Becoming boss in your own house

The impact of key repair shop characteristics on the controllability of internal repair shops

Gordian Logistic Experts

UNIVERSITY OF TWENTE.

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Management Summary

Research setting

This research is carried out in light of the assignment to obtain a master degree in Industrial Engineering and Management at the University of Twente and is facilitated by Gordian Logistic Experts. Data for this research was obtained at 4 case study companies who use and maintain high value capital assets such as planes, trams or radar systems. These case study companies are GVB, Air France/KLM, Naval Maintenance Establishment and DBGS.

Assets require maintenance for which spare parts are used. The spare parts are kept on stock in order to attain high availability of spare parts during the maintenance of assets and to minimize downtime. A decision function called inventory control is responsible for determining the amount of spare parts that need to be kept on stock. To determine the correct amount of spare parts on stock, inventory control makes agreements with repair shops on e.g. repair lead times. A repair shop is concerned with the repair of spare parts. This research focusses on internal repair shops. The 4 case study companies have, in total, 32 internal repair shops for the repair of spare parts.

Goal

The main research question is; What are the most important repair shop characteristics and to which extend should agreements and decisions between repair shop and inventory control be tailored to these characteristics?

Methodology

This research uses 4 sources of data. (1) Literature to identify possible agreements and decisions of inventory control and repair shops and characteristics that are likely to affect the repair lead time. (2) Qualitative repair shop characteristics were identified using interviews with repair shop managers and representatives from inventory control. (3) Quantitative characteristics were obtained from data analysis. (4) A statistical analysis is used to determine the relation between characteristics and the repair lead time.

Conclusions

The main conclusions of this research are:

- Agreements between repair shops and inventory control identified in literature are (1) agreements on min-max inventory levels for repairable items and (2) classes of repair lead times based on the repair time and item cost. Decisions from literature that can be taken on an operational level to attain the agreements between inventory control and repair shops are on (1) overtime and (2) dynamic priority rules in the repair shop.
- There are 15 characteristics from literature that impact the repair lead time. A regression analysis shows that the characteristics 'material demand rate' and 'average repair time' have the most impact on the waiting time. Also the qualitative characteristic 'degree of specialization' is likely to significantly impact the average waiting time. These are characteristics relating to both material uncertainty and capacity complexity. A qualitative analysis of repair jobs showed that characteristics relating to material uncertainty are slightly more important than characteristics relating to capacity complexity.

We identified that repair shops can have both high/low capacity complexity and high/low material uncertainty. It is not in the scope of this research to precisely define high/low. However, we are able to provide agreements and decisions tailored to each of the 4 combination of characteristics. These agreements and decisions were also discussed in a discussion session with Gordian consultants.

- Combination I Low material uncertainty/low capacity complexity: Inventory min-max levels, dynamic priority rules and overtime in the repair shop.
- Combination II High material uncertainty/low capacity complexity: Integrate control of materials and LRU's, disconnect inspection and repair, base priorities on inspection and minimize batch sizes.
- Combination III Low material uncertainty/High capacity complexity: Create classes of repair lead times based on the repair time and price of repairable items, overtime on tactical level to create capacity flexibility and priority rules to minimize the waiting time.
- Combination IV High material uncertainty/High capacity complexity: Insource or subcontract repairs, due dates should be based on inspection, integrate the control of LRU's and materials and disconnect inspection from repair.

Recommendations

- This research is an attempt to identify combinations of repair shop characteristics based on empirical data. However, the repair shops included in this research had limitations on the availability of data. Reliable data on utilization, number of operations and the number of repairmen was often missing. The validity of this research can be increased by (1) including data from repair shops which only perform component repairs and (2) increased data collection by the current case study companies. However, since the current regression model also explains a large percentage of the variation in waiting time, inclusion of the utilization is, based on current information, not a requirement to continue with this research.
- To aid companies in controlling the repair shops, we recommend performing an analysis where the repair shops can be positioned based on material uncertainty and capacity complexity. This will aid the case study companies in determining which agreements are beneficial in which repair shop.
- Some agreements and decisions come from literature, and have therefore been extensively studied. However, the combination of agreements and decisions is not yet studied. We therefore recommend to further study the effects of agreements and decisions in the different types of repair shops. We also recommend to further study the definition of high/low material uncertainty and high/low capacity complexity.

We also have the following recommendations for the case study companies:

- We recommend that GVB includes the repair time in the calculation of min-max inventory levels in specific repair shops to minimize inventory costs.
- KLM should categorize the agreed repair lead time based on the price and demand frequency of a repairable item to minimize inventory costs.
- NME should set due dates for repairs after inspection and integrate the control of LRU's and SRU's to decrease the (variability in) repair lead time
- We recommend DBGS to research what the optimal batch sizes of repairable items are to increase the material demand rate and the availability of materials.

Preface

Before you lies my master thesis for graduating in Industrial Engineering & Management at the University of Twente. This thesis is the result of a graduation period that took longer than expected. But nevertheless, I'm proud to be able to present it.

Presenting this thesis is not something that I could have done without the aid of several people.

First, I would like to thank all of my colleagues of Gordian. They made me feel very welcome and because of them I very much enjoyed the time I could spend here. Special thanks go out to Jan Willem whose pragmatic view often reminded me to focus more. Most of all, I would like to thank Maarten who was always available when I had questions and often helped me to get a birds I view of what I was exactly doing. With Maarten's help I was better able to combine my work and graduating. I am fully aware of the amount of time you spend on helping me.

I would also like to thank Matthieu and Ahmad for your comments on my work throughout the project. You aided me in having new ideas on how to best continue. I would also like to thank all of my friends for the support during this project. My family of course also provided great support during the last year.

Last but definitely not least, I want to thank my girlfriend Sabine for all the support and love you gave me the last year. As difficult it was in times for me, so difficult it must have been for you. The listening ear you gave me in times when my work didn't go as planned helped me stay on track. I know I haven't been the best boyfriend last year, but I'm going to make it up to you!

Unfortunately, there is one person I'm not able to thank for is support anymore. Dad, I want to dedicate this thesis to you. For all the fun and wonderful memories you gave me.

Deventer, xx-month-2013

Herman van Walree

Contents

1 Background & Research Questions

This chapter outlines the background and research questions that will be answered in this report. Section 1.1 outlines the setting of this research and the companies participating in this research. This is followed by Section 1.2 with an outline of the research setting and motivation for this research. Section 1.3 presents the main research question and the scope of this research. Section 1.4 outlines the research questions and approach of this research. Section 1.5 concludes this chapter with an outline of the remainder of this thesis.

1.1 Research background

This research is facilitated by Gordian Logistic Experts BV (Gordian) and four case study companies. The case study companies are Air France/KLM, GVB, the Royal Netherlands Navy (NME) and the Royal Netherlands Army (DBGS). These companies use and maintain high-value capital assets, such as airplanes, metros, trains and weapon systems. More detailed information on the case study companies is provided in Section 3.2.

Gordian is a logistics management consultancy and deployment firm located in Utrecht, specialized in service logistics and supply chain management (Gordian B.V., 2012). Gordian focusses on introducing new concepts, techniques and tools to clients. Gordian focus is on customers learning to work with the tools Gordian develops. The clients must have a lasting improvement of the collaboration.

In this research we focus on the control of repair shops. The added value of this research is that it gives improvements for the control of these repair shops. For the case study companies this knowledge can directly be applied. Gordian gains from this research with more knowledge on the control of repair shops. This knowledge can be used to give advice to companies other than the companies involved in this study.

1.2 Research setting

1.2.1 Maintenance of high value assets

Our case study companies use high-value capital assets in their primary process and hence it is important to keep these assets operative. Downtime of the assets leads to lost revenues, customer dissatisfaction or safety hazard.

Maintenance on these assets is conducted within the constraints of the maintenance concept. A maintenance concept is the "set of directives prescribing maintenance to be carried out" (Gits, 1992). The maintenance concept describes all operations required for maintaining an asset during its lifecycle. Maintenance has several drivers, i.e. triggers to start the maintenance. A list of possible drivers (based on interviews with repair shop managers) is given in Table 1.

Maintenance Type	Drivers
Corrective maintenance	Defects (non-deferrable)
Preventive maintenance	Hours in use, mileage, number of starts, calendar time
Modification maintenance	Reliability and/or safety issues, functional improvement of the system
Component repairs	Stock replenishment

Table 1. Drivers of maintenance

Corrective maintenance is applied when the decision is intentionally made to only replace a part after it fails. This can also be planned, when the replacement of the failed item is deferrable. Preventive maintenance is conducted when a specific criteria is met (such as mileage, number trips, or number of operating days without maintenance). Modification maintenance is conducted to improve the performance, reliability or safety of an asset. The maintenance of an asset requires spare parts. These parts are in some cases repairable. Component maintenance is used for stock replenishments of repairable spare parts. Companies are also experimenting with condition-based maintenance in an effort to further increase the availability of an asset. Companies experimenting with condition based maintenance seek more insight in the failure behavior of a part.

For high value assets, downtime of an asset is very costly. To reduce the downtime of assets, spare parts are used. The use of spare parts reduces the waiting time of the asset for maintenance. In the case of a tram, one of the spare parts is a hydraulic pump. The replacement of the pump is done at the base of the trams. This is called line maintenance. These parts are therefore called "Line Replaceable Units" (LRU's). An LRU can be a repairable or non-repairable (consumable). Repairable LRU's are repaired in a repair shop. Consumable LRU's are discarded after use. This research focusses on repairable LRU's.

For the repair of the pump, other parts might be required such as valves or seals. These parts are replaced in repair shops and are called "Shop Replaceable Units" (SRU's). An LRU can have zero to many SRU's. SRU's can also be repairable or non-repairable. Repairable SRU's might also require other SRU's. Spare parts are the whole of SRU's and LRU's that are kept on stock for the maintenance on an asset. An asset can also contain multiple SRU's and LRU's of which some are not kept on stock. Figure 1 shows a graphical representation of the different levels of repair.

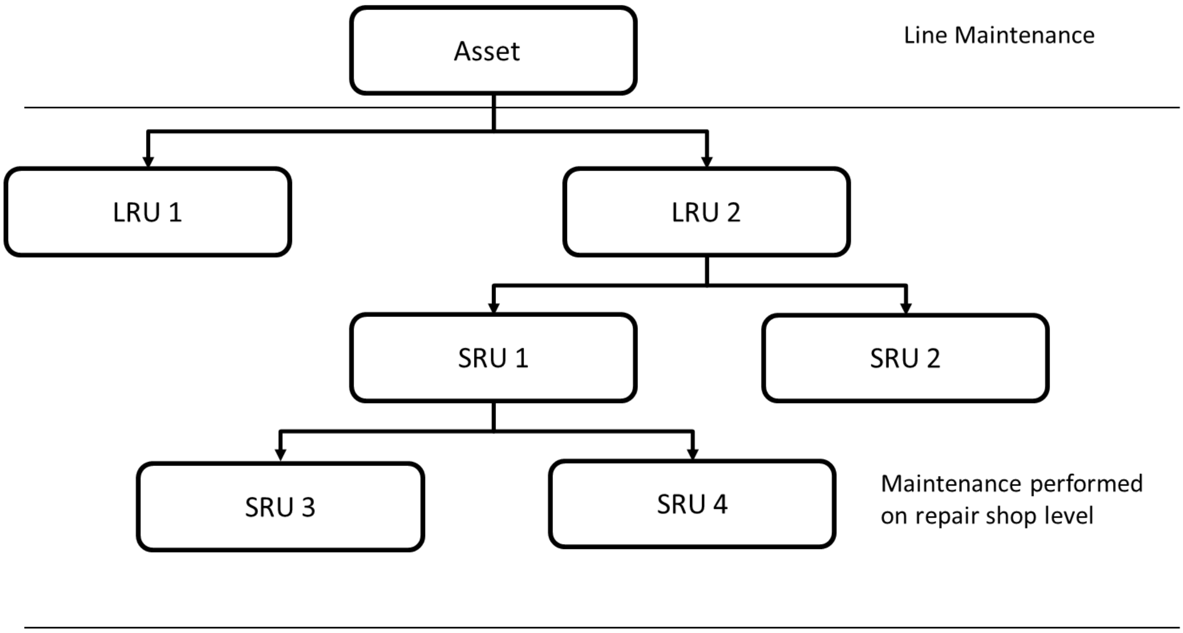

Figure 1. Description of different levels of repair

1.2.2 Research motivation

LRU's are kept on stock in order to minimize the time an asset is down for maintenance. A decision function called inventory control is responsible for having a sufficient amount of LRU's and SRU's on stock. In order to assure that a sufficient amount of LRU's is available, inventory control makes agreements with the suppliers of the LRU's and SRU's. These suppliers can be either other companies or internal repair shops. In our case study companies the important suppliers of repairable LRU's are internal repair shops.

In order to determine the amount of LRU's that should be kept on stock, inventory control requires repair lead times from the repair shops (Driessen et al., 2012).

Inventory wants to achieve a high availability of spare parts, but for the lowest amount of investment costs in the spare parts inventory.

The repair shop is responsible for determining the repair shop resource capacity and the scheduling of repairs such that repairs are performed within the repair lead times. In order to achieve this, the repair shop requires insight in (Driessen et al., 2012):

- The number of repairs
- The repair time per repair
- Availability of personnel with specific skills
- Possibilities for outsourcing

With an agreement on the lead times of repairs, inventory control and the repair shop make decisions independent of one another. Making integrating decisions between repair shops and inventory control, is therefore likely to improve the overall performance compared to repair lead time agreements where decisions are taken independent.

This does not need to be a single agreement, but it can also be a set of agreements and decisions. These are decisions and agreements on strategic, tactical and operational level. We call this integrated decision making. Integrated decision making is the set of decisions and agreements on strategic, tactical and operational level that are made between repair shops and inventory control. Strategic decisions provide an overall direction. Tactical agreements are the agreements made between repair shops and inventory control (e.g. lead times of repairs). Operational decisions are decisions on how the repair shops can operate achieve the agreements made on tactical level more efficiently. The integrated decision making overview is outlined in Figure 2.

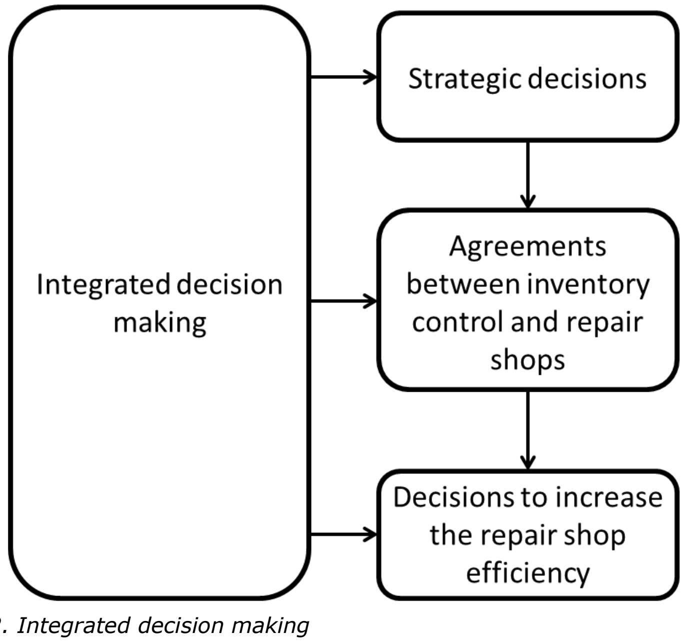

Figure 2. Integrated decision making

1.3 Main research question

The question this study wants to answer is twofold. (1) We want to determine which agreements and decisions need to be made or taken between repair shops and inventory control in order to attain high availability of spare parts and to reduce the repair lead time, (2) we are also interested to which extend these agreements/decisions should be tailored to repair shops with specific characteristics. It is unlikely that all repair shops are the same. Agreements and decisions will therefore need to be tailored to each specific repair shop. The main research question is as follows.

What are the most important repair shop characteristics, and to which extend should agreements and decisions between repair shop and inventory control be tailored to these characteristics?

In the following sections we will outline the scope an approach of this study.

1.3.1 Scope

Repairable items are often more expensive than consumable items (Guide Jr et al., 2000). Since inventory control determines the amount of stock based on the lead time, it is important to both shorten the lead time and to decrease the variability in the repair lead time. Both factors lead to higher safety stock and thus to higher investment costs compared to a situation with short lead times and low variability in lead times. In order to reduce the repair lead time, it is important to understand why the repair lead time is long. The repair lead time consists of both repair time and waiting time (for capacity and/or materials). In the repair shops of our case study companies the waiting time constitutes on average for 95% of the total repair lead time. We therefore focus on agreements that can be used to either shorten the repair lead time and/or reduce the variability in repair lead times by reducing the waiting time.

To tailor the agreements between repair shops and inventory control, we focus on repair shop characteristics that influence the repair lead time. To the best of our knowledge, only little literature is available on how to tailor agreements to specific repair shop settings. In order to make conclusions which are also generalizable, we focus on repair shops that are also representative to other repair shops not included in this study. We define a repair shop as a shop that is responsible for the repair of a set of LRU's. A repair shop is representative when the following minimum requirements when (1) there is enough work, on average, for at least 1 full time employee (FTE) and (2) failures of LRU's, for which the repair shop is responsible, occur on a regular basis throughout the year.

When these criteria are met, the repair shop is sufficiently large to be representative to other repair shops not included in the study. Examples are repair shops of other companies.

1.4 Research questions and approach

1.4.1 Research questions

We developed 5 research questions to answer the main research question. The research questions are outlined below. Figure 3 (in Section 1.5) shows a graphical representation of how the research questions lead to the main research question.

Research question 1: *What are possible agreements between inventory control and repair shop control based on literature?*

For research question 1 we identify possible agreements made in literature. Identifying which agreements exist in literature gives insight into which agreements repair shop and inventory control should make.

Research question 2: *What does the repair process look like and what are the characteristics of case study companies?*

In research question 2 we describe the repair process and provide general information on the case study companies. This in order to determine the setting in which this research is performed.

Research question 3: *Which repair shop characteristics could affect the repair lead time?*

As stated in Section 1.3 it is unlikely that one (set of) agreements is suitable for all repair shops. Most likely, a differentiation between repair shops will have to be made. For research question 3 we determine which characteristics affect the repair lead time using literature. These are also the characteristics we identified at the repair shops of the case study companies.

Research question 4: *What are the most important repair shop characteristics?*

In research question 3 we identified repair shop characteristics. However, it is unlikely that all characteristics have the same impact on the repair lead time. It is important to determine which characteristic has the largest impact, since the agreement is partly based on the repair shop characteristics. This impact is identified in research question 4.

Research question 5: *Which combinations of repair shop characteristics can we identify and to which extend need agreements and decisions be tailored to these combination of characteristics?*

In research question 5 we determine the agreements and decisions that can be made between repair shops and inventory control, considering specific repair shop characteristics.

1.4.2 Approach

In order to answer the research questions 4 sources of information are used (1) literature, (2) interviews, (3) data analysis and (4) statistical analysis. The information (except literature) originates from the 4 case study companies presented in Section 1.1.

To answer research question 1 we perform an analysis of relevant literature regarding possible agreements between inventory control and repair shops. The literature is collected with various search engines such as UTFind, Scopus, Web of Science and Google Scholar.

To answer research question 2 we use interviews. The interviews are held with repair shop managers and representatives from inventory control. These respondents will be able to provide us with more information on the repair process and on the background of the case study companies.

To answer research question 3 we determine which repair shop characteristics are relevant for this study. To answer this research question we use (1) literature to determine which characteristics should be identified at the case study companies and (2) data analysis and interviews to determine both quantitative and qualitative repair shop characteristics. For the interviews, the questions are sent beforehand to the interviewees so that they are able to prepare. The employees who are interviewed are responsible for either managing the repair shop (repair shop control) or inventory management. After the interview a report is written and sent to the respondents for feedback.

Research question 4 is answered with the development of a statistical model. In this model we determine which characteristics have the largest impact on the average waiting time of repair shops. We search for the relation to the waiting time, because the waiting time constitutes on average 95% of the repair lead time (as illustrated in Section 1.3.1).

In research question 5 we use information from previous research questions to determine how the interface agreement should be tailored to specific repair shop characteristics. This research question is answered with literature and insights following earlier research questions.

1.4.3 Validation

For this research we use 4 case study companies. These 4 case study companies have in total 32 repair shops. We use case studies, because it allows for early, exploratory research in which a phenomenon is not yet fully understood (Voss et al., 2002). The fact that we have different case study companies increases the validity of this research, although more detailed analysis could be done when fewer cases were included. But for the exploratory research, this scope is sufficient.

One of the sources of information for this research is interviews conducted at the case study companies. When using interviews, validation also becomes an issue. Since in interviews, the respondents and interviewer bias might influence the outcome of the interview. To cope with this problem several methods are used.

First, we conduct the research in not one, but multiple companies. This increases the number of cases and positively affects the research validity. Replicating logic (Yin, 1994) can also be of use in this research. With replication logic we will view each case as an experiment itself and regard each following experiment as a possibility to refute or confirm the earlier findings.

We also use triangulation to confirm findings from interviews. Triangulation is used by discussing findings with different employees within the same company in different functions. We will also compare findings from the interviews with quantitative data (when possible).

Furthermore, in conducting the interviews we will use a standardized case study protocol (Voss et al., 2002) which outlines the instruments, procedures and the set of questions that are asked. By doing so all respondents will be asked the same questions. The interview transcript will be sent back to be reviewed by the interviewed, a check for reliability. I will also discuss the findings with consultants of Gordian Logistic Experts B.V. who have much practical expertise.

1.5 Thesis outline

Figure 3 shows a graphical representation of the outline of this thesis. The remainder of this thesis is organized as follows. Chapter 2 presents literature on agreements between repair shops and inventory control on how to reduce the (variability of) the repair lead time. Chapter 2 provides an answer to research question 1. Chapter 3 answers research question 2 and outlines the repair shop setting in which this research is performed. Chapter 3 also presents the case study companies in which this study is performed. Chapter 4 uses literature to identify which repair shop characteristics impact the (variability of) repair lead time. In Chapter 4 we also identify quantitative and qualitative characteristics at the case study companies. By doing so, Chapter 4 answers research question 2. Chapter 5 answers research question 3 by outlining a statistical study in which the effect of characteristics on the average waiting time of repair shops is identified. Chapter 6 outlines the practical implications of this research and outlines agreements that can be used for specific repair shop characteristics. In this chapter an answer to research question 4 and the main research question is presented. Finally, Chapter 7 outlines our conclusions and recommendations for further research.

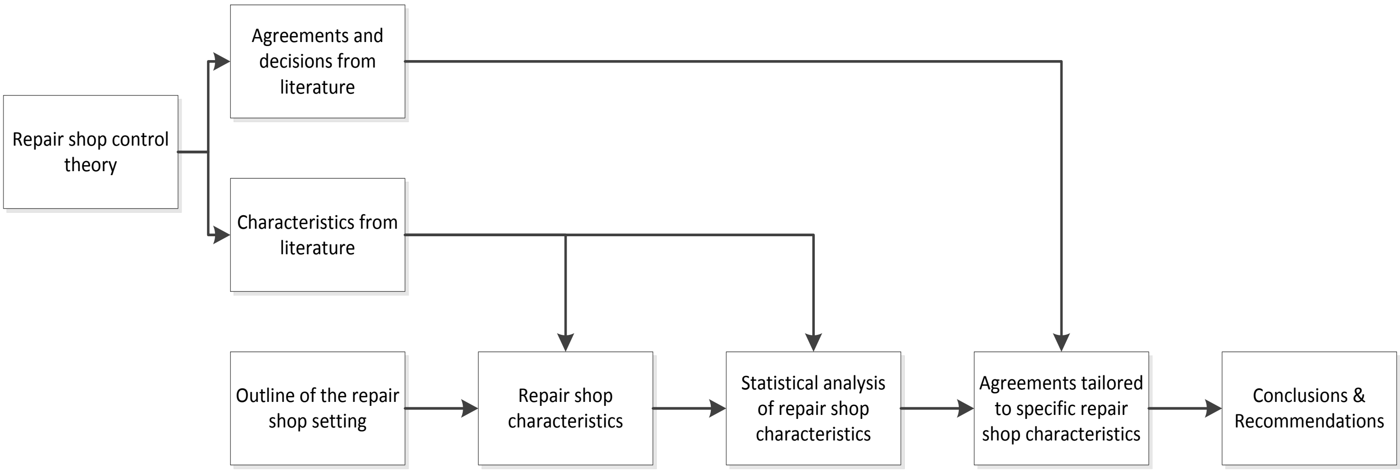

Figure 3. Graphical representation of the outline of this thesis

2 Agreements and decisions from literature

In this chapter we present literature on agreements that can be used to reduce the lead times of repairs. Section 2.1 identifies literature in which possible tactical agreements between inventory control and repair shops are outlined. Section 2.2 identifies decisions that can be made to increase the efficiency of repair shops. Section 2.3 concludes this chapter.

Before we outline agreements from literature, we want to define some terms that are often used in literature. The repair lead time is the time between the start of a repair job to the finish of a repair job. Some papers focus on reducing the number of expected backorders. A backorder occurs when there is demand for an item, but this demand cannot be fulfilled from stock. The fill rate is also a common term used in papers. The fill rate is defined as the percentage of demand that can be immediately delivered from stock.

2.1 Agreements between inventory control and repair shops

In Section 1.2.2 we briefly discussed the repair lead time. Well-known multi-echelon inventory models such as METRIC and VARI-METRIC determine the amount of LRU's (and SRU's) on stock based on the lead times of repairs (Sherbrooke, 1968, 1986). However, these models focus on ample capacity in a repair shop. This assumption is in practice often not valid.

Sleptchenko et al. (2005) show that repair priorities may provide an opportunity to reduce investments in the supply networks for repairable spare parts using an extension of VARI-METRIC. This is especially the case in situations with (1) high repair shop utilization, (2) dealing with items with different costs and repair times and (3) items share a limited repair capacity. The priorities are assigned a-priori and depend on the mean repair time and the price of items. The research of Sleptchenko et al. (2005) shows that differentiating between the priorities of items based on these characteristics reduces investments in the supply network.

Adan et al. (2009) study the effect of static priorities on backorders and total inventory holding costs. They assume that when an LRU fails it is immediately sent to the repair shop. The repair shops are modeled as a single server repair shop where each LRU has exponential repair time with the same mean. They show that static priorities can reduce the inventory cost and cost for downtime over an infinite horizon, compared a First Come First Serve priority rule (Adan et al., 2009). This is done by assigning high priority to expensive items, thus reducing the repair lead time of these items. The repair lead time of cheaper items increases. However, because the cheaper items require less investment, the total inventory holding cost is decreased. In their model the priorities are independent of the amount of on hand stock.

Loeffen (2012) describes in her master thesis two different types of agreements (1) the Min-Max agreements and (2) repair lead time agreements described above. The repair shop is modeled as an M/G/c queue model. An M/G/c queue model assumes exponentially distributed interarrival times and a general distribution (in this case gamma) distribution for the service times. There is no pre-emption of repairs, and all SRU's are available to perform the repair.

In the Min-Max agreement, repair shop control is responsible for maintaining a stock of Ready-for-Use LRU's between a pre-determined minimum and maximum level (Loeffen, 2012). This can be seen as a form of vendor managed inventory. The minimum and maximum levels are determined by inventory control and are formulated as inventory levels (the current inventory minus backlog). The thesis of Loeffen (2012) shows that in the case of high utilization, the Min-Max agreement outperforms lead time agreements in terms of expected backorders and fill rate.

2.2 Decisions to increase efficiency

Hausman and Scudder (1982) provide an extensive range of priority scheduling rules in combination with on-hand spares information. They compare priority scheduling rules for a finite-capacity repair shop with hierarchical product structure. In their formulation of the repair shop, several assumptions are made: (Hausman & Scudder, 1982)

- LRU’s fail with a constant Poisson rate
- Only a single component is assumed to fail with fixed failure rates
- The repair shop consists of 10 machine centers, each with a single machine
- There is a minimum of 3 operations and a maximum of 10 to complete repair
- Processing times are known, constant and setup times are included

Hausman and Scudder (1982) show that in this setting, the use of priority rules which include inventory status can lead to significant increase in the performance of repair shops. The performance is measured as the number of expected backorders. However, Hausman and Scudder (1982) focus mainly on capacity constraints. The effect of SRU’s required for repair is neglected.

Scudder and Chua (1987) study the effect of overtime policies in a specific repair shop setting. The repair shop that is described in their paper constitutes 12 repairmen, 4 in each of 3 divisions. Repairmen can change in a division, but not between divisions. Each division has a specific set of repairables. Scudder and Chua (1987) show that the use of overtime can dramatically decrease the number of backorders.

