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A Simulation Study of the Porter Service at Haukeland University Hospital

Impact of variability in the Porter Service, and effects on performance when experimenting with changes in variability, capacity, and dispatching policies.

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Master Thesis in Business Analysis and Performance Management

Abstract

In this thesis we have analyzed the Porter Service at Haukeland University Hospital based on the following research question:

How does variability in process times and incoming jobs affect the degree of delay, and how do capacity level and dispatching policies influence the performance of the Porter Service at Haukeland University Hospital?

First, we have performed a quantitative analysis on the degree of delay, variability, and the effects of assignment of jobs in the current process. The second part is a simulation analysis on how changes in variability, capacity, and queue disciplines influence the performance of the Porter Service.

The theoretical framework of the analysis is based on production and simulation theory, with main focus on variability.

The quantitative analysis discovered that there is a degree of delay in Normal and Preordered jobs in the current system, which may be caused by variability in process times and in the arrival rate. Also, the dispatching time may affect the performance. The results from the experiments showed that reduced variability in process times, or increased capacity, increase expected performance. We found that the existing queue discipline is a better alternative than First-come First-Served and prioritizing Preordered jobs, and that a reallocation in demand reduces the expected degree of delay. Further, the sensitivity analysis showed that increased demand increases the expected degree of delay.

The results from the analysis imply that the Porter Service's performance can be improved by increasing capacity, reducing variability in process times and redefining the current dispatching policies.

Preface

This thesis is a result of the independent study work in the Master of Science in Economics and Business Administration program at the Norwegian School of Economics (NHH). The thesis is written within the major profile Business Analysis and Performance Management.

Working with this master thesis has been a great experience. We have found it exciting to analyze the Porter Service at Haukeland, and it has been very interesting to learn about the process. The most challenging work was building the simulation model. It was a demanding process that required detailed insight, and we had to make difficult decisions about simplifications and assumptions. The work has been very educational, and we are left with a greater interest about processes in health care. We are very satisfied with the result, and we hope that Haukeland will benefit from the analysis.

For useful advice and insightful comments we would like to thank our advisor, Endre Bjørndal. We thank the Porter Service at Haukeland for useful information and cooperation. We would also like to thank Ingolf Ståhl Anderson for providing a professional version of the simulation program aGPSS, as well as helping us with technical issues. Finally, we would like to thank Tor-Håkon Hellebostad for editing our thesis.

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1.0 Introduction

In this thesis we will analyze the porter operations at Haukeland University Hospital, referred to as the Porter Service, with the objective to see how variability, capacity, and dispatching policies influence the precision in delivery. The Porter Service is a very important function in hospitals, and disruptions in transportation may affect the daily operations both for the Porter Service and for other departments. Furthermore, it might lead to increased queues and inefficiency for the whole hospital.

1.1 Haukeland University Hospital and the Porter Service

Haukeland University Hospital is the largest hospital on the western coast of Norway, and is a part of The Western Norway Regional Health Authority (WNRHA, "Helse Vest"). The hospital's approximately 11 000 employees, are seen as the most important resource for the organization. The number of patients treated by the hospital is nearly 600 000 per year (Haukeland, 2012). Haukeland's primary mission is to live by it motto: "It's all about people", and the goal is to provide the best treatment and care to all patients (Rammeplan, 2012).

The Porter Service at Haukeland University Hospital is an internal service department, organized under the Division of Engineering and Operations. It is mainly divided in three sectors: patient transport, supply-, and waste management. Patient transport accounts for the largest share of all jobs, and includes different job types such as transportation of patients, lab specimens, blood products, gas, and beds. In 2008, they provided approximately 130 000 patient transports at the hospital (Helse Bergen, 2012).

The main objective for the Porter Service is to provide the hospital with transport services, both internally and between institutions outside the hospital. Their goal is to provide transportation in an efficient, competent, and safe manner, with the patient's best interest in mind (Rammeplan, 2012). It is important to emphasize that the Porter Service does not have any responsibilities in relation to patients' medical health. Their main task is transportation, and assisting medical personnel if necessary.

The Porter Service plays an important part in the daily operations at the hospital, particularly by transporting patients to scheduled medical investigations. If the Porter Service does not deliver on time, the patient might lose the appointment and have to reschedule. Another consequence might be delays, both in treatment schedules and transportation, which causes further delays in the system and consequently longer waiting lines. The performance of the Porter Service is also dependent on the users of the service and their actions. In order to deliver on time it is important that the Porter Service receives requests for transportation within a reasonable time before jobs shall be completed. In addition, when the porter arrives the department must make sure that the patient is prepared and ready for transport. If these conditions are not fulfilled, the result may be further delays and inefficiency.

1.2 Thesis Structure

First, in Chapter 2, we will present the current process of the Porter Service at Haukeland. The presentation is based on observations and interviews with porters and managers of the Porter Service. The process will be documented through a value stream map that provides an overview of all activities and parties involved. Based on the process description, we will present identified challenges in the process. In addition, we have received data from Haukeland that provides the basis for a descriptive analysis and gives a better understanding of the challenges faced by the Porter Service.

In Chapter 3, we will present relevant theories for the analysis. The theoretical framework is based on production theory with main focus on variability. Simulation theory will also be a part of the theoretical framework. Furthermore, we will present previous research on health care systems, including some simulation studies. Based on identified challenges in the Porter Service and the theoretical framework, we will present and discuss the research question for further analysis in Chapter 4.

In Chapter 5, we will conduct a quantitative analysis based on data from Haukeland to measure the performance of the Porter Service in order to identify possible causes of delays. In addition, we will analyze the degree of variability in the process and the effects of assignment of jobs. Further, we will build a simulation model based on the value stream map and quantitative analysis, and use it as a tool to measure the impact of possible changes in the process. The assumptions are presented in Chapter 6. The results from the simulation model will be analyzed in light of the theoretical framework, and is presented in Chapter 7. Finally, in Chapter 8 and 9, we will present the findings and implications for further research.

2.0 Case Description

We have spent three days at the hospital observing both porters and dispatchers to collect information about the process. We also had several interviews and discussions with the managers of the Porter Service. The process description is based on this information and has resulted in a value stream map that illustrates the process step by step.

2.1 Process Description of the Porter Service

The scope of the process begins from when a department initiates an order requesting transportation from one location to another, until the job is completed and the object has been transported to the destination. An "object" will be used as a general term for patients, lab specimens or blood products. Figure 1 gives a general overview of the time span from when a job is received in the dispatching center until it is completed.

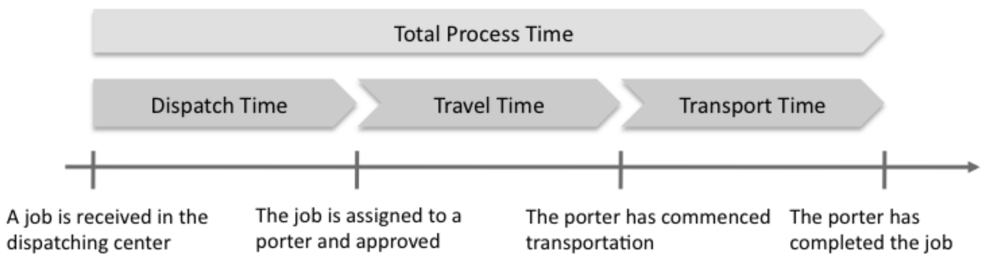


Figure 1 Illustration of the time span from when a job is received in the dispatching center until it is completed

The process is documented through a value stream map and displayed in Figure 2. The numbers from 2.2.1 to 2.2.3 represents challenges identified during observations and conversations, and are further explained in Chapter 2.2.

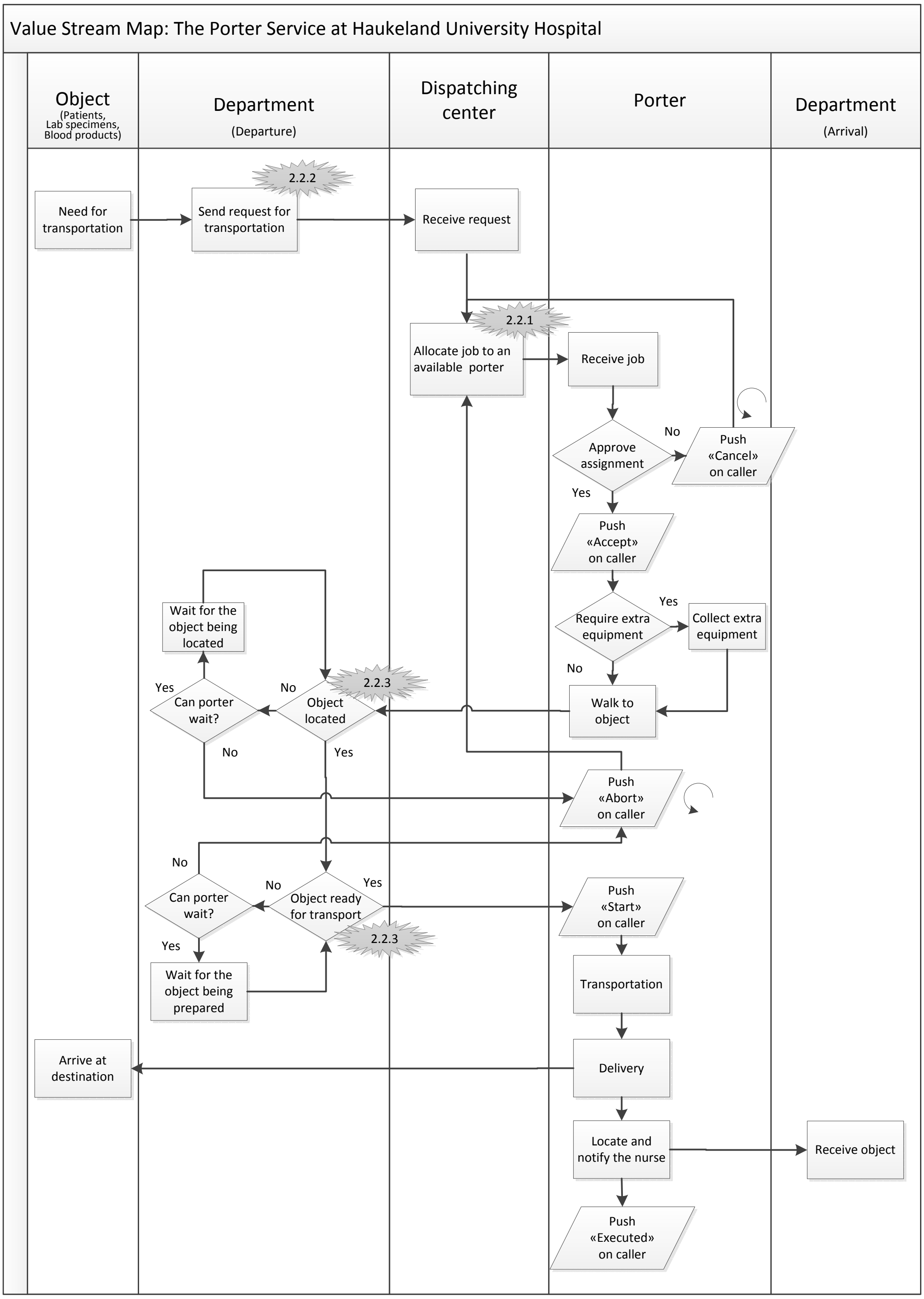


Figure 2 Value stream map of the Porter Service at Haukeland University Hospital

The process we are analyzing starts when a department sends a request for transportation from one location to another internally within the hospital. The request is initiated through a system called porterCOM. The dispatcher receives the request in the dispatching center and assigns the job to an available porter. The dispatcher assigns the jobs manually by selecting from the queue of jobs depending on different criteria such as priority level and queuing time.

The selected porter receives the job via the software system to his personal caller. The job contains detailed information about the object and its location, where the object is to be transported, and how the transport is to be executed. It also contains information about possible risk of infection and whether additional equipment is needed. Once the porter approves the job, it is commenced, and the status in the system is set to “approved” (“Godkjent”). If necessary, the porter collects extra equipment before proceeding to the department where the object is to be located. Upon arrival the porter locates the object and the transportation is commenced if the object is ready. When transportation is started, the porter changes the status to "commenced" ("Startet"). The porter has to notify the nurse when they arrive at the destination. After delivery the porter changes the status of the assignment to “completed” (“Utført”) via the personal caller. However, if the object cannot be located, or if the object is not ready for transport, the porter has to wait for the object to be prepared or cancel the job. If the job is cancelled for one of these reasons, and transportation is still needed, the nurse has to initiate a new order. The job will be registered as "aborted" ("BOM") in the system.

2.2 Identified Challenges in the Process

Through observations and conversations with porters, dispatchers, and managers of the Porter Service we have identified three main challenges in the process.

2.2.1 Assignment of Jobs

Observations of the Porter Service revealed that the precision in delivery is very dependent on efficient assignment of jobs in the dispatching center. Since the jobs are assigned manually, there are high requirements to the dispatchers’ skills, as they have to balance the distribution based on different criteria. The dispatchers have to consider the job’s priority, how long the job has been waiting in the dispatching center and which porter that is available. Also, they have to consider the location of the job’s destination point and the nearest located porter, in order to minimize the walking distance. Assigning the jobs is a demanding task considering the various criteria, especially at peak hours during the day. This might cause the assignment to be ineffective and lead to increased queues in the dispatching center.

According to managers of the Porter Service there is considerable variation in incoming jobs during the day, and the number of incoming jobs is peaking around 13.00. A reason for this might be that doctor consultations are often conducted at the same time of the day in all departments, something that triggers the ordering of various medical investigations. The consequence is a high demand for transportation in certain periods during the day, which causes an uneven utilization of porter capacity. Further, this may result in delays, congestion and long waiting time for patients. It is a challenge for the Porter Service to adjust their capacity to match the demand. In addition, the dispatchers decision on which job to assign next will have a large impact on delays, because they have to prioritize between jobs from a queue that builds up at certain points of the day.

2.2.2 Ordering Process

Observations of the Porter Service also gave an insight in the ordering process from the departments. There are some cases where the dispatching center receives orders with incorrect information. For instance there are some cases where a job has been double booked and the patient has already been transported by another porter or by the department itself. However, we have not observed the ordering process at the departments and therefore we do not have insights in possible reasons for incorrect orders.

2.2.3 Disruptions in Jobs

We also observed cases where the object was not ready for transportation, or could not be located, when the porter arrived. This may occur if the departments are not able to prepare the patient due to unexpected incidents, for example if the patient's medical condition gets worse. In other cases it might be difficult to keep the patient waiting for the porter because of personal needs, and so he cannot be located when the porter arrives. Problems with preparing the object before transport consequentially might lead to the transport being aborted. Further, it can lead to delays because the porter has to wait and it creates a greater risk that the patient loses the medical investigation. In addition, aborted jobs occupy the porter's capacity, which again might lead to further delays.

2.3 Quality Standards for the Porter Service

The Porter Service has developed a framework that includes the different services they are offering and quality standards that apply to these services (Rammeplan, 2012). The framework is used as a policy to define what the customers can expect from the service in terms of delivery deadlines and quality. It also defines how to deal with discrepancies and complaints. There are however no direct consequences if the Porter Service does not manage to deliver according to the standards. The framework also states the responsibilities of the customers using the service. Among other things, it states that transportation is to be ordered through the software porterCOM, and that the patient must be prepared for transportation at least 15 minutes before transport. The quality standards apply mainly to transport of patients, lab specimens and blood products.

Table 1 Quality standards given the different priorities

Priority level	Normal	Preordered	Urgent	Emergency
Quality standards	Initiated transportation within 35 minutes after order time	Completed at appointment time	Assigned within 15 minutes after order time	Assigned within 3 to 5 minutes after order time

Table 1 shows the quality standards given the different priorities. The quality standards define how the different priorities should be handled. Note that the standards define whether the jobs shall be *initiated*, *completed* or *assigned* within a given time or time span.

There are four different type of priority levels defined in the quality standards; *Normal, Urgent, Emergency, and Preordered.* Normal jobs shall be initiated within 35 minutes after they are received in the dispatching center. Urgent jobs shall be assigned to a porter as soon as possible and at most within 15 minutes after they are received in the dispatching center. Emergency jobs shall be assigned to a porter immediately, and at most within 3-5 minutes after they are received in the dispatching center. Preordered jobs imply that the transport shall be completed within appointment time, and are often used when patients have prescheduled appointments.

If a job is not fulfilled according to the quality standards, it means that the transport is delayed. For example, if a Normal job is not assigned to a porter and initiated after 35 minutes, it is considered a delayed job. We will therefore use the quality standards to measure the degree of delay, which in the further analysis will be a measure of the Porter Service’s performance.

2.4 Descriptive Analysis

The data used in the analysis consists mainly of secondary data received from the Porter Service at Haukeland. The data is selected for our purposes by the Porter Services’ IT manager and put together in a data set. We have also collected primary data from meetings with the management and by observing the porters and dispatchers to get a better understanding of the process. The data is from a private source, which is not meant for publication. However, Haukeland is a public hospital, and the thesis will be available for public viewing. Therefore, the data has been anonymized from confidential information about the objects.

