OCSD_j** := Order Customer Service Degree for local warehouse \( j \in J \)
- **OCSD** := Customer Service Degree for the complete network
- **OLD_j** := Average number of long downs per machine per year for local warehouse \( j \in J \) on order level
- **OLD** := Average number of long downs per machine per year for the complete network on order level
- **OXLD_j** := Average number of extreme long downs per machine per year for local warehouse \( j \in J \) on order level
- **OXLD** := Average number of extreme long downs per machine per year for the complete network on order level
- **OWT_j** := Average (waiting) time between an order request and the actual delivery of the complete order for local warehouse \( j \in J \)
- **OWT** := Average (waiting) time between an order request and the actual delivery of the complete order for the complete network
- **P(o,j)** := product of the service difference and cost difference if the base stock levels of the SKU-s in option \( o \in O \) are increased in location \( j \in J \)
- **R(o,j)** := ratio of the service difference and cost difference if the base stock levels of the SKU-s in option \( o \in O \) are increased in location \( j \in J \)
- **R_i** := the rank of the i-th run in the RVN-test
- **\( \bar{R} \)** := the average rank in the RVN-test
- **RVN** := the rank version of von Neumann's ratio
- **S_{i,j}** := the base stock level of SKU \( i \in I \) in local warehouse \( j \in J \)
- **S(i) := (S_{i,1}, \ldots, S_{i,J})** := the vector with base stock levels for SKU \( i \in I \) in all local warehouses \( j \in J \)
- **S'(v) := (S_i; i \in I_v)** := the vector of base stock levels for all SKU-s \( i \in I \) which are part of demand stream \( v \)
- **S := \{S(i); i \in I\}** := vector of base stock levels for all SKU-s in all local warehouses
- **\( s_i \)** := the set of tool kits that can substitute tool \( i \in I_t \)
- **\( \xi_{i,j,k} \)** := the set of tool kits that can substitute tool \( i \in I_t \) for delivery to local warehouse \( j \in J \) and that are in inventory at local warehouse \( k \in K \)
- **\( \xi_{i,j} \)** := the set of tool kits that can substitute tool \( i \in I_t \) and that are in inventory at local warehouse \( j \in J \)
- **\( \xi_{i,sub,j} \)** := the set of tool kits that can be used to substitute one or more of the items \( i \in I_{sub} \) from local warehouse \( j \in J \)
- **\( \xi_{i,sub,j}^{pow} \)** := the set of all possible subsets of \( \xi_{i,sub,j} \)
- **\( \xi_{i,sub,j}^{pos} \)** := the set of all sets of tool kits that can be used to substitute all SKU-s in \( I_{sub} \)
- **\( \xi_{i,sub,j}^{del} \)** := the set of tool kits delivered
\[ \mathcal{S}_{i_{\text{sub}},j,k} := \text{the set of tool kits that can be used to substitute one or more of the items } i \in I_{\text{sub}} \text{ from main local warehouse } k \in K \text{ to local warehouse } j \in J \]

\[ \mathcal{S}^\text{pow}_{i_{\text{sub}},j,k} := \text{the set of all possible subsets of } \mathcal{S}_{i_{\text{sub}},j,k} \]

\[ \mathcal{S}^\text{POS}_{i_{\text{sub}},j,k} := \text{the set of all sets of tool kits that can be used to substitute all SKU-s in } I_{\text{sub}} \text{ by lateral supply from main local warehouse } k \in K \text{ to local warehouse } j \in J \]

\[ \mathcal{S}^\text{del}_{i_{\text{sub}},j,k} := \text{the set of tool kits delivered by lateral supply from main local warehouse } k \in K \text{ to local warehouse } j \in J \]

\[ T := \text{Number of runs in the simulation model} \]

\[ TRC(S) := \text{Yearly total relevant costs for the complete network given base stock levels } S \]

\[ \Delta TRC(o,j) := \text{Cost difference if the base stock levels of the SKU-s in option } o \in O \text{ are increased in location } j \in J \]

\[ t^e_{z,j} := \text{emergency shipment time from central warehouse } z \in Z \]

\[ t^\text{lat}_{j,k} := \text{lateral transshipment time from main local warehouse } k \in K \text{ to local warehouse } j \in J \]

\[ t^\text{loc}_{i,k} := \text{local transshipment time} \]

\[ t^\text{return}_{i,j} := \text{return time of SKU } i \in I \]

\[ V = \{1,2,\ldots,|V|\} := \text{the (non-empty) set of demand streams} \]

\[ WT^I_j := \text{Average (waiting) time between an item request and the actual delivery of the item for local warehouse } j \in J \]

\[ WT^I := \text{Average (waiting) time between an item request and the actual delivery of the item for the complete network} \]

\[ WT^P_j := \text{Average (waiting) time between a part request and the actual delivery of the part for local warehouse } j \in J \]

\[ WT^P := \text{Average (waiting) time between a part request and the actual delivery of the part for the complete network} \]

\[ WT^T_j := \text{Average (waiting) time between a tool request and the actual delivery of the tool for local warehouse } j \in J \]

\[ WT^T := \text{Average (waiting) time between a tool request and the actual delivery of the tool for the complete network} \]

\[ XLD_j := \text{Average number of extreme long downs per machine per year for local warehouse } j \in J \text{ on item level} \]