Research of Guide Jr et al. (2000) distinguishes several priority dispatching rules in a repair shop. Their research aims to minimize the repair lead time of LRU’s. Their repair shop environment is characterized by, (1) stochastic operation times, (2) variable (probabilistic) routings for an LRU, (4) part matching (the exact matching of parts in reassembly) and (5) a large number of work-centers with no two operations on the same work-center. Guide Jr et al. (2000) show that priority rules yield significant benefits of the repair lead time in repair shops with different utilization and different product structures.

Chua et al. (1993) study the effect of batching on the expected backorders. They model a system in which an LRU fails, because of only a single SRU. The repair shop is modeled as a single server queue where LRU’s are processed in batches. The parts do not leave the repair shop until the entire batch completes processing. Chua et al. (1993) consider the following trade-off in batching:

(1) Larger batch sizes require fewer setups and therefore require less capacity.
(2) If batch sizes are too large, parts will have excessive delays and the end-users will experience long 'downtimes'.
(3) Given that the repair shop has an inventory of spares, it is the 'downtime' experienced by the end-user, not necessarily the flow time of parts repair that should be minimized.

The paper of Chua et al. (1993) shows that batching is usable, and desirable, in order to increase resource utilization without increasing the number of expected backorders. However, it is important to note that batching is only useful when the setup times are at least 3 times as large as the run time (excluding setup times).

2.3 Conclusion

Based on the analysis of literature presented in this chapter we make the following conclusions on the agreements between inventory control and repair shop control:

- In repair shops with ample capacity, repair lead time agreements without priorities are sufficient to minimize the repair lead time.
- In capacity constrained repair shops the use of a-priori priorities may lead to significant reductions in the repair lead times and/or investment costs.
- The use of a Min-Max agreement outperforms repair lead time agreements for repair shops with high utilization.

Regarding the methods to increase the efficiency of the repair shops by the introduction of dynamic priority rules we make the following conclusions:

- Dynamic priority rules and overtime policies are beneficial to reduce the repair lead times in capacity constrained repair shops.
- Repair shops can increase the utilization with the use of batching while decreasing the expected number of backorders in the case of very high setup times.

As outlined above, each agreement seems to be optimized for a specific setting. Also, many models take either capacity constraints into account or the availability of materials which are required for repair jobs. Based on this literature review, we are uncertain to which extend these agreements can be used to reduce the lead time of repairs for every repair shop.

3 Outline of the repair shop setting and case study companies

This chapter provides the reader with background information of the repair shop setting and the case study companies. Section 3.1 outlines the repair process and repair phases. Section 3.2 presents the case study companies and outlines some background information. Section 3.3 outlines the repair shop layout and provides first insight into different types of repair shops we identified at the case study companies. Section 3.4 presents the current agreements used in the case study companies. Section 3.5 concludes this chapter with a summary. Data for this chapter is gathered via interviews with repair shop managers of the four case study companies. An overview of the interview scheme (in Dutch) is presented in Appendix A.

3.1 Repair process description

The repair process of the case study companies is a closed loop supply chain. In this process failed LRU's are repaired and re-used as spare part. An LRU is only discarded when it is not economically viable to repair, or is already too much degraded. The closed loop supply chain is depicted in Figure 4. Figure 4 also illustrates the shop level and line maintenance and includes the repair process of SRU's. In the following section, the different stages of the repair process are explained in detail.

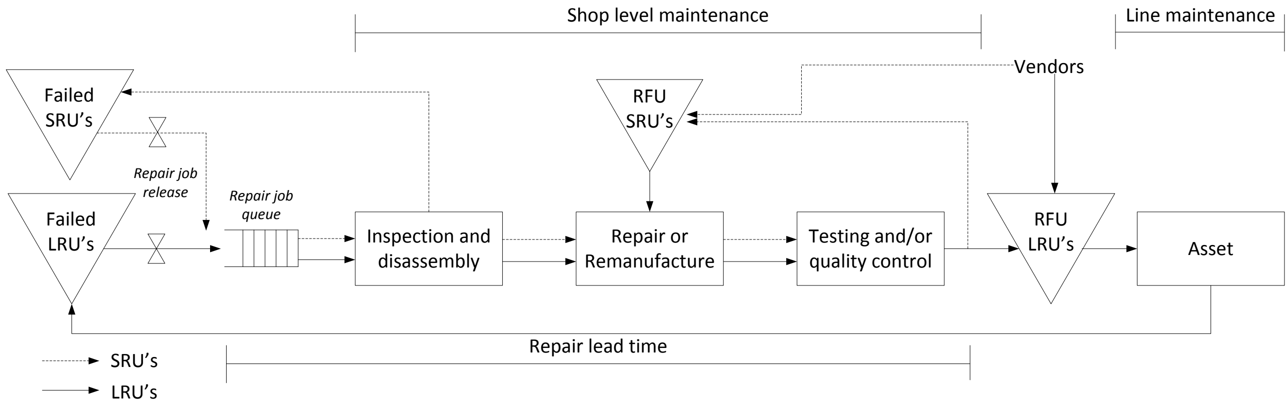

Figure 4. The closed loop supply chain

Stock locations

In the closed loop supply chain, two stock locations for LRU's exist. A failed LRU is replaced by an LRU from the Ready-for-Use (RFU) LRU stock. The RFU LRU stock holds all parts that can be used for the replacement of failed LRU's in assets. The other stock location for LRU's is the failed LRU stock. Here, the failed LRU is stored until the RFU LRU inventory level drops beneath a reorder point. When the RFU LRU inventory level drops beneath the reorder point, inventory control orders LRU's at the repair shop. The repair shop supplies the RFU LRU stock by the repair of an LRU from the failed LRU stock. This mechanism is used at GVB, DBGS and NME. KLM has a slightly different repair process. KLM does not have a failed LRU or SRU stock. Failed items are directly placed in the repair job queue of a repair shop. KLM controls the RFU LRU stock by the removal or addition of items in repair and in RFU stock. When too many LRU's are in stock and in repair, failed LRU's are not repaired but sold. In the case too few LRU's are on stock and in repair, additional LRU's are bought from vendors.

Repair job release

A repair job is released to the repair shop to supply both repairable SRU's and LRU's. The repair process for both items is the same. When a repair job is released, the item enters the repair job queue. The repair job queue contains all repair jobs that are waiting for processing. A repair shop manager decides which repair job should be processed first. This decision is based on multiple factors, 4 of which are:

(1) The agreements with inventory control. When using priority rules (such as those outlined in Chapter 2) some repairs will have priority over other repairs.
(2) Availability of repairmen. In a repair shop not all repairmen are capable of performing all repairs. Because of this, the decision on which repair job should be repaired first is dependent on the availability a specific repairmen.
(3) Repair time. In some cases, repair jobs with short repair times have higher priority than repair jobs with long repair times. This is because multiple short repair jobs can be handled in the same time only one long repair job can be handled. This priority rule is called shortest processing time first.
(4) Availability of SRU’s always required for repair. Some LRU’s always require the same SRU’s for repair. A repair job is not released until these SRU’s are available. However, in most cases this concerns small and cheap SRU’s and availability is not an issue here. As we outline below, more SRU’s are ordered on inspection.

Repair phases
When the repair job is assigned by the repair shop manager to a repairman, the repair process begins. A single repairman performs the entire repair, when possible, without interruption (although in some cases another repairman is added to speed up a repair). The repair process generally contains three phases:

(1) Inspection and disassembly

On inspection, the diagnosis of why an item failed is conducted. On inspection the repairman also determines if an item should undergo a repair or remanufacture. In repair, failed SRU’s identified during inspection are replaced and every repair is different. In remanufacture, a list is available with SRU’s that are always replaced and therefore each remanufacture is the same. This list is always the same for a specific LRU. For both types of maintenance, SRU’s and capacities required for the repair are identified on inspection. When SRU’s or capacities required for the repair are not available, the item is put apart until the SRU’s or capacities become available. When both SRU’s and capacities are available, the item immediately goes into the repair/remanufacture phase.

(2) Repair or remanufacture

In the repair phase the repair or remanufacture of the item takes place. SRU’s are used to perform maintenance on the repairable item. However, since repairable items may also be SRU’s, we refer to SRU’s required to perform maintenance on a repairable item as materials. The repair/remanufacture contains multiple operations. Examples of operations are machining, stitching, saw/cutting, welding. For example, KLM distinguishes a total of 187 unique operations.

(3) Testing and quality control

The final phase is quality control. In the quality control the LRU and repairable SRU’s are tested to determine whether the quality is up to standards. At DBGS, KLM and NME the quality control is done by a different (second) repairman. Some repair shops require specialized equipment for the final testing of LRU’s and SRU’s.

3.2 Case study companies

This section provides a short description of the case study companies of this research. The case study companies were selected from the clientele of Gordian. We selected these case study companies, because these companies have internal repair shops for LRU’s. We briefly describe the companies as well as the internal repair shops of these companies. Additional information on the maintenance concept, the organization of the repair shop and some interesting figures can be found in Appendix B.

3.2.1 GVB

GVB is the public transportation organization of Amsterdam. They are responsible for running a transportation network which is used by 700.000 passengers each day. The installed base is 216 trams and 106 metros (excluding the new M5 which is not yet in use at the time of this writing).

For the repair of LRU's, GVB has four internal repair shops. GVB has recently decided to continue with the internal repair of LRU's because of economic motivation (lower repair costs) and higher flexibility with respect to the lead times. GVB has 4 repair shops at the same location, each outlined below:

- Metal workshop; Repairs metal parts of trams and metro's such as the 3rd rail for electricity.
- Electronics; Repairs small electronic parts such as the OV-chipkaart reader and printed circuit boards (PCB's).
- Electric; Repairs large electric parts such as the electric engines.
- Pneumatic/Hydraulics; Repairs hydraulic and pneumatic components such as a compressor.

3.2.2 Air France/KLM

KLM Engineering & Maintenance is the maintenance organization of Air France/KLM. This organization has several business units. The unit Component Services is responsible for the availability of LRU's. The business unit consists of several divisions. The division Operations is responsible for the repair of LRU's. Two of the departments that perform the repairs on LRU's are (1) Avionics & Accessories (A&A) and (2) Base Maintenance Support Shops (BMSS). A&A focusses on avionics and hydraulic repairable parts and BMSS on the "plane parts". Engine Services is a third business unit but falls out of the scope of this research.

Air France/KLM repairs LRU's internally, because of 4 reasons:
1. It is more cost-effective to repair the LRU's internally
2. Revenues are earned to repair LRU's from other airline companies
3. Increased flexibility compared to outsourced repairs
4. Shorter lead times compared to outsourcing repairs

The repairs on LRU's are done in shops that are called Cells. A&A consists of 8 Cells, 4 Cells focus on hydraulics and 4 Cells on avionics. BMSS consists of HUB Support and two LINES. LINE1 consists of 9 Cells and LINE2 focusses on wheels and brakes and consists of 3 Cells. These Cells focus on "plane parts" such as engine components, fire extinguishers, wheels, breaks etc. Hub Support consists of 4 Cells and repairs parts from the body of the plane. An example of such a part is a (part of the) wing. However, HUB Support is omitted in the remainder of this research, because it operates in support of the larger plane maintenance and not specifically on component maintenance for spare parts.

3.2.3 DBGS

DBGS is the maintenance organization of the Royal Netherlands Army. This organization is responsible for the maintenance of army vehicles such as vehicles of the type Fennek, CV'90 or the YPR.

DBGS is faced with a diminishing installed base. This makes the internal repair of parts less cost effective. Because of this, many component repairs are outsourced. Internal repairs are still done in order to ensure availability of knowledge on how LRU's should be repaired. This knowledge is required because non-military repairmen may not want to work in a war zone where assets are stationed (and repairs need to be performed).

Repairmen of DBGS can work in a war zone and thus require the knowledge to repair the LRU's. The shops of DBGS are the following:

- Mechanics; Responsible for the repair engines and crankshafts of vehicles.
- Electronic; Repairs the electronic LRU's.
- Hydraulics/Pneumatics; Repairs the hydraulic and pneumatic LRU's.

3.2.4 Naval Maintenance Establishment

The Naval Maintenance Establishment (NME) is the maintenance organization of the Royal Netherlands Navy. This organization is responsible for the maintenance of the Dutch navy. The Royal Netherlands Navy consists of around 60 ships (destroyers, mine hunters, support ships, frigates etc.) and 4 submarines.

The Royal Netherlands Navy repairs the parts internally, because this ensures the flexibility in repair lead times. Also in some cases, very specialized expertise is required which is difficult to outsource. To perform repairs, the organization has several repair shops. We focus on the following shops:

- The repair shops of the division MTP ("Platform"); The repair shops in this division repair the "ship parts". Two examples are engines and metal plating of a ship.
- The repair shops of the division SWS ("SEWACO"). The division SWS repairs parts that form the weapon systems of a ship. Examples are radar systems, sonar systems and Goalkeepers.
- The repair shops of the division C4i; C4i repairs all communications, cryptography and PCB parts of the ship. These are usually smaller electronic components.

In total, the scope of this research at the Naval Maintenance Establishment includes 10 repair shops. 4 Are in SWS, 3 in C4i and 3 in MTP.

3.2.5 Conclusion

In this section we outlined the case study companies and the different repair shops of the case study companies. We showed that repairs are performed internally because of:

- Increased flexibility
- Decreased cost
- Keeping in-house knowledge of repairable items
- High levels of expertise required for repairs

In the following section we outline in more depth the different types of repair shops that exist in the case study companies.

3.3 Repair shop layout of the case study companies

The internal repair shops repair a wide variety of LRU's and SRU's. The number of different LRU's and SRU's that the internal repair shops maintain varies from as little as 5 different items[1] to as many as 600 different items[2] in a 2 year period.

The repair shops in the case study companies are technology based. This means that each repair shop has its own discipline. Disciplines we identified at all case study companies are:

[1] Repair shop KL12
[2] Repair shop NME10

- Avionics & electronics; Repair shops with this discipline generally repair smaller electronic items. For example, flight indicators, printed circuit boards and communication systems.
- Mechanics; Repair shops with a mechanical discipline generally repair large items, such as engines, crankshafts etc.
- Pneumatics & hydraulics; Repair shops with a pneumatic & hydraulic discipline repair items such as water or air pumps, or oxygen bottles. Also items of lower complexity such as coffeemakers are repaired in a pneumatic/hydraulics repair shop.

An example of LRU's repaired in repair shops of the three disciplines are presented in Figure 5.

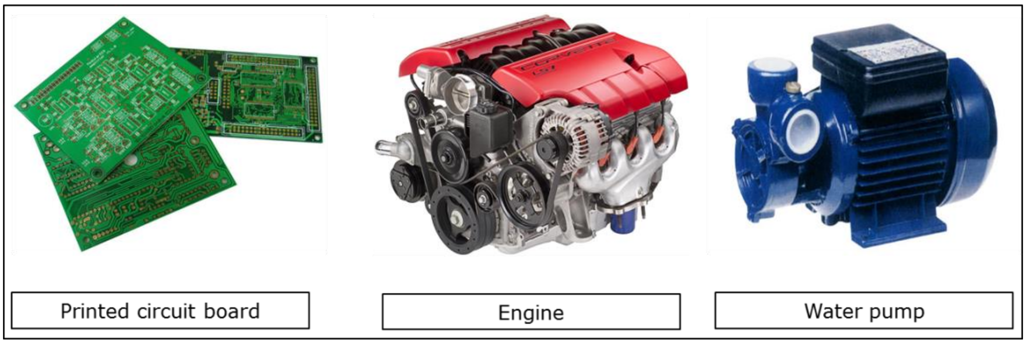

Figure 5. Three examples of LRU's repaired in different repair shops.

The repair shops of the case study companies have either a task or product oriented layout. Product oriented repair shops are responsible for the repair of a fixed set of LRU's and SRU's. An item is repaired in a single product oriented repair shop. Therefore, the product oriented repair shops operate independently of one another. For specific operations, the item may be send to a task oriented repair shop. Task oriented repair shops are responsible for a part of the repair. These repair shops are also called backshops. Examples of backshops are painting and cleaning. This research focusses on the product oriented repair shops. This research focusses on the product oriented repair shops, because these repair shops are more complex in terms of capacity requirements and material usage than task oriented repair shops. The 4 case study companies have a total of 32 product oriented repairs shops within the scope of this research[3].

3.4 Agreements between repair shops and inventory control

Table 2 presents an overview of the interface agreements currently used in our case study companies. The overview of current agreements is based on interviews with repair shop managers and inventory control of the different case study companies. The case study companies use one type of agreement for all repair shops in the company. GVB uses a Min-Max inventory levels agreement between inventory control and the repair shop. KLM, NME and DBGS use repair lead time agreements.

[3] GVB has 4 repair shops, KLM has 15 repair shops, NME 10 and DBGS has 3 repair shops that fall within scope. For confidentiality, the repair shops are anonymous. Repair shops of GVB are coded with GVB#, KLM repair shops are coded with KL#, NME repair shops with NME# and repair shops of DBGS are coded with DBGS#. The "#" indicates the repair shop.

Case study company	Agreement between repair shop and inventory control
GVB	Min-Max inventory levels per repairable item
KLM	Repairable items have an agreed lead time
NME	Agreed lead time of 3 months for all repairable items
DBGS	Fixed repair lead time agreements & batch size per repairable item

Table 2. Overview of current agreements between repair shop and inventory control per case study company.

Although KLM, NME and DBGS use the same type of agreement, the content of the agreement is different for each of the companies. At KLM, inventory control and repair shop control mainly have lead time agreements of 7, 14 or 21 days although other lead times are also possible. 80% of the repairable items have a repair lead time of 14 or 21 days. The length of the agreed lead time is dependent on the type of item and the time it takes to repair an item.

NME uses one repair lead time for all parts. The repair lead time, agreed between inventory control and repair shops, is set on 3 months. However, this serves only as an indication. Per repair job a different repair lead time is set by inventory control. This repair lead time is set based on the current state of the system in terms of demand and available capacity.

DBGS also uses repair lead time agreements for repairable items. At DBGS, agreements between inventory control and repair shop control are not only made on repair lead times, but also on the batch sizes that are send to the repair shop.

Table 3 outlines the % of repairs on time for both KLM and NME. This is can be used as an indicator for the performance of the current agreements. For KLM the scope is January 2012 to November 2012 and for NME the scope is January 2010 to December 2012. The table shows the percentage of repairs performed within the agreed lead time. For NME this is the lead time set by inventory control. The table shows that for KLM the performance ranges from 65% to 94% of repairs performed on time. For NME this ranges from 38% to 87%.

Repair shop	% of repairs on time	Repair shop	% of repairs on time
KL1	74%	NME1	38%
KL2	88%	NME2	61%
KL3	78%	NME3	58%
KL4	83%	NME4	67%
KL5	90%	NME5	87%
KL6	94%	NME6	64%
KL7	88%	NME7	70%
KL8	74%	NME8	48%
KL9	88%	NME9	39%
KL10	76%	NME10	52%
KL11	80%		
KL12	65%		
KL13	80%		
KL14	71%		
KL15	89%		

Table 3. Performance of repair shops

Table 3 illustrates that in some repair shops the current agreements work well and in other repair shops the agreements do not work well. For DBGS no data on performance is available.

GVB uses a min-max inventory system in which minimum and maximum inventory levels are set by inventory control. The minimum and maximum inventory levels are calculated based on the expected demand in a 4 week period.

3.5 Conclusion

Based on this chapter we conclude that:

- The repair process can be modeled as a closed loop supply chain
- There are both task oriented repair shops and product oriented repair shops. The focus of this research is on the product oriented repair shops
- The 4 case study companies (GVB, KLM, NME and DBGS) have in total 32 product oriented repair shops in the scope of this research
- The case study companies use 1 type of agreement between inventory control and repair shops for all repair shops. GVB makes agreements on min-max inventory levels. KLM uses 3 main repair lead times of 7, 14 and 21 days. NME has repair lead times of 3 months, but for each repair order a lead time is set by inventory control. DBGS has lead times and batch sizes which are unique for each repairable item
- In some repair shops the current agreements between inventory control and repair shops work well, where in other repair shops the agreements are considerably unmet.

4 Identification of repair shop characteristics

This chapter identifies the repair shop characteristics of the case study companies. Section 4.1 identifies characteristics that are important for the repair lead times based on general production unit literature. In Section 4.2 we present literature on queue and inventory models in order to identify the characteristics that influence the repair lead times. Section 4.3 presents the characteristics that are identified at the repair shops. Section 4.4 presents an overview of quantitative repair shop characteristics. These are characteristics identified using the analysis of quantitative data. In Section 4.5 we present qualitative characteristics. These are repair shop characteristics identified using interviews. Section 4.6 presents a preliminary analysis of the effect of characteristics on the waiting time. Finally, Section 4.7 concludes this chapter. This chapter answers research question 2.

This chapter identifies characteristics that influence the repair lead time. As illustrated in Section 1.2.4, 95% of the repair lead time consists of waiting time. Because of this we identify literature that explains where waiting time occurs.

4.1 Lessons learned from general production unit literature

Based on the literature presented in Chapter 2, no conclusive description of the repair shop environment could be found. However, researchers often refer to a job shop environment as a reference to repair shops (Guide Jr et al., 2000; Hausman & Scudder, 1982; Scudder & Chua, 1987). We therefore also refer to more general production unit literature to identify which characteristics impact the lead time of repairs.

Browne et al. (1981) provides insights in the resources that are required to scheduling a job. They distinguish the following resources (the 4M's):

- Machine, Tooling and equipment (Machines)
- Labor (Men)
- Raw materials/partly processed components (Materials/SRU's)
- Methods and documentation (Methods)

When one or more of these resources are unavailable, the job cannot be started on a machine. This means that if any of the resources is unavailable, waiting time is incurred which increases the lead time of repairs.

Bertrand et al. (1990) goes into further detail of these resources, in particular the machines, men and materials, and developed a typology of production units. The typology was created in order to determine the benefit of using MRP. The typology is based on the complexity of materials coordination and capacity-use coordination, see Figure 6. Material complexity refers to the material requirements for work orders and the effect this has on complexity in a Production Unit (PU). Capacity-use complexity refers to the number of different capacity types and corresponding available capacity in the PU and the complexity of relationships in the capacity requirements of production orders. (Bertrand & Wortmann, 1992)

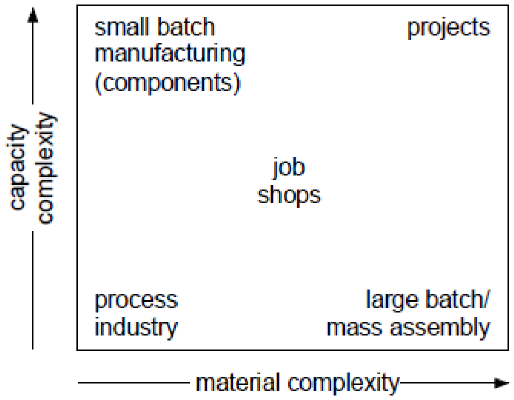

Figure 6. Production unit typology. Source: (Bertrand et al., 1990)

In the model of Bertrand, material complexity is high if (Bertrand & Wortmann, 1992):

- Different work order orders require different materials
- Work orders require many materials
- Required materials are difficult to come by

Capacity-use complexity is high if (Bertrand & Wortmann, 1992):

- Many work orders require different routings
- Work orders require different capacity
- Different capacities have different manufacturing characteristics, such as set-up times, cycle times and batch sizes

Capacities are, among other, repairmen, machines and/or operations required for the work order.

The model of Bertrand et al. (1990) outlines both the effect of characteristics related to the capacity of a production unit and to the materials required for repair of a production unit. As Browne et al. (1981) illustrates, the both materials and capacity is required in order to load a job. This is also the case for a repair jobs. It is therefore likely that the characteristics discussed by Bertrand et al. (1990) also impact the lead time of repairs.

4.2 Queuing theory and inventory management models

Figure 7 depicts a graphical representation of where waiting time is incurred. The total repair lead time starts when a job enters the repair job queue and is finished after the testing/quality control. Waiting time is incurred in either the repair job queue, or during repair. Waiting time in the repair job queue is incurred, because of the unavailability of capacity (such as repairmen or equipment) and/or documentation. Waiting time during repair is incurred primarily because of the absence of materials required for repair and which are identified on inspection. Also the unavailability of equipment may be an issue.

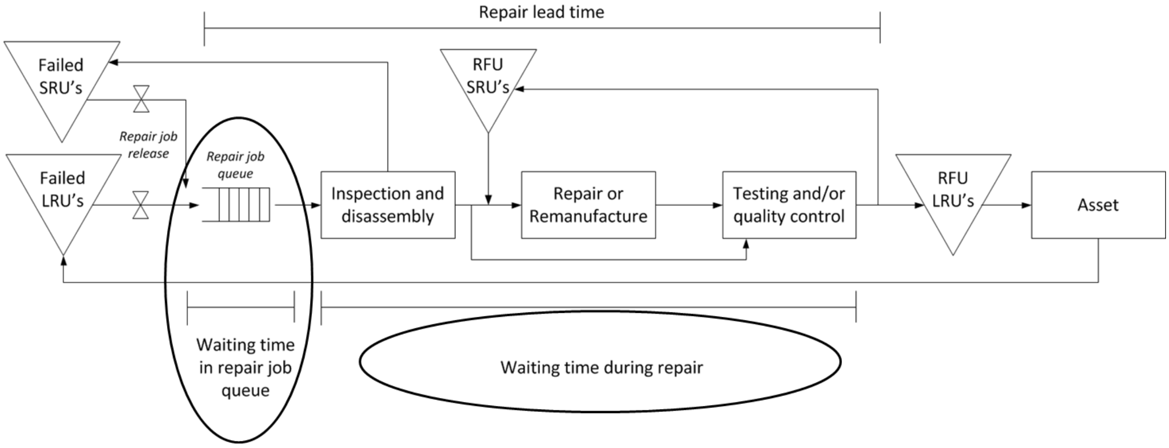

Figure 7. Graphical representation of where waiting time is incurred

To identify which characteristics should be included in this study we refer to queuing theory and inventory management models. We use queuing theory, because in literature, repair shops are often modeled as a single/multiple server queues and queuing theory is used to model the waiting time in queue. We also apply inventory models to identify how materials affect the repair lead time. In the following two sections, we briefly discuss both queuing theory and inventory models.

4.2.1 Introduction to queuing theory

Queuing theory is the mathematical modeling of queues and/or waiting times (Winston, 2003, p. 1051). In everyday life, everyone is faced with queues. For example when standing in line for the cash register in a supermarket. In order to mathematically model a queue, an input process and an output process must be specified. The input process is called the arrival process. Arrivals are for example customers who want to pay at the cash register. In a repair shop, the arrivals are the repair jobs. The customers arrive according to a specific arrival rate. The arrival rate per hour is depicted as λ. For example, when per minute 5 customers get in line for the cash register, λ equals 300 customers per hour. Queuing models assume that the arrival rate is independent of the number of customers waiting in line. It doesn't matter whether there are 5 or 10 customers in line. Every customer who wants to pay will also get in line. Some queuing models assume that there is a maximum size of customers in queue. These models are not relevant for this study.

The output process is usually a specific probability distribution, called the service time distribution (Winston, 2003, p. 1052). The service time distribution governs the service time of customers. The number of customers served per hour is called the service rate and is depicted as μ. Queuing models differentiate between servers in parallel and servers in series. Servers are in parallel if all servers provide the same service and a customer needs to pass one of the servers. Servers are in series if a customer must pass through all servers before completing service (Winston, 2003, p. 1052). A graphical representation of a system with *c* parallel servers is depicted in Figure 8.

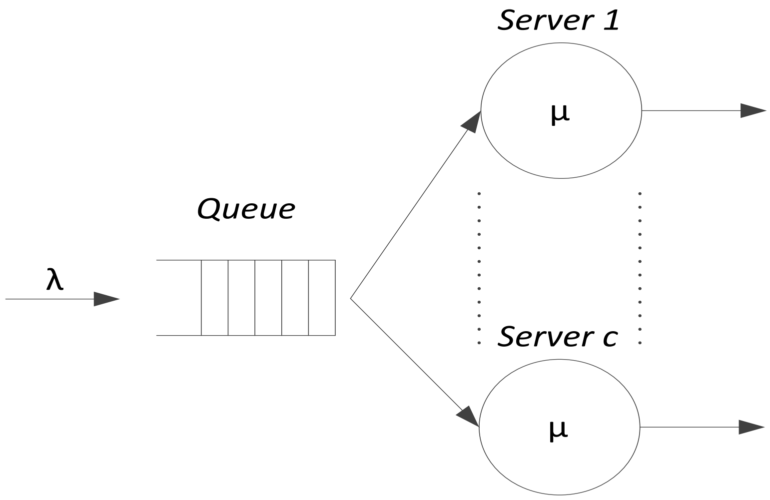

Figure 8. Overview of a multiple server queue system

An estimation for the waiting time in a queue with a general distributed arrival rate and repair rate and *c* servers is presented by Kingman's formula for a G/G/c queue (Kingman, 1961). This formula is presented in Equation (1).

$$W_q \approx \left(\frac{C_s^2 + C_a^2}{2}\right)\left(\frac{\rho^{\sqrt{2(c+1)-1}}}{c(1-\rho)}\right)E(s) \tag{1}$$

In Equation (1), *c* is the number of servers, C_s^2 is the squared coefficient of variation of the service time, C_a^2 is the squared coefficient of variation of the arrival rate, ρ is the utilization (see Equation (4)) and *E(s)* is the service time. Further detailed information on queue models can be found in Appendix C.