The data set contains quantitative information on all jobs that are initiated through the software PorterCOM for 4 months; September, October and November 2011 and January 2012, including 84 186 observations in total. For each job we have information on priority, date, the time when the transport was ordered, started and completed by the porter, and finally, explanation for possible delay or cancellation. We also have information about the job type, and which department that initiated the job.

We have adjusted the data set for our purposes by deleting the job types and priorities that are excluded from the analysis. In addition we have deleted all duplicate jobs (jobs with StatusID 41-44). All jobs of 30 November 2011 are deleted, as there were only 39 observations on this day. This is probably due to a problem with the software system on this particular day.

2.4.1 General Overview

We have performed a descriptive analysis of the data to obtain a better understanding of the challenges in the Porter Service at the hospital.

Table 2 Overview of incoming jobs

	Total number of jobs	Number of days	Arithmetic mean	Standard deviation
All days	84 186	120	702	226
Weekdays	71 554	85	842	63
Weekends	12 632	35	361	27
StatusID:				
Completed ("Utført")	78 430	120	654	206
Cancelled ("Kansellert")	3 629	120	30	19
Printed ("Utskrift")	12	6	2	1
Aborted ("BOM")	2 115	120	35	10

Table 2 displays the number of all incoming jobs registered in porterCOM for the 4 months, with the corresponding mean and standard deviation. The number of jobs varies little from month to month, and the further analysis is therefore performed regardless of month.

During the months of September through November 2011 and January 2012 the Porter Service at Haukeland University Hospital received a total of 84 186 requests for transport, of which 71 554 were on weekdays and 12 632 were on Saturdays and Sundays. The standard deviation of all days is relatively high, and reflects the difference in number of incoming jobs between weekdays and weekends. By performing analysis on weekdays and weekends separately the standard deviation is considerably lower relatively to the mean.

Of the 84 186 jobs, 78 430 are completed (“Utført”). 3 629 jobs are cancelled, which means that either the Porter Service or the department that initiated the job has cancelled it *before* transport has begun. Printed ("Utskrift") means that the job is printed, and accounts for only 12 jobs of the total. Jobs with this status are most likely completed, but are excluded in further analysis because of this uncertainty. Around 2 115 jobs are classified as aborted ("BOM"), which means that it is cancelled for some reason *after* the porter has accepted the job.

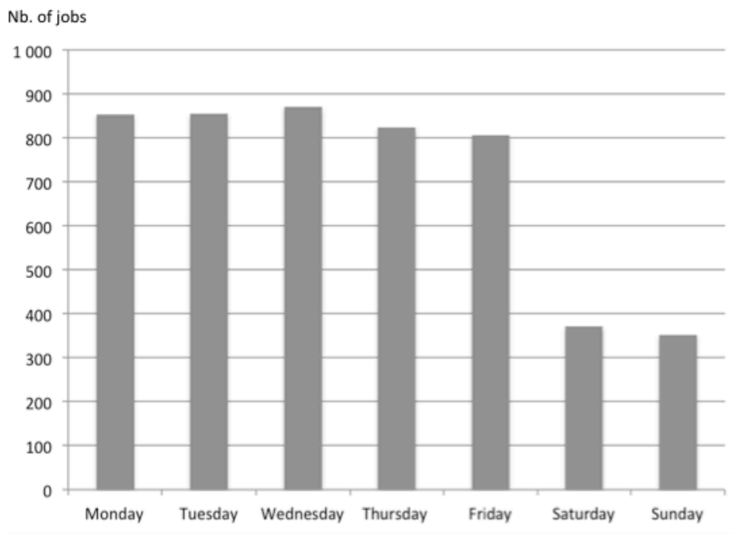


Figure 3 Overview of average number of incoming jobs each day

Figure 3 displays the average number of incoming jobs distributed on the different days of the week. The number of incoming jobs on weekdays is almost the same each day, while there is a lower level of incoming jobs on weekends. However there is a slight increase on Wednesday compared to the other weekdays. The reason for this might be that in general, Mondays and Tuesdays are typical days for hospital admissions and Thursdays and Fridays are typical days for hospital discharge.

2.4.2 Distribution of Jobs

The following section explores how the jobs are distributed within the different job types and priorities.

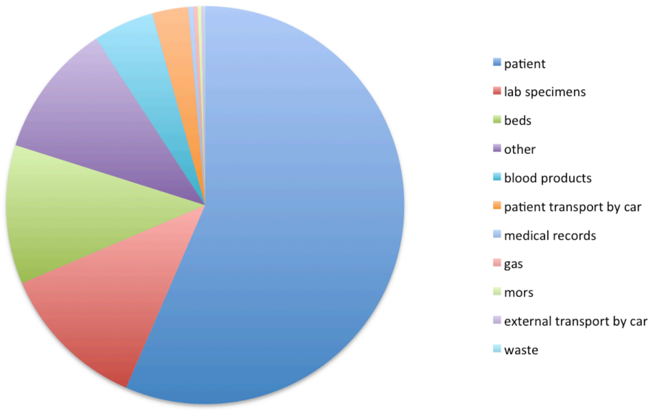


Figure 4 Distribution of jobs based on type of job

Figure 4 shows that patient transport is the largest group based on job type and accounts for approximately 57 % of all jobs. Transport of lab specimens and beds are also large groups and account for about 12 % each. The type called "other" consists mainly of regular assignments and accounts for about 11 % of the total. Transportation of blood products accounts for around 5 %, and patient transport by car accounts for about 3 % of the total. The remaining job types are small groups and account for less than 0,5 % each.

Further analyzes will only focus on the largest groups, which are patient transport, transport of lab specimens, beds, blood products and other.

Table 3 Percentage distribution according to priority for the largest job types

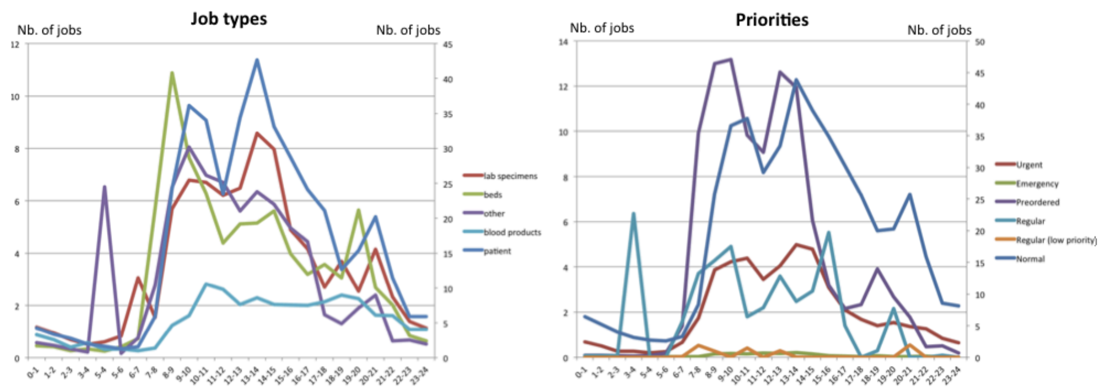
	Grand Total	Normal	Preordered	Urgent	Emergency	Regular	Regular (low priority)
Patient	**47 569**	74,2 %	21,0 %	4,8 %	0,1 %	0,0 %	0,0 %
Lab specimens	**10 170**	74,9 %	0,5 %	14,1 %	0,4 %	10,0 %	0,0 %
Beds	**9 511**	68,7 %	15,5 %	13,5 %	0,4 %	2,0 %	0,0 %
Other	**9 163**	38,4 %	8,9 %	6,0 %	0,3 %	43,6 %	2,8 %
Blood products	**4 163**	85,8 %	5,8 %	6,1 %	1,9 %	0,4 %	0,0 %

Note: The percentage of the different priorities is calculated based on the grand total for each job type

Table 3 display the distribution of jobs based on priority for the five largest job types. In addition to the priorities already defined in the quality standards, there are two other priorities used by the Porter Service. Regular and Regular (low priority) priorities are often used for routine jobs, and are considered having a lower priority than the other jobs. Normal priority occur most frequently for all job types except Other, while Preordered jobs are the second largest group in patient transport and transport of beds. Jobs classified as Urgent occur most frequently within transport of lab specimens and beds. As expected, Regular priority occurs most frequently for transport of Other, since the duties of this job type are mostly routine tasks. Emergency and Regular (low priority) jobs does not occur very often. However, Emergency represents almost 2 % of transport of blood products, and this is remarkably higher than for the other job types.

2.4.3 Number of Incoming Jobs

This section explores how the number of incoming jobs is distributed during a day based on job type and priority.



Note:
Graph on the left side: Patient jobs are measured on the right axis
Graph on the right side: Normal orders are measured on the right axis

Figure 5 Average number of incoming jobs distributed over 24 hours for the 5 largest job types

Figure 5 shows the average number of incoming jobs during a day. The highest level of incoming jobs for all job types and priorities is between 8.00-17.00. The graph on the left side shows that the demand for patient transport has clearly defined peaks between 9.00-10.00, 13.00-14.00 and 20.00-21.00. It also looks like lab specimen jobs and other jobs have the same variation during the day. However, the variation in incoming bed jobs is slightly different from patient jobs and lab specimen jobs. In the morning and the evening it peaks one hour *before* patient jobs, and in the afternoon one hour *after.*

The graph on the right side shows that number of Normal jobs is at the highest level between 8.00-17.00, while Preordered jobs is at the highest level between 8.00-14.00. It seems like Normal and Preordered jobs follow the same variation over time. Normal jobs peak between 8.00-10.00, 13.00-14.00 and 20.00-21.00. However, Preordered jobs tend to peak one hour before Normal jobs. The other priority levels seem to be evenly distributed between 8.00-17.00.

3.0 Theory

3.1 Variability

According to Factory Physics (Hopp & Spearman, 2000) variability exists in all production systems, which can affect the performance in a process. It is therefore important to measure and understand the variability in order to handle it and achieve effective management of production. The further presentation of theory in Chapter 3.1 is mainly based on Factory Physics (Hopp & Spearman, 2000).

3.1.1 Variability and Randomness

Hopp & Spearman (2000) define variability as "*the quality of non-uniformity of a class of entities*" (p. 249). Examples of entities prone to non-uniformity are process times, machine failure, repair times and quality measures. Variability is related to randomness and probability. It is important to understand these two concepts in order to understand the cause and effect of variability. To do so, we have to distinguish between controllable and random variation. Controllable variation occurs as a direct result of decisions, while random variation is a consequence of events beyond our control. Both types of variations can be disruptive in a production system.

The production system is often subject to random variation because of imperfect information. Hopp & Spearman emphasize that there always will be some level of imperfect information, and therefore it is not possible to predict the future precisely. This means that we can only get statistical estimates of how the production system will appear. As a result, a production system can never be perfectly managed, and it is important to find robust policies that will work well in the long run. Good probabilistic measures can be a powerful tool to identify robust policies. Probabilistic measures with randomness can be expressed by the mean and variance of the random variables involved.

3.1.2 Process Time Variability

Processing times can be analyzed by using probabilistic measures, e.g., the mean and standard deviation. By using the mean and standard deviation we can calculate the coefficient of variation (CV), which is a relative measure of variability. If t denotes the mean process time and σ denotes the standard deviation, the formula for the coefficient of variation (CV) is equal to:

$$CV = \frac{\sigma}{t}$$

The coefficient of variation classifies the level of variability for the different process times, and can be defined as in Table 4.

Table 4 Classes of variability

Variability Class	Coefficient of Variation
Low	CV < 0,75
Moderate	0,75 ≤ CV < 1,33
High	CV ≥ 1,33

3.1.3 Flow Variability

When talking about variability in a production process, one must also consider flow variability. Flow variability is how variability in one workstation affects the behavior and variability in another workstation, meaning how transfer of jobs flow from one station to another. For example, highly variable process times in an upstream workstation will probably cause the flow to the next workstation to be highly variable.

The arrival rate of jobs explains how the jobs arrive at a workstation, and are measured in jobs per unit time. By calculating the average arrival rate to a workstation, denoted by r_a, we can determine the mean time between arrivals, t_a, by the formula:

$$t_a = \frac{1}{r_a}$$

When the average arrival rate is determined, we can calculate the coefficient of variation of inter arrival times, by the formula:

$$ACV = \frac{\sigma_a}{t_a}$$

The arrival coefficient of variation classifies the level of variability in the same way as for process times in Table 4, Chapter 3.1.2. Low ACV indicates evenly spaced arrivals while high ACV indicates uneven arrivals. When defining the arrival CV it is important to stress that the capacity level in the workstation must exceed the arrival rate in order for the workstation to keep up with the arrivals.

3.1.4 VUT Equation

The VUT equation is an approximation of expected waiting time in a queue, and is a multiplicative relationship between three elements; a variability term (V), an utilization term (U) and a time term (T). The variability term consists of the arrival CV and the CV of effective process time. The utilization term is defined by the capacity utilization, while the time term is the mean effective process time. The VUT equation implies that high variability in process times and arrival rate, high capacity utilization, or high effective process time increase the expected waiting time in the queue.

3.1.5 The Corrupting Influence of Variability

After we have characterized and evaluated the variability in process times and flows, we can use these as tools to describe the behavior of manufacturing systems that involves variability. If there is variability in a production system, it has to be managed in order to minimize operational problems.

Hopp & Spearman claims that an increase in any source of variability will degrade at least one efficiency measures, like for instance throughput, utilization, cycle time, lead time, customer service, or quality. Further, a fundamental law of physics states that "*Increasing variability always degrades the performance of a production system"* (Hopp & Spearman, 2000, p 295*).* The interpretation of this variability law is that it is essential to reduce variation to improve performance.

Further, increasing variability will impact the production along three general dimensions: inventory, capacity, and time. Inventory impact is measured by inventory efficiency, capacity impact is measured by efficiency in production, and utilization and time impact is measured by efficiency in cycle time, lead-time, and service. In addition, the impact of the whole system is measured by quality efficiency. For instance, cases of rework and duplication of work will require additional capacity, additional time and add inventory. The three impacts of increased variability can be seen as buffers that can be controlled in order to manage the production system. This leads us to the second law of variability, stating that "*Variability in a production system will be buffered by some combination of inventory, capacity and time"* (Hopp & Spearman, 2000, p 295). If variability in the process degrades performance, the variability has to be buffered by increasing one or several of these elements.

3.1.6 Queuing Systems

A queuing system consists of an arrival process, a queue and a service mechanism (Hillier & Lieberman, 2005). The relationship between these elements is illustrated in Figure 6.

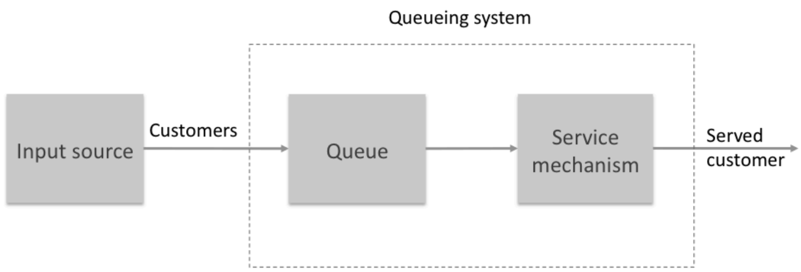


Figure 6 The basic queuing process (Hillier & Lieberman, 2005, p. 766)

The arrival process creates the input source, and the customers enter the queuing system and join a queue. The time between each arrival of customers is called inter arrival time. The members of the queue receive service, and are selected by a known rule, called a queue discipline. The queue discipline can be first-come first-served (FCFS), earliest due date (EDD) or according to some priority scheme.

The queue discipline called FCFS implies that the customer that has waited the longest in the queue is selected first. On the other hand, priority schemes means that customers are selected according to given priorities. For example in an emergency room at a hospital the most acute cases will be prioritized over other cases. EDD is a sequencing rule that minimizes the maximum lateness on a single machine. This is done by ordering the jobs according to due dates, and selecting the job with the first due date (Hopp & Spearman, 2000).

3.2 Simulation

Simulation is defined as "*the imitation of the operation of a real-world process or system over time*" (Banks, 1998, p. 3). In simulation models, probability distributions are used to randomly generate events that occur in the real system, to obtain statistical observations of the performance resulting from different events. The use of simulation is an important tool, especially in operations research studies where the stochastic system is too complex to be analyzed by mathematical models, as for example queuing models (Hillier & Lieberman, 2005).

Simulation models are often classified as either discrete event or continuous simulations. Discrete event simulation is defined as "*a system where changes in the state of the system occur instantaneously at random points in time as a result of the occurrence of discrete events*" (Hillier & Lieberman, 2005, p. 932). An example is queuing systems where the number of customers in the system is determined by arrival and departure of customers, as well as the service time of each customer. Continuous simulation is defined as "*a system where changes in the state of the system changes continuously over time*" (Hillier & Lieberman, 2005, p. 932). An example is a simulation of an airplane in flight, where the current position of the airplane is changing continuously over time.