\[ XLD := \text{Average number of extreme long downs per machine per year for the complete network on item level} \]

\[ Y_{i,j} := \text{the physical stock of SKU } i \in I \text{ in local warehouse } j \in J \]

\[ Z = \{1,2,\ldots,|Z|\} := \text{the (non-empty) set of central warehouses} \]

\[ z_i := \text{the central warehouse that supplies SKU } i \in I \text{ in case of an emergency} \]

\[ \alpha_{i,j,k} := \text{the fraction of demand for SKU } i \in I \text{ at local warehouse } j \in J \text{ that is delivered from main local warehouse } k \in K \text{ via lateral supply or via lateral supply by substitution} \]
\[ \alpha_{i,j,k} = \text{the fraction of demand for SKU } i \in I \text{ at local warehouse } j \in J \text{ that is delivered from main local warehouse } k \in K \text{ by means of lateral supply by substitution, that does not result in extra lateral transshipment costs} \]

\[ \alpha_{v,j,k}^V = \text{for the fraction of demand for demand stream } v \in V \text{ at local } j \in J \text{ that is delivered from main local warehouse } k \in K \text{ by means of a lateral transshipment or lateral supply via substitution} \]

\[ \beta_{i,j} = \text{the fraction of demand for SKU } i \in I \text{ at local warehouse } j \in J \text{ that is delivered via local supply or via local supply by substitution} \]

\[ \beta_{v,j}^V = \text{the fraction of demand for demand stream } v \in V \text{ at local warehouse } j \in J \text{ that is delivered via local supply or via local supply by substitution} \]

\[ \theta_{i,j} = \text{the fraction of demand for SKU } i \in I \text{ at local warehouse } j \in J \text{ that is delivered from a central warehouse by means of emergency shipment} \]

\[ \theta_{v,j,z}^V = \text{for the fraction of demand for demand stream } v \in V \text{ at local } j \in J \text{ that is delivered from central warehouse } z \in Z \text{ by means of an emergency shipment} \]

\[ \omega(j) := (\omega_1(j), ..., \omega_{|K|}(j)) = \text{the permutation of main local warehouses } K \text{ that represents the order of main local warehouses for local warehouse } j \in J \]
Appendix II Extra Performance indicators of simulation model

(Order) Long Downs and (Order) Extreme Long Downs

The performance indicator Long Downs \((LD)\) is defined as the number of item deliveries per machine per year that take longer than 4 hours and less than 12 hours. The performance indicator Extreme Long Downs \((XLD)\) is defined as the number of item deliveries per machine per year, which take longer than 12 hours. LD and XLD can be defined per location and for the network as a whole.

\[
LD_j = \frac{24 \times 365}{N_j} \times \sum_{i \in I} M_{i,j} \times \left[ \sum_{t_k \in K} \left( 1_{\{t_{lok} < t_{lok} + 4 \text{ and } t_{lok} + 12 < t_{lok} + 12\}} \alpha_{i,j,k} + 1_{\{t_{lok} + 4 < t_{lok} + 12\}} \theta_{i,j} \right) \right]
\]

\[
LD = \frac{\sum_{j \in J} M_j \times LD_j}{\sum_{j \in J} M_j}
\]

\[
XLD_j = \frac{24 \times 365}{N_j} \times \sum_{i \in I} M_{i,j} \times \left[ \sum_{t_k \in K} \left( 1_{\{t_{lok} + m > 12\}} \alpha_{i,j,k} + 1_{\{t_{lok} + m < 12\}} \theta_{i,j} \right) \right]
\]

\[
XLD = \frac{\sum_{j \in J} M_j \times XLD_j}{\sum_{j \in J} M_j}
\]

It is assumed that \(t_{lok}\) cannot be larger than 4 hours.

Similar performance indicators can be computed on order level \(OLD\) and \(OXLD\). OLD and OXLD are defined per location and for the network as a whole.

\[
OLD_j = \frac{24 \times 365}{N_j} \times \sum_{v \in V} M_{v,j} \times \left[ \sum_{t_k \in K} \left( 1_{\{t_{lok} + m > 12\}} \alpha_{v,j,k} + \sum_{z \in Z} 1_{\{t_{lok} + m < 12\}} \theta_{v,j,z} \right) \right]
\]

\[
OLD = \frac{\sum_{j \in J} M_j \times OLD_j}{\sum_{j \in J} M_j}
\]

\[
OXLD_j = \frac{24 \times 365}{N_j} \times \sum_{v \in V} M_{v,j} \times \left[ \sum_{t_k \in K} \left( 1_{\{t_{lok} + m > 12\}} \alpha_{v,j,k} + \sum_{z \in Z} 1_{\{t_{lok} + m < 12\}} \theta_{v,j,z} \right) \right]
\]

\[
OXLD = \frac{\sum_{j \in J} M_j \times OXLD_j}{\sum_{j \in J} M_j}
\]
Appendix III Performance of optimization approaches of Model II

Figure III.1: Cost difference compared to the Item-Start approach for varying DTWL in the Hong Kong network

Figure III.2: Cost difference compared to the Item-Start approach for varying DTWL in the US network

Figure III.3: Difference between DTWL target and simulation DTWL in the Hong Kong network
Figure III.4: Difference between DTWL target and simulation DTWL in the US network