4.2.2 Introduction to inventory management for repairable spare parts

The impact of SRU's on the repair lead time is best illustrated by inventory models such as the MOD-METRIC of Muckstadt (1973) and the VARI-METRIC model from Sherbrooke (1986). These models aim to maximize the availability of assets by minimizing the number of expected backorders on both LRU's and SRU's. These models achieve this by explicitly incorporating the logistical relation between LRU's and SRU's. This is modeled by making the number of expected backorders on LRU's dependent on the number of expected backorders of SRU's. The results of both the MOD-METRIC and VARI-METRIC show that the models lead to improved performance compared to inventory models that do not explicitly incorporate this relation.

Both models use a greedy approach for the spare parts inventory level optimization. This means that the item (LRU or SRU) is kept on stock which reduces the expected number of LRU backorders the most in relation to the additional investment costs of adding the item to stock. This is done by keeping the items that have high probability of failure, low cost and short lead times on stock (Sherbrooke, 1986). The main difference between the MOD-METRIC and the VARI-METRIC model is that the VARI-METRIC model assumes negative binominal distributed number of items in the pipeline and the MOD-METRIC poisson distributed number of items in the pipeline.

4.3 Quantitative characteristics that affect the repair lead time

In Section 4.1 and 4.2 we determined literature that explains which characteristics are important to determine at the case study companies. Based on the findings from these sections we model a repair shop as a queue in which the repair lead time consists of (1) the waiting time in queue for capacity, (2) the waiting time for materials and (3) the processing time. Figure 9 shows a graphical representation of the queue model we use. We also take into account the number of servers in a repair shop.

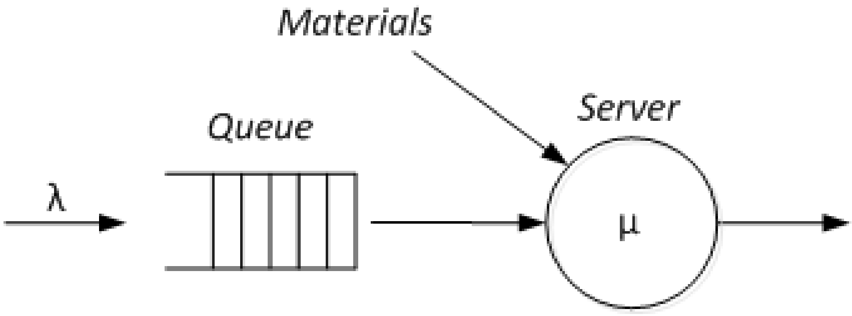

Figure 9. Graphical representation of a single server queue model for repair shops

Based on this model we identify quantitative characteristics that influence the lead time of repairs. The characteristics are based on 4 sources of information:

- Inventory management models and queuing theory
- Assumptions and specific repair shop settings described in Chapter 2
- The resources required for the loading of a repair job from Browne et al. (1981)
- Opinions from Gordian consultants

We first outline characteristics related to high repair lead times based on queuing theory. Next, we focus on characteristics related to high repair lead times due to the absence of materials. Finally, we outline a characteristic related to failure rate of LRU's. Per characteristic we discuss why the characteristic is included (based on which source of information). We state how the characteristic is measured and what the expected impact is on the repair lead time (variability) of a repair shop. In Chapter 5 we discuss in detail the impact of characteristics on the repair lead time. In Appendix C we outline the mathematical basis for our statements on the effect of characteristics on the repair lead time.

4.3.1 Characteristics relating to capacity complexity

Outlined below are characteristics relating to the capacity constraints of repair shops.

- *Average repair time per repair job*. The average repair time is based on queuing theory. The repair time is measured as the number of hours a repairman spends on a repair job, excluding the extra waiting time due to material or equipment unavailability. By using the repair time per repair job, we also include the effects of batching. This is because the repair job might be for a batch size larger than 1. High repair times indicate high waiting times in queue (as is illustrated in Appendix C) and long repair lead times.

- *Squared coefficient of variation of the actual repair time per repair job*. The squared coefficient of variation of actual repair time is also based on queuing theory. The calculation of the squared coefficient of variation of the actual repair time per repair job is presented in Equation (2). A high value indicates a high variability in the repair process and thus high repair lead times.

$$CV_r^2 = \left(\frac{\sigma_r}{E(R)}\right)^2 \tag{2}$$

In this calculation E(R) is the average repair time and σ_r is the standard deviation of the repair time. We use the squared coefficient of variation to highlight differences between repair shops.

- *Average number of operations per repair job*. The inclusions of the characteristic average number of operations per repair job is based on Guide Jr et al. (2000). The number of operations per repair job is measured as the number of operations a repairman performs on a repair job. A high number of operations indicates long repair times and thus long repair lead times.

- *Squared coefficient of variation of the number of repair operations per repair job.* This characteristic is based on the same literature as the previous characteristic. A high value indicates a high variability in the repair process and hence a high variability in repair lead times. The calculation for the squared coefficient of variation of the number of repair operations per repair job is presented in Equation (3). The coefficient of variation on the number of repair operations is also an indicator for the different routings of work orders. When repair jobs require many different operations, it is likely the routings will also vary.

$$CV_o^2 = \left(\frac{\sigma_o}{E(O)}\right)^2 \qquad (3)$$

In this calculation E(O) is the average number of operations and σ_o is the standard deviation of the number of operations.

- *Number of repair men in a repair shop*. This characteristic is based on the 4M's of Browne et al. (1981) and queuing theory. A low value indicates a high repair lead times as the possibility that a repairman is available is relatively low. The number of repairmen is defined as the number of repairmen dedicated to LRU and/or SRU repairs.

- *Percentage of moving items that is responsible for 80 percent of total repair load in a repair shop*. This characteristic is based on opinions from Gordian consultants and Browne et al. (1981). Moving items are items that failed at least once in a (company specific) period. The repair load is calculated as the sum of repair times over the previously mentioned period. A high value indicates a high product mix because many different items are responsible for the repair load. Furthermore we suspect that a high product mix leads to high repair lead times due to the absence of documentation. We use the term items for both repairable LRU's and SRU's, because based on data from the case study companies it is unknown which part is a repairable LRU and which part is a repairable SRU. It is important to note that when a repair shop has only few (say 5) different items to repair, it is likely that this characteristic is not a good indicator of the product mix. Therefore, when analyzing this characteristic, the number of different items repaired in the repair shop needs to be taken into account.

- *Utilization (ρ)*. This characteristic is based on queuing theory. A high value indicates high capacity complexity. The utilization is based on the arrival rate of failed items per week (λ) and not the arrival rate per hour as is common. We use the arrival rate and repair rate of failed items per week, because we have insufficient data to calculate the arrival rate per hour. However, according to Heffes and Lucantoni (1986) Equation (4) also holds for the arrival rate and service rate per week.

$$\rho = \frac{\lambda}{c\mu} \qquad (4)$$

The calculation further depends on the number of repairmen in the repair shop (c) and the repair rate (μ).

4.3.2 Characteristics relating to material uncertainty

In this section we outline the characteristics that relate to materials and are likely to affect the repair lead time. We call this material uncertainty. As outlined in Section 3.1, materials are all repairable and consumable SRU's that are required for repair.

- *Percentage of repair jobs in which no materials are required*. This characteristic is used as an indicator for the uncertainty in materials required for repair. A high value indicates a little waiting time due to the absence of materials. The fact that some repair jobs do not require materials is because not all repair jobs require materials that are registered on the repair job. For example, nuts and bolts are usually stored in a two-bin system and not ordered specifically for a repair job. Therefore, it is possible no materials are registered on the repair job.

- *Percentage of repair jobs in which at least one slow moving material is required*. This characteristic is based on opinions from Gordian consultants. We suspect that a high value indicates high waiting time due to the absence of materials. This is based on the fact that in METRIC, fast moving items are put on stock more than slow moving items (Sherbrooke, 1968). A material is marked as slow moving if the demand rate is smaller than 2 per year.

- *Average number of materials required per repair job*. This characteristic is an indicator for the uncertainty in materials required for repair. The average number of materials required per repair job is based on the materials registered in the Information System for a repair job. A high value indicates that it is more likely that waiting time occurs due to unavailability of SRU's. The possibility that one or more required materials are not available is higher in case more materials are required.

- *Material demand rate*. This characteristic is based on opinions of Gordian consultants. This characteristic indicates whether a repair shop requires many of the same materials. A high value indicates that, on average, materials are required often. This makes the forecasting of materials more accurate (Fortuin & Martin, 1999). It is thus less likely that waiting time occurs due to the absence of materials. The calculation for the material demand rate is presented in Equation (5) and is calculated over a 1 year period.

$$Material\ demand\ rate = \frac{Total\ number\ of\ material\ demands}{number\ of\ moving\ materials} \tag{5}$$

  A material demand is when a material is required for the repair job, the size of the demand is of less importance. We exclude the size of the demand, because the number of demands and not the size of the demands illustrate whether forecasts are accurate. Moving materials are materials for which there is demand at least once, in a company specific period.

4.3.3 Characteristic related to the failure rate of LRU's

To identify the relation between the failure rates of LRU's and waiting times in queue we use one characteristic.

- *Variance to mean ratio (VMR) of the number of arrivals per week*. This characteristic is based on queuing theory. The number of arrivals is calculated per week, because we do not have the specific time intervals between arrivals. The

VMR of the number of arrivals per week is under some conditions equal to the squared coefficient of variation of interarrival times. A high value indicates high variation in failed items and thus high repair lead times due to variability. In the case of a poisson distributed arrivals, the VMR equals 1. For a negative binominal distribution, the VMR is larger than 1.

Based on queuing theory, we expect to find that some characteristics are correlated (such as the average repair time and the average number of operations). To include these correlation effects we present a correlation analysis in Chapter 5.

4.4 Overview of quantitative repair shop characteristics

Section 4.4.1 discusses data reliability of the case study companies. Not all companies have all required data since the case study companies have different systems from which data is collected. When possible, we made assumptions to fill gaps in the data. Section 4.4.2 presents the quantitative repair shop characteristics.

4.4.1 Data reliability

KLM has the most detailed data of the 4 case study companies. Multiple information systems are used for the registration of data (e.g. Crocos, SAP). A unique identifier for a repair job is used to acquire data from the different information systems. In total we obtained 24571 repair jobs with sufficient data between the period January 2012 and November 2012 for the 15 repair shops of KLM. The material demand rates are calculated for the year 2012. KLM performs repairs for both pool and non-pool companies. We only include pool orders, because these receive priority over non-pool orders.

For GVB we obtained data on 2689 repair jobs from January 2011 to December 2012. The material demand rates are calculated over the years 2011 and 2012. The data is stored in a single information system. However, GVB doe s not store the precise amount of operations required for repair jobs. Therefore, an analysis on the number of operations cannot be performed for the 4 repair shops of GVB.

For DBGS we obtained 1025 repair jobs with sufficient data between the period January 2011 and December 2012. The repair times are stored per repair shop (for example, painting, cleaning or the Mechanics repair shops). No data is stored on individual operations. Materials are registered per repair job. The material demand rates are also calculated over the period 2011 and 2012. For the repair shop DBGS2 we removed repair jobs for 1 item, a tackle (in dutch: "Takel"). We removed repair jobs of this item, because this item is not a representative item, but did have a significant impact on the characteristics of the repair shop. For DBGS2, of the total of 307 repair jobs, 108 are left.

NME uses two systems which contain data on repair jobs. One system contains data on failed items and material usage required for repair jobs. The second system contains data on operations and repair times. Data on repair jobs could only be collected when the work planner enters the repair job ID in both systems. When the repair job ID is not entered, material requests and repair times cannot be linked to repair jobs. This resulted in a limited data set for the 10 repair shops NME. To increase the data set, two assumptions on data were made:

(1) We assume that for repair jobs on which data on repair times were available, we also have the correct data on materials required for the repair job. This leads to an increase in the % of repair jobs that do not require materials.
(2) In the calculation of the repair load, items for which no repair times were available, the repair time of an item is equal to the average repair time of items repaired in the repair shop.

In total we obtained 1899 repair jobs with sufficient data between the period 2011 and 2012 for the 11 repair shops of NME. The material demand rates are also calculated over 2011 and 2012.

4.4.2 Overview of quantitative repair shop characteristics

Table 4 shows the quantitative repair shop characteristics we identified at the case study companies. The first column gives the name of the repair shop. In the second column the utilization is displayed. Unfortunately, not for all repair shops we were able to calculate the utilization, because we do not have the number of repairmen dedicated to component repairs. Furthermore for the repair shops of which data on utilization is available, we suspect the data is not accurate. This is because in many repair shops, different types of repairs are performed. For example at KLM both pool and non-pool repairs are performed. The utilization is calculated only for the pool components, because these have priority over the non-pool components. Because of this the utilization is in many repair shops very low (e.g. KL2, KL3, KL4). On the other hand, the utilization for the repair shops of KL9, KL10 and KL13 is larger than 1 which should not be possible. These repair shops also use temporary repairmen which are not included in the system. Because of these imperfections in the data, we suspect that the utilization, as it is currently measured, will not be a good indicator for the average waiting times in repair shops.

For the average repair time and the squared coefficient of variation of the actual repair time data could be obtained for all repair shops.

For the characteristic number of repairmen we only list the data for repair shops of which we know the number of dedicated repairmen. For the characteristics average number of operations and squared coefficient of variation we were only able to collect data for the repair shops of KLM.

For the remaining characteristics we calculated the characteristics as outlined in Section 4.3. For the characteristic '% repair jobs without materials' at the repair shops of NME we assume that repair jobs of which we had the data available of repair times we also had the data available of the materials required for the repair job. However, this assumption may lead to an overestimation of the % of repair jobs without materials.

Shop	Average repair time per repair job (in hours)	Squared coefficient of variation of the actual repair time	Average number of operations per repair job	Squared coefficient of variation of the number of operations	Number of repairmen	% of items responsible for 80% of the repair load	Utilization	Average number of materials required for repair	% repair jobs without materials	% of repair jobs with at least 1 slow moving item	Material demand rate	Variance to mean of the number of arrivals per week
GVB1	12.5	0.9			3.0	20%	0.87	6.5	11%	16%	4.9	7.5
GVB2	3.7	1.6			4.0	35%	0.78	1.8	81%	3%	1.9	16.4
GVB3	10.8	1.0			7.0	30%	0.56	4.4	22%	24%	4.7	4.8
GVB4	23.2	0.9			10.0	40%	0.42	13.9	18%	27%	4.4	3.3
KL1	3.4	1.1	6.7	0.3	7.6	30%	0.25	3.6	78%	3%	3.4	3.0
KL2	1.9	0.7	8.1	0.3	12.6	23%	0.23	6.3	65%	0%	24.2	4.3
KL3	15.1	1.1	8.8	0.1	10.1	22%	0.42	4.9	31%	8%	4.9	1.3
KL4	7.0	3.1	8.8	0.1	7.5	9%	0.38	4.0	42%	3%	10.2	3.1
KL5	5.6	1.2	7.7	0.2	6.0	32%	0.35	3.3	56%	7%	2.8	2.7
KL6	3.9	0.6	8.8	0.1	8.7	21%	0.31	5.1	41%	7%	5.5	2.9
KL7	6.7	2.3	6.9	0.7	11.0	22%	0.43	7.7	61%	4%	7.3	3.1
KL8	11.1	1.2	9.6	0.7	9.1	40%	0.32	11.0	41%	16%	3.6	2.9
KL9	22.8	5.5	7.0	0.4	8.6	25%	1.45	5.8	17%	8%	6.9	9.3
KL10	10.1	0.5	23.0	0.4	14.6	55%	1.58	17.8	20%	3%	29.3	2.2
KL11	4.8	0.4	27.2	0.2		35%	0.64	1.7	75%	0%	10.7	6.9
KL12	7.4	0.5	10.4	0.1	2.2	50%	0.06	4.1	16%	1%	19.0	1.9
KL13	2.3	4.1	6.1	0.2	3.2	45%	1.28	5.6	35%	6%	9.4	4.3
KL14	2.5	0.8	5.1	0.7	3.1	18%	0.49	8.3	50%	3%	12.9	6.1
KL15	8.8	0.3	10.2	0.1	4.7	55%	0.38	5.8	26%	13%	4.4	1.5
NME1	49.8	4.5				16%		29.0	50%	46%	0.5	7.5
NME2	26.8	1.1				40%		7.1	50%	68%	0.6	11.5
NME3	13.6	1.9				26%		9.6	45%	48%	0.7	7.3
NME4	25.3	1.1				32%		2.4	53%	50%	0.6	29.7
NME5	28.0	5.4				41%		7.0	36%	30%	0.7	5.5
NME6	25.9	0.7				15%		12.1	35%	38%	0.6	7.1
NME7	33.4	4.0				43%		3.6	30%	36%	0.9	37.8
NME8	34.9	0.9				14%		2.3	16%	32%	0.6	6.5
NME9	16.6	1.3				32%		2.7	46%	22%	0.7	49.5
NME10	8.7	1.2				44%		1.7	68%	15%	0.6	5.6
DBGS1	63.3	1.5				45%		9.5	25%	44%	1.0	5.7
DBGS2	26.4	3.7				37%		10.5	24%	20%	0.8	7.5
DBGS3	70.4	2.0				69%		16.7	14%	35%	2.0	5.6

Table 4. Overview of quantitative repair shop characteristics

4.5 Overview of qualitative repair shop characteristics

The repair shop characteristics described in the previous sections are all quantifiable. However, some repair shop characteristics cannot be quantified but do have an impact on the repair lead time. These characteristics are:

- The degree of specialization of repairmen
- Priority of repairs
- Pre-emption of repairs

The source of information for the qualitative repair shop characteristics are interviews held with repair shop managers from the 4 case study companies. Interviews were held with one repair shop manager of GVB, three of KLM, one of DBGS and 4 of NME.

4.5.1 Specialization of repairmen

In task oriented repair shops, every repairmen has (more or less) the same skill level. This is not always the case in product oriented repair shops. For example, in several repair shops KLM[4] only few repairmen are authorized to perform a final check of a repairable item. At NME, the repair shops of SWS have highly specialized repairmen. At these repair shops, in some cases only a single repairman is capable of performing certain repairs. A high degree of specialization of repairmen indicates that only limited repair capacity is available and thus long repair lead times. However, it is not possible to quantify the degree of specialization of repair shops within the time constraints of this research.

Note, not in all product oriented repair shops do repairmen have specific skill levels. For example, the repair shops of GVB and DBGS have only little difference between the skill levels of repairmen in a repair shop. In these repair shops, capacity is less constrained by a high degree of specialization.

4.5.2 Priorities of repairs

This research focusses on the repair of LRU's and SRU's (repairable items). However, not all repair shops in this study focus solely on the repair of items. Many repair shops also perform other repairs than component repairs. For example, the repair shops of NME also perform repairs on the bodywork of ships or entire radar systems. Also the repair shops of DBGS perform other repairs than only component repairs.

The repair shops of DBGS and NME do not have repairmen dedicated to component repairs. Repairmen perform both component repairs and other repairs. The fact that two types of repairs are performed has an impact on the priority of repairs. According to repair shop managers of both NME and DBGS, the component repairs have lower priority than the other repairs. Priority is given to the other repairs, because these require more capacity.

The repair shops of KLM (within the scope of this study) do focus solely on component repairs. However, in these repair shops repairs that are from the "pool" have priority over repairs from the "non-pool". Non-pool repairs are repairs performed for customers for which no contract exists. This research focusses on the "pool" repairs. This means that all characteristics are only calculated over "pool" repairs.

The precise effect of the priority on non-component repairs on the waiting time for component repairs is difficult to determine due to the fact that no data is available for this study on the other type of repairs. However, it is unlikely that the component repairs

[4] For example, repair shop KL5 which repairs high frequency LRU's.

will wait in the repair job queue for very long time since these components are also required in assets.

4.5.3 Pre-emption of repairs

Pre-emption of repairs is the interruption of repair jobs for other jobs with higher priority. Companies have different views on the concept of pre-emption. Repair shop managers of KLM state that the pre-emption of repairs is not allowed. According to the repair shop managers, pre-emption of repairs leads to a process which is more out-of-control. When repair shops use pre-emption, there are more unfinished repair jobs. This increases the variation in repair lead times. At KLM, repairmen are obligated to perform repairs from start to finish without interruption. This is, of course, not possible in the case not all required resources to perform are available (such as materials or documentation).

Repair shop managers of DBGS, NME and GVB stated that, although not preferable, pre-emption was allowed in the case of high priority of other repair jobs. A repair shop manager of GVB even stated that the pre-emption of repairs was the primary reason for waiting time in the repair shop.

Unfortunately, no data is available on when a repair job is interrupted. The precise effect of pre-emption of repairs on the average waiting time can therefore not be calculated.

4.6 Analysis of waiting times

In Chapter 1 we illustrated that the repair lead time consists for 95% of waiting time. In Section 4.2, we illustrated that waiting time can be incurred in the repair job queue, due to capacity constraints, and during repair, in the case of absence of materials. For 7 repair shops of KLM we have data available on where waiting time is incurred (in queue or during repair). Table 5 outlines the % of waiting time that is incurred in queue and during repair for each repair shop.

Repair shop	% of waiting time incurred in queue	% of waiting times incurred during repair
KL2	76%	24%
KL4	79%	21%
KL7	27%	73%
KL10	5%	95%
KL11	34%	66%
KL13	23%	77%
KL15	87%	13%

Table 5. Overview of where waiting time is incurred

Table 5 shows that it differs per repair shop where the most waiting time is incurred. In 3 out of 7 repair shops, the most waiting time is incurred in the repair job queue. For the remaining repair shops, most waiting time is incurred during the repair phase. Given that pre-emption is not allowed at KLM and repairs are performed when possible without interruption, it is likely that the waiting time here is incurred due to the absence of materials. The difference is not mainly caused by the type of repairs performed in the repair shops. For example, both KL4 and KL7 repair hydraulic items. We suspect that the difference in where waiting time is incurred is caused by the characteristics of a specific repair shop.

Table 5 illustrates that it differs per repair shop which characteristics is most important. However, the Table does not show which characteristic(s) is/are most important. Furthermore, the number of repair shops on which we have data to perform this analysis is too limited to make it generalizable. Therefore, a more generalizable analysis is performed in Chapter 5.

4.7 Conclusion

Based on literature, we conclude that the following quantitative characteristics are likely to affect the repair lead time:

- Utilization
- Average repair time per repair job
- Squared coefficient of variation of the repair time per repair job
- Variance to mean ratio of the interarrival rate
- Number of repairmen
- Average number of operations per repair job
- Squared coefficient of variation of the number of operations per repair job
- % of items responsible for 80% of the repair load
- Average number of materials required for repair
- % repair orders without materials
- % of repair jobs with at least 1 slow moving item
- Material demand rate

Based on interviews we also conclude that the following non-quantifiable information is also likely to impact the repair lead time of repairs:

- Degree of specialization of repairmen
- Pre-emption of repairs
- Priority of repairs

We also conclude that waiting time can be incurred in different stages of the repair process. These stages are in the repair job queue and during repair.

- Waiting time in the repair job queue is mainly incurred because of capacity complexity
- Waiting time during repair is mainly incurred, because of the absence of materials

Based on an analysis of where waiting times were incurred we are unable to make conclusions on which characteristics are most important.

Finally, we observed that in many for many cases data availability is limited. Characteristics which showed difficulty in measuring are the characteristics 'utilization', 'number of repairmen', 'Average number of operations per repair job' and 'squared coefficient of variation of the number of operations per repair job'. In order to make in depth analysis more valid we recommend to improve the data collection at the case study companies.

5 Statistical analysis of repair shop characteristics

In this chapter we present statistical analysis on the average waiting times of repair shops. We perform an analysis on waiting times because waiting time constitutes over 95% of the repair lead time. Section 5.1 provides an introduction to statistical analysis in this section we compare statistical analysis with other well-known methods for analysis and how we perform a regression analysis. The regression analysis itself is presented in Section 5.2. Section 5.3 presents a statistical analysis on repair job level to further validate the findings from the regression model. Section 5.4 presents the conclusion of this chapter. In this chapter we answer research question 3.

5.1 Introduction to the statistical analysis

5.1.1 Models for assessment of the effect of characteristics on the average waiting time

In this chapter we analyze the effect of characteristics on the waiting time. To perform such an analysis, multiple methods are available. Three well-known methods for analysis are:

- A simulation model
- An analytical model
- A statistical model

A simulation model is suitable in the (re)design phase of a system. A simulation model aids the designer in understanding the behavior and/or evaluating various strategies for (re)design of a system.

An analytical model is a mathematical model in which the outcomes are a result of some algorithm. In respect to a simulation model, an analytical model is faster and optimization is easier and better. However, an analytical model is not well suited for a complex environment. It is, for example, difficult to incorporate random events in an analytical model. Furthermore, as with a simulation model, it is mostly used to evaluate different strategies for the (re)design and/or improvement of systems.

This study is not focused on improving or the redesign of a system, but on the impact of characteristics on the waiting time. Therefore we do not use a simulation or an analytical model, but a statistical analysis. Statistics is the collection, classification, summarizing, organizing, analysis and interpretation of numerical information (McClave et al., 2009, p. 4). We use a statistical analysis, because a statistical approach is well suited to identify the relations between variables.

To analyze the relation between variables, several statistical tools exist. The statistical tools used in this chapter are (1) multiple regression and (2) two-sample reliability intervals. A regression model is useful in exploring the relation between 2 or more variables (Montgomery & Runger, 2003, p. 373). A two-sample reliability interval can be used to analyze whether there is a relation between characteristics and the average waiting time of repair jobs. Two-sample reliability intervals are used to further validate the relation between characteristics and the average waiting time in repair shops.

5.1.2 Background of a regression analysis

A general linear multiple regression model is displayed in Equation (6).

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k \tag{6}$$

In a multiple regression model there are K independent variables that might influence the output variable Y. In a regression model:

$K = The\ number\ of\ repair\ shop\ characteristics\ that\ influence\ Y$
$Y = The\ average\ waiting\ time\ in\ queue\ and\ in\ repair\ of\ repair\ jobs\ in\ a\ repair\ shop$

β_n represents the factor for which Y changes for each change of X_n and is also called the regression coefficient. β_0 is the intersect with the y-axis when all variables are 0. The betas are unknown and need to be calculated using software. This is done in Microsoft Excel. The regression coefficients are calculated using the least squares method in Equation (7). In Equation (7), *n* represents the number of observations and *K* represents the number of characteristics. (Montgomery & Runger, 2003, p. 414)

$$L = \sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{K} \beta_j x_{ij} \right)^2 \tag{7}$$

In Equation (7) ϵ_i^2 is the error in the model. The betas are calculated such that the aggregated error is minimized.

Appendix D outlines all statistical tests and methods that are used to analyze the accuracy and validity of regression models. The most important tests are:

- The adjusted R^2 which measures the percentage of variation between the average waiting times of repair shops that can be explained by the model. For the adjusted R^2, higher is better.
- Mallows C_p value which indicates whether relevant characteristics are not included in the model. For Mallows C_p value, lower is better.

A full description of how these tests and other tests are calculated is outlined in Appendix D.

5.2 Regression analysis of repair shop characteristics

A regression model assumes linear relations between the regression coefficients of the characteristics and the average waiting time (Montgomery & Runger, 2003, p. 447). When the relations are not linear, transformations have to be applied. In Section 5.2.1 we identify how relations should be modeled based on literature. In Section 5.2.2 we outline a preliminary analysis performed on the repair shop characteristics. Section 5.2.3 outlines the regression analysis performed on repair shop characteristics. Section 5.2.4 presents a sensitivity analysis. In this analysis we will further study the correlations between characteristics and present the result of an analysis only on KLM repair shops.

5.2.1 Relation between characteristics and the average waiting time

In order to model the relations between characteristics and the average waiting time, we performed an analysis on the theoretical relation between repair shop characteristics and the average waiting time. This analysis is outlined in Appendix C but the results are summarized below.