3.2.1 Advantages and Disadvantages of Simulation

Simulation can be used to explore the effects of new policies and operating procedures without experimenting with the real system. It is expensive and risky to implement changes in organizations, and simulation can be a helpful tool to test the effects of such changes before decision is made. Also, simulation models may give a better understanding of the interactions in complex systems, and might be helpful in diagnosing problems. Simulation is often used in bottleneck analysis and can provide an understanding of underlying causes of delays in processes.

However, simulation modeling and analysis can be very time consuming and expensive, and sometimes the cost may exceed the benefit. Also, it might be difficult to interpret the results from simulation outputs. This is because simulation outputs usually are based on random inputs, and it may be difficult to determine whether the results are based on system interrelationships or only randomness (Banks, 1998).

3.2.2 Simulation of Service Systems

In service systems, waiting time tends to have a greater importance than throughput, and queue time will be the most important measure of performance. In service industries, the performance of the systems are often heavily dependent on human beings, and people tend to be more unpredictable and variable than machines in a manufacturing system. Therefore the overall performance is determined by the performance of each individual in the process. In many systems there is great variability in the work of personnel, both when it comes to service times and quality. This is a natural consequence of people being different and having varying experience and training. As a result the variability in service systems are often much higher than in manufacturing systems, and therefore of greater importance.

Service systems provide assistance to customers, for example restaurants and banks. A hospital is also a service system, where the entities in the process are patients, or objects originated from patients, as lab specimens. Processes in healthcare are dependent on people, as both the entities in the flow and the recourses are human beings. This increases the variability inherent in the process because people are different and act differently. For example patients may be late for appointments or they fail to arrive at all (Banks, 1998). Simulation is a good tool for analyzing processes in healthcare and has many advantages over more traditional approaches to process improvement (Banks, 1998). Analysis on variability can be conducted, and the effect of different alternative changes can be quantified.

3.2.3 Input Data

The simulation analyst must determine a way to represent random variables for each element modeled in the system. The input data varies depending on the amount of available data, the degree of reliability, and whether the variables are independent of other input data or related to the outputs. If the variables are independent, there are three ways of determining the input data. One way is to assume that the variable is deterministic based on historic data, as for example the average. However, it is important to remember that if there is variation in the real system, deterministic input data can invalidate the simulation results. The second way to determine the input data is to fit a probability distribution to the data. Often there are underlying processes, which create distributions that can be predicted to some degree, for example the arrival of customers. If the arrivals occur one at a time, completely random without rush periods or completely independent, it can be shown that the number of arrivals follows a Poisson distribution. If no distribution fits the data using conventional techniques, the third way is to decide the input data based on the empirical distribution of the historic data (Banks, 1998).

3.2.4 Terminating versus Non-Terminating Systems

The duration of the simulation should be based on whether the process is a terminating or a non-terminating system. Terminating systems are processes which have a fixed length of duration, for example stores which are open from 9.00 to 21.00, or manufacturing processes which processes a fixed number of jobs each day. On the other hand the duration in non-terminating systems are not finite, for example assembly lines that operates 24-hours, all days of the week. In a terminating system the duration of the simulation should be equal to the duration of the real system, and the number of runs should be adapted so that the confidence interval is within acceptable limits. In non-terminating system the objective of the simulation is to analyze the steady state behavior, and the duration of the simulation should therefore be adapted to this. If there is a transient phase in the simulation, it should be removed from the results in order to analyze the steady state.

3.2.5 Comparing Systems via Simulation

When comparing systems in a simulation model, the choice of random number streams is an important part of the simulation experiment. When using different streams to different systems, outputs from the systems are statistically independent. On the other hand, using the same stream leads to dependence among the corresponding outputs. It can be useful to assign the same random number stream when comparing experiments. This technique is called Common Random Numbers (CRN). CRN induces a fairer comparison between systems, since the systems have the same experimental conditions.

The simplest comparison problem is to estimate the difference in expected performance of two systems (Banks, 1998). The sample mean and variance of n outputs X_1, X_2, ... X_n can be defined as:

$$\overline{X} = \frac{1}{n}\sum_{j=1}^{n} X_j$$

$$S^2 = \frac{1}{n-1}\sum_{j=1}^{n}(X_j - \overline{X})^2 = \frac{1}{n-1}\sum_{j=1}^{n} X_j^2 - n\overline{X}^2)$$

The estimator $\overline{D} = \overline{Y}_1 - \overline{Y}_2$ is used to estimate the expected difference in performance, $\mu_1 - \mu_2$ (Banks, 1998). When the systems are simulated with common random numbers, the appropriate confidence interval is defined as:

$$\overline{Y}_1 - \overline{Y}_2 \pm t_{1-\alpha/2,n-1}\sqrt{\frac{S_D^2}{n}}$$

Where $t_{1-\alpha/2,n-1}$ is the $1-\alpha/2$ quantile of the t-distribution with n-1 degrees of freedom. S_D^2 is the variance of the estimate $Y_{1n} - Y_{2n}$.

3.2.6 Verification and Validation

Verification and validation of the model is important to ensure that the representation of the real process is accurate. Verification is defined as "*a determination of whether the computer implementation of the conceptual model is correct"* (Banks, 1998, p. 22). Verification is to ensure that the simulation model reflects the real process correctly, and can be performed in different ways. It is important to compare the flow in the model with flowcharts, but first the analyst must be sure that the flowcharts are a correct description of the real process. Flowcharts should therefore be examined and confirmed by a team who are familiar with the real process. Involvement from personnel and experts from the organization are important to achieve acceptance of the model. Also, more than one person should check the model code, and check whether values of the input data are used appropriately.

Validation is defined as "*a determination of whether the conceptual model can be substituted for the real system for the purpose of experimentation"* (Banks, 1998, p. 23). There are many ways to perform validation. Validation should be conducted with the use of more than one method to ensure that the model is a good representation of the real process. An example of model validation is comparison of historical data and outputs from the model. There are two main groups of validation methods, subjective and objective techniques. Examples of subjective techniques are sensitivity analysis, extreme-condition test, and validation of model assumptions. Sensitivity analysis is based on the idea that when input data changes, output data should also change in a predictable direction. For example, when capacity in a system is increasing the queue should be decreasing. Extreme-condition tests can be performed by observing how the model behaves when changing input data to extreme values. Validation of model assumptions is subjective and should be performed by a team who knows the real process. Also, validation of input data should be conducted using statistical tests and estimating parameters of the assumed distribution, or consulting with personnel and experts.

Examples of objective techniques are validating input-output transformations and validation using historical input data. The idea behind these techniques is to validate the output data from the model with real historical data. However, validation using historical input data is done by running the model with real input data. It is reasonable to assume that the output data from the model is close to the real output data, within acceptable statistical error.

3.3 Previous Research

3.3.1 Hospital Logistics

In recent years, a discussion has developed in the Norwegian society about the health care system in Norway. Many Norwegian hospitals struggle with long waiting lines and clutters in the system, making patients insecure and contribute to a general distrust of the health care system.

In the article "*Berit Irene Helgheim: Fra sykepleier til doktor I logistikk*" Helgheim talks about her PhD thesis called “Production Processes in Health Care” (Logistikk og ledelse, 2007). The thesis addresses the use of production economics in health care, and is based on data from American hospitals. The study shows that quality depends on the treatment processes, and that variation in treatment processes can have an effect on costs and efficiency in hospitals. In the article, Helgheim claims that there is a huge potential in improving health care systems by using logistic thinking, and that the results from the study also may be relevant for Norwegian health care (Logistikk og ledelse, 2007).

Helgheim (Logistikk og Ledelse, 2007) points out that the Norwegian health care system traditionally does not think of efficiency and productivity as defined in the manufacturing industry. Applying the concepts from a production factory to the operations in a hospital has a tendency of being contradictory, and in some cases unethical, to many health care employees. However, Helgheim (Logisitkk og Ledelse, 2007) emphasizes that the operations in a hospital can be described by the same terminology as in a manufacturing company. Also, she claims that a production economic approach is the key solution to improve the efficiency at hospitals.

3.3.2 Study of The Porter Operations in Two Hospitals in Vancouver

A previous study of the porter operations in two hospitals in Vancouver, Canada "Improving the Efficiency of Porter Operations in Two Vancouver Hospitals" (Chen et al., 2005), explores the importance and challenges of the porter operations. The study is based on both qualitative and quantitative measurements with the objective to improve the efficiency of porter operations.

The porter operations at Vancouver General Hospital (VGA) are mainly centralized and most of the porters are dispatched through a common dispatch center, and some are dedicated to special units or services. At St. Paul's Hospital (SPH) the situation is the opposite, where only a few porters are dispatched through a centralized system and most of the porters are managed locally in the different departments in the hospital. Chen et al. (2005) identified several challenges facing the porter operation in each hospital, and discovered great differences mainly due to how the services were organized. In VGA, the main challenges were linked to communication issues, dispatching software issues and lack of performance metrics and measurement. At SPH, the challenges were related to the lack of an overall management of the porter operations and their services differed according to the different departments.

Different study approaches and analysis were adapted at the two hospitals and their specific challenges. At VGA, they developed an optimal staff schedule by linear programming, and found a way to measure the impact of system changes using simulation. They also came to the conclusion that it was beneficial to move a centralized porter to one department for a specific shift. The study at SPH mainly resulted in recommendations on how to design and manage the porter operations.

For our purpose, the most relevant part from the study is the simulation model of the centralized system and how they modeled the dispatching of porters. The system is modeled as a multiple server priority queuing system, and they use discrete event simulation. The requests arrive, and are thereby distributed to an available porter by a dispatcher. The distribution of jobs is modeled by assigning a "score" to the jobs according to their priority and waiting time in the system, and jobs with the highest score are distributed first. However, pre-scheduled jobs are treated differently, where the system generates a dispatch time and places the jobs in a separated queue. For pre-scheduled jobs, the score is based on the difference between the suggested dispatch time and the current time, and when the difference increases the score of the order will increase accordingly.

4.0 Research Question

Based on observations and the process map we have identified three different challenges; the assignment of jobs, the ordering process and disruptions in jobs. The challenges are further discussed in Chapter 2.2. We believe that these challenges are affecting the Porter Services' performance. The performance is measured by the degree of delay in transport, and is based on the quality standards discussed in Chapter 2.3. The identified challenge regarding the ordering process will be not be a part of further analysis. An analysis of the ordering process would be very demanding and time consuming, and therefore we had to exclude this because of time limitations.

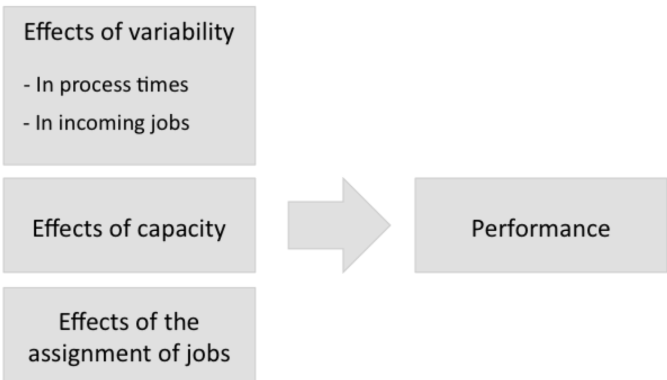


Figure 7 Hypothesis about the relationship between identified challenges and performance

Figure 7 illustrates our hypothesis about the relationship between identified challenges and performance. We have observed that disruptions in commenced jobs affect the process times, and thereby performance because they result in unnecessary use of capacity. This is especially true if the porter has to wait for the object or if the job has to be reordered by the department. In addition, the large variation in incoming jobs during a day may have an impact on the performance, since it is difficult to adjust the capacity level to the workload. It may result in uneven use of capacity with high utilization during peak periods. Also, we have observed that the assignment of jobs is challenging, and it has a large impact on the process flow. Dispatching time may also affect each job's total process time, and thereby the performance.

We believe that some of the challenges are related to variability in the process, and that it has a negative impact on performance. According to theory, the variability law states that increased variability in a production system degrades the performance (Hopp & Spearman, 2000). Also, the VUT equation implies that high utilization, combined with variability cause queues building up and thereby a negative effect on the degree of delay (Hopp & Spearman, 2000). Further, we believe that the queuing system will affect the assignment of jobs and performance.

As a result the research question for further analysis is:

How does variability in process times and incoming jobs affect the degree of delay, and how do capacity level and dispatching policies influence the performance of the Porter Service at Haukeland University Hospital?

Based on the descriptive analysis, further analysis will only involve transport of patients, lab specimens and blood products, which are the main groups of services in demand. Transport of beds and other are excluded because the quality standards do not apply for these job types. Also, we have limited the analysis to only include transportation within the hospital. In addition the priorities Regular and Regular (low priority) will not be included in further analysis, because they mainly consist of routine jobs and the quality standards do not apply to these priorities.

5.0 Analysis of Performance

In order to conduct analysis on the Porter Service's performance we will use a quantitative research design based on the dataset received from Haukeland, presented in Chapter 2.4.

First, we will determine the Porter Service's performance based on the quality standards. If the performance does not match the quality standards, it is assumed that the job is delayed. The degree of delay is measured by calculating when the job is received in the dispatching center and when it is *commenced*, *assigned* or *completed*, depending on the priority level and corresponding quality standard. The quality standards are given in Table 1 in Chapter 2.3. It turned out that the quality standards were difficult to comprehend and interpret correctly. However, after several meetings and discussions with the managers of the Porter Service we reached a common understanding.

Second, we will determine the degree of variability in the process by measuring the coefficient of variance in process times and in the arrival rate. We will also conduct further analysis on possible causes of variability in process times. The effects of variability are analyzed based on production theory. Further, we will analyze the relationship between performance and assignment of jobs.

The analysis in this chapter is performed on weekdays only, and weekends are therefore excluded from the dataset. The main operation at the hospital is on weekdays, and this is also reflected in number of incoming jobs, which is significantly higher on weekdays than weekends. As a result the largest challenges is on weekdays. The further analysis is based on a total of 51 557 observations, on 85 weekdays. The results from the analyses are presented in tables and figures and are commented on continuously during the analysis.

5.1 Quantitative Analysis based on Quality Standards

When a job is completed, it means that the transport is executed and the porter has finished the job. However, it is not determined whether or not the job was carried out in accordance with quality standards that the Porter Service has committed to. If the quality standards are not fulfilled it means that the transport is delayed. Table 1 summarizes the quality standards for the different priorities presented in Chapter 2.3.

Table 1 Quality standards for different priorities

Priority level	Normal	Preordered	Urgent	Emergency
Quality standards	Initiated transportation within 35 minutes after order time	Completed at appointment time	Assigned within 15 minutes after order time	Assigned within 3 to 5 minutes after order time

To calculate the delay, the quality standards are used as "deadlines" for when the jobs should be completed. The quality standards require that Normal jobs should be *initiated* within 35 minutes after order time, while Preordered jobs should be *completed* within appointment time. Urgent and Emergency jobs, on the other hand, should be *assigned* to a porter within 15 and 5 minutes, respectively, after the job is received in the dispatching center.

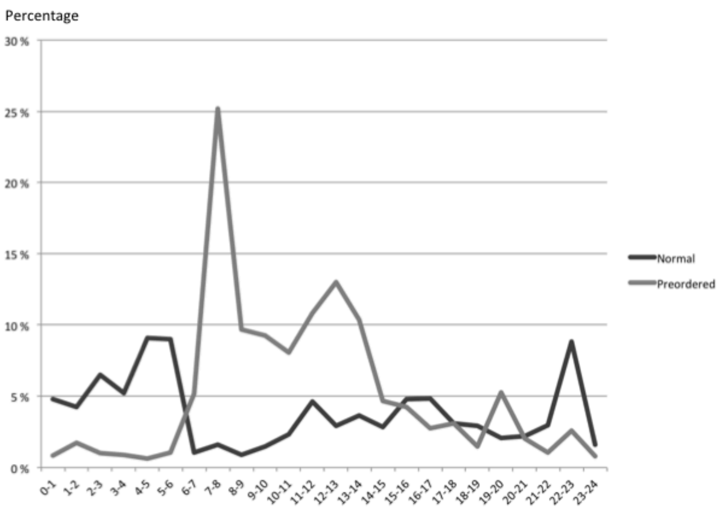
Table 5 Overview of delayed jobs

	Normal	Preordered	Urgent	Emergency	Grand Total
Completed ("Utført")	35 359	8 290	3 185	117	46 951
Delay	1 485	3 359	3	0	4 847
"missing time" [1]	890	0	88	6	984
Percentage delay [2]	**4,2 %**	**40,5 %**	**0,1 %**	**0,0 %**	**10,3 %**
Percentage delay > 5 min	2,5 %	21,4 %	-	-	5,6 %
Percentage delay > 10 min	1,5 %	11,3 %	-	-	3,1 %
Average delay in minutes [3]	11,11	8,37	-	-	9,21
Standard deviation	17,55	10,25	-	-	13,00

Note:
1. "missing time" refers to observations without the time the job was commenced and/or completed, and are not included in Grand Total.
2. Percentage delay is calculated on the basis of completed ("Utført") jobs and delays for each priority.
3. Average delay is calculated on a 24-hour basis.

Table 5 presents an overview of completed jobs, percentage delay and average delay in minutes based on priorities. Percentage delay is calculated on the basis of completed jobs. “Missing time” refers to observations in the dataset without registered time, and these observations are not included in the calculations.

There are in total 4 847 delays, which represent 10,3 % of total completed jobs. 4,2 % of Normal jobs are delayed, and 2,5 % are delayed with more than 5 minutes. Average delay in Normal jobs is around 11 minutes, with a standard deviation of over 17 minutes. This implies that there is a high variation in the length of delays for this priority. Over 40 % of Preordered jobs are delayed, and about half of these are delayed more than 5 minutes. They are on average delayed with 8,37 minutes, with a standard deviation of 10,25 minutes. Preordered jobs are important to complete on time because they often involves patients who need transport to prescheduled treatments or appointments. Percentage delay in Urgent and Emergency jobs are close to 0, and are therefore excluded from further analyses related to delays.

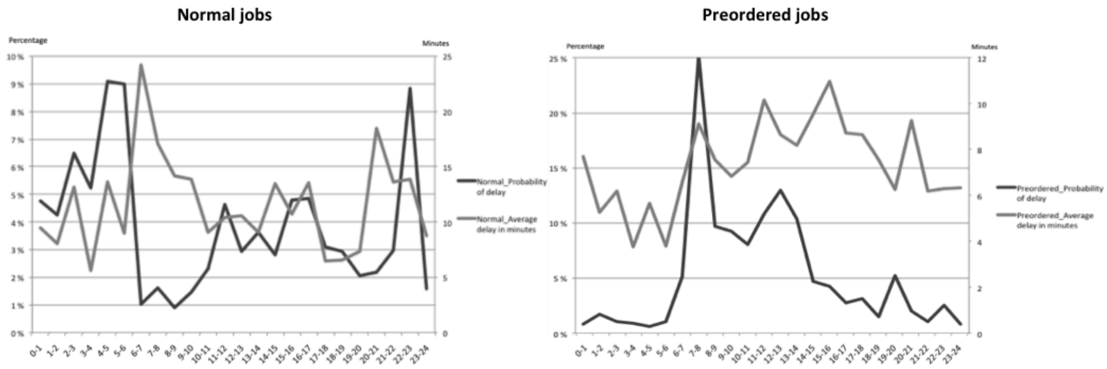


Note:
Probability is calculated on the basis of number of delays within each priority and total completed jobs, within each time interval.

Figure 8 Probability of delay distributed over 24-hours for Normal and Preordered jobs

Figure 8 shows the probability of a job being delayed within the different time intervals during a day. The graph shows that the probability of delay in Preordered jobs increases significantly at certain times of the day, at 6.00-7.00 and 12.00-13.00

with 25 % and 13 % probability of delay, respectively. A reason for this might be that the porter capacity at 6.00-7.00 is relatively low. The capacity levels are illustrated in Figure 16 in Chapter 6.1.2. Also, Figure 5 in Chapter 2.4.3 shows that the number of incoming jobs is increasing from 6.00-7.00, and is at peak level at 12.00-13.00. This relationship is supported by the VUT equation, where high utilization has a negative impact on expected queue time. When utilization is high, queues may build up and affect the degree of delay. The probability of delay in Normal jobs is generally lower and more stable, ranging from 3-6 % during the day.



Note:
Probability is calculated on the basis of number of delays within each priority and total completed jobs, for each time interval.
Average delay in minutes is measured within each priority, for each time interval.

Figure 9 Probability of delay and average delay in minutes distributed over 24-hours

Figure 9 shows the relationship between the probability of a job being delayed and the average delay in minutes within the different time intervals. The probability of delay and average delay in Normal jobs follow the same variation, except from 6.00-15.00 where the average delay in minutes seems to increase when the probability of delay decreases. Our results indicate that Normal jobs on average have longer delays than Preordered jobs. There are large variations in the probability of delay in Preordered jobs during the day. The average delay is on the other hand more stable, between 4 and 10 minutes throughout the day. The tendency is that the average delay increases when the probability of delay increases, particularly when the probability of delay is at its highest levels, around 6.00-7.00 and 12.00-13.00.

To summarize, the analysis showed that the Porter Service has difficulties performing in accordance with the current quality standards for Normal and Preordered jobs. We have identified possible reasons for why the Porter Service has difficulties performing transport on time, and thus has delays. One cause might be that queues are building up during the day because of high capacity utilization, resulting in delays. We will in the following sections investigate how the effects of variability and assignment of jobs affect the Porter Service's performance.

5.2 Effects of Variability

According to production theory, variability exists to some extent in all processes and can have a significant impact on performance. The variability law states that increased variability degrades performance in a process (Hopp & Spearman, 2000). It is therefore interesting to measure the degree of variability in process times and arrival rate in the Porter Service.

5.2.1 Measure of Variability in Process Times

Process time variability can be measured by calculating the coefficient of variation (CV). The process times for transport are divided in travel time and transport time, as illustrated in Figure 1 in Chapter 2.1. The data set does not include the process time of assigning jobs in the dispatching center, because waiting time is not separated from the dispatch time. We have therefore decided not to calculate variability in dispatching time because it could potentially be misleading.

Table 6 Measure of variability in process times

	Normal	Preordered	Urgent	Emergency	Grand Total
Travel time					
Mean process time	7,92	11,00	6,24	4,09	8,34
Standard deviation	5,99	6,80	4,77	3,03	6,20
CV	0,76	0,62	0,76	0,74	0,74
Variability class	*Moderate*	*Low*	*Moderate*	*Low*	*Low*
Transport time					
Mean process time	5,39	5,91	5,90	5,60	5,52
Standard deviation	3,69	4,44	4,44	3,64	3,89
CV	0,68	0,75	0,75	0,65	0,70
Variability class	*Low*	*Moderate*	*Moderate*	*Low*	*Low*

Note:
CV = c = σ/t
t = mean process time, measured in minutes
σ = standard deviation, measured in minutes

Table 6 shows the mean process time and standard deviation for travel time and transport time. The variability in travel and transport time in the Grand Total is classified as low, indicating that there is some variation in the total process time. The CV of travel time in Normal jobs is moderate, while CV of transport time is low. The situation is the opposite for Preordered jobs, where the CV of travel time is low and CV of transport time is moderate. Urgent jobs have moderate variability in both travel and transport times, and Emergency jobs have low variability in travel and transport times. We observe that the CV in all process times, including the Grand Total, are close to moderate variation (CV ≥ 0,75). The implication is that they resemble moderate variability distributions, where the most likely times are lower than the mean. Observations and discussions with porters revealed that the variability in travel and transport times is mainly due to walking distance and possible disruptions during the job.

It is interesting to note that variability in travel time for Preordered jobs is lower than for the other jobs, while the mean travel time is much higher. The reason for this might be that the porters know they have to reach destination within appointment time, and are therefore more determined and aware of the time when walking to the object. As a result the travel time might be less variable. Higher mean travel time may be caused by long walking distances. Considering that preordered jobs has to be completed at a specific time, the dispatcher must choose an available porter at that time, regardless of where he is located. As a result, there might be cases where the porter has to walk far to reach its destination, resulting in a high mean travel time. Another cause might be that the porters are more patient when a job is preordered, because the object is scheduled for an appointment. Therefore, the porters might wait longer for the object to get ready for transport. For instance, if a patient is scheduled for a cancer treatment, the porters might be willing to wait while the patient is prepared, in order to reach the scheduled appointment. Also, in some cases preordered jobs may have been assigned well in advance before the scheduled appointment. As a result, the porter might wait a few minutes before walking to destination.

It is important to emphasize that these causes are only assumptions based on observations and conversations with the porters and the management. We are not able to make any calculations or measures for the high mean travel times, because the travel time is only registered from the moment the porter accepts the job until the transport is initiated.

5.2.2 Causes of Variability in Process Times

We have identified low and moderate variability in the process times, but we need a better understanding of the underlying causes in order to analyze further the effects of variability and possibilities of reducing it. In Chapter 2.2.3 we identified that disruptions during jobs is a challenge for the Porter Service. If the porter arrives at destination and cannot commence the job because the object is not ready for transport or cannot be located, it results in extra waiting time or aborted jobs. Disruptions consequently lead to increased probability of delay as it affects the process times. It is interesting to further quantify the impact of variability from disruptions in the process. However, it is difficult to analyze this because waiting time before transport is included in the travel time. One solution is to measure how often a porter had to wait for the object to be ready or located.

Table 7 Percentage disrupted jobs

	Normal	Preordered	Urgent	Emergency	Grand Total
Commenced jobs [1]	37 093	8 968	3 354	127	49 542
Disrupted jobs [2]	777	642	71	2	1 492
Percentage disrupted	**2,1 %**	**7,2 %**	**2,1 %**	**1,6 %**	**3,0 %**

Note:
1. Commenced jobs are the sum of completed (”Utført”) and aborted (”BOM”) jobs.
2. Disrupted jobs means that the object was not ready, it could not be located or it was already transported.

Table 7 displays the number of commenced and disrupted jobs, and percentage disrupted jobs. In total, 3 % of the jobs were disrupted, and we observe that Preordered jobs have a relatively high percentage of the disrupted jobs. As discussed in Chapter 5.2.1, a reason for this might be that porters are more patient when it is a Preordered job. In addition, extra waiting time may cause the patient to be late for the scheduled appointment, thus increasing the probability that the job will be aborted.

Another effect of aborted jobs is that departments have to reorder the job if the patient still needs transport. The implication is that aborted jobs often have to be performed one more time by the Porter Service, which can be seen as duplication of work. Aborted jobs are therefore highly undesirable for all parties concerned. First, because it implies longer waiting time since the patient in most cases will have to wait for a new porter. In addition, it results in unnecessary use of capacity of the porters and creates variability in the process. However, the data set does not contain information to quantify the effect of duplication of work, but we can assume that if a job has not been executed, the need for transport is still present and that a significantly share of aborted jobs have to be reordered. In order to estimate the amount of reordered jobs, we will take a closer look on the reasons for aborted jobs.

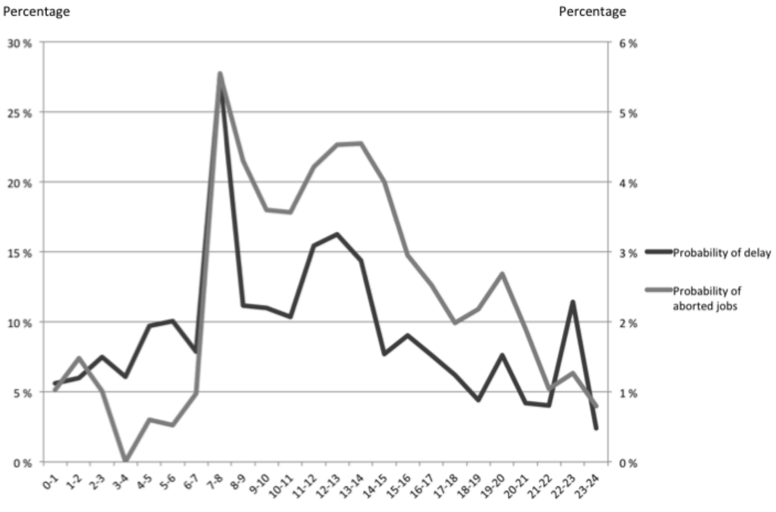
Table 8 Overview of aborted jobs

	Normal	Preordered	Urgent	Emergency	Grand Total
Commenced jobs [1]	37 093	8 968	3 354	127	49 542
Aborted ("BOM")	844	678	81	4	1 607
Percentage aborted jobs	**2,3 %**	**7,6 %**	**2,4 %**	**3,1 %**	**3,2 %**
Reasons for aborted jobs [2]	*100 %*	*100 %*	*100 %*	*100 %*	*100 %*
Patient not ready	29,5 %	30,7 %	27,2 %	50,0 %	29,9 %
Patient not located	43,2 %	42,2 %	42,0 %	0,0 %	42,6 %
Patient already transported	14,9 %	17,0 %	16,0 %	0,0 %	15,8 %
Unknown	12,3 %	10,2 %	14,8 %	50,0 %	11,6 %

Note:
1. Commenced jobs are the sum of completed ("Utført") and aborted ("BOM") jobs.
2. The percentage of reasons for aborted jobs is calculated based on the number of aborted ("BOM") jobs.

Table 8 presents an overview of aborted jobs. There are in total 1 607 aborted jobs, which represent 3,2 % of the total number of commenced jobs. In 85 % of the cases, jobs are aborted because the patient is not ready or cannot be located, while about 15 % is because the transport has already been performed. Consequently, we assume that 85 % of all aborted jobs are reordered and result in duplication of work.

An interesting topic for further investigation is the relationship between probability of delay and aborted jobs, because aborted jobs is a possible source of variability in the process.



Note:
Probability of aborted jobs are measured on the right axis

Figure 10 Probability of delay and aborted jobs distributed over 24-hours

Figure 10 displays the probability of a job being delayed and the probability of a job being aborted, distributed over 24 hours. It seems like there is a strong correlation between probability of delay and aborted jobs since they follow the same variation during the day. The probability of delay resulting in a job being aborted increases significantly at 6.00-7.00 and 11.00-12.00. A reason might be high capacity utilization in addition to unnecessary use of capacity because of excessive waiting time and aborted jobs. Also, aborted jobs supply variability in the process, which according to the VUT equation implies increased expected waiting time in queues. The combination of high utilization and high degree of variability might therefore have a negative impact on performance.

5.2.3 Effects of Variability in Incoming Jobs

The previous section identified causes of variability in process times, but it is also important to take into consideration that variability in one workstation will affect the rest of the process. The variability in the arrival rate is an important element that will affect the flow in the process and the Porter Service's performance. The descriptive analysis in Chapter 2.4.3 showed considerable variation in the number of incoming jobs during a day, especially for Normal and Preordered jobs. Therefore, it is interesting to measure the coefficient of variation of inter-arrival times (arrival CV) in order to define the variability.

Table 9 Measure of variability in arrival rate

	Grand Total
Average arrival rate	25,27
Mean time between arrivals	2,37
Standard deviation	2,37
Arrival CV	1,00
Variability class	*Moderate*

Note:
Mean time between arrivals, $t_a = 1 / r_a$. Arrival CV = $c_a = \sigma_a / t_a$,
r_a = average arrival rate, measured in jobs per hour
t_a = mean time between arrivals, measured in minutes
σ_a = standard deviation, measured in minutes

Table 9 shows the mean time and standard deviation between arrivals, and the arrival coefficient of variance (arrival CV). We have fitted the distribution of the arrival rate, based on historical data, illustrated in Figure 23 in the appendix. This is further discussed in Chapter 6.1.4. We have estimated that the IAT of total incoming jobs is exponentially distributed, and the standard deviation is therefore equal to the mean. The arrival CV is equal to 1 and can be defined as moderate. This indicates that the arrivals of jobs are uneven and affects the flow variability further in the process.

Another important element when considering flow is that the capacity of porters has to exceed the arrival rate in order to keep up with arrivals, meaning that the average utilization is below 100 %. Since the dispatching center only distributes the jobs, we can assume that flow of jobs to the porters is close to the arrival rate of incoming jobs. Consequently, we can analyze porter capacity in relation to the arrival rate of incoming jobs. The average process time of completed jobs is 13,86 minutes, and therefore we assume that one porter can complete 4 jobs per hour.

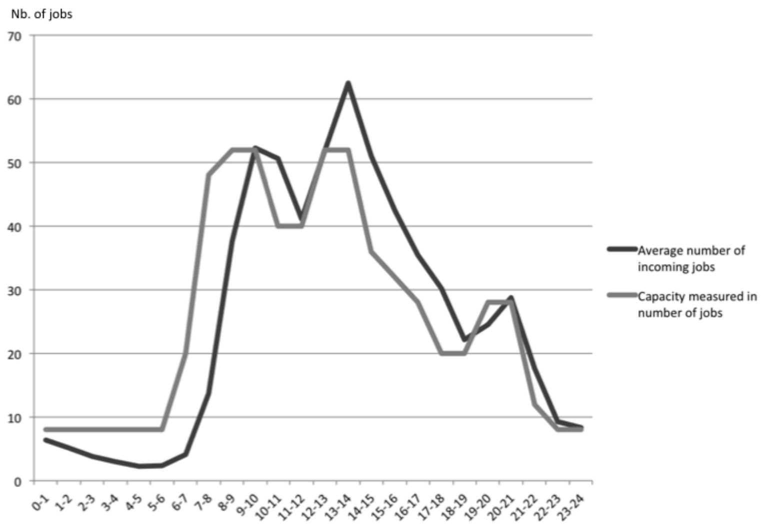
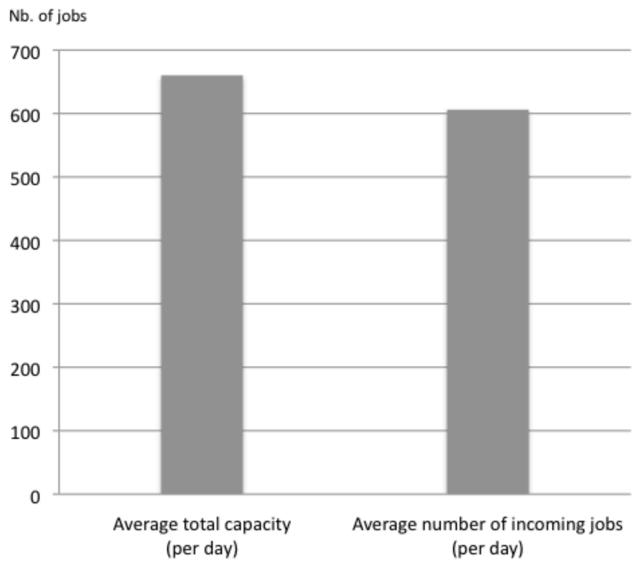


Figure 11 Average arrival rate and corresponding capacity during a day

Figure 11 illustrates the arrival rate of incoming jobs and capacity during a day. The capacity level only exceeds the arrival rate until 9.00, the rest of the day it is lower than the arrival rate. Especially, lunch breaks cause the capacity to drop between 10.30 - 12.30 and 18.00-19.30. This indicates that the capacity level is not high enough in order to complete all jobs within reasonable time during some periods of the day, and might be a reason for delays.