The waiting time is a nonlinear increasing function of the characteristics 'utilization' and 'average repair time'. This means that as the utilization and/or the average repair time increases, the average waiting time rises at increasing rate. This suggests a transformation will have to be applied in order to create a linear relation. Equation (8) shows how the relation between the characteristics and the average waiting time should be modeled, based on literature. In Equation (8) *a* represents β_0 and *b* represents β_1.

$$Y = aX^b\ with\ b > 1 \tag{8}$$

The characteristics 'squared coefficient of variation of the repair time' and 'variance to mean ratio of the number of arrivals' have a linear relation to the average waiting time. Therefore, no transformation needs to be applied.

The average waiting time is a nonlinear decreasing function of the characteristics 'number of repairmen'. This means that as the number of repairmen increases, the average waiting time decreases at a declining rate. Equation (9) shows how the relation between the characteristics and the average waiting time can be modeled. (Cohen et al., 2003, p. 262)

$$Y = \frac{X}{a + bX} \tag{9}$$

The characteristic 'average number of materials' has a nonlinear increasing relation to the average waiting time. This means that as the number of materials increases, it is likely that the average waiting time increases at a decreasing rate. For this characteristic we therefore also assume that a transformation will have to be applied. Equation (10) shows how the relation between the characteristics and the average waiting time can be modeled.

$$Y = aX^b \; with \; 0 < b < 1 \tag{10}$$

For the characteristics '% of repair jobs without materials', '% of repair jobs with at least 1 slow moving item' and 'material demand rate' no literature was found with which we could model the relation between the characteristics and the average waiting time. For these characteristics we will use graphical tools to determine the relation with the average waiting time.

Before we model the relations based on the theoretical relations, we perform a preliminary analysis of the data. Based on the preliminary analysis we will determine if transformation of the data is required.

5.2.2 Preliminary analysis of repair shop characteristics

In this section we present correlation plots and –coefficients in order to identify the relation between characteristics and the average waiting time in repair shops. The correlation coefficient is an easy to interpret measure for the relation between two variables. The formula for the correlation coefficient is presented in Equation (11). (Montgomery & Runger, 2003, p. 174)

$$\rho_{XY} = \frac{cov(X,Y)}{\sigma_X * \sigma_Y} \tag{11}$$

The correlation coefficient is an indicator for the relation between two variables (X and Y). A correlation coefficient close to 1 or -1 indicates a strong positive or negative relation. A correlation coefficient close to 0 indicates that there is hardly any relation between two variables. The correlation coefficients are calculated using excel.

However, not for all repair shops we were able to obtain sufficient data on all characteristics. For the characteristics 'number of repairmen' and 'utilization' we were unable to obtain data from NME and DBGS. For the characteristics, 'average number of operations per repair job' and 'squared coefficient of variation of the number of operations' we were only able to obtain sufficient data from KLM. Because of these data imperfections, the correlation coefficients for these characteristics are only calculated for the repair shops of which we have sufficient data. For the characteristics 'number of repairmen' and 'utilization' this is 19 repair shops. For the other two characteristics we have a sample size of 15 repair shops.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
Average Waiting time	0.20	0.65	0.22	0.45	0.03	-0.09	0.53	0.11	0.35	0.00	0.81	-0.51

Table 6. Correlation coefficients of characteristics and the waiting time

Table 6 displays the correlation coefficients between the characteristics and the repair shop waiting time. The letter indicates the characteristic outlined below.

(a) Utilization
(b) Average repair time per repair job
(c) Squared coefficient of variation of the actual repair time per repair job
(d) Variance to mean ratio of the number of arrivals per week
(e) Number of repairmen
(f) Average number of operations per repair job
(g) Squared coefficient of variation of the number of operations per repair job
(h) % of items responsible for 80% of the repair load
(i) Average number of materials required for repair
(j) % repair orders without materials
(k) % of repair jobs with at least 1 slow moving material
(l) Material demand rate

Table 6 shows that the characteristics (b), (g), (k) and (l) seem to have a strong correlation to the repair shop waiting time. That is, these show a correlation coefficient of larger than 0.5. All the other characteristics show far less relation to the repair shop waiting time. However, correlation coefficients are also impacted by the type of relation. We therefore also construct correlation plots of the characteristics and the average waiting time of repair shops.

The scatter plots are a graphical tool that we use to identify the relation between characteristics and the average waiting time in repair shop. When no apparent relation between characteristics and the waiting time in repair shops exists, the scatter plots will show a random cloud of points.

Figure 10 shows the correlation plots of characteristics on the x-axis and the average waiting time of repair shops on the y-axis. Each dot represents a repair shop. The Figure shows the correlation scatter plots in the same order as the correlation coefficients. This means that in Figure 10.a the characteristics 'utilization' is positioned on the x-axis and in Figure 10.b the average repair time. The blue dots are for the repair shops of which all data is available. The red dots are repair shops of which not all data is available.

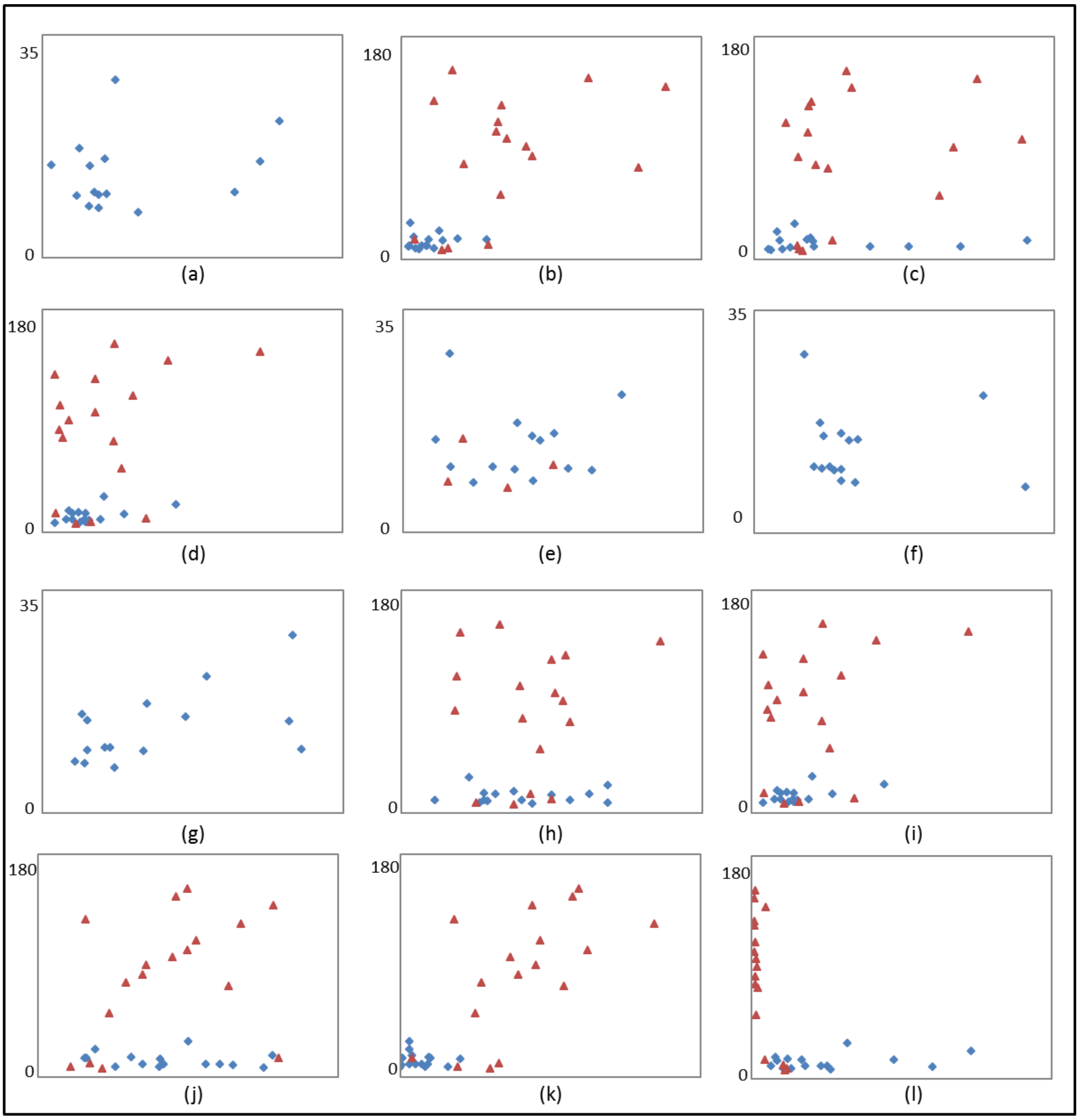

Figure 10.a to 10.l. Correlation plots of characteristics and the average waiting time

Based on the scatter plots, we conclude that the characteristics (b), (g), (k) and (l) seem to have a strong relation to the average waiting time of repair shops. However, based on the scatter plot 10.l we determine that the characteristic 'material demand rate' needs to be transformed in order to create a linear relation between the characteristic and the average waiting time of repair shops. The scatter plot suggests that not the material demand rate, but the mean time between material demands is a better indicator. The transformation applied to this characteristic is depicted in Equation (12).

$$Mean\ time\ between\ material\ demands = \frac{1}{\text{material demand rate}} \tag{12}$$

The transformation applied in Equation (12) is called a hyperbolic transformation. Figure 11 shows the scatter plot of the time between material requests and the average waiting time of repair shops. The figure shows that the relation between the characteristic and the average waiting time is now linear. Furthermore, the transformed material demand rate shows a partial correlation coefficient of 0.88 with the average waiting time in repair shops. This also indicates that the transformed characteristic is a better representation of the linear relation between the average waiting time of repair shops and the material demand rate.

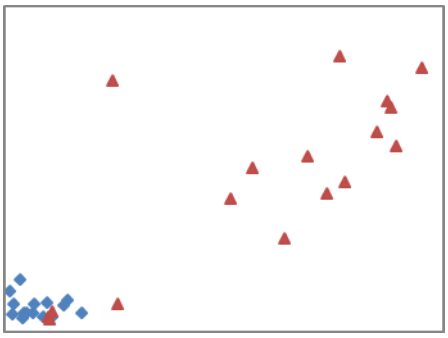

Figure 11. Scatter plot of the transformed characteristic 'material demand rate' and the average waiting time of repair shops.

The characteristics (a), (e), (f) and (g) are excluded from the remainder of the regression analysis because of three reasons. (1) Table 6 showed only little correlation with the average waiting time in repair shops. (2) The correlation plots do not show a relation between these characteristics and the average waiting time in repair shops. (3) We have insufficient data of these characteristics for all repair shops. If we chose to include these characteristics in the model, we would lose half of the observations. But since these characteristics show only little relation to the average waiting time of repair shops, we choose to omit these characteristics from the regression analysis. However, since especially the removal of the characteristic 'utilization' is counterintuitive we also perform a regression analysis on only the KLM repair shops. This analysis is outlined in Section 5.2.4.

The scatter plots do not show a relation as we expected based on the analysis presented in Section 5.2.1. For some characteristics a linear relation can be identified while for other characteristics no apparent relation can be identified. Therefore, we start with a regression analysis were we assume a linear relation between the characteristics and the average waiting time of repair shops (except for the material demand rate). Using a residual analysis we will determine whether other transformations are required.

5.2.3 Regression analysis on repair shop characteristics

Since we are not sure which characteristics should be included in the model, we apply an adjusted factorial design. In a factorial design with *K* regressors, there are 2^K possible combinations (Montgomery & Runger, 2003, p. 453). We have, in total, 8 repair shop characteristics on which we perform the regression analysis. Therefore, we have 256 possible combinations of characteristics on which a regression analysis can be conducted. Since an analysis on 256 possible combinations of repair shop characteristics is very time consuming, we apply the following heuristics.

1. Select the characteristics with the highest correlation with the average waiting time of repair shops
2. Construct a regression model for each characteristics individually
    a) Estimate the regression coefficients and calculate the adjusted R^2 and the C_p.
    b) Select the model/characteristics with the highest adjusted R^2 and the smallest C_p or the closest C_p to p. Where p is the number of regressors in the model plus 1.
    c) Introduce each characteristic to the model and calculate the adjusted R^2 and C_p values.
    d) Repeat steps a) b) and c) until the adjusted R^2 increases only little and/or C_p is close to p or starts to increase.

3. Check whether the regression model assumptions are met for each model.

By applying the above heuristic, we were capable of significantly reducing the number possible combinations that we needed to examine. The results from the heuristic are outlined in Table 7. An “x” indicates that the characteristic is included in the model.

Step	Model	Adj R^2	C_p	(b)	(c)	(d)	(h)	(i)	(j)	(k)	(l)
Step 1	1	82.6%	9.00	x	x	x	x	x	x	x	x
	2	39.7%	76.05	x							
	3	9.3%	117.87					x			
	4	64.5%	29.03							x	
	5	**76.1%**	**10.45**								x
Step 2	**6**	**81.7%**	**2.50**	x							x
	7	75.5%	12.05		x						x
	8	75.5%	15.22			x					x
	9	78.7%	7.54				x				x
	10	80.3%	6.80					x			x
	11	75.9%	14.16						x		x
	12	79.0%	9.08							x	x
Step 3	13	81.0%	6.56	x	x						x
	14	81.1%	6.56	x		x					x
	15	82.1%	4.84	x			x				x
	16	**82.3%**	**4.44**	x				x			x
	17	81.5%	5.79	x					x		x
	18	81.4%	6.00	x						x	x
Step 4	19	81.7%	6.38	x	x			x			x
	20	81.7%	6.40	x		x		x			x
	21	**83.0%**	**4.39**	x			x	x			x
	22	82.2%	5.58	x				x	x		x
	23	82.0%	6.00	x				x		x	x

Table 7. Results of the regression analysis

First, we created a regression model for the full *K+1* regression model. This in order to calculate the C_p values for the other regression models. Next, we created a regression model for the characteristics ‘average repair time’, ‘% of slow moving repair jobs with at least 1 slow moving material’ and the transformed ‘material demand rate’ since these characteristics have the highest correlation with the average waiting time of repair shops (step 1). We determined that the characteristic ‘material demand rate’ has the largest adjusted R^2 value and the lowest C_p value. Therefore, this characteristic was selected. Next (step 2), other characteristics were added one-by-one. Adding the characteristics ‘average repair time’ yielded the largest increase in adjusted R^2 and the smallest increase in C_p. Two additional iterations resulted in the inclusions of the characteristic ‘average number of materials’ (step 3) and ‘% of items responsible for 80% of the repair load’ (step 4). However, as Table 7 shows, the C_p value starts to rise significantly.

Next, we performed a residual analysis on models 6, 16, 21 to determine whether the assumptions of a regression model are met. These models are selected for a residual analysis because these models are the best models with *K* regressors. The residual analysis outlined in Appendix E showed that no model had any outliers. Furthermore, residual plots showed no anomalies and the residuals were fairly normally distributed. Also a check for multicollinearity of the variables yielded no significant implications. Therefore, we can base conclusions on the models we created.

Next we determine which model was most suitable to explain the variation in average waiting times of repair shops. The adjusted R^2 of the three models show only little difference. Therefore we looked at the statistical significance of the regression model. Table 8 displays the p-values for the entire regression model of each model.

Model	p-values
6	0.000
16	0.000
21	0.000

Table 8. Statistical significance of the regression

Table 8 shows that each model has a p-value that approximates 0. A model is statistically significant when the p-value is <0.05. This means that all regression models are statistically significant. Based on the p-values no best model can be selected.

To further analyze the models Table 9 displays the p-values of the regression coefficients for the different models. A p-value of less than 0.05 indicates a statistically significant regression coefficient. Table 9 shows that only for model 6 all regression coefficients are statistically significant. For model 16 the regression coefficient for the characteristic ‘average number of materials required for a repair job’ is not statistically significant. For model 21 all regression coefficients except for the transformed ‘material demand rate’ are not statistically significant.

Characteristic	Model 6	Model 16	Model 21
Material demand rate	0.00	0.00	0.00
Average repair time per repair job	0.00	0.05	0.15
Average number of materials required for repair		0.16	0.12
% of items responsible for 80% of the repair load			0.16

Table 9. P-values of the regression coefficients

Based on Table 9 we select model 6 as the model that provides the best explanation of the variation in average waiting time of repair shops. The formulation of the model is presented in Equation (13).

$$average\ waiting\ time\ in\ repair\ shop = -2.83 + \frac{60.42}{material\ demand\ rate} + 0.91 * average\ \ repair\ time \quad (13)$$

This model explains 81.7% of the variation in waiting times of repair shops.

5.2.4 Sensitivity analysis

In this section a sensitivity analysis is performed. In a sensitivity analysis we determine to which extend the outcome of the analysis changes when adjustments to the model are made. First, we identify whether the waiting time is under- or overestimated for a specific case study company. We also identify possible substitutes for the regression that currently exist in the regression model. Next we perform a regression analysis on a subset of observations of which all data is available. This, in order to identify other characteristics not taken into account in the current model also impact the average waiting time of repair shops.

Analysis of residuals
Appendix E outlines a residual analysis of the model described in Section 5.2.3. In the residual analysis we searched for patterns in the residuals to identify whether the model was valid. However, we did not yet take into account the residuals of the repair shops per case study company. Figure 12 shows the residuals versus the predicted *Y* values of the model selected in Section 5.2.3. Residuals of the observations of each case study company can be identified by a unique color. The figure shows that for the case study companies KLM, NME and DBGS the residuals are all located around the zero line. For GVB however, all observations have negative residuals. This suggests that for the repair

shops of GVB, the average waiting time is overestimated. This should be taken into account when making conclusions based on this model.

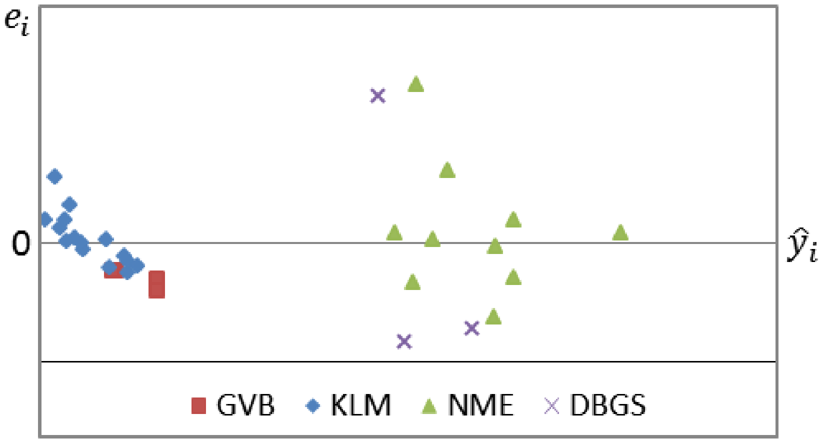

Figure 12. Residuals per company

Correlation coefficients

We calculated the correlation coefficient between characteristics in order to identify possible substitutes for the characteristics used in the current model.

	(b)	*(c)*	*(d)*	*(h)*	*(i)*	*(j)*	*(k)*	*(l)*
(b)	1							
(c)	0.30	1						
(d)	0.25	-0.04	1					
(h)	0.27	-0.05	-0.37	1				
(i)	0.51	0.22	0.03	0.10	1			
(j)	-0.43	-0.13	-0.10	-0.24	-0.28	1		
(k)	**0.69**	0.14	0.38	0.08	0.32	-0.20	1	
(l)	0.49	0.20	0.50	-0.08	0.15	0.09	**0.80**	1

Table 10. Correlation coefficients between characteristics

Table 10 shows that characteristic 'material demand rate' and 'average repair time' highly correlate (defined as a correlation coefficient of more than 0.6) with the characteristic '% of repair jobs with at least 1 slow moving material'. This suggests that these characteristics can be replaced by the characteristic '% of repair jobs with at least 1 slow moving material'. Replacing the characteristic 'average repair time' with this characteristic leads to model 12, which is significantly less accurate than model 6.

We can also replace the characteristic 'material demand rate' with the characteristic '% of repair jobs with slow moving material'. When this characteristic is used to construct a regression model along with the characteristic 'average repair time', the adjusted R^2 equals 74.7%. This is substantially less than the model presented in Equation (13).

We also repeated the analysis from Table 7 by excluding characteristics (b) and (l) and repeating all the steps. This resulted in a regression model which only included the '% of repair jobs with at least 1 slow moving material' and an adjusted R^2 of 64.5%. The model is outlined in Equation (14).

$$\begin{aligned}&\mathit{Average\ waiting\ time\ in\ repair\ shops}\\&\qquad = 6.26 + 250.83 * \%\ \mathit{of\ repair\ jobs\ with\ at\ least\ 1\ slow\ moving\ material}\end{aligned} \tag{14}$$

This shows that including the characteristic '% of repair jobs with at least 1 slow moving material' is not a complete substitute to the characteristics 'average repair time' and 'material demand rate'.

Regression analysis on repair shops with all characteristics
Appendix F outlines a regression analysis performed on the repair shops of KLM. In this analysis only the repair shops of KLM are included, because only for these repair shops all data is available.

The regression model shows that, for the repair shops of KLM, the regression model displayed in Equation (15) leads to the best results.

$$\begin{aligned} &Average\ waiting\ time\ in\ repair\ shops \\ &\quad = 16.92 + 16.91 \\ &\quad * Squared\ coefficient\ of\ variation\ of\ the\ number\ of\ operations\ per\ repair\ job \\ &\quad - 0.96 * number\ of\ repairmen \end{aligned} \tag{15}$$

This model has an adjusted R^2 of 46.3% and a C_p value of -0.9. Equation (14) shows that two different characteristics are included in the model, namely the characteristics 'number of repairmen' and 'squared coefficient of variation of the number of operations per repair job'. Although the adjusted R^2 is quite low, the fact that two other characteristics are included in the model suggests that also in the regression model on all repair shops these characteristics might have a significant impact.

We also observed that the utilization of repair shops does not have a statistical significant impact on the average waiting time even though there is a strong theoretical basis which suggests such a relation. We suspect that the utilization does not have a significant impact on the average waiting time, because of the different types of repairs performed in the repair shops (as outlined in Section 4.5). The utilization is currently calculated only for the pool repairable items. Because of this, the utilization is low in many of the repair shops. A low utilization has less impact on the waiting time in queue.

5.3 Statistical analysis on repair jobs

In this analysis we want to determine whether there is a statistical significant relation between characteristics and the waiting time of repair jobs of a specific repair shop. This is done to validate the findings from the previous section. To do so, we create two samples based on the characteristics. We measure the difference between the average waiting times of two samples and perform a test whether this difference is statistically significant. Section 5.3.1 outlines the statistical tests that we used. Section 5.3.2 outlines the characteristics which are included in the statistical analysis and how the samples are created. Section 5.3.3 presents the results of the statistical analysis. Section 5.3.4 outlines whether this study validates the findings from the regression model.

5.3.1 Statistical tests used in the analysis

We used two different tests to calculate the difference between samples. The statistical test we perform depends on whether we can apply the central limit theorem (McClave et al., 2009, pp. 183-185). The central limit theorem states that when we randomly select a sufficiently large sample size from a population, the sample mean (in our case: average waiting time) will approximate a normal distribution at the sample mean. A sufficiently large *n* is considered to be at least a sample size of 30. (McClave et al., 2009, p. 186)

For sample sizes larger than 30 we can apply the central limit theorem and assume normally distributed estimate of the waiting time. For these repair jobs, we construct a 95% reliability interval for the expected difference in average waiting time between the two samples. The calculation for the reliability interval is presented in Equation (16).

$$\bar{x}_1 - \bar{x}_2 \pm z_{\alpha/2}\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} \tag{16}$$

In Equation (16) $\bar{x}_n$ is the average waiting of repair jobs in a sample size, $z_{\alpha/2}$ is the standard score with $= 0.05$. In a 95% reliability interval $z_{0.025} = 1.96$. The σ_n^2 is the standard deviation of a sample and n_n is the sample size. When the reliability interval contains 0, there is no statistically significant difference between the average waiting time of the two sample sizes.

Figure 13 shows a graphical representation of the average waiting time of the two samples and the difference for which a reliability interval is constructed. The reliability interval also compensates for different sample sizes, when these occur.

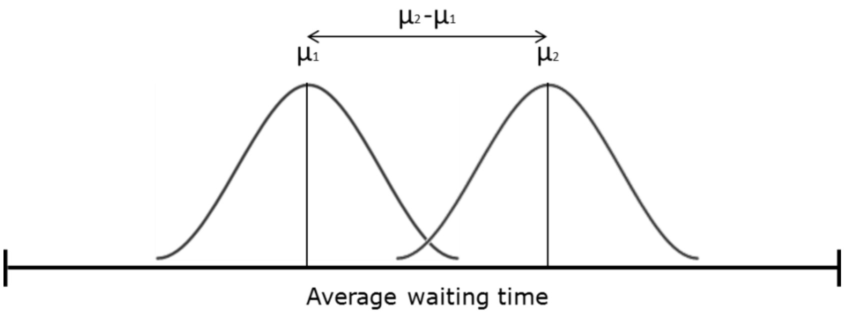

Figure 13. Reliability interval for the difference in mean waiting time in two independent samples

In the case that (one of) the sample sizes is not sufficiently large, we cannot assume a normal distribution at the sample mean based on the central limit theorem. In these instances the Wilcoxon rank-sum test is used (McClave et al., 2009, pp. 621-624). In this test the observations of both sample sizes are combined and ranked according to their value. The test checks for statistically significant differences in the sum of ranks in either sample size. Because this test is performed on ranks and not on the values it is independent of its distribution. This means that normality of the sample size is not required. Again, we will be able to state with 95% accuracy whether to reject or retain the hypothesis.

5.3.2 Characteristics on which the statistical test is performed and hypotheses

Before the statistical analysis is conducted, we need to determine which characteristics can be included in this study. The analysis is performed for each repair shop separately. To perform this analysis, data on repair job level is required. Some characteristics do not vary on repair job level and are aggregated on repair shop level, for example the utilization of a repair shop, or the coefficient of variation of the repair time. Therefore, we cannot properly use these characteristics in this statistical analysis. The characteristics included in the statistical analysis are presented below.

- Average repair time
- Average number of operations
- Number of materials [5]
- % of repair jobs with slow moving materials

[5] This includes both the characteristics "% of repair jobs without materials" and "average number of materials required per repair job".

The characteristics not included in the statistical analysis because of the before mentioned reasons (the fact that these are not measured on repair job level) are:

1. Coefficient of variation of the actual repair time per repair job
2. Coefficient of variation of the number of operations
3. Number of repairmen
4. Utilization
5. % of items responsible for 80% of the repair load
6. Variance to mean ratio of the number of arrivals
7. Material demand rate

To analyze whether capacity characteristics “average repair time” and “average number of operations” show a relation with the waiting time of repair jobs, two hypotheses are formulated. The hypotheses are based on the theoretical relation between the average waiting time and characteristics outlined in Appendix C. The first hypothesis addresses the repair times. The second hypothesis considers the number of operations per repair job. This test can only be conducted for KLM, since only at this company sufficient data is available.

1. The average waiting time of jobs, in which repairable items have high repair times, does not statistically differ from the average waiting time of jobs in which items have short repair times.
2. The average waiting time of jobs, in which items require many operations, does not statistically differ from the average waiting time of jobs in which items require few operations.

To analyze whether the material characteristics “number of materials” and “% of repair jobs with slow moving materials” show a relation with the waiting time of repair jobs we consider two hypotheses. The hypotheses are based on the theoretical relation between characteristics and the average waiting time outlined in Appendix C. The two null hypotheses are as follows:

3. The average waiting time of jobs, in which materials are required, does not statistically differ from the average waiting time of jobs in which no materials are required.
4. The average waiting time of jobs, in which slow moving materials are required, does not statistically differ from the average waiting time of jobs in which no slow moving materials are required.

5.3.3 Result of the statistical analysis on the average waiting times of samples

This section outlines the results of the statistical analysis per characteristic. We provide aggregate results over all repair shops. For the results per repair shop we refer to Appendix G.

Tables 11 to 14 display the result of the statistical tests. In the case the hypotheses are rejected, there is a statistically significant difference between the average waiting time of the two samples. We then state that there is a positive H_0 hypothesis rejection.

However, a rejection of the null hypothesis does not necessarily mean that the impact of characteristics is as we expected. For example, we might identify that in a repair shop repair jobs in which materials are required have shorter average waiting times than repair jobs in which no materials are required. This is contradictory to what we expected, based on literature. In the Tables 11 to 14 these observations are called ‘negative H_0 rejections’. When possible, an explanation is provided for the deviating result.

Statistical analysis of average repair times

For this analysis, we created two samples. One sample contains repair jobs which require short repair times and the other sample contains repair jobs which require long repair times. We defined "long" has having higher repair times than the median. We used the median, because there are high values for repair times that increase the average repair time. When using the median there are two groups of equal size. Table 11 shows that for 72% of the repair shops, we were able to reject the null hypothesis.