Note:
Average total capacity is calculated based on the assumption that there on average is 22 porters working during 24 hours, and that one porter completes 4 jobs per hour.

Figure 12 Comparison between average total capacity and average total number of incoming jobs per day

Figure 12 shows that the average total capacity is higher than the average total number of incoming jobs. However, the large variation in number of incoming jobs during the day results in high utilization in some periods and low utilization during for example the night shift. Even though the total capacity exceeds the total demand, there are queues building up in some periods causing delays.

5.3 Dispatching Policies

The Porter Service's system can be determined as random, because the need for transportation is beyond their control. Previous analysis showed that there is moderate variability in the arrival rate, which indicates an uneven arrival of jobs. Also, we have seen that the there is a very high number of incoming jobs in the middle of the day that makes it difficult for the dispatchers to assign effectively. This will further influence the Porter Service’s performance, because the porters' ability to complete the job on time is dependent on the job being assigned in reasonable time.

In order to handle and manage variability, it is important to have robust policies. The quality standards are the only guidelines for the dispatchers, indicating what job to be assigned next. The analysis in Chapter 5.1 showed that there are no delays in Urgent and Emergency jobs, and a reason might be that they have a higher priority level than Normal and Preordered jobs. Also, they have dispatching times defined by the quality standards; Emergency and Urgent jobs should be *assigned* within 5 and 15 minutes, respectively. On the other hand, the dispatchers do not have any specific instructions for when Normal and Preordered jobs should be assigned in order for the porter to complete the job on time. For example, according to the quality standards Preordered jobs are to be *completed* within appointment time. There is no suggested dispatching time, it is solely based on the dispatchers' individual judgment. Also, Normal and Preordered jobs are by definition equally important, and it is therefore difficult for the dispatcher to choose between them. This requires personal evaluations of what job to assign first, given the composition of various jobs at the time. We therefore believe that a reason for delays in Normal and Preordered jobs is that the policies are not robust enough for these priorities.

We have a hypothesis that there is a relationship between dispatching time and the degree of delay. In order to analyze this relationship we have calculated the difference between the time Preordered jobs were assigned and the scheduled time of appointment.

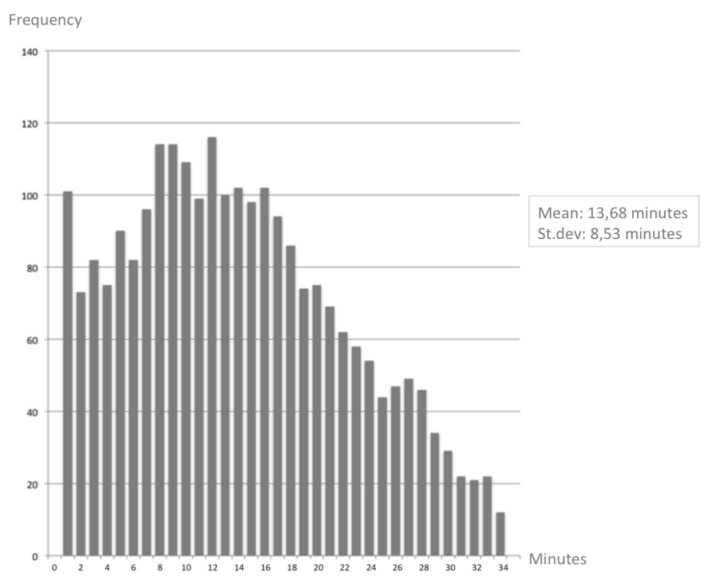


Figure 13 Time difference between when Preordered jobs were assigned and should be completed

Figure 13 shows that Preordered jobs were on average assigned 13,7 minutes before appointment time, with a standard deviation of 8,5 minutes. According to the porter management, Preordered jobs should be assigned at least 15 minutes before scheduled time of appointment, in order to complete the job on time. The graph above shows that many of the jobs were assigned later than 15 minutes. This indicates that a reason for delay in Preordered jobs is that they were assigned to late, and as a result the porters have too little time to complete transportation within the scheduled time.

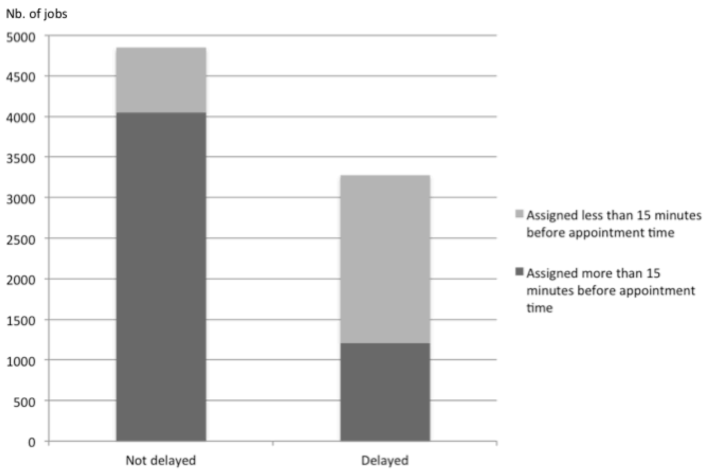


Figure 14 The assignment of Preordered jobs and delays

Figure 14 shows that of over 50 % of delayed Preordered jobs, were assigned to porters less than 15 minutes before scheduled time. This indicates that the dispatcher has difficulties with distributing the jobs within a reasonable time and reflects the challenges of assigning jobs effectively. Another reason for the jobs being assigned to late might be that there are no porters available. As shown in Chapter 5.2.3, the capacity level is too low to handle the arrival rate during some specific periods in the day. This indicates that a cause of delay is a combination of too low capacity and challenging situations for the dispatchers.

Probabilistic measures of process times can be a useful tool to make the quality standards more robust, for instance suggested dispatching times. From the data we have estimated average process times, which indicate needed time to initiate or complete a job in line with the quality standards.

Table 10 Suggested dispatching time for Normal and Preordered jobs

	Normal	Preordered
Mean process time [1]	7,92 minutes	16,91 minutes
Standard deviation	5,99 minutes	8,10 minutes
Suggested dispatching time [2]	25 minutes	15 minutes

Note:
1. Normal: Process time equals travel time.
Preordered: Process time equals travel and transport time.
2. Suggested dispatch time is based on the mean process time and the quality standards.

Table 10 shows the suggested dispatch time for Normal and Preordered jobs. For Normal jobs, the porters have used on average 7,92 minutes from acceptance of the job until it was initiated. The standard deviation is relatively high, which indicates that the porter needs more time than the mean travel time in order to initiate the job on time. It is therefore reasonable that Normal jobs should be assigned about 10 minutes before they should be initiated, i.e. the dispatch time should be maximum 25 minutes. The same assumptions apply for Preordered jobs. The porters used on average 16,91 minutes from the job was assigned until it was completed. The standard deviation is also relatively high, and therefore Preordered jobs should be assigned about 20 minutes before appointment time. As a result the dispatch time should be maximum 15 minutes. By giving the dispatchers some time limits for when the jobs should be assigned, it might increase the probability of performing in accordance with the quality standards.

5.4 Summary of Quantitative Analysis

In the quantitative analysis in Chapter 5.0, we found that the Porter Service has difficulties performing in accordance with the current quality standards, for Normal and Preordered jobs. On average, 10,3 % of all jobs was delayed. Preordered jobs had the highest probability of delay, while Normal jobs had the longest delay in minutes. The probability of delay was especially high at some specific times during the day, at 6.00-7.00 and 12.00-13.00.

Further analysis showed that there exists variability in the Porter Service, both in process times and in the arrival rate. We found that there is low and moderate variability in the process times. According to theory this might have a large effect on the Porter Service's performance and might be a possible cause of delay. For instance, excessive waiting time and duplication of work result in unnecessary use of capacity. We also found that there is moderate variability in the average arrival rate, causing variability in the flow of jobs. It is a challenge to handle this variation, especially because the capacity level is lower than the arrival rate during some periods of the day. As a result queues build up in the dispatching center, which may be a cause of delay.

Another important challenge is to assign the jobs in time, in order for the porters to complete the job according to the quality standards. From analysis of the dispatching time, we found that over 50 % of delayed Preordered jobs were assigned less than 15 minutes before appointment time. We believe that this corresponds with the lack of defined criteria for when Normal and Preordered jobs should be assigned. This indicates that the dispatching policies need to be improved in order to increase performance.

6.0 Simulation

There are several advantages of using simulation as a tool to measure the effects of changes in the process. The simulation model can be used to explore how new polices and decisions might influence the system, before implementing changes in the real process. Also, it provides a better understanding of interactions in complex systems. In this chapter we will present the basis of the simulation model used to conduct experiments on changes in variability, capacity and the assignment of jobs.

6.1 Foundations of the Simulation Model

To build the simulation model we have used aGPSS (a General Purpose Simulation System), which is a discrete time simulation language (Born & Ståhl, 2011). The jobs in the process are modeled as transactions entering the system and passed on from one service to another. The jobs are selected from a queue based on a known rule, defined as the queue discipline (Hillier & Lieberman, 2005). The queue discipline in our simulation model is based on both priorities and waiting time, and is explained in Chapter 5.3.2.

The simulation model is based on information from the data set and results from the quantitative analysis in Chapter 5.0. However, the model is a simplified image of reality and it is important to emphasize that the results must be interpreted with caution. The results cannot be integrated directly into the real process, but needs to be tested in the real process before making any finite adjustments and decisions in the real system.

The real process is a non-terminating system, because the Porter Service is operating 24-hours, 7-days a week. It is therefore important to decide the correct length of the simulation in order to analyze the steady state in the model. However, the Porter Service does not have storages or long queues building up over time, since they have to perform transport within reasonable time. Even though it is a non-terminating system, we will not include a warm up period in the model, as the storage and queue values from one day to another are close to zero. We have performed simulations with different lengths to test when the results stabilize, and based on this we decided to run the model for 85 days.

In order to build the model we had to make some assumptions and simplifications. We have also calculated necessary input variables used in the model. This is explained and discussed in the following chapters.

6.1.1 Dispatching Center

The dispatching center in the simulation model assigns jobs based solely on their priority level and how long they have been waiting in the queue. The queue discipline in the model is therefore similar to a combination of FCFS and priorities. However, the priority levels of Preordered and Normal jobs increase when the due time approaches, as illustrated in Figure 15. As a result, the queue discipline is similar to EDD, where the quality standards define the "due date" of the jobs. For example Preordered jobs will have a low priority at first, and a very high priority when the scheduled time of appointment approaches.

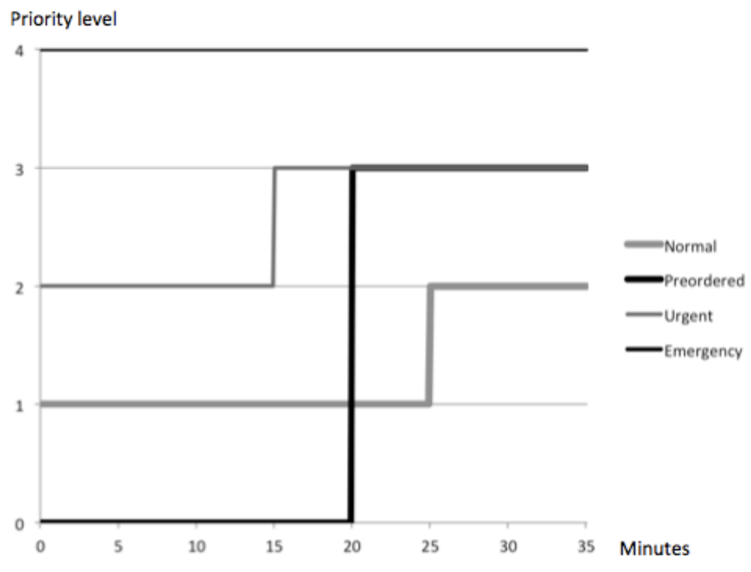


Figure 15 Illustration of priority level over time

Figure 15 illustrates the relationship between priority level and how long time a job has been waiting in the queue. Emergency jobs have the highest priority, and will therefore always be chosen over other jobs. Urgent jobs will always be prioritized before Normal jobs, and also before Preordered jobs waiting less than 25 minutes. The relationship between the priority level of Preordered and Normal jobs is shifting depending on how long the jobs have waited.

The model does not take discretionary judgments into account, and so it excludes the dispatcher’s ability to make individual assumptions of what job to be assigned before another. This is a weakness in the model, because in reality the jobs are also assigned based on where the object is located, how far the porter is from the location and personal assumptions about which job that is the most important at that time.

6.1.2 Capacity of Porters

The capacity of porters in the real system depends on shift schedules that vary from day to day. Also, the porters perform transport of different job types, explained in Chapter 2.4.2. After discussions with the porter management we estimated the average number of porters only working with transport of patients, lab specimens, and blood products during one ordinary weekday. The number of porters varies throughout the day according to the shift plan, where the capacity increases and decreases. However, the total number of porters working each day is constant.

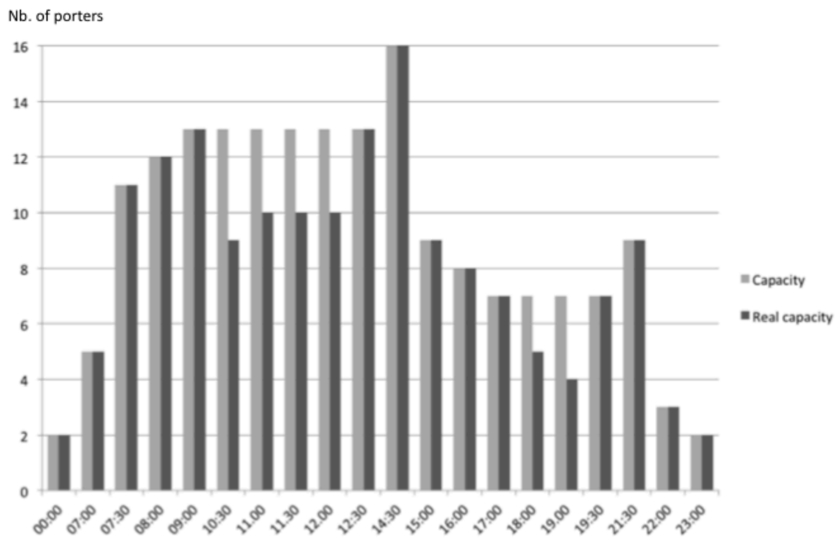


Figure 16 Changes in capacity of porter during a day

Figure 16 illustrates the changes in capacity during the day. The light grey columns display the original capacity, which is the total number of workers. However, all workers have a lunch break during their shift, and this is illustrated by the dark grey columns, called real capacity. The capacity in the simulation model is equal to real capacity.

The simulation model does not distinguish between the different porters, meaning that some porters are working 24 hours a day, while others only work for a few hours. Therefore, we had to calculate manually the capacity utilization of each porter, as well as the total capacity utilization. The total capacity utilization is calculated as a weighted average.

6.1.3 Cancelled and Aborted Jobs

In the real process some of the jobs are cancelled or aborted for different reasons. Cancelled and aborted jobs may occur if the object is not ready for transport or if it cannot be located when the porter arrives. It may also be because the transportation is already performed, porters are delayed, or if the orders contain errors. Ideally we would like the simulation model to calculate the number of cancelled and aborted jobs on the basis of the mentioned reasons. However, we do not have any determinant to decide whether or not this occurs. To consider this we have therefore calculated the probability of a job being cancelled of aborted for each priority, from historical data. Table 11 is a summary of the input data.

Table 11 Percentage cancelled and aborted jobs

	Normal	Preordered	Urgent	Emergency	Grand Total
Total incoming jobs	38 135	9 826	3 463	133	51 557
Cancelled	1 041	858	109	6	2 014
Aborted	844	678	81	4	1 607
Percentage cancelled	2,7 %	8,7 %	3,1 %	4,5 %	3,9 %
Percentage aborted	2,2 %	6,9 %	2,3 %	3,0 %	3,1 %

6.1.4 Functions of Inter Arrival Time (IAT)

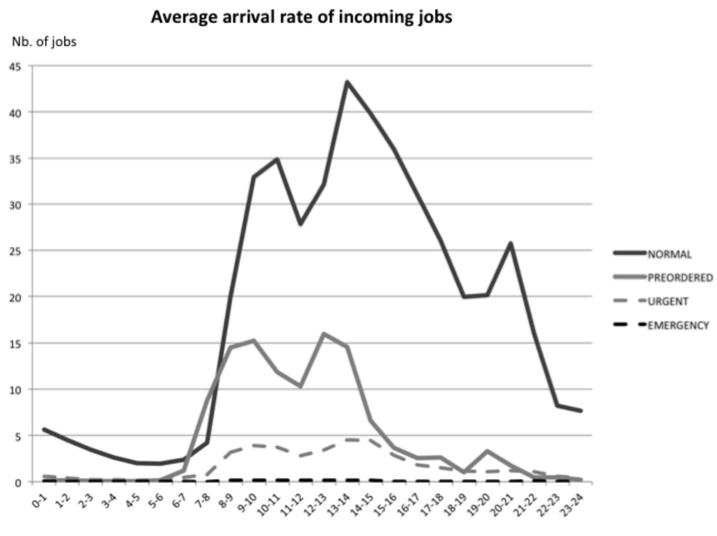


Figure 17 Average arrival rates of incoming jobs, for the different priorities

Figure 17 illustrates the average arrival rate for the different priorities, measured in number of incoming jobs on average per hour. From this information, retrieved in the data set, we calculated inter-arrival time (IAT) functions for each priority. However, the IAT functions only decide the average number of incoming jobs each day. The variability in arrivals for all priorities is included by fitting probability distributions to the data, illustrated in the appendix, Figure 23. We have estimated that the IAT for Normal jobs is exponentially distributed (Hillier & Lieberman, 2005). The IAT is therefore multiplied with a built-in exponential function in the model. It was difficult to fit a probability distribution to the other priorities, because they do not have a clear statistical distribution. It seems like the IAT for Preordered jobs has a lower variation than Normal jobs, because most of the Preordered jobs arrive with fixed intervals, for example every 15 minute. The IAT function in the model is therefore multiplied with a built in Erlang function, with shape parameter equal 2, to reflect the lower degree of variation (Hillier & Lieberman, 2005). On the other hand, Urgent and Emergency jobs arrive more randomly. This is also reflected with a high standard deviation, and is especially true for the IAT for Emergency jobs. To reflect the high degree of variation we have multiplied the IAT functions with a built-in exponential function.

6.1.5 Travel and Transport Times

The jobs are conducted in different pace, given the nature of the jobs' priority level. For instance, an Emergency job will be conducted as fast as possible while a Preordered job is conducted based on the scheduled time of appointment. This results in different travel and transport times. We have calculated the mean and standard deviation of travel and transport times, for all priorities. Also, we have investigated their statistical distribution to include variability in the model. This is illustrated in the appendix, Figure 24 and 25. We have estimated that the travel and transport times for all priorities are close to Erlang distribution, with shape parameter = 2. We have also tested Erlang distributions with different shape parameters, however k = 2 seems to be the best approximation. The estimation of k is showed in Table 24, in the appendix. We have therefore included variability in the process times with a built-in Erlang 2 function.

6.2 Verification and Validation of the Simulation Model

To verify the model, we have presented and discussed the value stream map with the management of the Porter Service. After some changes and updates, they agreed upon our analysis and confirmed that our flow chart was consistent with the real process. In addition, we have worked thoroughly to understand how dispatchers decide which job to assign next and how they interpret the priority levels. It was difficult to reach an agreement on the practice of assignment of jobs, because it relies upon many different criteria. In addition, the decision is based on individual interpretation. However, we managed to reach consensus, but we had to simplify so that only priority level and queuing times are considered in the queue discipline. As a result, discretionary judgments will not be included in the model. Finally, the value stream map, illustrated in Figure 2, is directly modeled in aGPSS.

To validate the model we have chosen to use both subjective and objective techniques. First, we have validated the input data by running the simulation for 85 days, and compared the number of incoming, cancelled, and aborted jobs each day with real observations. In addition, we have compared selected distributions, means and standard deviation.

Table 12 Validation of input data

	Normal		Preordered		Urgent		Emergency		Grand Total	
Simulation: 85 days	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Incoming jobs [1]	443,2	23,3	109,8	16,4	34,7	11,2	2,0	1,6	589,7	29,2
Cancelled jobs [1]	13,3	3,6	9,8	3,4	1,1	1,2	0,1	0,3	24,3	5,0
Aborted jobs [1]	8,6	2,9	7,1	2,4	0,7	0,9	0,1	0,3	16,4	3,7
Travel time [2]	7,97	5,6	10,94	7,8	6,23	4,46	4,45	2,94	-	-
Transport time [2]	5,36	3,81	5,99	4,26	5,98	4,2	5,47	4,08	-	-
Historical data: 85 days										
Incoming jobs [1]	448,6	38,0	115,6	16,7	40,7	7,6	2,2	1,4	606,6	51,4
Cancelled jobs [1]	12,2	3,8	10,1	4,4	1,7	1,0	1,0	0,0	23,7	6,4
Aborted jobs [1]	9,9	3,8	8,0	3,3	1,6	0,8	1,0	0,0	18,9	5,5
Travel time [2]	7,9	6,0	11,0	6,8	6,2	4,8	4,1	3,0	-	-
Transport time [2]	5,4	3,7	5,9	4,4	5,9	4,4	5,6	3,6	-	-

Note:
1: Mean and standard deviation for delay is calculated on the basis of outputs from 85 days, measured in number of jobs.
2: Mean and standard deviation for travel and transport time is calculated based on the total number of jobs from 85 days, measured in minutes

The results from Table 12 show that the output is close to the real data. We observe that the standard deviation in incoming jobs is lower than in the historical data. This implies that the variability in the inter-arrival times is a little underestimated. On the other hand, experiments with different distributions in the arrival times showed that the exponential distribution and Erlang 2 are the closest approximations to the real data. The observations of travel and transport times from the simulation are also close to the real data, and support the use of Erlang 2. However, the standard deviation of travel time in Preordered jobs is overestimated, and it seems like the variability is larger than in the real system.

We have also performed sensitivity analysis and extreme-condition tests. A reduction in capacity showed that the queue of jobs and the degree of delay increased. Also, we decreased the mean of the travel and transport times, and observed that the queue and degree of delay decreased. This is reasonable, and the model behaves in a predictable manner. In addition, we changed input variables to extreme values, and the model still acted the way we expected.

As an overall validation of the model we have performed validation of input-output transformations, presented in Table 13.

Table 13 Validation of Input-Output transformations

	Normal		Preordered		Urgent		Emergency		Grand Total	
Simulation: 85 days	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Incoming jobs [1]	443,2	23,3	109,8	16,4	34,7	11,2	2,0	1,6	589,7	29,2
Completed jobs [1]	421,2	22,5	92,9	14,7	32,9	10,8	1,9	1,6	549,0	27,6
Percentage delay [2]	6,3 %	-	33,4 %	-	0,3 %	-	8,8 %	-	10,4 %	-
Delay [1]	26,7	29,0	31,0	16,6	0,1	0,4	0,2	0,4	57,4	34,4
Delay > 5 min [1]	17,8	23,2	26,6	16,3	0,0	0,2	0,0	0,2	44,5	31,6
Delay > 10 min [1]	12,1	17,8	23,3	16,1	0,0	0,0	0,0	0,0	35,4	26,7
Historical data: 85 days										
Incoming jobs [1]	448,6	38,0	115,6	16,7	40,7	7,6	2,2	1,4	606,6	51,4
Completed jobs [1]	426,5	35,8	97,5	14,5	38,5	7,4	2,1	1,3	563,9	47,4
Percentage delay [2]	4,1 %		40,5 %	-	2,6 %	-	0,0 %	-	10,1 %	-
Delay [1]	17,5	9,8	39,5	11,7	1,0	0,0	0,0	0,0	57,0	18,2
Delay > 5 min [1]	10,2	6,7	20,9	9,0	1,0	0,0	0,0	0,0	31,2	13,4
Delay > 10 min [1]	6,3	4,9	11,0	6,5	1,0	0,0	0,0	0,0	17,3	9,6

Note:
1: Mean and standard deviation for delay is calculated on the basis of outputs from 85 days, measured in number of jobs.
2: Percentage delay is calculate on the basis of Completed jobs and Delay

The output from the model is the number of completed jobs and the number of delays. The number of completed jobs is close to the historical data, and the small difference is related to the difference in number of incoming jobs. Further, we observe that average delay in Preordered jobs are underestimated, and average delay in Normal and Emergency jobs are a little overestimated. However, it is reasonable that delays in Emergency jobs are overestimated, because they do not preempt the execution of other jobs in the model. The standard deviation is overall higher than the historical data.

In total, the degree of delay is close to the real data with an average delay of 10,3 %. However, the standard deviation is overestimated, which indicates that the degree of variability in the model is larger than in the real system. There might be several reasons for this error. The simplification of the queue discipline in the dispatching center might have a large impact on degree of delay. In the real process the dispatcher decide which job to assign next based on several criteria, and these trade-offs changes depending on for example the queue in the dispatching center or capacity level. Another reason might be that we have constant capacity during the 85 days. The Porter Service has different schedules from day to day, and even though they do not vary a lot, a reduction or increase of one porter from one day to another can have a large impact on the degree of delay. In addition, the total practical capacity of porters is lower in the model than in the real process, because dispatchers can, in busy periods, assign certain jobs to porters performing other job types, for example transport of beds. As a result, the real system is more flexible than the model when it comes to handle variability, since both queue discipline and capacity, to some degree, can be adjusted. Also, we observe that delays with more than 5 and 10 minutes are overestimated in the model. The reason for this is that the model has difficulties in prioritizing between jobs that have been waiting in the queue and new incoming jobs with the same priority level. This results in a small amount of jobs waiting too long in the dispatching center, which may affect the statistics. Also, it might be affected by the probability distribution being an approximation of the real data.

However, the overall validation shows that the results are reasonable and comparable to real data. Also, we will only use the model to perform experiments within the model and even though the results differ a little from historical data, we can observe and measure the effects from changes in the process. Therefore, we believe that the model is solid for our purposes. We would nevertheless like to emphasize that the simulation model is a simplified picture of reality, and that the results from the model must be interpreted with caution.

The analysis has been based on 51 557 observations from four previous months. We consider this as a good database for our results. The data is highly informative and contains important details in order to explore the research question. The data comes from a secondary source but it is assumed to be 100 % reliable. It is retrieved from the Porter Services data system porterCOM and selected for our purposes, which enhances the internal validity. After receiving the data set we have had several conversations with the IT manager to make sure that we understand and interpret the information correctly. In addition, the database is much more comprehensive than we would have been able to collect our self. We could have made our own data set by collecting the process times on several observations, but this would have been very time consuming. An important element when discussing the validity of the data is system failure during the data period. System failure occurs occasionally but is not registered in porterCOM. Therefore, one must take into consideration that some of the observations might be defect and influence the statistics.

The porterCOM software is adjusted for the Porter Service at Haukeland, and the statistics from the system is based on how they perform their services. The porter operations at different hospitals are likely to be organized in different ways, and the external validity may therefore be questioned and the results from the analysis cannot be generalized directly. However, there may be some similarities between porter operations at various hospitals, and there might be a possibility that some of the results from this analysis can be applied to other hospitals.

6.3 Experiments Using the Simulation Model

To see how the effects of variability in the process influence the Porter Service's performance we have simulated different scenarios in the model. We have chosen to use common random streams (CRN) in the different experiments in order to provide the same experimental conditions. Also, the initial conditions and input variables are the same as the validated model. All of the experiment results are based on simulation of 85 days. The different experiments are independent from each other, meaning that we will only change one parameter at the time and compare them against the initial system. We have performed a comparison between two systems at a time, the initial system and one experimental system, to estimate the difference in expected performance. The different experiments and the results are presented in Chapter 7.

7.0 Results from Experiments

We will use simulation to perform experiments on how variability and capacity affect the performance in the system. Also, we will conduct experiments using different queue disciplines to analyze how the assignment of jobs affects performance. Further, we will conduct a sensitivity analysis on the effects of changes in demand.

In the experiments we have not changed any variables related to Urgent and Emergency jobs. Given the nature of these jobs, they occur very randomly and have to be processed as soon as possible. Therefore, it is difficult to affect the variability in the real process in these two priorities, and we have chosen not to measure the degree of delays in Urgent and Emergency jobs. Initially these priorities do not have any delays, and average delay from the simulation model is approximately zero. Therefore, we will only present results for Normal and Preordered jobs. However, the results for Urgent and Emergency jobs are included in the Grand Total, and all of the results are presented in complete tables in the appendix, Table 25-28.

7.1 Variability in Process Times

In Chapter 5.2.2 we found that variability in process times due to disruptions in transport might have a large impact on performance. In the following experiments we will reduce variability from extra waiting time and duplication of work, and estimate the degree of delay. According to theory, performance in a production system is affected negatively by variability. Based on this, our hypothesis is that reduced variability in process times has a positive impact on the Porter Service's performance.

The first experiment analyzes the effect of reduced variability in travel times. Variability in travel time is mainly caused by differences in walking distance, but also waiting time when the object is not ready for transport. To reduce variability in travel time in the system, we will change the shape parameter of the Erlang distribution in Normal and Preordered jobs. Increasing the shape parameter implies lower variability in service times relatively to the mean (Hillier & Lieberman, 2005). We want to emphasize that an increase in the shape parameter does not change the mean travel time, it only crates new standard deviation.

Table 14 Estimating coefficient of variation with Erlang 5

	Normal	Preordered
Shape parameter k = 2		
Mean travel time (μ)	7,92	11,00
Standard deviation (σ)	5,99	6,80
CV	0,76	0,62
Variability class	Moderate	Moderate
Shape parameter k = 5		
Lambda (λ) [1]	0,6315	0,4546
E(x) [2]	7,92	11,00
σ(x) [3]	3,54	4,92
CV(x) [4]	0,45	0,45
Variability class	Low	Low

Note:
1. λ = k / μ
2. E(x) = k/ λ
3. σ(x) = √(k/(λ^2))
4. CV(x) = σ(x)/ E(x)

In the experiment, we have changed the shape parameter (k) from 2 to 5. From table 14 we see that an increase in the shape parameter results in a lower standard deviation and thereby a lower CV, indicating low variability.

The second experiment analyzes the effects of reduced variability as a result of reduced probability of aborted jobs. As discussed in Chapter 5.2.2, aborted jobs imply duplication of work and supply variability in the system. It is difficult to say to what extent the Porter Service and the departments can reduce duplication of work, because the number of aborted jobs is highly dependent on human beings. Therefore, we will measure the total effect of duplication of work by changing the probability of a job being aborted to zero.

The experiments on reduced variability in travel times and reduced duplication of work estimate the effects independently. These effects are however closely related since reduced waiting time might also imply that objects are ready for transport when the porter arrives. As a result, we assume that fewer jobs are aborted. We believe there is a relationship between the two effects, and we will therefore perform one experiment taking both effects into consideration. An expected result from this experiment is a larger reduction in delay compared to the previous experiments.

Table 15 Summary of changes in the system from experiments on variability

Experiment	Changes in the system
Variability Travel time	Erlang shape parameter (k) = 5
Variability Aborted jobs	Aborted jobs = 0
Variability Travel time, Aborted jobs	Erlang shape parameter (k) = 5 Aborted jobs = 0

Table 16 Results from experiments on variability

	Normal		Preordered		Grand Total	
Initial system	Mean	St.dev	Mean	St.dev	Mean	St.dev
Percentage delay [1]	6,3 %	6,9 %	33,4 %	17,8 %	10,4 %	6,3 %
Variability Travel time						
Percentage delay [1]	5,5 %	6,5 %	32,1 %	17,7 %	9,6 %	6,5 %
Expected diff. in delay [2]	-0,8 %	5,5 %	-1,9 %	18,8 %	-0,9 %	8,2 %
Confidence interval [3]	[-2,0%, 0,3%]		[-6,0% ,2,2%]		[-2,7%, 0,9%]	
Variability Aborted jobs						
Percentage delay [1]	4,4 %	4,5 %	31,7 %	16,7 %	8,8 %	5,1 %
Expected diff. in delay [2]	-1,9 %	7,4 %	-1,3 %	21,0 %	-1,6 %	7,7 %
Confidence interval [3]	[-3,5%, -0,3%]		[-5,9% ,3,2%]		[-3,3%, 0,1%]	
Variability Travel time, Aborted jobs						
Percentage delay [1]	3,8 %	4,5 %	28,3 %	16,5 %	7,9 %	4,6 %
Expected diff. in delay [2]	-2,5 %	7,7 %	-3,9 %	23,3 %	-2,5 %	7,2 %
Confidence interval [3]	[-4,2%, 0,9%]		[-8,9% ,1,1%]		[-4,1%, -1,0%]	
Utilization						
Initial system					78,8 %	
Variability Travel time					78,6 %	
Variability Aborted jobs					77,7 %	
Variability Travel time, Aborted jobs					77,9 %	

Note:
1: Percentage delay is calculate on the basis of completed jobs and number of delayed jobs
2: Expected difference in delay is expected delay in experiments minus expected delay in initial system
3: 95 % confidence interval, t-distribution with n-1 degrees of freedom

The results from the experiments show that reduced variability reduce the degree of delay, and hence improving the performance. The percentage delay in the Grand

Total is reduced from 10,4 % to 9,6 %, 8,8 %, and 7,4 %, respectively, in the three experiments. We also observe that the standard deviation of percentage delay is lower, indicating reduced variability in performance.