H_0 hypothesis	Number of shops	Reject H_0 Positive	Reject H_0 Negative	Do not reject H_0	% of H_0 positive rejections
The average waiting time of jobs, in which repairable items have high repair times, does not statistically differ from the average waiting time of jobs in which items have short repair times.	32	23	5	4	72%

Table 11. Aggregate results of statistical analysis on repair times

The hypothesis on the repair times had 5 negative H_0 rejections[6]. Unfortunately, neither we nor repair shop managers have an explanation for why there are 5 negative rejections of the null hypothesis.

For two repair shops we were unable to reject the null hypothesis with 95% certainty. But we are able to reject the hypothesis with 90% certainty[7]. In that case, we would have a total of 25 positive null hypothesis rejections.

Statistical analysis of number of operations

In this case, a "high number of operations" is considered to be more operations than on average in the same repair shop. We used the average number of operations in a repair shop two create to samples, because there are no very high values. This indicates that the average is a reliable measure for 'many operations'. In the case of the statistical analysis on the number of operations, we only took KLM into account, since this is the only company with sufficient data. Table 12 shows that for 80% of the repair shops we were able to reject the null hypothesis.

H_0 hypothesis	Number of shops	Reject H_0 Positive	Reject H_0 Negative	Do not reject H_0	% of H_0 positive rejections
The average waiting time of jobs, in which items require many operations, does not statistically differ from the average waiting time of jobs in which items require few operations.	15	12	2	1	80%

Table 12. Aggregate results of statistical analysis on operations

There are two repair shops of which the hypothesis was negatively rejected[8]. We were unable to obtain a specific reason for the negative rejections of the null hypothesis for these two shops.

Statistical analysis of materials requirements

Table 13 provides an overview of the tested H_0 hypotheses and the aggregate results of the statistical analysis. The Table shows that for 75% of the repair shops the H_0

[6] KL 4, KL7, KL12, DBGS3 and NME10
[7] NME4 & NME7
[8] KL11 & KLM12

hypothesis could be rejected. In these cases, there is a statistical significant difference between the average waiting times of repair jobs as was expected based on the analysis of characteristics. We conclude that it is likely that there is a relation between the characteristic and the waiting time of repair orders.

H_0 hypothesis	Number of shops	Reject H_0 Positive	Reject H_0 Negative	Do not reject H_0	% of H_0 positive rejections
The average waiting time of jobs, in which materials are required, does not statistically differ from the average waiting time of jobs in which no materials are required.	32	24	2	6	75%

Table 13. Aggregate results of statistical analysis of material requirements.

However, in the case of the first hypothesis, there are 2 repair shops of which we were able to reject the null hypothesis, but because of the wrong reason[9]. In these shops the average waiting time was larger for repair jobs without materials than for repair jobs that require materials. The negative rejection of shop GVB 110A can be partially explained. Here, over 80% of the repair jobs do not require materials. It is more likely that the waiting is more affected by another characteristic.

Statistical analysis of slow moving material requirements
Table 14 shows the results of the statistical test on the average waiting times for repair jobs in which slow moving materials are required and repair jobs in which no slow moving materials are required. One repair shop (KLM R3E) that had to be excluded since this repair shop didn't require any slow moving materials. The table shows that for 71% of the repair shops we could positively reject H_0.

H_0 hypothesis	Number of shops	Reject H_0 Positive	Reject H_0 Negative	Do not reject H_0	% of H_0 positive rejections
The average waiting time of jobs, in which slow moving materials are required, does not statistically differ from the average waiting time of jobs in which no slow moving materials are required.	31	22	2	7	71%

Table 14. Aggregate results of statistical analysis on slow moving material requirements

In the case of repair jobs which require slow moving materials there is Here we also see two shops for which the H_0 hypothesis is negatively rejected[10]. No apparent reason for these findings could be found.

5.3.4 Relation between the average waiting time of repair jobs and repair shops

The analysis in Section 5.3.3 showed that the null hypothesis could always be rejected for at least 71% of the repair shops. However, we are not only interested in the number of null hypothesis rejections, but also which characteristic showed the strongest correlation with the average repair time. This might further validate the findings from the regression analysis.

In order to make statements on which characteristics have an effect on the waiting time of repair jobs, we performed a qualitative analysis of 26 repair shops in which we did not perform the Wilcoxon rank-sum test. Appendix H presents an overview of the repair

[9] GVB2 & NME8
[10] Repair shops NME7 and DBGS3

shops with the difference in average waiting time (in days) between the samples based on a characteristic. Based on the difference between average waiting times of samples in the Appendix H, we conclude that for 14 out of the 26 analyzed repair shops there is no significant difference in the impact of different characteristics on the waiting time. For 12 out of 26 repair shops the material related characteristics show a significantly higher impact on the average waiting time of repair jobs.

These findings further validate the results from the regression analysis. Material related characteristics have slightly more impact on the average waiting time as is also illustrated by the high correlation coefficient of the material demand rate. But, the capacity related characteristics should not be neglected.

5.4 Conclusion

Based on this chapter, we conclude that:

- The characteristics 'material demand rate' and 'repair time' have the largest impact on the difference in average waiting time of repair shops. These two characteristics were able to explain 81.7% of the variation in average waiting between repair shops.
- The arrival rate seems to have less impact on the repair lead time. Most likely, this is because of the failed LRU stock before repair jobs are released to the repair shop.
- Counter intuitively, the utilization of repair shops is also of less importance. However, this is due to missing data and different types of repairs performed in repair shop which make the utilization not representative.
- A sensitivity analysis of in which a regression model was constructed for only the KLM repair shops lead to a model with the characteristics 'number of repairmen' and 'squared coefficient of variation of the number of operations per repair job'. This suggests that data on these characteristics needs to be obtained for all repair shops in order to increase the validity of our conclusions.
- 2-sample reliability intervals showed that repair jobs with high repair times have a longer waiting time in 72% of the repair shops. Repair jobs with many operations have higher waiting times in 80% of the repair shops of KLM. Repair jobs which require materials have higher waiting times in 75% of the repair jobs. Repair jobs which require slow moving items have higher average waiting times compared to repair jobs with materials in 71% of the repair shops.
- A qualitative analysis showed that for 12 out of 26 analyzed repair material related characteristics have a larger impact on the average waiting time of repair jobs. In 14 out of 26 repair shops no significant difference could be identified. This validates the earlier findings that both capacity and material related characteristics impact the average waiting time.

6 Practical implications

In this section we outline the practical implications of this research. Section 6.1 outlines the combinations of characteristics for which we propose agreements and decisions. Section 6.2 provides advice to the case study companies regarding the current agreements. This chapter answers research question 5.

6.1 Agreements for combinations of characteristics

6.1.1 Combinations of characteristics

In Chapter 4 we outlined the characteristics that affect the lead times of repairs. These characteristics related to capacity complexity, materials required for repair and the arrival rate of repairs. In Chapter 5, a statistical analysis showed that the capacity characteristic 'average repair time' and the material characteristic 'material demand rate' have the largest impact on the difference of average waiting times between repair shops. We also suspect that the qualitative characteristics 'degree of specialization' impacts the waiting time in queue based on the interviews. The characteristic relating to the arrival rate of repairable items was less important in explaining the difference between the average waiting times of repair shops.

The characteristics 'average repair time' and 'degree of specialization' relate to capacity complexity. The capacity complexity is high when repair jobs have, on average, long repair times and the degree of specialization of repairmen is very high. Long repair times and a high degree of specialization of repairmen leads to long waiting times due to capacity complexity.

The characteristic 'material demand rate' relates to material uncertainty. When the material uncertainty is high, the material demand rate is low. This implies that the possibility of having a material not on stock is high. The possibility of waiting time due to the absence of materials increases.

Repair shops either have high or low material uncertainty and high or low capacity complexity. We also suspect that combinations exist (e.g. high material uncertainty and low capacity complexity). This resembles the typology of Bertrand et al. (1990) although there are small differences which we will not go into detail here. In this research we do not go into depth of the precise definitions of what is high or low, nor do we focus on where the repair shops of companies are positioned in terms of capacity complexity and material uncertainty. We focus more on the implications of this combination of characteristics.

6.1.2 Agreements and decisions for combinations of characteristics

In the previous section we outlined the different combinations of characteristics that exist in repair shops. This section outlines agreements and decisions for these combinations. However, because of time constraints we are unable to validate these agreements and decisions using a mathematical analysis or a simulation model. To still have a certain degree of validation, a discussion session was organized for Gordian consultants. During the discussion the 4 different combinations of characteristics that can be distinguished were outlined by me. Then, 4 groups were created. Each group was asked to identify strategic, tactical and operational agreements and decisions that could be made between the repair shops and inventory control in a specific setting in order to reduce the (variability) of the repair lead time. Each group was then asked to present the agreements to the other discussion groups. The result was a discussion in which all groups were able to comment on the agreements developed by the other groups. The result of the session was used to validate the agreements and decisions below.

Combination I: Low material uncertainty/low capacity complexity
In combination I, the materials required for repair are relatively certain and the availability of materials will be high. The repair times are reasonably short and there is a low degree of specialization of repairmen. For this combination of characteristics we developed the agreements and decisions outlined in Table 15.

Level	Agreements/Decisions
Tactical	Min-Max inventory agreements
Operational	Dynamic priority rules Overtime

Table 15. Agreements for repair shops with low capacity complexity and low material uncertainty

For repair shops with low material uncertainty and low capacity complexity we assume that the added value of repairs is limited. Therefore, the objective should be to make optimal use of the available capacity. As the research of Loeffen (2012) outlined, min-max inventory agreement outperform lead time agreements in the case of high utilization. Therefore, for repair shops with this combination of characteristics a min-max inventory level agreement between repair shops and inventory control is advisable.

The repair lead time can be decreased with the use of dynamic priority rules (e.g. MSTRQ2-SPT) as outlined by Hausman and Scudder (1982). As a means for temporary capacity improvement, overtime can be used on an operational level.

Combination II: High material uncertainty/low capacity complexity
In a repair shop with high material uncertainty priority rules prior to inspection will not be as effective as for repair shops with combination I characteristics. This is because the material uncertainty required for the repair of items is high. An outline of the agreements and decisions in repair shops with combination II characteristics is presented in Table 16.

Level	Agreements/Decisions
Tactical	Integrate inventory control of LRU's and materials Disconnect inspection and repair
Operational	Due dates on inspection Minimize batch size

Table 16. Agreements for repair shops with low capacity complexity and high material uncertainty

In a repair shop with high material uncertainty, inventory models need to be applied in order to minimize the waiting time due to the absence of materials. In Section 4.1.2 we discussed the MOD-METRIC model of Muckstadt (1973) and the VARI-METRIC model of Sherbrooke (1986). In these models the relation between LRU's and SRU's is explicitly incorporated in the setting of inventory levels. By introducing inventory models that integrate the decision for SRU's and LRU's an optimal balance of SRU holding cost and longer repair lead times (and thus high LRU holding cost) can be found.

In order to integrate the control of LRU's and materials the inspection and repair phases outlined in Section 3.1 have to be disconnected. By disconnecting the inspection and repair phases, an item is inspected and then put aside until it is repaired. By disconnecting the inspection and repair phases, priorities can be determined after inspection and based on the availability of materials required for repair.

We also want to illustrate the effect of batching on the material demand rate. For, batching, which is often used in repair shops increases the material uncertainty because materials are requested once for the entire batch. See Figure 14 for a graphical representation of the effect of batching on the material demand rate. The red columns are an upper bound for the material demand rate when the batch size is 1. Because of this relation, especially for repair shops with high material uncertainty, batching is unadvisable.

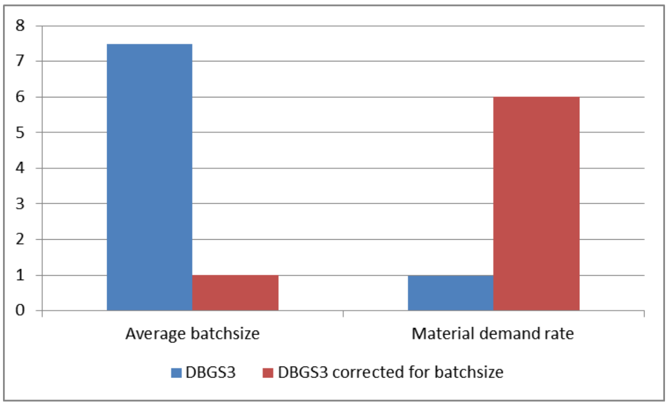

Figure 14. The effect of batching on the material demand rate

Combination III: Low material uncertainty/high capacity complexity
Repair shops with combination III, have characteristics that indicate high capacity complexity and low material uncertainty. This suggests that agreements in these repair shops should focus on minimize the waiting time on capacity. Table 17 outlines agreements that can be used to minimize the waiting time due to capacity.

Level	Agreements/Decisions
Tactical	Differentiated repair lead times Overtime
Operational	Priority rules

Table 17. Agreements for repair shops with high capacity complexity and low material uncertainty

The work of both Sleptchenko et al. (2005) and Adan et al. (2009) shows that in a repair shop with high capacity complexity, priorities based on repair times and price of repairable items can significantly decrease the investment costs for these repairable items. Furthermore, Adan et al. (2009) shows that 2 priority classes are sufficient to obtain 90% of the savings. Repair shops with this type of combination of characteristics should therefore differentiate repair lead time agreements in 2 classes.

Also overtime on tactical level can be used. Overtime on tactical level is to plan overtime (e.g. 2 weeks in advance) instead on the day itself. The work of Scudder and Chua (1987) on overtime policies in repair shops is likely to decrease the repair lead time. Using overtime on tactical level increases the capacity flexibility, because overtime can be compensated with additional days off for repairmen when less capacity is required.

An operational decision is to use priority rules that take into account the complexity of the LRU and/or the repair process. Priority rules found in literature can be based on the work of Guide Jr et al. (2000) or Hausman and Scudder (1982).

Combination IV: High material uncertainty/High capacity complexity
Repair shops with combination IV characteristics have characteristics relating to high material uncertainty and high capacity complexity. Agreements and decisions for this combination of characteristics should therefore diminish the waiting time due to capacity constraints and due the uncertainty in materials required for repair of LRU’s. An overview of agreements developed for this combination of characteristics is presented in Table 18.

Level	Agreements/Decisions
Strategic	Insourcing or subcontracting
Tactical	Integrate control of LRU's and materials Disconnect inspection and repair
Operational	Due dates based after inspection

Table 18. Agreements for repair shops with high capacity complexity and high material uncertainty

In order to decrease the material uncertainty and also decrease the capacity complexity an agreement could be to insource or subcontract repairs. An insourced repair is a repair performed for another company. By insourcing repairs the economies of scale might lead to a reduced material uncertainty, because the material requirements become more predictable because of a larger installed base. Because of the insourcing, also more capacity will be required which might reduce the capacity complexity because more (specialized) capacity will become available. A different approach is to subcontract repairs. In this case, another company will benefit from the economies of scale and will be able to reduce the repair lead time.

On operational level, due dates and priorities will have to be set after inspection. By disconnecting inspection and repair, items are put aside until the materials and capacity required for the repair become available. In order to achieve this, the inspection of an item will have to be improved ensure that all failed materials are identified.

6.2 Reflection on the case study companies

Although this study does not go into detail of which agreements should be used for which repair shops of the case study companies, we are able to make recommendations on the current agreements that are made between inventory control and the repair shops.

GVB currently uses a Min-Max inventory model. The maximum inventory levels are currently set equally for every item based on a standard lead time of four weeks. To further optimize the inventory levels, we suggest to differentiate the repair lead times for shops with a low and high repair time. Repair shops that repair items with on average short repair times have a lower waiting time, which means that repair lead times are shorter. Repair lead time differentiation may reduce the stock investments.

At KLM, fixed repair lead times are agreed between inventory control and repair shops. The lead times are based on experience and previously realized repair lead times. Although the use of differentiated lead times is useful, further improvements can be made by determining the repair lead times also on the price of LRU's. Sleptchenko et al. (2005) showed that priorities based on both price and realized repair lead times can significantly reduce the investment costs. By including the price of an item, expensive items will have a shorter repair lead than cheap items of which the investment cost is lower. A further improvement can be made by also taking the demand frequency of repairable items into account. A longer repair lead time may be applied to slow moving items than for fast moving items, because slow moving items are required less.

NME currently has an agreed lead time of 3 months, but in practice each repair job has a different repair lead time which is set by inventory control. The lead time is set before inspection usually in cooperation with the repair shop. As an improvement we recommend that inventory control sets due dates for repairs in cooperation with the repair shop after inspection. While also considering the upcoming demand for parts. In this manner, more realistic due dates can be set. Also useful for NME is to integrate the control of LRU's and SRU's in order to find an optimal balance of LRU and SRU holding costs.

DBGS currently uses lead time and batch sizes per repairable item. As the analysis in Section 6.1 showed, batching currently has a negative impact on the material demand rate and repair job waiting times. Therefore, we suggest DBGS to research what the optimal batch sizes are in order to gain the benefits of more accurate forecasts for (and availability of) materials.

6.3 Conclusion

In this section we outlined that there are 4 combinations of characteristics to which agreements should be tailored to. The main characteristic relating to material uncertainty is the material demand rate. The main characteristics relating to capacity complexity are the repair time and degree of specialization of repairmen. The 4 combinations of characteristics are:

- Combination I: Low material uncertainty/low capacity complexity
- Combination II: High material uncertainty/low capacity complexity
- Combination III: Low material uncertainty/High capacity complexity
- Combination IV: High material uncertainty/High capacity complexity

Agreements and decisions for repair shops with a combination of characteristics are:

- Combination I: Inventory min-max levels, dynamic priority rules and overtime in the repair shop.
- Combination II: Integrate control of materials and LRU's, disconnect inspection and repair, base priorities on inspection and minimize batch sizes.
- Combination III: Create classes of repair lead times based on the repair time and price of repairable items, overtime on tactical level to create capacity flexibility and priority rules to minimize the waiting time.
- Combination IV: On strategic level, a decision to insource or subcontract repairs can be taken. On tactical level, due dates should be made based on inspection and the control of LRU's and materials should be integrated. Also the inspection should be disconnected from repair.

The recommendations for the case study companies are:

- GVB should include the repair time in the calculation of min-max inventory levels in specific repair shops.
- KLM should categorize the agreed repair lead time based on the price and demand frequency of a repairable item.
- NME should set due dates for repairs after inspection and integrate the control of LRU's and SRU's.
- DBGS should research what the optimal batch sizes of repairable items are to increase the material demand rate.

7 Conclusion and recommendations

In this chapter we outline the final conclusions and recommendations of this research. Section 7.1 outlines the conclusions by providing the answer to the research questions we set in Chapter 1. Section 7.2 outlines the recommendations resulting from this research.

7.1 Conclusions

The objective of this research was to identify the most important repair shop characteristics and how agreements and decisions need to be tailored to these characteristics. Data for this research was gathered at 4 case study companies (GVB, KLM, NME and DBGS) with a total of 32 repair shops. Data was gathered on repair jobs and material requirements for January to December 2012 in the case of KLM, January 2011 to December 2012 for GVB and January 2010 to December 2011 for both NME and DBGS. Only for KLM we obtained accurate information on the number of operations. The utilization caused difficulties to calculate because of different types of repairs that are performed in the repair shops.

The 5 research questions and the answer of each research question is outlined below.

Research question 1: What are possible agreements between inventory control and repair shop control based on literature?

Answer: From literature we identified agreements and decisions that could be made between repair shops and inventory control. These agreements and decisions are:

- Agreements on min-max inventory levels for repairable items
- Classes of repair lead times based on repair time and item cost
- Overtime
- Batching in the case of very high setup times
- Dynamic priorities

The analysis of agreements in literature showed that many agreements and decisions work well, but do not take into account both capacity complexity and material complexity.

Research question 2: What does the repair process look like and what are characteristics of the case study companies?

Answer: The repair process can be modeled as a closed loop supply chain in which items are only discarded when these are degraded too much. The case study companies have 2 types of repair shops, task- and product oriented. Task-oriented repair shops have a single task whereas product-oriented repair shops perform multiple repair steps. This research focused on product-oriented repair shops. We also identified the current agreement between repair shops and inventory control. GVB uses min-max inventory levels and KLM, NME and DBGS use lead time agreements.

Research question 3: Which repair shop characteristics affect the repair lead time?

Answer: From literature on general production unit typology, queuing theory and inventory models we identified characteristics that are likely to have an effect on the repair lead time. We identified characteristics that relate to capacity constraints, materials required for repair and the arrival rate of failed LRU's. The characteristics are:

- Utilization
- Average repair time per repair job

- Squared coefficient of variation of the actual repair time per repair job
- Variance to mean ratio of the interarrival rate
- Number of repairmen
- Average number of operations per repair job
- Squared coefficient of variation of the number of operations per repair job
- % of items responsible for 80% of the repair load
- Average number of materials required for repair
- % repair orders without materials
- % of repair jobs with at least 1 slow moving item
- Material demand rate
- Degree of specialization of repairmen (qualitative)
- Pre-emption of repairs (qualitative)
- Priority of repairs (qualitative)

A preliminary analysis of the waiting time showed that further analysis of the effect of characteristics on the waiting time was required.

Research question 4: What are the most important repair shop characteristics?

Answer: In a statistical analysis we determined which characteristics have the largest effect on the repair lead times. A regression analysis on the effect of characteristics on the average waiting showed that the characteristics 'material demand rate' and 'average repair time' have the largest impact on the average waiting time of repair jobs. The model outlined below explains 81.7% of the difference in average waiting time between repair shops.

$$average\ waiting\ time\ in\ repair\ shop = -2.83 + \frac{60.42}{material\ demand\ rate} + 0.91 * Average\ \ repair\ time$$

A statistical analysis of repair jobs also showed that both the repair time and characteristics relating to material impact the waiting time of repair jobs in a repair shop. Both the regression model and the analysis on repair jobs indicate that characteristics relating to materials have slightly more impact on the waiting time than capacity related characteristics.

Research question 5: Which combinations of repair shop characteristics can we identify and to which extend need agreements and decisions be tailored to these combination of characteristics?

Answer: We identified that repair shops can have both high/low capacity complexity and high/low material uncertainty. Because of this we distinguished 4 different combinations of characteristics. Agreements and decisions needed to be tailored to the combination of characteristics.

- Combination I Low material uncertainty/low capacity complexity: Inventory min-max levels, dynamic priority rules and overtime in the repair shop.
- Combination II High material uncertainty/low capacity complexity: Integrate control of materials and LRU's, disconnect inspection and repair, base priorities on inspection and minimize batch sizes.
- Combination III Low material uncertainty/High capacity complexity: Create classes of repair lead times based on the repair time and price of repairable items, overtime on tactical level to create capacity flexibility and priority rules to minimize the waiting time.
- Combination IV High material uncertainty/High capacity complexity: Insource or subcontract repairs, due dates should be based on inspection, integrate the control of LRU's and materials and disconnect inspection from repair.

With this conclusion we obtained the objective of this research. We were able to identify agreements that between inventory control and repair shops and we were able to tailor these to specific repair shop characteristics.

7.2 Recommendations

In this section we provide recommendations for further research.

Increase the validity of this research with more data on other repair shops:
This research is an attempt to identify combinations of repair shop characteristics based on empirical data. The data we gathered is collected from 32 repair shops at 4 different case study companies. However, for a number of repair shops included in this research useful data was missing. For example, the utilization of repair shops (which is likely to have a significant impact) was difficult to calculate. Also, the repair shops included in this study also repair other parts than components. Data from repair shops which only perform component repairs would increase the data reliability and thus the conclusions. However, since the current regression model also explains a large percentage of the variation in waiting time inclusion of the utilization is, based on current information, not absolutely necessary to continue with this research.

Typology of repair shops:
In this research, we identified combinations of characteristics and how agreements can be tailored to these combinations. We did not study what the precise combination of characteristics of each repair shop is. To aid companies to control the repair shops, we recommend performing an analysis on where the repair shops can be positioned based on material uncertainty and capacity complexity. This includes defining high and low material uncertainty and capacity complexity. This will aid the case study companies in determining which agreements would be beneficial and in which repair shop.

Analysis of the effect of agreements in different types of repair shops:
The practical implications of this thesis were discussed in Chapter 6. We presented several agreements and decisions tailored to combinations of characteristics. Some agreements and decisions come from literature, and have therefore been extensively studied, whereas others such as the separation of inspection and repair are not yet studied. We therefore recommend to study the effects of agreements and decisions in the different types of repair shops.

We also have the following recommendations for the case study companies.

Improve data collection
We recommend the case study companies to improve the integration of systems and to collect more data on utilization and number of operations. This increases the reliability of analyses made on the repair shops.

Improve current agreements

- GVB should include the repair time in the calculation of min-max inventory levels in specific repair shops to minimize inventory costs.
- KLM should categorize the agreed repair lead time based on the price and demand frequency of a repairable item to minimize inventory costs.
- NME should set due dates for repairs after inspection and integrate the control of LRU’s and SRU’s to decrease the (variability in) repair lead time
- DBGS should research what the optimal batch sizes of repairable items are to increase the material demand rate and the availability of materials.

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Appendix A: Interview scheme

This appendix outlines the interview scheme we used to identify qualitative repair shop characteristics and the different types of repair shops. The questions in the interviews scheme are based on the literature presented in Chapters 2 and 4.

Introduction

- What is your function in [company name]; what do you do, responsibilities etc.

Objective: What are general characteristics of repair shops

- Which repair shops exist in this company? Why do you have different repair shops?
- What are the stock points? When are priorities given to repairs?
- Per repair shops; Relatively easy or complex repairs?
- Per repair shop; Which agreements are there in the repair process (e.g. pre-emption of repairs)?
- How do you determine which repair job should be repaired first?
- When are SRU’s required for repair determined?

Objective: Identification of relations between repair shops

- Are LRU’s repaired in different repair shops or only 1?
- Can repairmen be deployed within a single department on multiple workstations?
- How independent are the repair shops? Do the repair shops always require capacity/aid from other repair shops or do they operate completely independent?
- Where does the demand for capacity come from? Inventory control or other repair shops?
- Are there also repairable SRU’s. Do these repairs take place in the repair shop or in different repair shops?
- Which repair shops are used by other repair shops (e.g. painting and machining)

Objective: Identification of repair shop characteristics

- How are the repairs planned, singles or batch or continues process?
- How many workstations are involved in the repair of items? (process description)
- Within a repair shop, are there many different routings LRU’s take?
- How many workstations are required per routing? (1 person/machine or multiple persons/machines)
- Which resources are required per routing? What are the bottlenecks?
    - Repairmen?
    - Machines?
    - Materials?
- Do workstations require specific resources?
- Is there a large variety in required resources?
- Are the resources relatively easy obtainable?
- Can the capacity be increased and how?

Objective: identify current agreements between repair shops and inventory control

- KPI’s & Scheduling & interface agreement
    - How are repair jobs planned?
    - Who sets priorities and how are these priorities determined?
    - How is the performance of repair jobs determined?
    - What are the agreements with inventory control
    - Why do you have these agreements?
    - Do the current agreements work? Why (not)?

Appendix B: Background information of the case study companies

In this section we briefly discuss the case study companies in more detail. Per case study company we discuss the maintenance concept and how the repair process is organized.

GVB

Maintenance concept
Maintenance on trams and metros of GVB is done in workshops. Here parts are replaced by spares. These spare parts are called Line Replaceable Units (LRU's). The LRU's can be replaced either preventively or correctively. Preventive maintenance at GVB is in done in a project. In a project, all trams or metros of a specific type undergo the same maintenance. A project usually takes a long period of time (1 to 2 years). Which LRU's are replaced is dependent on the type of project. An example of a project is the P8. This is maintenance on trams performed every eight years.

In a project parts are replaced via a repair-by-repair policy. In a repair-by-repair policy the LRU is disassembled from the asset, repaired in the repair shops and reinstalled on the same asset. An example is a wheel set. In a project, LRU's are always overhauled. This means that the quality of the LRU is as good as new after the repair.

Corrective maintenance is required when a part fails and needs to be replaced in order for the asset to function. In corrective maintenance there are two types of replacement, (1) repair-by-repair and (2) repair-by-replacement. LRU's that are not kept on stock are repaired via a repair-by-repair policy. This is required when either an LRU is too expensive to store or when an LRU needs to fit perfectly in the asset. An example is the turntable at the turning points of trams which is repaired by the metal workshop. LRU's that are kept on stock are replaced via a repair-by-replacement policy. Most LRU's are replaced via a repair-by-replacement policy.

In repair-by-replacement the failed LRU can be either a repairable ('wisseldeel') or consumable. Consumables are disposed of when they fail. Repairables are repaired in one of the four repair shops of GVB. The LRU can be repaired by the replacement of parts. These parts are called Shop Replaceable Units (SRU's). Again, an SRU can be either replaceable or consumable. At GVB, almost all SRU's are consumables.

In corrective maintenance an LRU can be repaired in two manners. (1) Overhaul which is also used in preventive maintenance or (2) repair. When an LRU is repaired, only the failed SRU's are replaced. This different from an overhaul, because of the output quality of repair is not as good as new. In the following Section we explain the repair process for corrective maintenance in further detail.

Organization of the repair process
Inventory control is responsible for (1) setting the inventory levels for ready for use LRU's and (2) purchase orders and inventory levels for SRU's. The decision on which LRU's should be repaired next is based on these inventory levels. This is done via a "traffic light" model where colors indicate the priority of a repair.

With work order release, the LRU's are shipped from the failed LRU stock to the repair shops. Here they are placed in a buffer until repair. The final capacity planning and work order release is done by repair shop control in cooperation with inventory control. The following variables are taken into account to give priorities to work orders:

- Expected backorders; List of orders that cannot be fulfilled with the current RFU stock and work in progress.
- Available capacity

- Size of the turnaround inventory; the inventory in the failed & RFU warehouse as well as in repair.
- Priority of the order; based on minimum and maximum stock levels (traffic light).

Key figures

Table 19 shows some key figures of the repair shops of GVB.

Key figure	GVB1	GVB2	GVB3	GVB4
Number of unique failed LRU's	41	145	68	58
Number of failed LRU's	1435	2465	1768	1334
Average batch size	2.9	3.3	2.5	3.5
Average LRU Price	€1605	€670	€1291	€1541

Table 19. Key figures of the repair shops of GVB

Figure 15 shows a comparison of norm versus the actual repair times. The figure shows that for all repair shops there is a significant difference between the norm and actual repair times. Figure 15 shows that ratio norm versus actual repair times and the percentage of items for which this ratio falls in a specific category. A ratio of <1 indicates the actual repair time is smaller than the norm repair time.

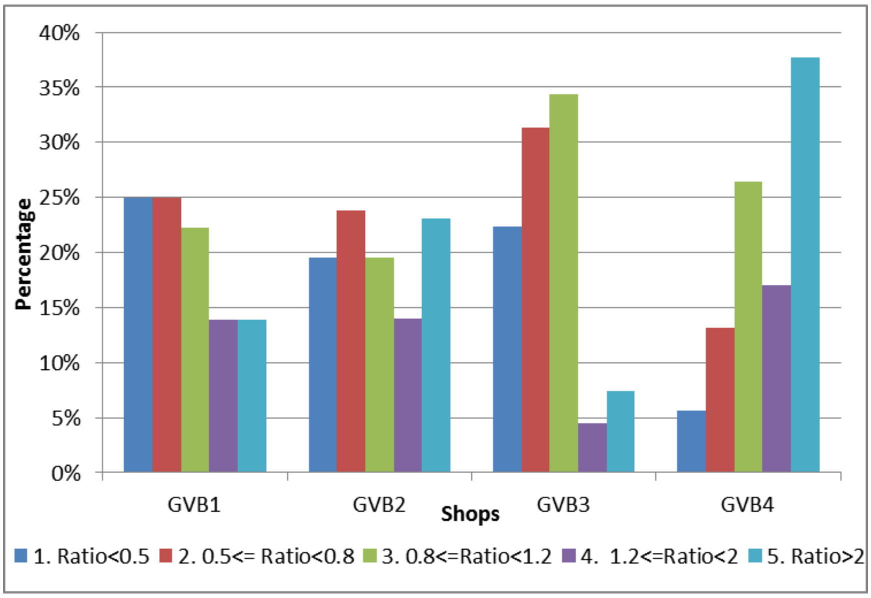

Figure 15. Norm and actual repair times of the repair shops of GVB.

Table 20 shows a table in which the % of SRU's and the % of total SRU demand is positioned based on the demand frequency and the price of SRU's. The table shows that about 75% of the total SRU demand is caused by 20% of the number of SRU's (column "f>=8").

	Demand frequency					
	f<2		2<=f<8		f>=8	
Price	% of SRU's	% of demand	% of SRU's	% of demand	% of SRU's	% of demand
<€25	39%	5%	42%	9%	12%	42%
>=€25 <€75	7%	1%	9%	3%	3%	9%
>=75	10%	2%	23%	5%	4%	23%

Table 20. SRU demand frequencies for GVB

KLM

Maintenance concept
Maintenance on planes is performed by replacing failed parts by spare parts. These spare parts are called Line Replaceable Units (LRU's). The LRU's can be replaced either preventively or correctively. Preventive maintenance is done after a fixed number of start/landings or flight hours. Corrective maintenance is done when a part fails.

A part is repaired in one of the Cells of A&A or BMSS. Here a repair-by-replacement policy is used. In a repair-by-replacement policy a failed LRU is replaced by a ready-for-use LRU. The failed LRU is repaired and after repair placed in the ready-for-use stock to replace another failed LRU.

At KLM, BMSS Hub Support is different from the other shops. Hub Support uses a repair-by-repair policy. In a repair-by-repair policy the failed LRU is repaired and put back on the plane. Hub Support uses this type of replacement, because the LRU's that are repaired here are specific for an airplane.

For the repair of LRU's, SRU's are used. These SRU's are consumable, repairable or partly repairable. The consumable SRU's are discarded after use and fall under the responsibility of the repair shops. The repairable SRU's can repaired indefinitely and fall under the responsibility of repairable LRU's. Partly repairable SRU's can only be repaired a certain number of times. The effect of partly repairable SRU's is out of the scope of this research. This is because only a limited number of SRU's is partly repairable.

Organization of the repair process
In the repair process different functions determine make decisions on the repair process. Supply Chain & Pool Management (SC&PM) sets the inventory levels for ready-for-use LRU's. This includes the repairable SRU's. Cell Development is responsible for the stock of consumable SRU's.

A failed LRU is brought to the shops by Logistics Department. The Customer Interface Repair (CIR) determines whether the 4M's (machine, methods, materials and manpower) are available to repair the LRU. When these are available, the LRU is released to the working stock of the Cell. The CIR is also responsible for all administrative issues regarding a repair.

In the Cell, the Cell Manager is responsible for allocating LRU's to repairmen. The Cell Manager has a board which states who can perform which tasks. With the use of this board, jobs are assigned to repairmen for repair.

When a repair cannot be finished, the Operational Trouble Shooter is responsible for solving the problem. The repairmen should only be worried about the repair of an LRU.

Key figures
Tables 21 and 22 show some key figures of the repair shops of KLM. The average price of LRU's is not presented, because the price of repairable items was not obtained. The average batch size for all repair shops is 1.

Key figure	KL1	KL2	KL3	KL4	KL5	KL6	KL7	KL8
Number of unique failed LRU's	131	121	74	190	100	128	81	97
Number of failed LRU's	941	4234	893	2649	842	1931	912	526

Table 21. Key figures of the repair shops KL1 to KL8

Key figure	KL9	KL10	KL11	KL12	KL13	KL14	KL15
Number of unique failed LRU's	52	9	21	5	108	76	79
Number of failed LRU's	453	578	7334	113	1573	1167	599

Table 22. Key figures of the repair shops KL9 to KL15

Tables 23 and 24 show the SRU demand frequencies for the repair shops of KLM BMSS and KLM A&A. These are separate, because these have a separate inventory control mechanism.

	Demand frequency					
	f<2		2<=f<8		f>=8	
Price	% of SRU's	% of demand	% of SRU's	% of demand	% of SRU's	% of demand
	32%	2%	41%	10%	28%	87%

Table 23. SRU demand frequencies for KLM BMSS

	Demand frequency					
	f<2		2<=f<8		f>=8	
Price	% of SRU's	% of demand	% of SRU's	% of demand	% of SRU's	% of demand
	35%	5%	45%	20%	20%	75%

Table 24. SRU demand frequencies for KLM A&A

The comparison of norm and actual repair times is not presented, because no data was obtained on norm repair times.

NME

Maintenance concept
When a part on a ship fails, this part is replaced by a ready-for use part. These parts are called LRU's. The LRU's can be replaced either preventively or correctively. Preventive maintenance on ships is done after a pre-determined time period. Corrective maintenance is performed when a LRU's fails.

The Naval Maintenance Establishment performs maintenance on parts, as well as systems. An example of a system is the Goalkeeper. In both preventive and corrective maintenance, systems that can be repaired within the down-time of the ship are replaced in a repair-by-repair policy. For systems that cannot be repaired in the down-time of a ship spare systems are available. These systems are replaced in a repair-by-replacement policy.

Also components replaced preventively. For example all fire extinguishers of a ship. When possible a repair-by-repair policy is applied. When this is not possible, repair-by-replacement is used. In corrective maintenance, parts are replaced via a repair-by-replacement policy. The failed part is replaced by a spare part. The failed part is sent to the repair warehouse to wait for repair. After repair the part is ready to replace other failed parts on ships.

In both preventive as well as corrective maintenance, LRU's are always revised. This is because of the high norms that are set by the Royal Netherlands Navy. Because of this, also corrective repairs lead to a revision of the LRU.

Organization of the repair process
There are certain decision points in the repair process. First, it has to be decided when an LRU needs to be repaired. At the Naval Maintenance Establishment this is done by inventory control. When the RFU LRU stock drops beneath a reorder point, a repair order is made. The material planner determines SRU's from the standard maintenance list (SOL) are available.

When the SRU's are available the repair order is sent to work preparation. In work preparation parts from the SOL are ordered. Work preparation also determines whether the due date that is set by the material planner is possible. Work preparation makes the consideration between capacity and planning. When capacity is available and SRU's are delivered, the work order is released to the repair shop.

In the repair shop the production manager allocates the work orders to repairmen. He is best informed of the capabilities of repairmen and thus who should perform which repair.

Key figures
Table 25 outlines some key figures of the repair shops of NME.

Key figure	NME1	NME2	NME3	NME4	NME5	NME6	NME7	NME8	NME9	NME10
Number of unique failed LRU's	126	390	434	142	404	88	188	449	279	588
Number of failed LRU's	1680	1417	2382	678	1720	3426	6809	7431	1300	1797
Average batch size	2.3	1.7	1.5	1.8	1.5	8.3	2.7	2.9	1.6	2
Average LRU Price	€17200	€4700	€7850	€55209	€70970	€40000	€95000	€21000	€8000	€2750

Table 25. Key figures of the repair shops of NME

Figure 16 outlines an analysis of the norm and actual repair times of the repair shops of NME. The figure shows that many repairs are performed in accordance to the norm repair time. However, this is mainly because the norm repair times are continuously based on the actual repair times.

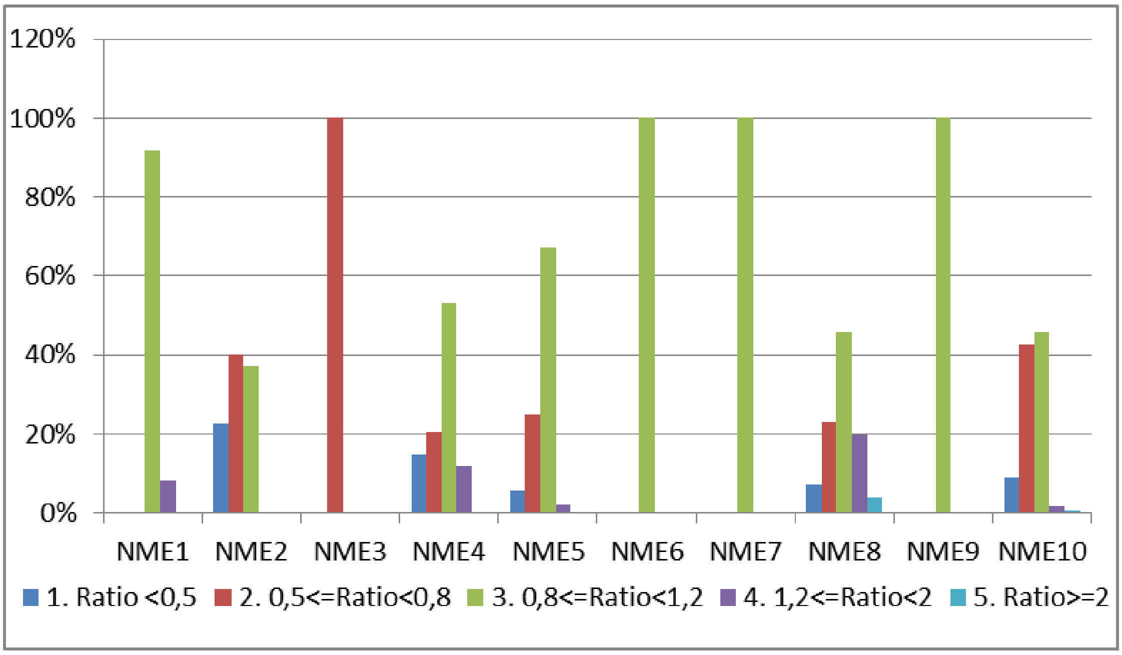

Figure 16. Comparison of norm and actual repair times of the repair shops of NME

Table 26 outlines the SRU demand frequencies for the repair shops of NME.

	Demand frequency					
	f<2		2<=f<8		f>=8	
Price	% of SRU's	% of demand	% of SRU's	% of demand	% of SRU's	% of demand
<€25	28%	5%	14%	8%	20%	51%
>=€25 <€75	6%	1%	3%	1%	4%	11%
>=75	14%	2%	6%	4%	5%	17%

Table 26. SRU demand frequencies for the repair shops of NME

DBGS

Maintenance concept

Maintenance on trams and metros of DBGS is done in workshops. Here parts are replaced by spares. These spare parts are called Line Replaceable Units (LRU’s). The LRU’s can be replaced either preventively or correctively. Preventive maintenance is done periodically, after a certain amount of usage or condition based. Corrective maintenance is performed when a part fails. Both preventive as well as corrective maintenance a repair-by-replacement policy is used. In a repair-by-replacement policy a failed part is replaced by a different spare part.

In the Royal Netherlands Army, three maintenance levels exist.
1. Organic Level Maintenance (OLM)
2. Intermediate Level Maintenance (ILM)
3. Depot Level Maintenance (DLM)

When a vehicle fails, first on the OLM a diagnosis is made and when possible small corrective repairs. When the defects are larger the vehicle goes to the ILM. Here, failed parts are replaced by spares. The failed part is sent to a failed LRU stock.

The DLM repairs these failed parts and is responsible for the supply of ready-for-use LRU’s.

Organization of the repair process

Inventory control makes the decision on which LRU’s should be repaired first. They make a request to the repair shops for repair. This request contains the number of LRU’s to repair and the due date for the repair.

The work planners in the repair shop accept or decline the request. A request can only be accepted when:
1. Capacity is available
2. The 70% OB100 list SRU’s are available. These are SRU’s that are required in at least 70% of the repairs.
3. The request does not exceed the prognosis of the Year Work Plan.

If these constraints are not met, a different due date needs to be determined. The work planner releases jobs to the repair shops.

In the repair shop the repair shop manager (cluster manager) determines who should work on which repair order. He has the most insight in which repairmen can do which repairs.

Key figures

Table 27 outlines some key figures of the repair shops of DBGS. The average price of LRU’s is omitted, because these were not obtained.

Key figure	DBGS1	DBGS2	DBGS3
Number of unique failed LRU's	47	53	90
Number of failed LRU's	1130	490	2763
Average batch size	7	2.5	7.5

Table 27. Key figures of the repair shops of DBGS

Figure 17 shows a comparison of norm versus actual repair times. The figure shows that the norm repair times are a precise estimate of the actual repair time of repairable items.

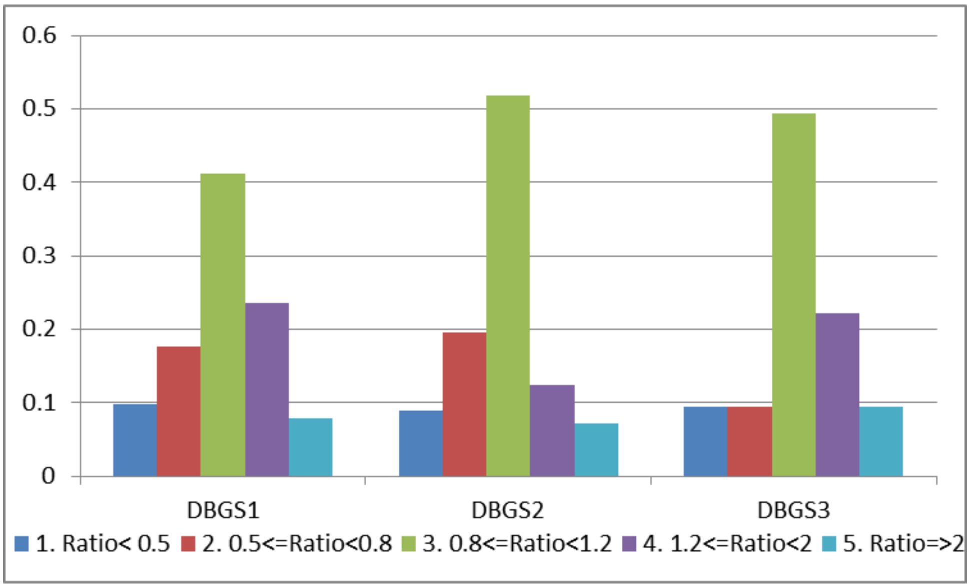

Figure 17. Norm versus actual repair times of the repair shops of DBGS

Table 28 shows the SRU demand frequencies. The table shows that 30% of the total SRU demand is for slow moving SRU's (column f<2). Compared to the other case study companies this is a lot.

	Demand frequency					
	f<2		2<=f<8		f>=8	
Price	% of SRU's	% of demand	% of SRU's	% of demand	% of SRU's	% of demand
<€25	51%	22%	16%	37%	1%	7%
>=€25 <€75	9%	4%	3%	8%	0%	3%
>=75	15%	7%	5%	10%	0%	2%

Table 28. SRU demand frequencies of DBGS

Appendix C: Overview of theoretical relations between characteristics and the average waiting time of repair shops

For the following characteristics, no literature could be found. Therefore, we have to rely on the other graphical tools to determine the relation between these characteristics.

- % of items responsible for 80% of the repair load
- Squared coefficient of variation of the number of operations
- % of repair jobs without materials

Relations modeled using queuing theory
This section outlines per characteristic the relation between the characteristic and the average waiting time in a repair shop. Figure 18.a to 18.c show graphical representations of the relation between the characteristics and the waiting time. In each graph the y-axis is the average waiting time and the x-axis is the value of the characteristic. The line represents the waiting time as a function of the characteristic.

Utilization
As stated in Section 4.1, λ is the arrival rate and μ is the service rate (or repair rate). In a queuing system with a single server, the utilization of a system (ρ) is defined as the fraction of time a server is busy (Stewart, 2009, p. 399). The utilization is calculated as a function of the failure rate and the repair rate. The utilization is calculated in Equation (17).

$$\rho = \frac{\lambda}{\mu} \tag{17}$$

To apply queuing theory, the utilization of (parallel) servers should be 1 at most. If the utilization is larger than 1, the capacity is lower than the demand and the system will overload. Considering that μ is the repair rate per hour, the average repair time E(R) can be calculated as the inverse of the repair rate. Equation (18) shows this calculation.

$$E(R) = \frac{1}{\mu} \tag{18}$$

One of the most common queuing models is a single server system with exponential time between arrivals and repair times, called the M/M/1 queue model. Equation (19) provides the formula for the average waiting time in queue for a M/M/1 queue system. (Hopp & Spearman, 2001, p. 269)

$$W_q = \frac{\rho}{(1-\rho)} E(R) \tag{19}$$

In this formulation W_q depicts the waiting time in queue. The utilization is depicted by ρ and the average repair time is depicted by E(R). This formula shows that as ρ nears 1, the waiting time becomes very large. The average waiting time in queue rises at increasing rate utilization grows larger. We therefore expect to find a nonlinear relation between the utilization of repair shops and the repair shop waiting time. A graphical representation is can be found in Figure 18.a.

Average repair time
Equation (19) showed the relation between the utilization and the average waiting time in queue. In Equation (18), E(R) depicted the average repair time of repair jobs. Considering Equation (18), Equation (19) can be rewritten to Equation (20).

$$W_q = \frac{\rho}{(1-\rho)}E(S) = \frac{\frac{\lambda}{\mu} * \frac{1}{\mu}}{\left(1-\frac{\lambda}{\mu}\right)} = \frac{\frac{\lambda}{\mu^2}}{\left(1-\frac{\lambda}{\mu}\right)} = \frac{\lambda E(S)^2}{(1-\lambda E(S))} \tag{20}$$

Equation (20) shows the relation between the average repair time and the average waiting time in queue. The equation shows that the waiting time in queue will rise at an increasing rate as repair time increases.

We therefore expect to find that the average repair time will show a nonlinear relation with the repair shop waiting time. The expected relation between the average repair time and the average waiting time in repair shops is depicted in Figure 18.a.

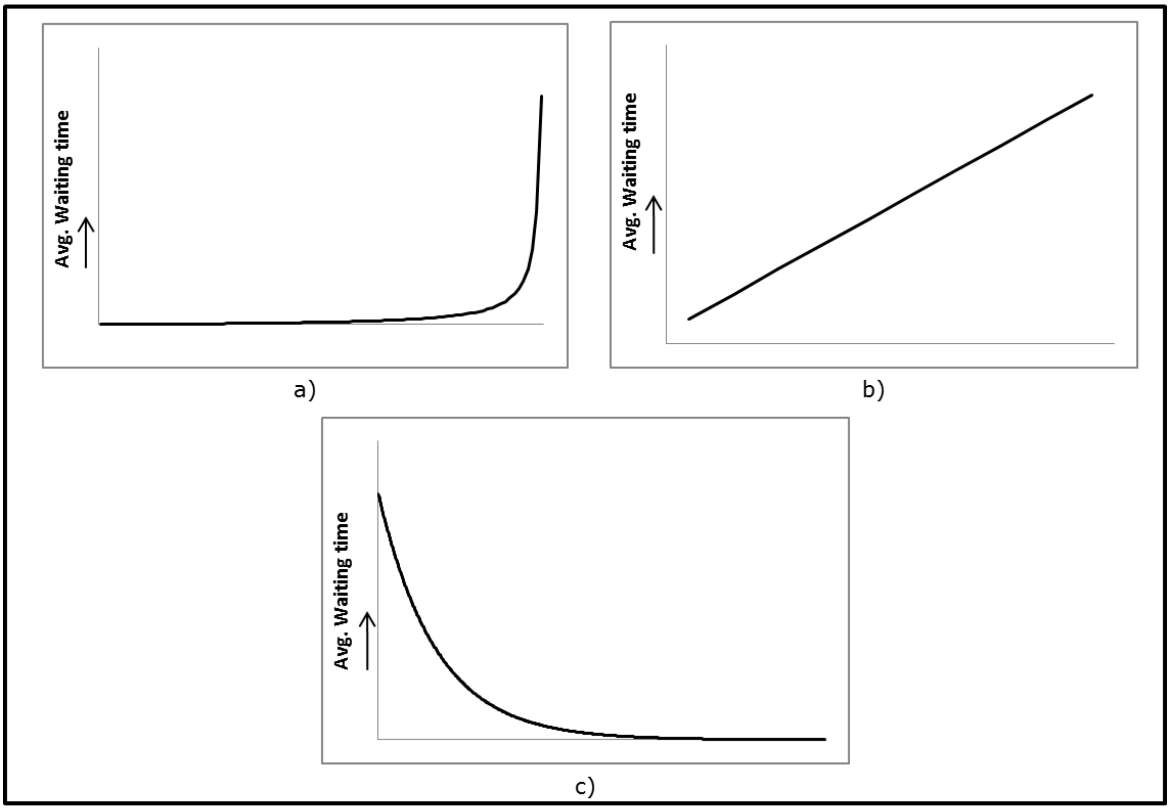

Figure 18.a to 18.c. Graphical representations of the average waiting time as the function of characteristics.

Squared coefficient of variation of actual repair times

The previous model show showed the expected waiting time in an M/M/1 queue with exponential repair times. However, some system cannot be modeled by exponential repair times, but by some other more general distribution. When we use some other general distribution, we need to incorporate the variability in average repair times. Using the Pollaczek-Khinchine formula we can calculate the average waiting time in queue with general distributed service times (Stewart, 2009, p. 571). This equation is presented in Equation (21).

$$W_q = \left(\frac{1+C_s^2}{2}\right)\left(\frac{\rho}{(1-\rho)}\right)E(S) \tag{21}$$

In this formulation C_s^2 is the squared coefficient of variation of the repair time. This formulation shows that the squared coefficient of variation has a linear relation with the waiting time in queue. A graphical representation of the relation between the squared coefficient of variation of the actual repair times and the average waiting times in repair shops is presented in Figure 18.b.

Variance to mean ratio of the number of arrivals
In METRIC the number of items in the pipeline is a poisson distributed (Sherbrooke, 1968). A poisson distribution has a variance to mean (VMR) of 1. In VARI-METRIC, the number of items in pipeline is modeled as a negative binominal distribution (Sherbrooke, 1986). A negative binominal distribution has a VMR of larger than 1.

In queuing theory, variability in interarrival times are taken into account using Kingman's formula. With this formula we can estimate the expected waiting time in queue in a G/G/1 queue (Kingman, 1961). This estimation is presented in Equation (22).

$$W_q \approx \left(\frac{C_s^2 + C_a^2}{2}\right)\left(\frac{\rho}{1-\rho}\right)E(s) \tag{22}$$

In Equation (22) the C^2_a depicts the squared coefficient of variation of the time between arrivals. The equation shows that similarly to Equation (21), there is a linear relation between the squared coefficient of time between failures and the queue waiting time. This suggests that the coefficient of variation of the time between failures shows a linear relation to the repair shop waiting time. A graphical representation of this relation can be found in Figure 18.b.

Since the VMR of the number of arrivals does not illustrate the precise relation between waiting time and the VMR of the arrival rate, we refer to Kingman's formula and expect to find a linear distribution.

Number of repairmen
So far, we only illustrated queuing systems with a single parallel server. However, in many cases, a repair shop has more than one server to provide service. Equation (23) shows the calculation of the utilization ρ in a queuing system with c parallel servers. (Hopp & Spearman, 2001, p. 272)

$$\rho = \frac{\lambda}{c\mu} \tag{23}$$

In a system with 2 or more parallel servers, the calculation for the average waiting time in queue also has to be adjusted. We again consider a queuing system with exponential distributed repair times and failure rates. Equation (24) shows the formula for the waiting time in queue in a system with c parallel servers. (Hopp & Spearman, 2001, p. 272)

$$W_q = \frac{\rho^{\sqrt{(2(c+1)}-1}}{c(1-\rho)}E(S) \tag{24}$$

In the case c=1, the Equation (24) is equal to the queue waiting time for single parallel server M/M/1 model given in Equation (18). Equation (24) shows that as the number of parallel servers' increases, the added effect of an additional server decreases.

This illustrates the effect of the number of repairmen on the average waiting time of repair jobs in a repair shop. Assuming that all repairmen have the same capabilities, we therefore expect to find a nonlinear decreasing relation between the number of repairmen and the average waiting time in repair shops. The relation between the number of repairmen and the waiting time is graphically depicted in Figure 18.c.

Average number of operations
In a repair shop a repair job is serviced by a single repairman. However, shared tooling or equipment may be required for the repair. When shared tooling is required, each operation can be modeled as having a queue. Suppose that a repair job requires k operations. Jackson's theorem states that: "If (1) interarrival times for a series queuing system are exponential with rate λ, (2) service times for each stage *i* are exponential, and (3) each stage has an infinite-capacity waiting room, then interarrival times for arrivals to each stage of the queuing system are exponential with rate λ" (Winston, 2003, pp. 1104-1106).

When these assumptions are valid, the total waiting time is the sum of waiting times in queue before each operation. This is represented in Equation (25).

$$Total\ waiting\ time\ in\ queue = \sum_{i} W_q \tag{25}$$

Jackson's theorem is only valid when the repair shop should have sufficient capacity for each operation. This means that each operation should have a utilization of less than 1 (Winston, 2003, pp. 1104-1106). Based on Equation (25) we expect to find a linear relation between the average number of operations and the waiting time. It is important to note that, unlike the other characteristics, the waiting time for the average number of operations occurs during repair, and not in the repair job queue.

Relations modeled using inventory management models
In this section we outline the relations between characteristics and the average waiting time, based on inventory management models. Unfortunately, not for all characteristics we were able to determine the theoretical relation between the characteristics and the average waiting time. However, in these instances we were able to identify literature that indicates that, based on literature, there should be a relation.