The expected difference in percentage delay from reduced probability of aborted jobs is higher than for reduced variability in travel times. The reason for this might be that reducing aborted jobs has a larger impact on capacity utilization because of reduced duplication of work. Experiment 3, with reduced variability in both travel times and duplication of work, gives the highest expected reduction in delay with -2,5 %.

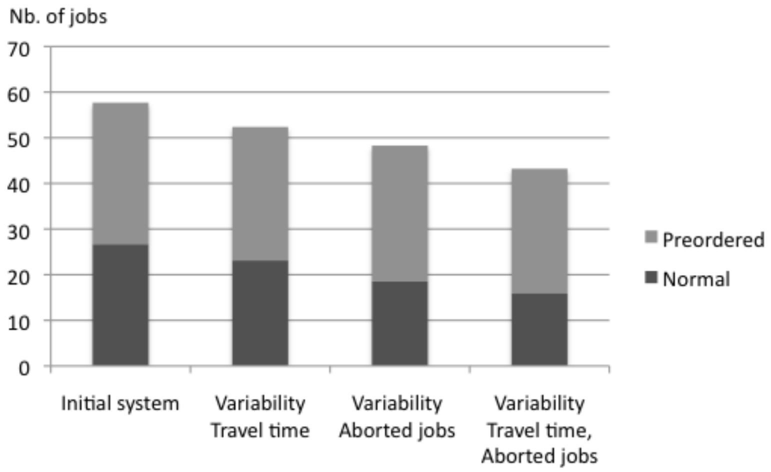


Figure 18 Summary of results from experiments on variability, measured in number of delayed jobs

Figure 18 summarizes the results from the experiments on variability. The figure shows that a reduction in variability results in a lower expected number of delayed jobs and improved performance. The results are in line with what we expected and imply that variability in the process has a negative impact on performance. The experiments on variability show that eliminating aborted jobs has the largest impact on performance. To reduce the probability of aborted jobs in the real system, the Porter Service should communicate the importance of preparing the object before transportation to the departments. Also, the Porter Service should focus on reducing variability in waiting time when the object is not ready for transportation. We have observed that a lack of policies makes it difficult for porters to decide how long time they should wait. The Porter Service should therefore define and communicate guidelines for acceptable waiting time.

7.2 Changes in Capacity

In Chapter 5.2.3 we found that the initial capacity level is too low to manage the average number of incoming jobs during certain periods of the day. According to theory, the capacity level has to exceed the arrival rate in order to keep up with arrivals. If variability in the process degrades performance, the variability has to be buffered, for instance by increasing capacity. Our hypothesis is therefore that an increase in capacity will reduce the degree of delay and have a positive impact on the Porter Service's performance.

There are three different shifts in the real system, day, evening and night shift. In the following experiments we will increase the capacity level in day and evening shifts, and analyze the effects on delay.

Table 17 Summary of changes in the system in experiments on capacity

Experiment	Changes in the system	Work hours (lunch)
Capacity +1	Increased by one porter	9-17 (12.00-12.30)
Capacity +2	Increased by two porters	9-17 (12.00-12.30) 10-18 (14.00-14.30)
Capacity +3 Day shift	Increased by three porters	9-17 (12.00-12.30) 10-18 (14.00-14.30) 10-18 (14.00-14.30)
Capacity +3 Evening shift	Increased by three porters	9-17 (12.00-12.30) 10-18 (14.00-14.30) 12-20 (15.30-16.00)

Table 18 Results from experiments on capacity

	Normal		Preordered		Grand Total	
Initial system	Mean	St.dev	Mean	St.dev	Mean	St.dev
Percentage delay [1]	6,3 %	6,9 %	33,4 %	17,8 %	10,4 %	6,3 %
Capacity +1						
Percentage delay [1]	3,7 %	4,8 %	21,0 %	10,9 %	6,4 %	4,6 %
Expected diff. in delay [2]	-2,6 %	4,5 %	-12,8 %	16,6 %	-4,0 %	7,4 %
Confidence interval [3]	[-3,6%, -1,6%]		[-16,4 ,-9,2%]		[-5,6%, -2,4%]	
Capacity +2						
Percentage delay [1]	1,9 %	2,0 %	12,9 %	7,2 %	3,7 %	2,4 %
Expected diff. in delay [2]	-4,4 %	6,0 %	-20,2 %	16,5 %	-6,7 %	6,4 %
Confidence interval [3]	[-5,7%, -3,1%]		[-23,8%, -16,6%]		[-8,1%, -5,4%]	
Capacity +3 Day shift						
Percentage delay [1]	1,3 %	1,3 %	8,5 %	4,0 %	2,5 %	1,5 %
Expected diff. in delay [2]	-5,0 %	6,7 %	-24,7 %	17,5 %	-8,0 %	6,3 %
Confidence interval [3]	[-6,5%, -3,6%]		[-28,5% ,-21,0%]		[-9,3%, -6,6%]	
Capacity +3 Evening shift						
Percentage delay [1]	1,2 %	1,2 %	8,8 %	4,8 %	2,4 %	1,4 %
Expected diff. in delay [2]	-5,2 %	6,6 %	-25,0 %	17,2 %	-8,1 %	6,2 %
Confidence interval [3]	[-6,6%, -3,7%]		[-28,7, -21,3%]		[-9,4%, -6,7%]	
Utilization						
Initial system					78,8 %	
Capacity +1					75,8 %	
Capacity +2					73,9 %	
Capacity +3 Day shift					72,0 %	
Capacity +3 Evening shift					71,1 %	

Note:
1: Percentage delay is calculate on the basis of completed jobs and number of delayed jobs
2: Expected difference in delay is expected delay in experiments minus expected delay in initial system
3: 95 % confidence interval, t-distribution with n-1 degrees of freedom

The results from the experiments on capacity show that increasing the capacity level has a positive impact on performance. The expected degree of delay in the Grand Total is reduced to respectively 6,4 %, 3,7 %, 2,5 % and 2,4 % in the four experiments. The standard deviation of percentage delay is also reduced considerably.

Increased capacity reduces the utilization of porters, from 78,8 % to respectively 75,8 %, 73,9 %, 72 % and 71,1 %. However, this is only a slight reduction, indicating that the initial capacity level is too low during some specific periods in the day. We observe that when the capacity increases from one to two porters the expected reduced delay is almost doubled, while adding a third porter does not have the same effect. This indicates that when increasing the number of porters the marginal utility is diminishing, meaning that the first porter yields more utility than subsequent porters (Frank 2003). In addition, there is not a great difference in performance when the third porter works day or evening shift.

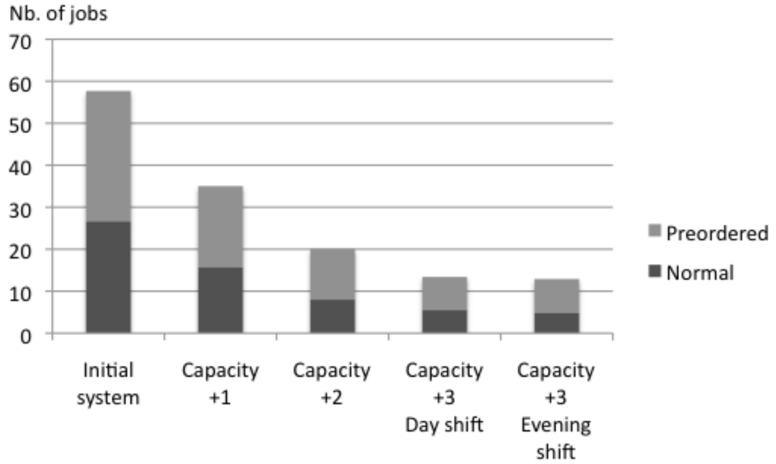


Figure 19 Summary of results from experiments on capacity, measured in number of delayed jobs

Figure 19 summarizes the results from experiments on capacity. It is clear that an increase in capacity results in expected decreased number of delayed jobs and improved performance. The results indicate that the initial capacity level is too low, and that it can be used as a buffer to handle variability. The results are as we expected and support our hypothesis.

7.3 Assignment of Jobs

Analyzes in Chapter 5.3 showed that it is important to have robust dispatching policies and that the queue discipline might impact performance. As discussed in Chapter 6.1.1, the existing queue discipline is similar to a combination of first-come first-served (FCFS) and earliest due date (EDD). According to theory, EDD is the queuing system that minimizes the maximum delay. However, we have observed a significant degree of delay in the initial system for Normal and Preordered jobs. It is therefore interesting to analyze the effect of using different dispatching policies in order to compare existing queue discipline against other queue disciplines. We will perform experiments on the effect of using two different queue disciplines, first-come first-served (FCFS) and priority.

In the FCFS experiment, Normal and Preordered jobs are given the same priority during the whole simulation. This implies that the dispatcher exclusively considers waiting time in the queue when assigning jobs to porters. According to theory, FCFS is traditionally regarded the fairest queue discipline in service systems, since customers are served in the same order as they arrive in the queue. Since the initial system is similar to EDD, we expect that the degree of delay will increase when using FCFS.

Queue discipline based on Priority selects one specific job type over another based on the job's importance. In the experiment based on Priority, we are changing the jobs' priority level, assigning Preordered jobs a higher priority than Normal jobs during the whole simulation. The rationale is that the degree of delay in Preordered jobs is initially very high and the porter management has stated that Preordered jobs are of greater importance to complete on time, than Normal jobs. Due to the change in priority, we expect the degree of delay to be reduced for Preordered jobs, and increased for Normal jobs.

In the final experiment we will see how a reallocation in the demand of Preordered and Normal jobs are affecting the assignment of jobs. The dispatcher has a higher degree of flexibility in assigning Normal jobs, because Preordered jobs are to be completed at the scheduled time of appointment. Also, the mean travel time and the probability of aborted jobs are larger for Preordered jobs, which have an effect on the utilization of porters. The most preferable level of Normal and Preordered jobs has been discussed by the porter management. They believe it is possible to reallocate 5 % of total demand from Preordered to Normal jobs. We assume the total number of incoming jobs to be constant, as the demand is not controllable. In the experiment we have reduced Preordered jobs with 5 % of total demand, and increased Normal jobs with 5% of total demand.

By changing the distribution in demand, we expect a reduced degree of total delay as a consequence of increased flexibility in the assignment of jobs.

Table 19 Summary of changes in the system in experiments on queue discipline

Experiment	Changes in the system
Queue discipline FCFS	First-come First-Served (FCFS)
Queue discipline Priority	Prioritizing Preordered jobs over Normal jobs
Reallocation in demand	Reduced Preordered jobs with 5 % of total demand Increased Normal jobs with 5 % of total demand

Table 20 Results from experiment on queue discipline

	Normal		Preordered		Grand Total	
Initial system	Mean	St.dev	Mean	St.dev	Mean	St.dev
Percentage delay [1]	6,3 %	6,9 %	33,4 %	17,8 %	10,4 %	6,3 %
Queue discipline FCFS						
Percentage delay [1]	12,0 %	9,8 %	17,1 %	10,8 %	12,1 %	9,0 %
Expected diff. in delay [2]	5,7 %	7,1 %	-16,3 %	16,8 %	1,7 %	9,9 %
Confidence interval [3]	[4,1%, 7,2%]		[-19,9 ,-12,7%]		[-0,4%, 3,8%]	
Queue discipline Priority						
Percentage delay [1]	14,3 %	11,2 %	5,4 %	2,5 %	11,9 %	8,7 %
Expected diff. in delay [2]	8,0 %	8,6 %	-28,2 %	17,7 %	1,5 %	9,5 %
Confidence interval [3]	[6,1%, 9,8%]		[-32,0%, -24,4%]		[-0,6%, 3,5%]	
Reallocation in demand						
Percentage delay [1]	5,5 %	5,9 %	31,4 %	17,4 %	8,5 %	5,9 %
Expected diff. in delay [2]	-0,4 %	8,1 %	-13,3 %	30,0 %	-1,9 %	9,2 %
Confidence interval [3]	[-2,2%, 1,3%]		[-19,8 ,-6,9%]		[-3,9%, 0,1%]	
Utilization						
Initial system					78,8 %	
Queue discipline FCFS					78,6 %	
Queue discipline Priority					77,7 %	
Reallocation in demand					77,9 %	

Note:
1: Percentage delay is calculate on the basis of completed jobs and number of delayed jobs
2: Expected difference in delay is expected delay in experiments minus expected delay in initial system
3: 95 % confidence interval, t-distribution with n-1 degrees of freedom

The results from the experiments on queue discipline show that FCFS and Priority increase the total degree of delay, 12,1 % and 11,9 % respectively. The corresponding standard deviations have also increased. The effects are however different for Normal and Preordered jobs. The results from the experiments show that the expected degree of delay for Normal jobs has increased, while it has decreased for Preordered jobs. This is because the experiments imply a change in priority from the initial system, where Preordered jobs have a lower priority than Normal jobs up until due date approaches. In FCFS Normal and Preordered jobs are prioritized equally and the system only considers waiting time in the queue. In the priority experiment, Preordered jobs are prioritized over Normal jobs during the whole simulation. Both experiments result in a lower degree of delay for Preordered jobs and an increase in Normal jobs.

In the experiment with reallocated demand we observe that the degree of total delay decrease to 8,5 %. This indicates that the reallocation in demand has a positive impact on performance. Reasons for this are increased flexibility and that Normal jobs have a shorter processing time than Preordered jobs, resulting in a more effective use of porters.

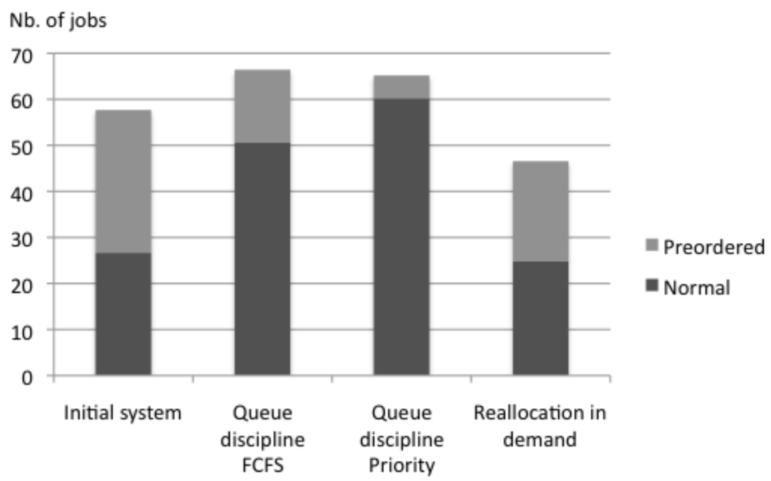


Figure 20 Summary of results from experiments on queue disciplines, measured in number of delayed jobs

Figure 20 summarizes the results from the experiments on different queue disciplines and reallocation in demand. The figure shows that the results from the experiment on queue discipline are in line with our expectations, as the total number of delay is increased. It also shows that using different queue disciplines have an effect on performance. Further, the simulation model estimates that the initial system, with queue discipline similar to EDD, is the system with the lowest degree of delay. However, the difference in number of delays is not as large as we expected it to be. A reason might be that the initial system is a combination of different queuing disciplines, and that it is not a pure EDD approach. The results from the experiment on reallocation in demand are also as expected, with a significant reduction in delay.

The results show that the initial queuing discipline is a better solution than FCFS and prioritizing Preordered jobs when the objective is to minimize the maximum delay. However, according to the analysis on dispatching time in Chapter 5.3, we believe that there are possibilities of improving existing policies to minimize variability in the assignment of jobs. Also, according to the experiments, it is preferable to reallocate the demand to increase the dispatcher's flexibility when assigning jobs.

7.4 Sensitivity Analysis

Finally, we will conduct a sensitivity analysis on changes in total demand. Over the last 5 years the number of "In-patient stays" (both genders) in Norwegian hospitals has increased with about 5 %. The graph below displays the development over the last 22 years (SSB, 2012).