Average number of materials
The fill rate is the fraction of demand that is satisfied directly from stock on hand. The fill rate for all N items required for the repair job is equal to the product of the fill rate of each individual item Equation (26):

$$Fill\ rate\ for\ \mathrm{N}\ materials\ required\ for\ repair\ job\ = \prod_{i=1}^{N} A_i \tag{26}$$

In Equation (26), *N* is the number of unique materials required in the repair job. A_i is the fill rate for item *i* required in the repair job. In Equation (26), the fill rate of N items declines at a decreasing rate as N becomes larger. Therefore, we expect to find that the repair shop waiting time will show an increase of the waiting time at a decreasing rate. Figure 19 presents a graphical representation of this relation.

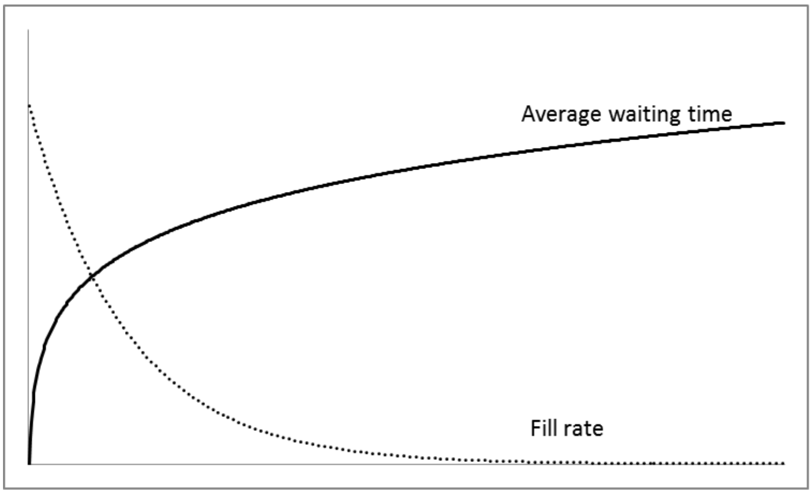

Figure 19. Graphical representation of the relation between fill rate and waiting time

% of repair jobs with slow moving materials
In METRIC, the objective is to maximize the availability of assets by minimizing the backorders for the lowest investment costs (Sherbrooke, 1968). Using a METRIC, the optimal stocks for parts are determined. Parts that have high failure rates and are low in cost have will be kept on stock more than expensive parts with low failure rates. This is because the expected backorders versus investment cost decreases more with the addition of one cheap fast moving items in stock than with the addition of one expensive slow moving item.

In a repair shop with a high percentage of slow moving materials, the slow moving materials will not be kept on stock much. However, the precise relation to the average waiting time is difficult to determine.

Material demand rate
Assuming the METRIC model, parts that are expensive and slow moving will have lower fill rates than parts that are fast moving. This is because the decrease in expected backorders is larger when adding one fast moving part to stock than adding a slow moving part.

A repair shops with a low average demand rate implies that there are many slow moving parts. In METRIC, this might result in keeping additional LRU's on stock instead of SRU's. Therefore, we suspect that the average waiting time will increase when the material demand rate declines. However, we are unable to determine how the relation between this characteristics and the waiting time should be modeled based on literature.

Appendix D: Statistical tests

In this section we outline the statistical tests performed for the regression analysis.

Statistical tests for model fit

When the regression coefficients are estimated, tests have to be performed to measure the adequacy of the model. To test the adequacy of the model itself, statistical tests can be used to (1) test for significance of the regression and (2) test the validity of each regression coefficient (Montgomery & Runger, 2003, pp. 428-435).

Statistical test for significance of the regression

A test for the significance of the regression is a test to determine whether a linear relationship exists between the average waiting time in repair shops and a subset of regressor variables $x_1, x_2, \ldots, x_k$. The hypotheses are:

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_k = 0$$
$$H_1: \beta_j \neq 0 \; for\ at\ least\ one\ j$$

To measure the statistical significance of regressor variables, the F test statistic is calculation. Equation (27) displays the calculation for the F test statistic.

$$F = \frac{MS_R}{MS_E} \tag{27}$$

The null hypothesis is rejected when the F test statistic is larger than the critical value of the F-distribution with 95% reliability. When the hypothesis is rejected, at least one of the regressor variables contributes statistically significantly to the model. In Equation (27) MS_R is the mean square of the regression model, MS_E equals the mean square of the error in the model. The Equation or the MS_R is presented in Equation (28).

$$MS_R = \frac{SS_R}{p}, where\ SS_R = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2 \tag{28}$$

In Equation (28), p equals the number of variables in the model (excluding the intercept), $\hat{y}_i$ is the predicted Y value from the regression model and $\bar{y}$ is the mean Y value. The Equation for MS_E is presented in Equation (29).

$$MS_E = \frac{SS_E}{n-2}, where\ SS_E = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{29}$$

In Equation (29) y_i depicts the actual Y value and $\hat{y}_i$ depicts the predicted Y value based on the regression model.

Statistical test for significance for each regression coefficient

For each regression coefficient a similar test is conducted as for the significance of all regression model. Performing a statistical test on each regression coefficient indicates, whether the variable is significant to the model. The hypotheses are:

$$H_0: \beta_j = 0$$
$$H_1: \beta_j \neq 0$$

The test statistic is displayed in Equation (30).

$$t_0 = \frac{\hat{\beta}_j}{s_{\hat{\beta}_j}} \tag{30}$$

In Equation (30) $\hat{\beta}_j$ equals the estimated regression coefficient and $s_{\hat{\beta}_j}$ is the standard error of the regression coefficient. The hypothesis is rejected when the statistical t_0 is larger than the critical value of the student distribution with 95% reliability. When the null hypothesis is rejected, a regression coefficient is statistically significant for the model.

Statistical tests for model accuracy

The statistical tools described above only state whether the regression is statistically significant, not whether the model is a good fit (Montgomery & Runger, 2003, p. 431). To test the fit of the model two methods are used (1) the adjusted R^2 value and (2) Mallow's C_p value. Equation (31) outlines the calculation for the adjusted R^2 test statistic.

$$R^2_{adj} = 1 - \frac{MS_E}{\frac{SS_R}{n-1}} \tag{31}$$

The adjusted R^2 is a measure for the percentage of variation in the average waiting time of repair shops that can be explained by the model. The adjusted R^2 also guards for over fitting the model. That is when in the model regressors are included which are not useful to increase the reliability of the model. (Montgomery & Runger, 2003, p. 432)

In total we have 12 variables that can be included in a regression model, as discussed in Section 4.5. Therefore, there is range of possible sets of variables which may impact the average waiting time in repair shops. To further analyze the different subsets of variables Mallow's C_p value is used. The C_p measures the bias of a model with p regressors (including β_0) compared to the full $K+1$ model (Montgomery & Runger, 2003, p. 454). The bias is measured as $E(\hat{y}_i) - E(y_i)$ and is a measure for the lack of fit of the model. When not significant characteristics are included in the model, or important characteristics are left out, the C_p value (or bias/lack of fit) increases. The formula for the C_p value is outlined in Equation (32).

$$C_p = \frac{SS_E(p)}{\hat{\sigma}^2} - n + 2p \tag{32}$$

SS_E is the total sum of squares for the model with p parameters, $\hat{\sigma}^2$ is the mean squared error for the full $K+1$ term model. Note that when there is only little lack of fit in the model (i.e., if $E(y_i^*) - E(y_i) = 0$) it follows that C_P equals p, *see* Equation (33).

$$C_p = \frac{SS_E(p)}{\hat{\sigma}^2} - n + 2p \approx \frac{(n-p)\sigma^2}{\sigma^2} - n + 2p = p \tag{33}$$

However, this does not suggest that C_p cannot be lower than p. When the error in the model with p regressors is smaller than the error in the $K+1$ model, the C_p will be lower than p. In analyzing the subsets of variables a tradeoff have to be made between maximizing the adjusted R^2, and a C_p that is small or close to p. (Hocking, 1976)

Multicollinearity in the full model does not affect the C_p statistic, because multicollinearity primarily affects the stability of the regression coefficients (Montgomery & Runger, 2003, p. 461). This means that variables might be deemed not statistically significant while in fact they are. However, multicollinearity in the full model has only little impact on the full model. Therefore, the C_p statistic is also in this case usable.

Residual analysis
Fitting a regression requires several assumptions to have been met. The errors should be uncorrelated random variables with mean zero and constant variance and normally distributed. The relation between characteristics and the waiting time should also be modeled as a linear relation. (Montgomery & Runger, 2003, p. 395)

To test the assumptions regarding the errors, a residual analysis can be conducted. Residuals are the difference between the actual waiting time y_i and the predicted waiting time by the regression model $\hat{y}_i$. Equation (34) outlines this relation.

$$e_i = y_i - \hat{y}_i \; for \; i = 1,2, \dots, n \tag{34}$$

To test whether the assumption of the errors are met we conducted the following four tests.

(1) We created scatter plots of residuals versus the predicted waiting time and residuals versus the characteristics included in the model. The goal is to identify anomalies in the plots. An anomaly is when the residuals show a relation with either the predicted waiting time or any of the characteristics. In this case, some type of transformation has to be applied in order to create a linear relation to the average waiting time of repair shops (Montgomery & Runger, 2003, p. 396). These transformations are based on the analysis performed in Chapter 4.

(2) A normal probability plot is created to test the residuals for normality. In a normal probability plot, the distribution of the residuals is tested against the standard score. The standard score is the number of standard deviations an observation is above the mean. If it is a straight line, the residuals are normally distributed. To calculate the standard scores, the residuals are ranked from small to large. The calculation for the standard score is given in Equation (35).

$$z_i = \Phi^{-1}\left(\frac{i - 0.5}{n}\right) \tag{35}$$

(3) Standardized residuals are created to test for outliers. Standardized residuals that are outside the range [-3;3] are outliers and have to be removed from the model. We use the range [-3;3] because in a normal distribution 99,7% of the observations fall within this interval (Montgomery & Runger, 2003, p. 111). Outliers are removed because these have a significant effect on the adjusted R^2 and C_p values.

(4) Variance inflation factors (VIF) are calculated to test for multicollinearity. The multicollinearity measure is used to analyze the impact of decencies of regressors on the regression analysis. The VIF(β_j) is the factor by which the variance of an estimated regression coefficient is increased because of multicollinearity (Montgomery & Runger, 2003, p. 460). The formula is outlined in Equation (36).

$$C_{jj} = \frac{1}{1 - R_j^2} \quad j = 1,2, \dots, k \tag{36}$$

C_{jj} are the diagonal elements on the matrix $C=(X'X)^{-1}$. This is the inverse of the correlation matrix of the characteristics in the model (and not including the waiting time). A VIF(β_j) of 4 or higher indicates that multicollinearity exists between variables which is undesirable.

Appendix E: Residual analysis

This section outlines the residual analyses performed on the models that yielded the best results. We first performed an outlier analysis. This is followed by a residual analysis and an analysis for multicollinearity of each model.

Outlier analysis
For each regression model, we determined whether there are any outliers. To determine the outliers, we use the standardized residuals. In Section 5.1.3 we outlined how the residuals are calculated. Standardized residuals that were outside the range [-3;3] are considered as outlier. For the regression models 6, 16 and 21 we identified no observation that can be considered as an outlier.

Residual analysis and multicollinearity model 6
Figure 20 outlines the scatter plots of the characteristics and the residuals. The value of the characteristic is plotted on the x-axis and the value of the residual on the y-axis. Figure 20.a shows the transformed demand rate of materials and Figure 20.b the average repair time. The figure shows no clear pattern. Therefore we conclude that no further transformation of characteristics is required.

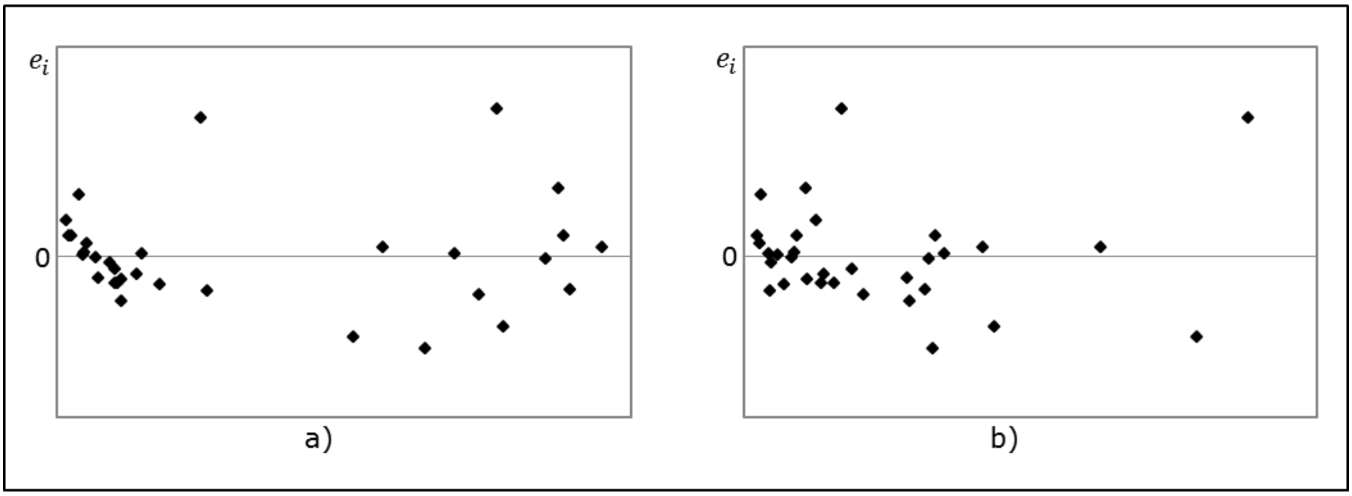

Figure 20.a and 20.b. Scatter plot of characteristics and residuals of model 6

Figure 21.a shows the predicted waiting time from the model on the x-axis and the residuals on the y-axis. Since no clear pattern is apparent, we conclude that the model is sufficient. Figure 21.b shows a normal probability plot. The plot shows a reasonable straight line. We therefore conclude that the residuals are normally distributed.

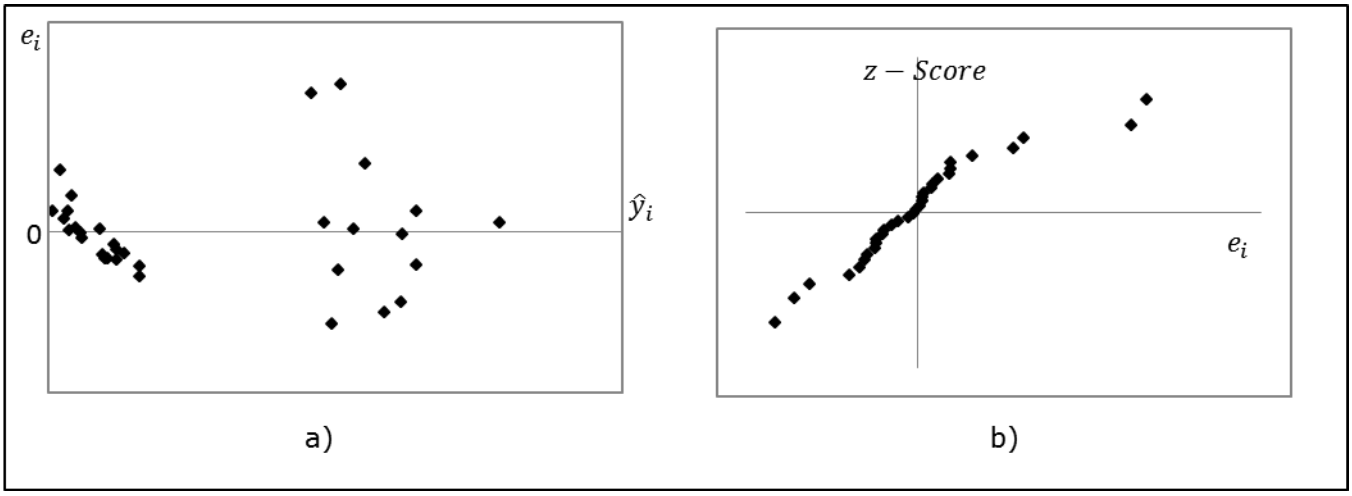

Figure 21.a and 21.b. Normal probability plot and scatter plot of the predicted values versus the residuals of model 6

Table 29 shows the variance inflation factors of the model. Since none of the factors on the diagonal is above 4, we conclude that there is no multicollinearity.

	1/(Demand rate materials)	*Average repair time per repair job*
1/(Demand rate materials)	**1.32**	-0.65
Average repair time per repair job	-0.65	**1.32**

Table 29. Variance inflation factors for model 6

Based on the findings from the residuals, we conclude that we are allowed to make conclusions based on this model.

Residual analysis and multicollinearity model 16

Figure 22 shows the scatter plots of residuals versus the characteristics included in the model. Figure 22.a shows the residuals versus the material demand rate. Figure 22.b shows the residuals versus the average repair time and Figure 22.c shows the residuals versus the average number of materials required for repair. The scatter plot shows no apparent relation to the residuals. We therefore conclude that no further transformation is required.

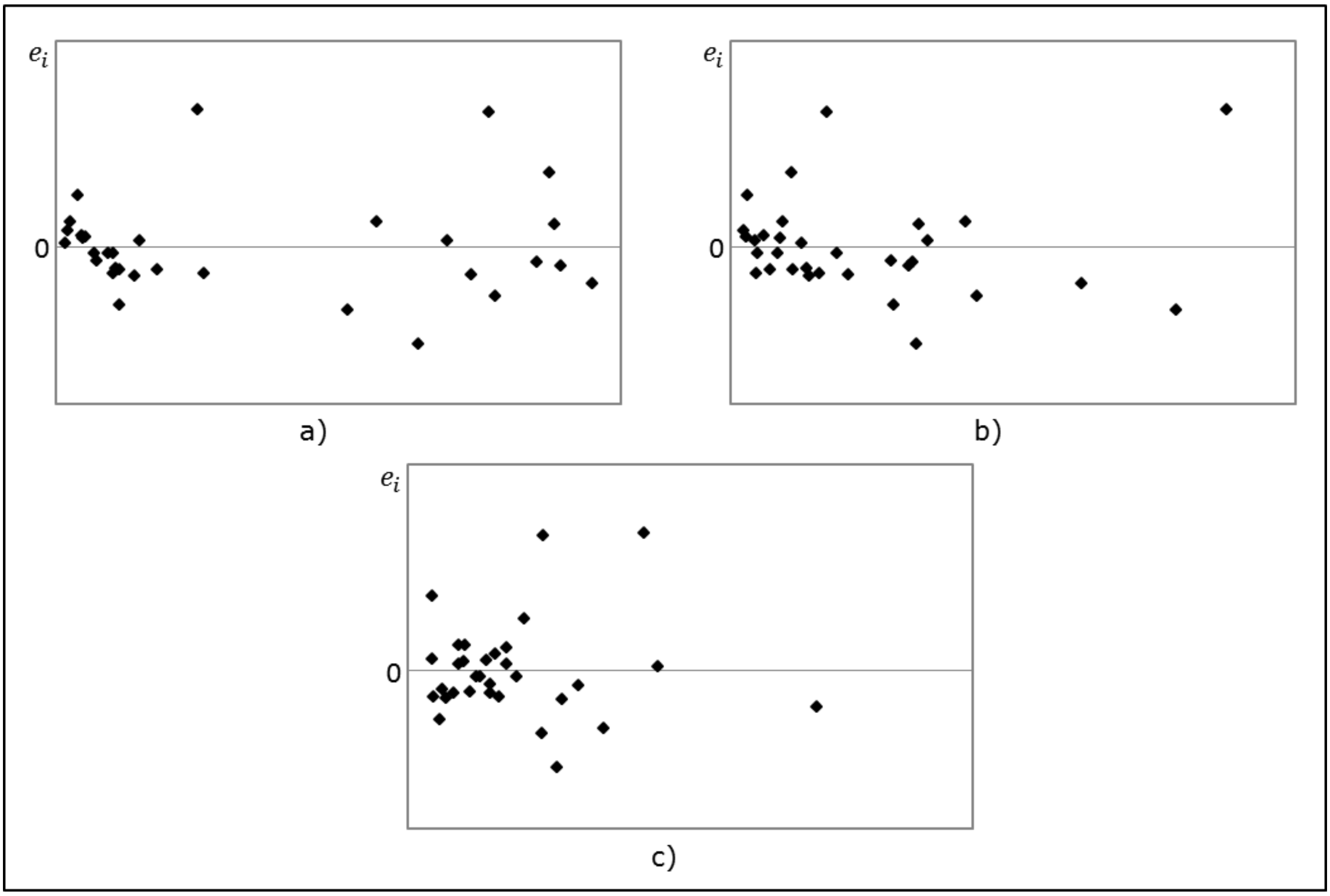

Figure 22.a to 22.c. Scatter plot of characteristics and residuals of model 16

Figure 23.a shows the predicted waiting time from the model on the x-axis and the residuals on the y-axis. Since no clear pattern is apparent, we conclude that the model is sufficient. Figure 23.b shows a normal probability plot. The plot shows a reasonable straight line. We therefore conclude that the residuals are normally distributed.

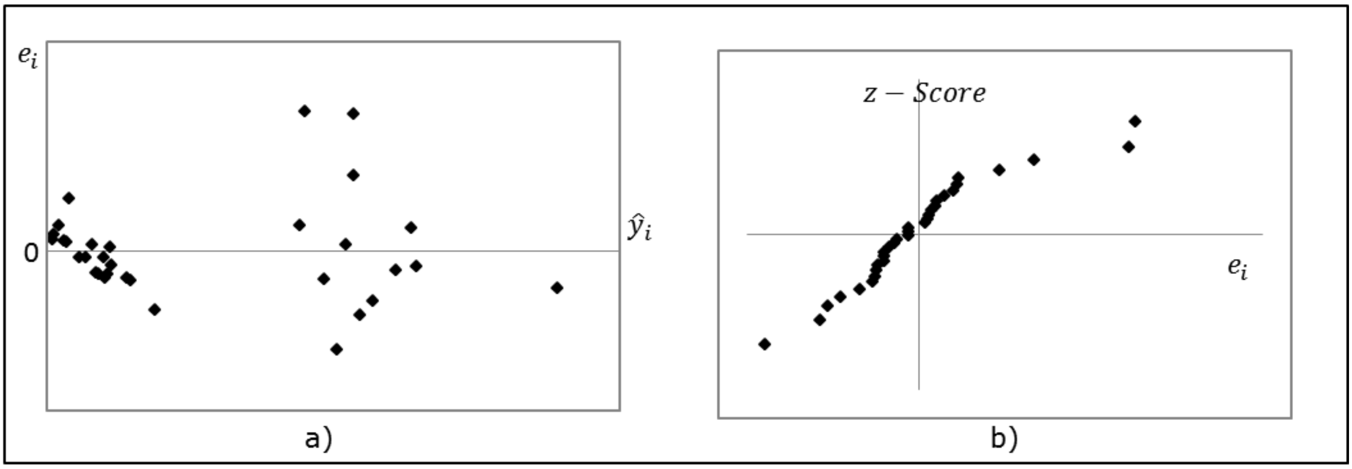

Figure 23.a and 23.b. Normal probability plot and scatter plot of the predicted values versus the residuals of model 16

Table 30 shows the variance inflation factors of the model. Since none of the factors on the diagonal is above 4, we conclude that there is no multicollinearity.

	1/(Demand rate materials)	*Average repair time per repair job*	*Average number of materials required for repair*
1/(Demand rate materials)	**1.34**	-0.75	0.18
Average repair time per repair job	-0.75	**1.77**	-0.78
Average number of materials required for repair	0.18	-0.78	**1.37**

Table 30. Variance inflation factors for model 16

Based on the scatter plots and the variance inflation factors, we conclude that there are no fundamental issues with model 16. It is therefore possible to make conclusions based on this model.

Residual analysis and multicollinearity model 21
Figure 24 shows the scatter plots of residuals versus the characteristics included in the model. Figure 24.a shows the residuals versus the material demand rate. Figure 24.b shows the residuals versus the average repair time. Figure 24.c shows the residuals versus the average number of materials required for repair and Figure 24.d shows the residuals versus the % of items responsible for 80% of the repair load. The scatter plots show no apparent relation to the residuals. We therefore conclude that no further transformation is required.

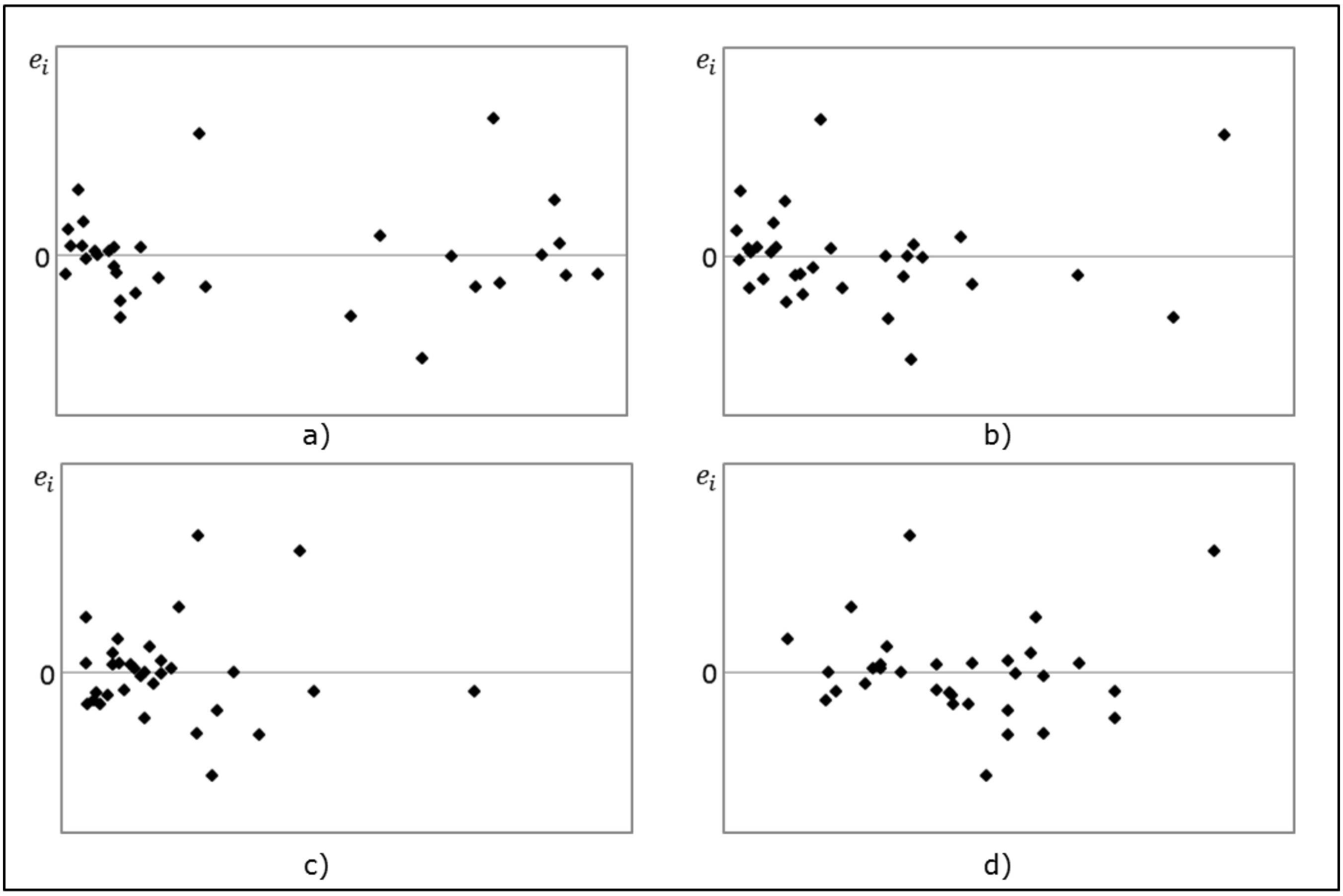

Figure 24.a to 24.d. Scatter plot of characteristics and residuals of model 21

Figure 25.a shows the predicted waiting time from the model on the x-axis and the residuals on the y-axis. Since no clear pattern is apparent, we conclude that the model is sufficient. Figure 25.b shows a normal probability plot. The plot shows a reasonable straight line. We therefore conclude that the residuals are normally distributed.

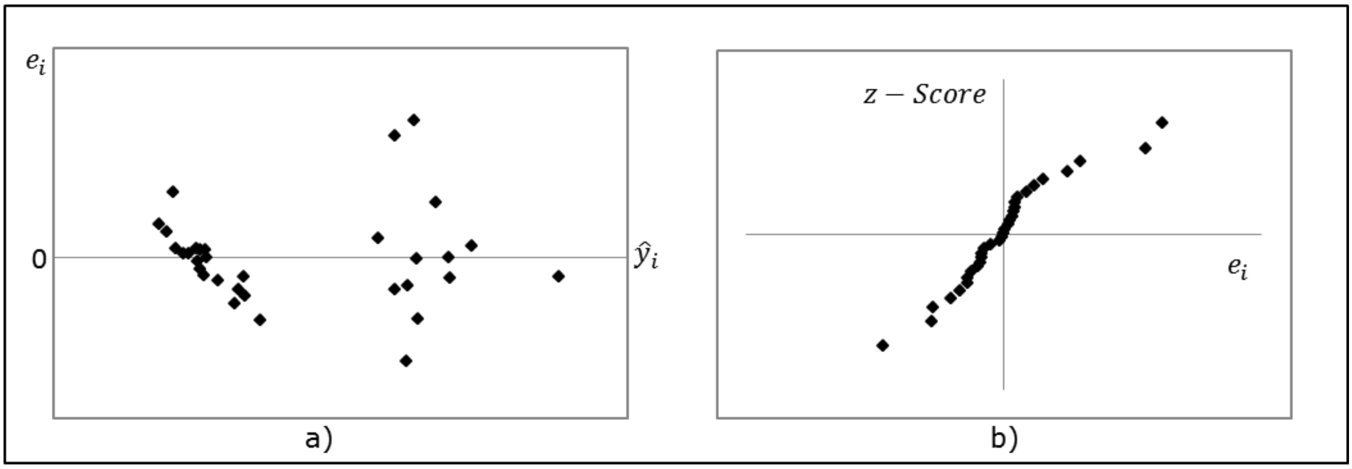

Figure 25.a and 25.b. Normal probability plot and scatter plot of the predicted values versus the residuals of model 21

Table 31 shows the variance inflation factors of the model. Since none of the factors on the diagonal is above 4, we conclude that there is no multicollinearity.

	1/(Demand rate materials)	*Average repair time per repair job*	*Average number of materials required for repair*	*% of items responsible for 80% of the repair load*
1/(Demand rate materials)	**1.44**	-0.91	0.20	0.34
Average repair time per repair job	-0.91	**2.01**	-0.83	-0.53
Average number of materials required for repair	0.20	-0.83	**1.38**	0.10
% of items responsible for 80% of the repair load	0.34	-0.53	0.10	**1.16**

Table 31. Variance inflation factors for model 21

Based on the scatter plots and the variance inflation factors, we conclude that there are no fundamental issues with model 21. It is therefore possible to make conclusions based on this model.

Appendix F: Regression analysis of the KLM repair shops

For the regression analysis on the repair shops of KLM, we applied the same heuristic as described in Section 5.2.3. Table 32 outlines the results of the different regression models that were constructed. Each model assumes a linear relation between the characteristics and the average waiting time of repair shops.

Model	Adj R^2	C_p	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
1	20.4%	13.00	x	x	x	x	x	x	x	x	x	x	x	x
2	16.7%	2.62					x							
3	22.7%	1.62							x					
4	21.8%	1.78									x			
5	2.2%	4.98												x
6	19.3%	3.18	x						x					
7	17.1%	3.51		x					x					
8	17.9%	3.39			x				x					
9	16.3%	3.62				x			x					
10	**46.3%**	**-0.90**					x		x					
11	16.5%	3.60						x	x					
12	16.6%	3.59							x	x				
13	24.4%	2.41							x		x			
14	24.8%	2.34							x			x		
15	21.2%	2.89							x				x	
16	24.2%	2.43							x					x
17	41.5%	1.09	x				x		x					
18	43.4%	0.82		x			x		x					
19	43.0%	0.88			x		x		x					
20	42.6%	0.94				x	x		x					
21	41.4%	1.10					x	x	x					
22	**50.3%**	**-0.12**					x		x	x				
23	41.8%	1.05					x		x		x			
24	41.5%	1.09					x		x			x		
25	47.0%	0.33					x		x				x	
26	43.9%	0.75					x		X					x
27	45.9%	1.80	x				x		X	x				
28	48.7%	1.44		x			X		X	X				
29	50.8%	1.18			x		X		X	X				
30	45.5%	1.85				x	X		X	X				
31	49.2%	1.39					X	x	X	X				
32	49.0%	1.41					X		X	X	x			
33	45.4%	1.86					X		X	X		x		
34	48.1%	1.53					X		X	X			x	
35	50.2%	1.25					x		X	X				x

Table 32. Overview of results of the regression models for the KLM repair shops

We first constructed the full *K+1* regression model in order to calculate the C_p values of the other models. Next, we selected the characteristics with the highest correlation with the average waiting time of repair shops and build a regression model only on these characteristics. The characteristic 'squared coefficient of variation of the number of operations' yielded the highest adjusted R^2 and the lowest C_p value. Next we included the characteristic 'number of repairmen', followed by the characteristic '% of items responsible for 80% of the repair load'. After adding this characteristic, the addition of any further characteristics yielded no improvements to either the C_p value and/or the adjusted R^2. Therefore, we stopped the heuristic. Based on the results, the models 10 and 22 were selected as most promising to explain the difference in average waiting times between repair shops of KLM. Next we performed an analysis of residuals to identify whether the models were valid to base conclusions on.

Regression coefficients
Table 33 shows the F test statistical for the regression model. Since both values are less than 0.05, we conclude that both models are statistically significant.

Model	F test statistic
10	0.009
22	0.013

Table 33. F-test- statistics for the regression models of the KLM repair shops

Table 34 shows the p-values of the regression coefficients. The Table shows that model 22 has 1 characteristic which is statistically significant. Model 10 has no characteristics which are not statistically significant.

Characteristic	Model 10	Model 22
Number of repairmen	0.02	0.01
squared coefficient of variation of the number of operations per repair job	0.01	0.02
% of items responsible for 80% of the repair load versus the residuals		0.19

Table 34. Regression coefficients for the models of the KLM repair shops

In order to determine which model is the best, we perform a residual analysis and an analysis for multicollinearity.

Residual analysis of model 10
Figure 26 displays the residuals of model 10. Figure 26.a shows the number of repairmen versus the residuals and Figure 26.b the 'squared coefficient of variation of the number of operations per repair job' versus the residuals. No apparent relation between the characteristics and the residuals can be found.

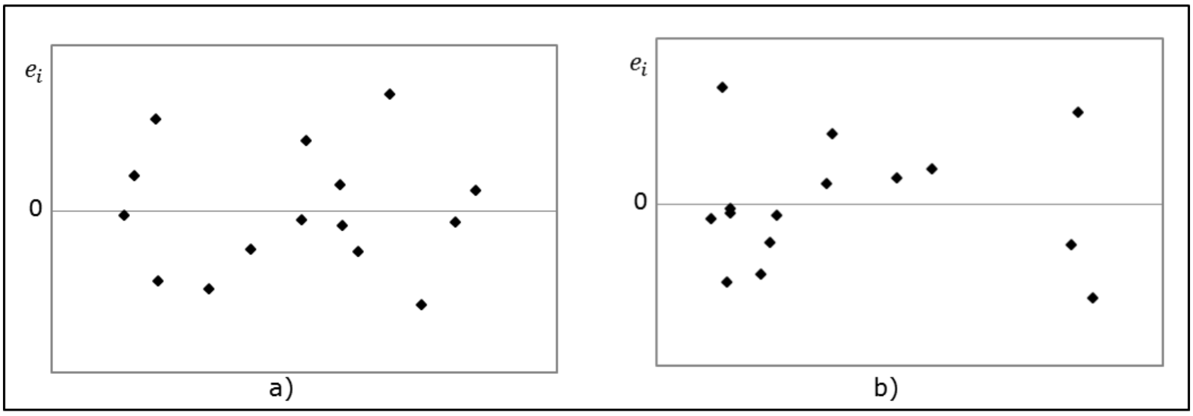

Figure 26.a and 26.b. Residual plots of model 10

Figure 27.a shows a scatter plot of the predicted y-values versus the residuals. This Figure also shows that the residuals are placed at random. Figure 27.b shows a normal probability plot. Since the plot shows a straight line, it is likely that the residuals are normally distributed.

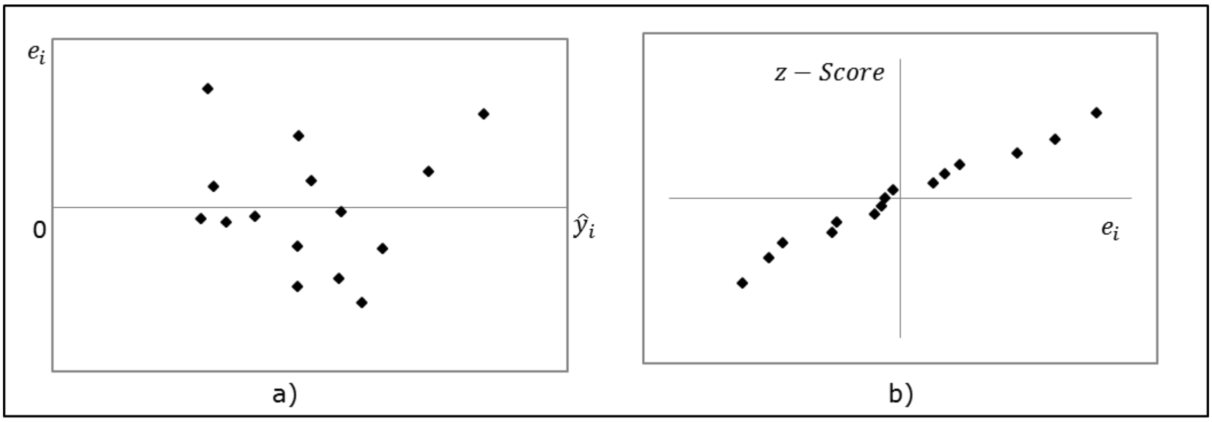

Figure 27.a and 27.b. Normal probability plot and scatter plot of the predicted values versus the residuals of model 10

Table 35 shows the VIF factors on the diagonal. The Table shows that the VIF factors are below which indicates no multicollinearity.

	Number of repairmen	*Squared coefficient of variation of the number of operations per repair job*
Number of repairmen	**1.00**	-0.06
Squared coefficient of variation of the number of operations per repair job	-0.06	**1.00**

Table 35. Variance inflation factors of model 10

Residuals of model 22

Figure 28 displays the residuals of model 22. Figure 28.a shows the number of repairmen versus the residuals, Figure 28.b the 'squared coefficient of variation of the number of operations per repair job' versus the residuals and Figure 28.c the '% of items responsible for 80% of the repair load versus the residuals'. No apparent relation between the characteristics and the residuals can be found.

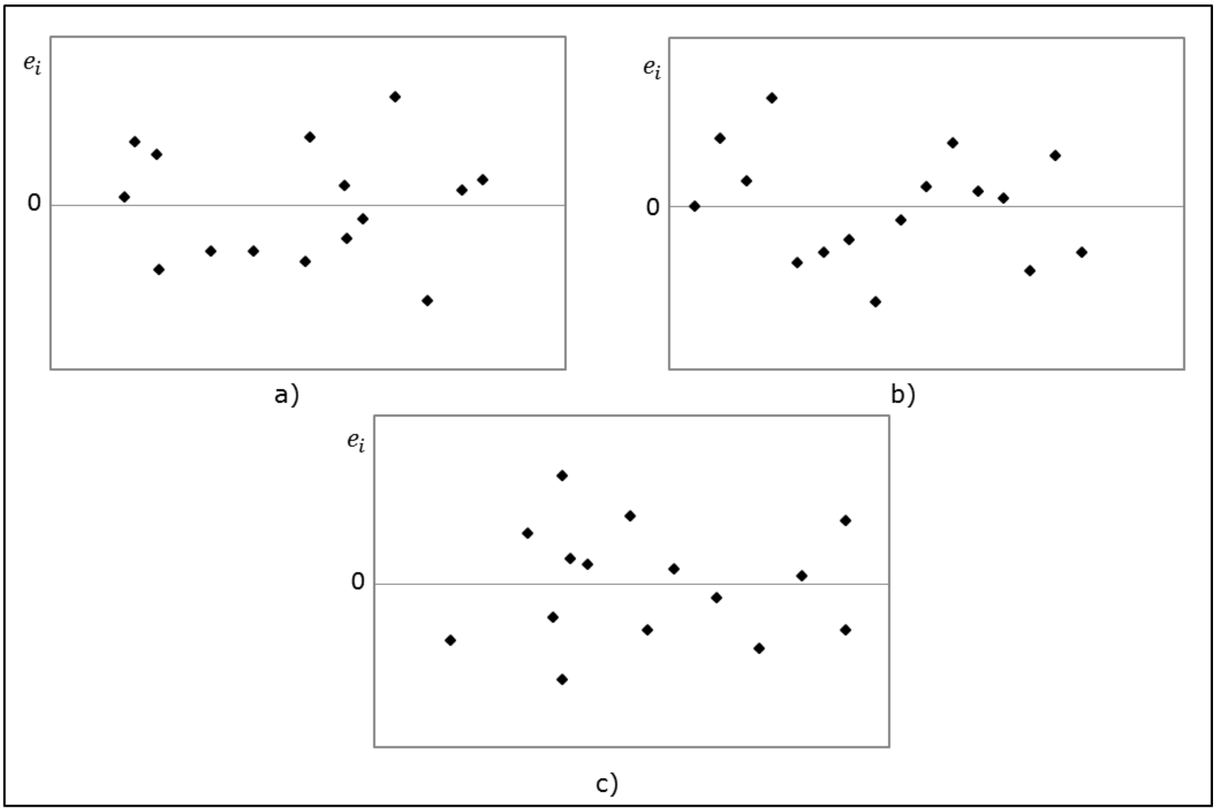

Figure 28.a to 28.c. Residual plots of model 22

Figure 29.a shows a scatter plot of the predicted y-values versus the residuals. This Figure also shows that the residuals are placed at random. Figure 29.b shows a normal probability plot. Since the plot shows a straight line, it is likely that the residuals are normally distributed.

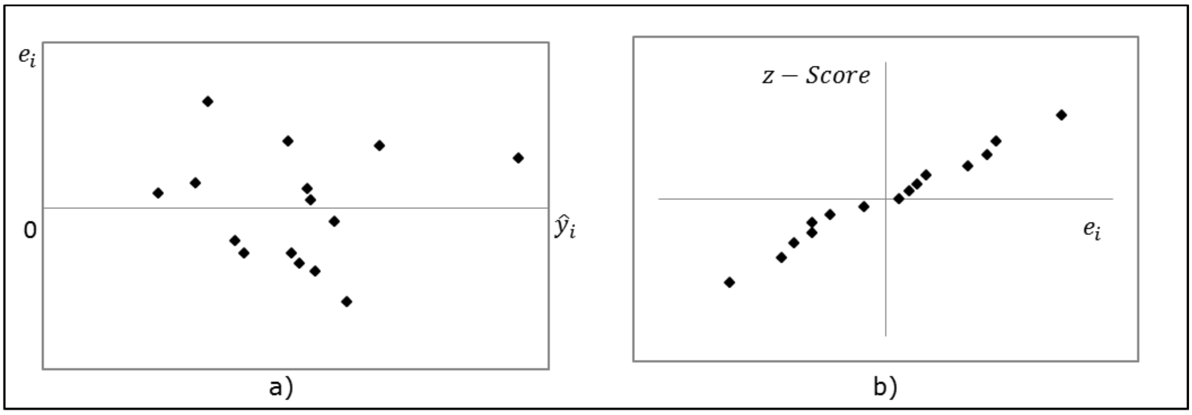

Figure 29.a and 29.b. Normal probability plot and scatter plot of the predicted values versus the residuals of model 22

Table 36 shows the VIF factors on the diagonal. The Table shows that the VIF factors are below which indicates no multicollinearity.

	Number of repairmen	*Squared coefficient of variation of the number of operations per repair job*	*% of items responsible for 80% of the repair load*
Number of repairmen	**1.40**	0.00	0.75
Squared coefficient of variation of the number of operations per repair job	0.00	**1.01**	0.10
% of items responsible for 80% of the repair load	0.75	0.10	**1.41**

Table 36. Variance inflation factors of model 22

Conclusion
For both model 10 and 22, the residuals showed no apparent relation to the characteristics or the predicted *Y* value. Also, the residuals were normally distributed. The models also showed no sign of multicollinearity. Model 22 yielded the highest adjusted R^2. However, model 10 yielded the lowest C_p value and an adjusted R^2 which is close to that of model 22. Furthermore, all characteristics included in model 10 were statistically significant. This was not the case in model 22. Therefore, we consider model 10 as the model which is best suitable to explain the difference between the average waiting time of characteristics.

Appendix G: Results of statistical analysis on repair jobs

The following Section outlines per characteristic the difference in mean waiting time between 2 samples. In the case both samples were larger than 30, the central limit theorem was applied. In this case, a confidence interval was constructed. Figures 31 to 34 show the lower bound and upper bound of the reliability interval. When 0 lies between the upper and lower bound, the difference between samples is not statistically significant. In the case (one of) the sample sizes was smaller than 30, the Wilcoxin Rank sum test was used. In this case, the Figure shows the mean ranks of the two samples. The final column states the conclusion of the statistical test. Here we state to either reject the H_0 hypothesis with 95% accuracy or that there is no statistical significant difference.

Figure 31 displays the outcome of the statistical test between repair jobs higher and lower repair times that than the median. The shops NME S12 and NME S16 do have a statistical significant difference between the mean waiting times in the case of 90% reliability.

	Reliability interval for the difference in average waiting time for repair jobs with long and short repair times			Wilcoxin Rank sum test		
Repair shop	Difference in mean	LB	UB	mean rank sample 1	Mean rank sample 2	Conclusion
KL1	-10.1	-11.0	-9.2			Reject H0
KL2	-8.0	-8.3	-7.8			Reject H0
KL3	-4.1	-4.8	-3.4			Reject H0
KL4	0.6	0.3	0.8			Negatively reject H0
KL5	-1.1	-1.7	-0.4			Reject H0
KL6	-2.4	-2.7	-2.0			Reject H0
KL7	1.3	0.9	1.7			Negatively reject H0
KL8	-15.2	-16.0	-14.3			Reject H0
KL9	-7.1	-8.1	-6.1			Reject H0
KL10	-15.3	-16.2	-14.4			Reject H0
KL11	-0.8	-1.0	-0.6			Reject H0
KL12	13.4	12.0	14.8			Negatively reject H0
KL13	-0.7	-1.2	-0.3			Reject H0
KL14	-10.6	-11.5	-9.7			Reject H0
KL15	-2.2	-3.0	-1.5			Reject H0
GVB1	-6.2	-6.9	-5.4			Reject H0
GVB2	-14.1	-14.8	-13.4			Reject H0
GVB3	-1.5	-2.3	-0.7			Reject H0
GVB4	-8.6	-9.6	-7.7			Reject H0
DBGS1	-55.3	-58.2	-52.3			Reject H0
DBGS2	-133.5	-137.5	-129.4			Reject H0
DBGS3	78.6	76.6	80.6			Negatively reject H0
NME1				6.18	11.5	No statistically significant difference
NME2				12.38	20.86	No statistically significant difference
NME3				18.74	31.46	Reject H0
NME4				12.31	12.88	No statistically significant difference
NME5	-22.1	-24.9	-19.2			Reject H0
NME6				30.6	36.14	Reject H0
NME7				16.31	22	No statistically significant difference
NME8	-5.6	-7.5	-3.7			Reject H0
NME9	-3.6	-5.9	-1.4			Reject H0
NME10	17.5	14.4	20.7			Negatively reject H0

Figure 30. Results of the statistical analysis on the characteristic 'repair time'

Figure 32 displays the outcome of the statistical test between repair jobs with more and less operations that on average.

	Confidence interval for the difference in average waiting time for repair jobs with few and many operations			
Repair shop	Difference in mean	LB	UB	Conclusion
KL1	-12.2	-13.0	-11.3	Reject H0
KL2	-15.1	-15.5	-14.8	Reject H0
KL3	-3.3	-4.0	-2.6	Reject H0
KL4	-1.2	-1.5	-0.9	Reject H0
KL5	-3.1	-3.8	-2.5	Reject H0
KL6	-1.8	-2.1	-1.5	Reject H0
KL7	-1.9	-2.3	-1.4	Reject H0
KL8	-14.9	-15.9	-13.9	Reject H0
KL9	-1.8	-2.7	-0.8	Reject H0
KL10	-19.0	-19.9	-18.1	Reject H0
KL11	0.3	0.1	0.4	Negatively reject H0
KL12	13.6	12.0	15.2	Negatively reject H0
KL13	0.1	-0.4	0.5	No statistically significant difference
KL14	-11.1	-11.9	-10.2	Reject H0
KL15	-6.1	-6.7	-5.4	Reject H0

Figure 31. Results of the statistical analysis on the characteristic 'number of operations'

Figure 33 displays the results of the statistical analysis between repair jobs with materials and repair jobs without materials.

	Confidence interval for the difference in average waiting time for repair jobs with and without materials			Wilcoxin Rank sum test		
Repair shop	Difference in mean	LB	UB	mean rank sample 1	Mean rank sample 2	Conclusion
KL1	-15.6	-16.6	-14.5			Reject H0
KL2	-12.2	-12.5	-12.0			Reject H0
KL3	-5.8	-6.5	-5.2			Reject H0
KL4	-1.3	-1.6	-1.1			Reject H0
KL5	-2.9	-3.5	-2.2			Reject H0
KL6	-2.1	-2.4	-1.8			Reject H0
KL7	-2.4	-2.8	-1.9			Reject H0
KL8	-13.7	-14.5	-12.9			Reject H0
KL9	-7.7	-9.3	-6.2			Reject H0
KL10	-18.5	-19.4	-17.6			Reject H0
KL11	-7.4	-7.7	-7.2			Reject H0
KL12				11.5	64.6	Reject H0
KL13	0.3	-0.2	0.8			No statistically significant difference
KL14	-4.6	-5.4	-3.7			Reject H0
KL15	-6.3	-6.9	-5.6			Reject H0
GVB1				132.0	145.0	No statistically significant difference
GVB2	5.2	4.3	6.0			Negatively reject H0
GVB3	0.4	-0.8	1.5			No statistically significant difference
GVB4	-4.8	-5.6	-3.9			Reject H0
DBGS1	-43.5	-46.4	-40.7			Reject H0
DBGS2	-148.6	-152.1	-145.0			Reject H0
DBGS3	-106.4	-108.6	-104.2			Reject H0
NME1				6.6	7.5	No statistically significant difference
NME2				8.3	17.4	Reject H0
NME3				13.6	31.4	Reject H0
NME4				12.1	12.9	No statistically significant difference
NME5	-54.3	-57.1	-51.4			Reject H0
NME6	-31.0	-36.6	-25.4			Reject H0
NME7				15.3	19.9	No statistically significant difference
NME8	11.9	9.9	13.8			Negatively reject H0
NME9	-48.6	-51.3	-45.9			Reject H0
NME10				61.0	89.0	Reject H0

Figure 32. Results of the statistical analysis on the characteristic 'number of materials'

Figure 34 displays the outcome of the statistical test between repair jobs without slow moving materials and repair jobs with slow moving materials.

	Confidence interval for the difference in average waiting time for repair jobs with and without slow moving materials			Wilcoxin Rank sum test		
Repair shop	Difference in mean	LB	UB	mean rank sample 1	Mean rank sample 2	Conclusion
KL1	-16.1	-18.9	-13.3			Reject H0
KL2				726.0	1111.6	Reject H0
KL3	-21.9	-23.7	-20.2			Reject H0
KL4	-13.2	-14.5	-12.0			Reject H0
KL5	-12.6	-14.3	-10.8			Reject H0
KL6	-8.4	-9.3	-7.6			Reject H0
KL7	-0.1	-1.2	1.0			No statistically significant difference
KL8	-11.1	-12.6	-9.6			Reject H0
KL9	-18.4	-21.0	-15.7			Reject H0
KL10				216	274	No statistically significant difference
KL11				895	1172	No statistically significant difference
KL12	Sample size too small					
KL13	-9.8	-10.9	-8.7			Reject H0
KL14	-14.1	-16.5	-11.6			Reject H0
KL15	-17.1	-18.7	-15.6			Reject H0
GVB1	-9.9	-11.4	-8.3			Reject H0
GVB2	-10.3	-12.8	-7.8			Reject H0
GVB3	-2.4	-3.4	-1.4			Reject H0
GVB4	-6.4	-7.7	-5.1			Reject H0
DBGS1	-33.6	-37.0	-30.2			Reject H0
DBGS2				26	39	Reject H0
DBGS3	50.3	47.9	52.7			Negatively reject H0
NME1				6.57	7.5	No statistically significant difference
NME2				8.33	17.42	Reject H0
NME3				14.48	31.29	Reject H0
NME4				12.08	12.92	No statistically significant difference
NME5	-44.4	-46.8	-42.0			Reject H0
NME6				32.05	33.25	No statistically significant difference
NME7				15.33	19.92	No statistically significant difference
NME8	11.7	7.7	15.6			Negatively reject H0
NME9	-43.8	-46.9	-40.6			Reject H0
NME10				61.89	86.61	Reject H0

Figure 33. Results of the statistical analysis on the characteristic 'slow moving material'

Appendix H: Impact of characteristics on the average waiting time

Table 37 provides an overview of the difference in average waiting time per characteristic. Observations from a negative rejection or, based on the Kruskal-Wallis test are excluded[11]. The values of the negative null hypothesis rejections are removed, because the characteristic does not negatively impact the waiting time. Values from the Kruskal-Wallis test are removed, because the Kruskal-Wallis test uses ranks to determine whether there is a statistical significant difference between two samples. Therefore, we cannot make statements on the difference in mean waiting time between samples.

	Characteristics on which the samples are based				**Characteristic with most impact**
Company	**Repair time**	**Number of operations**	**Materials**	**Slow moving materials**	
KL1	10	12	16	16	(Slow moving) Materials
KL2	8	15	12		Insignificant
KL3	4	3	6	22	Insignificant
KL4		1	1	13	Slow moving materials
KL5	1	3	3	13	Slow moving materials
KL6	2	2	2	8	Slow moving materials
KL7		2	2		Insignificant
KL8	15	15	14	11	Insignificant
KL9	7	2	8	18	Materials
KL10	15	19	18		Insignificant
KL11	1		7		Materials
KL13	1			10	Insignificant
KL14	11	11	5	14	Insignificant
KL15	2	6	6	17	Insignificant
GVB1	6			10	Insignificant
GVB2	14		5	10	Insignificant
GVB3	2			2	Insignificant
GVB4	9		5	6	Insignificant
DBGS1	55		44	34	Insignificant
DBGS2	133		149		Insignificant
DBGS3			106		Materials
NME5	22		54	44	Materials
NME6	0		31		Materials
NME8	6			12	Materials
NME9	4		49	44	(Slow moving) Materials
NME10			16		Materials

Table 37. Overview of the difference in average waiting time for samples.

Table 37 shows 26 repair shops for which the difference in average waiting time between samples is presented. Of the 26 repair shops, 12 repair shops show that (slow moving) materials have the largest impact on the average waiting time. 14 Repair shops show only little difference between the average waiting time of samples for characteristics.

[11] Repair shops KL12, NME1, NME2, NME3, NME4 and NME7 are therefore excluded from the table 37.

Appendix I: Glossary

Term/abbreviation	Drivers
Asset	A capital intensive item (i.e. airplane or tram) used in the primary process of an organization
Spare part	Item used to maintain assets
LRU	Line Replaceable Unit, parts that are replaced "on the line"
SRU	Shop Replaceable Unit, parts that are replaced in the repair shop
Repair shop	Workshop in which LRU's and SRU's are repaired
RFU LRU	Ready-for-Use LRU, LRU's that can be used to replace failed LRU's from an asset
Line Maintenance	Maintenance performed at the base of an asset
Shop Maintenance	Maintenance performed in repair shops
Closed loop supply chain	Repair process in which failed items are repaired
Consumable	Items that are not repaired but discarded after use
Repairable	Item that is repaired when it fails
Items	The whole of both repairable LRU's and SRU's
Materials	The whole of consumable and repairable SRU's to repair both LRU's and repairable SRU's
Fill Rate	The percentage of demand that can be supplied from stock on-hand
Backorder	When there is demand for an item, but this cannot be fulfilled from stock
Repair	The replacement of failed materials on inspection
Remanufacture	The replacement of a predetermined set of materials
Product oriented layout	Repair shop layout in which multiple repair tasks are performed
Task oriented layout	Repair shop with only one task (i.e. painting)

Table 38. Overview of terms and abbreviations and their explanations