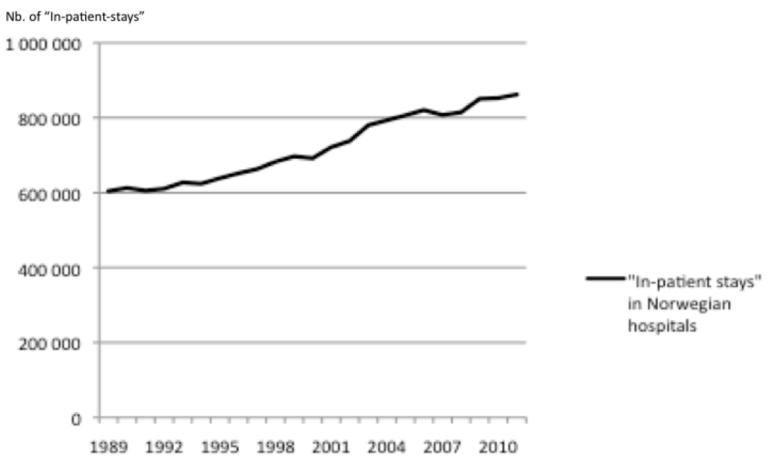


Figure 21 Development of "In-patient stays" (both sexes) in Norwegian hospitals over the last 22 years.

According to the statistics retrieved from SSB, the number of "In-patient stays" has increased during the last 22 years. It is therefore fair to assume that the number of incoming jobs will continue to increase, and that the Porter Service will experience increased demand in the future. It is interesting to analyze the effect of an increase, in order to say something about how the Porter Service can handle future events with current process times and capacity level. Also, we will analyze the effects of a possible decrease in total demand.

First, we will experiment with respectively a 5 % and 10 % increase in demand. Second, we will present scenarios with a decrease in demand of respectively 5 % and 10 %. We expect an increase in the degree of delay when increasing the demand, and a decrease in the degree of delay when decreasing the demand, all else equal.

Table 21 Summary of changes in the system in sensitivity analysis

Experiment	Changes in the system
Sensitivity analysis +5 %	Increased demand = 5 %
Sensitivity analysis +10 %	Increased demand= 10 %
Sensitivity analysis -5 %	Decreased demand = 5 %
Sensitivity analysis -10 %	Decreased demand = 10 %

Table 22 Results from sensitivity analysis

	Normal		Preordered		Grand Total	
Initial system	Mean	St.dev	Mean	St.dev	Mean	St.dev
Percentage delay [1]	6,3 %	6,9 %	33,4 %	17,8 %	10,4 %	6,3 %
Sensitivity analysis +5 %						
Percentage delay [1]	8,4 %	7,9 %	43,2 %	17,9 %	13,8 %	7,0 %
Expected diff. in delay [2]	2,4 %	9,6 %	11,4 %	24,4 %	3,9 %	9,5 %
Confidence interval [3]	[0,3%, 4,5%]		[6,2%, 16,7%]		[1,8%, 5,9%]	
Sensitivity analysis +10 %						
Percentage delay [1]	12,9 %	8,6 %	53,9 %	15,9 %	19,3 %	7,6 %
Expected diff. in delay [2]	7,1 %	10,4 %	23,9 %	22,0 %	9,7 %	8,6 %
Confidence interval [3]	[4,9%, 9,3%]		[19,2%, 28,7%]		[7,9%, 11,6%]	
Sensitivity analysis -5 %						
Percentage delay [1]	3,7 %	4,1 %	23,0 %	12,2 %	6,8 %	4,3 %
Expected diff. in delay [2]	-3,0 %	8,3 %	-11,9 %	21,0 %	-4,2 %	7,6 %
Confidence interval [3]	[-4,8%, -1,2%]		[-16,4%, -7,4%]		[-5,9%, -2,6%]	
Sensitivity analysis -10 %						
Percentage delay [1]	1,8 %	1,9 %	19,9 %	11,0 %	4,8 %	2,5 %
Expected diff. in delay [2]	-5,2 %	8,0 %	-17,8 %	23,3 %	-6,9 %	7,9 %
Confidence interval [3]	[-6,9%, -3,5%]		[-22,92%, -12,8%]		[-8,6%, -5,2%]	
Utilization						
Initial system					78,8 %	
Sensitivity analysis +5 %					75,8 %	
Sensitivity analysis +10 %					73,9 %	
Sensitivity analysis -5 %					72,0 %	
Sensitivity analysis -10 %					71,1 %	

Note:
1: Percentage delay is calculate on the basis of completed jobs and number of delayed jobs
2: Expected difference in delay is expected delay in experiments minus expected delay in initial system
3: 95 % confidence interval, t-distribution with n-1 degrees of freedom

The results from the first two experiments show that an increase in demand will have a negative effect on performance, with an increase in delay of respectively 13,8 % and 19, 3 %. This is as we expected since the capacity level in the initial system is too low to manage the current arrival rate of jobs. If the Porter Service experience a reduction in demand, the last two experiments show that the degree of delay is expected to be reduced with respectively 6,8 % and 4,8 %. This is also as we expected, and implies that reduced demand will have a positive effect on performance.

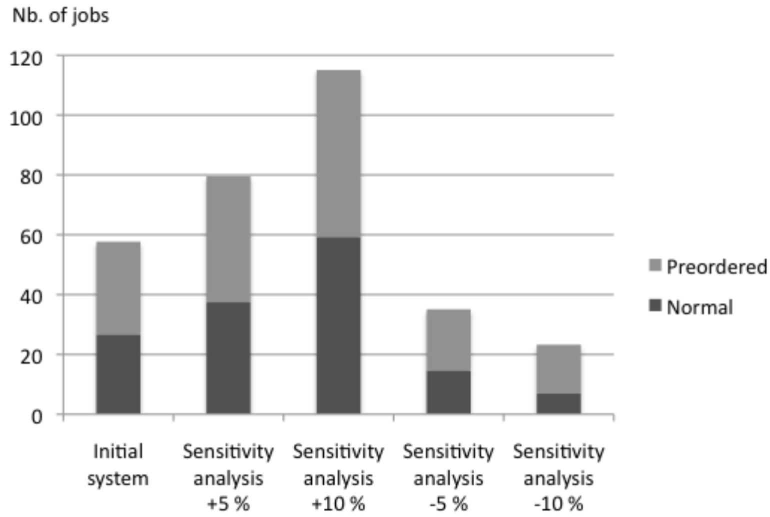


Figure 22 Summary of results from sensitivity analysis, measured in number of delayed jobs

Figure 22 summarizes the results from the sensitivity analysis. The results are as we expected, an increase in demand has a negative impact on performance, and a decrease in demand has a positive impact on performance.

7.5 Summary of Findings

In Chapter 7.0 we conducted experiments in order to analyze how changes in the initial system affected performance.

Table 23 Overview of results from all experiments

Expected difference in delay	Grand Total	
	Mean	St.dev
Variability Erlang 5	-0,9 %	8,2 %
Variability Aborted jobs = 0	-1,6 %	7,7 %
Variability Erlang 5, Aborted jobs = 0	-2,5 %	7,2 %
Capacity +1	-4,0 %	7,4 %
Capacity +2	-6,7 %	6,4 %
Capacity +3 Day shift	-8,0 %	6,3 %
Capacity +3 Evening shift	-8,1 %	6,2 %
Queue discipline FCFS	1,7 %	9,9 %
Queue discipline Priority	1,5 %	9,5 %
Reallocation in demand	-1,9 %	9,2 %
Sensitivity analysis +5 %	3,9 %	9,5 %
Sensitivity analysis +10 %	9,7 %	8,6 %
Sensitivity analysis -5 %	-4,2 %	7,6 %
Sensitivity analysis -10 %	-6,9 %	7,9 %

Through experiments on reduced variability in process times (Erlang with shape parameter = 5) and reduced number of aborted jobs, we found that eliminating aborted jobs has the greatest effect on performance. The experiment where these two elements were combined resulted in an expected reduction in delay of 2,5 %. If the Porter Service manages to reduce variability in process times and reduce the amount of duplication of work, there will be a better use of the porters and it will increase the possibility of reducing delays. The results are as we expected and according to theory.

Further, we found that increased capacity reduced the expected degree of delay. The results were as we expected and in accordance with theory. We found that the first and second additional porter had the largest effect on performance, and that the third additional porter only gave a slight improvement. However, the experiments with an increase of three porters gave the largest expected reduction in delay of 8 %.

The experiments on queuing discipline showed the total delay increased when changing to FCFS and Priority, and that the initial system is a better solution. Using FCFS and prioritizing Preordered jobs resulted in increased total expected degree of delay of 1,7 % and 1,5 % respectively. Results from the experiment on reallocation in demand showed that expected delay was reduced with 1,9 %, and that it had a positive effect on performance. This implies that the dispatcher has increased flexibility in the assignment of jobs when reducing the amount of Preordered jobs in the system.

Finally, we performed a sensitivity analysis on the initial system, by increasing and decreasing the total demand. We found that the Porter Service is not able to handle a large increase in demand. If demand increases with 5% or 10 %, the total expected delay increased with respectively 3,9 % and 9,7 %, all else held equal. However, we found that a decrease in demand of 5% or 10 %, reduced the total degree of delay with respectively 4,2 % and 6,9 %, all else equal. It is a fair assumption to make that the total demand increases over time, and that the Porter Service should consider a possible increase in demand in order to maintain their performance.

8.0 Conclusions

In this thesis we have analyzed the Porter Service at Haukeland University Hospital, exploring the following research question:

How does variability in process times and incoming jobs affect the degree of delay, and how do capacity level and dispatching policies influence the performance of the Porter Service at Haukeland University Hospital?

In order to analyze the research question we have performed a quantitative analysis on the current performance based of data received from the Porter Service. In addition, we have built a simulation model based on historical data. We have performed experiments to analyze the effects of variability in process times, the effect of capacity level, and assignment of jobs. We have also conducted a sensitivity analysis to see how possible changes in demand affects the performance.

The quantitative analysis discovered that there is a degree of delay in Normal and Preordered jobs in the current system, which may be caused by variability in the process. We found that there is low and moderate variability in process times that can be explained from excessive waiting time if the patient is not prepared for transport, and duplication of work if the job is aborted. Also, we found that there is moderate variability in the arrival rate and that the capacity level does not exceed the arrival rate at all times during the day. In addition, we have showed that the probability of delay increases at certain times during the day, especially at times when the utilization of porters is high. Another identified cause of delay is the dispatching time, where the jobs in some cases were assigned too late in order to be delivered on time. We believe that there is a need to define dispatching times for Normal and Preordered jobs, in order to improve the Porter Service's performance and reduce the probability of delay.

Further, we conducted different experiments using the simulation model to analyze the effects of variability in process times and capacity. Also, we have analyzed how the assignment of jobs and possible future changes in demand may affect the degree of delay. The results show that a reduction of variability in process times or an increase of capacity will increase the expected performance. We found that the existing queue discipline results in lower expected degree of delay, than FCFS and when prioritizing Preordered jobs. The results show that a reallocation in demand, with a decreased number of Preordered jobs in the system, reduces the expected degree of delay. Further, the sensitivity analysis shows that increased demand will have a negative impact on performance. This is an important observation as the future demand is expected to increase, and should be taken into consideration by the Porter Service.

From the experiments we can conclude that reducing or a better handling of variability in the process can improve the performance of the Porter Service. The easiest way to handle variability is to increase the capacity level. Based on our findings, this will increase the Porter Service's ability to handle the large variation in demand during the day. However, we do not believe this is the only solution. Improving the quality standards is another way of managing the variation in demand. If the dispatchers have more defined criteria for when a job should be assigned, we believe this will reduce the probability of delay, regardless of increased capacity. In Chapter 5.3 we suggested a maximum dispatching time of 25 minutes for Normal jobs and 15 minutes for Preordered jobs. We have also seen that a reallocation in demand, with a smaller number of Preordered jobs in the system, can reduce the degree of delay.

A final solution is to reduce the variability in process times. According to the quality standards, the departments have committed to prepare the patient for transport when the porters arrive. However, this commitment not always fulfilled and affects the travel times and the probability of a job being aborted. We found that excessive waiting time and duplication of work have an effect on the degree of delay, and it is therefore important to reduce these sources of variability in the process.

9.0 Limitations and Future Research

9.1 Limitations

First of all we would like to emphasize that the quantitative analysis and the simulation model are based on historical data, from September, October, November 2011 and January 2012. As a result, special events during this period might have influenced the analysis, as well as possible errors in the data. Also, a limitation might be that we have do not have data from a full year, and that we therefore have not considered possible differences in variability during different seasons, such as variability in demand in the summer versus winter months.

Second, the validation of the model showed that there were some differences between the real system and the simulation model. Therefore, we would like to emphasize that the simulation model is only a simplified representation of the real system, and that the results must be used as indications of how changes in the system affects the performance. We had to make several simplifications that may have affected the results from the simulation model. Especially, the simplification of the assignment of jobs caused the model to not consider human variability in the dispatching center.

It is also difficult to say to what extent the results from the experiments are based on relations in the system or randomness. However, the input data is based on historical data fitted to distributions, and we have therefore minimized the risk that the results are based solely on randomness.

9.2 Future Research

This thesis considers the Porter Service and the process of transport of patients, lab specimens and blood products, internally in the hospital. However, the Porter Service performs many other tasks that may affect the overall performance. It would be interesting to perform an analysis that includes all the services performed by the Porter Service, and analyze the effect of flexibility in the system. Our validation results in Chapter 5.3.4 indicate that the real system has a higher degree of flexibility because the porters can perform a wider range of tasks when taking all of the services into consideration.

Also, we have not analyzed the ordering process in the departments. There might be possibilities in simplifying and clarifying the order system to reduce the amount of errors. In addition, we recommend analyzing the underlying causes for why the departments in some cases do not manage to prepare the patient before transport. Our analysis indicates that there is a close relationship between the number of aborted jobs and probability of delay, and it would be interesting to conduct further analysis to explore whether there is a correlation.

10.0 Literature

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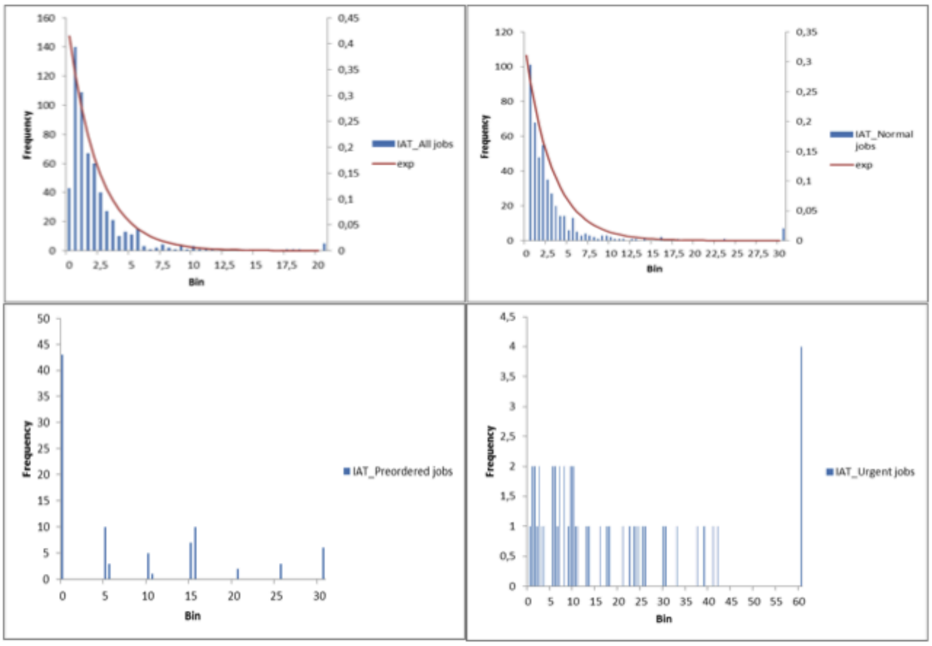
11.0 Appendix

11.1 IAT Distributions

Figure 23 Histograms of IAT during one day, for the grand total and each priority



Note: The histogram of IAT for Emergency jobs is not illustrated because the average number of incoming Emergency jobs is very low, only 2 jobs on average each day.

11.2 Process Time Distributions

Table 24 Estimation of Erlang shape parameter

	Travel time and transport time in minutes				
	Normal	**Urgent**	**Emergency**	**Preordered**	**Grand Total**
Travel time					
Mean	7,92	6,23	3,98	11	8,41
St.dev	5,99	4,72	2,82	6,79	6,41
k	2	2	2	2	2
Lambda	0,2526	0,3211	0,5025	0,1819	0,2379
E(x)	7,92	6,23	3,98	11	8,41
St.dev(x)	5,6	4,4	2,81	7,78	5,94
Transport time					
Mean	5,39	5,9	5,51	5,91	5,51
St.dev	3,69	4,44	3,53	4,44	3,95
k	2	2	2	2	2
Lambda	0,3710	0,3392	0,3627	0,3385	0,3627
E(x)	5,39	5,9	5,51	5,91	5,51
St.dev(x)	3,81	4,17	3,9	4,18	3,9

Figure 24 Distribution of travel times for the different priorities

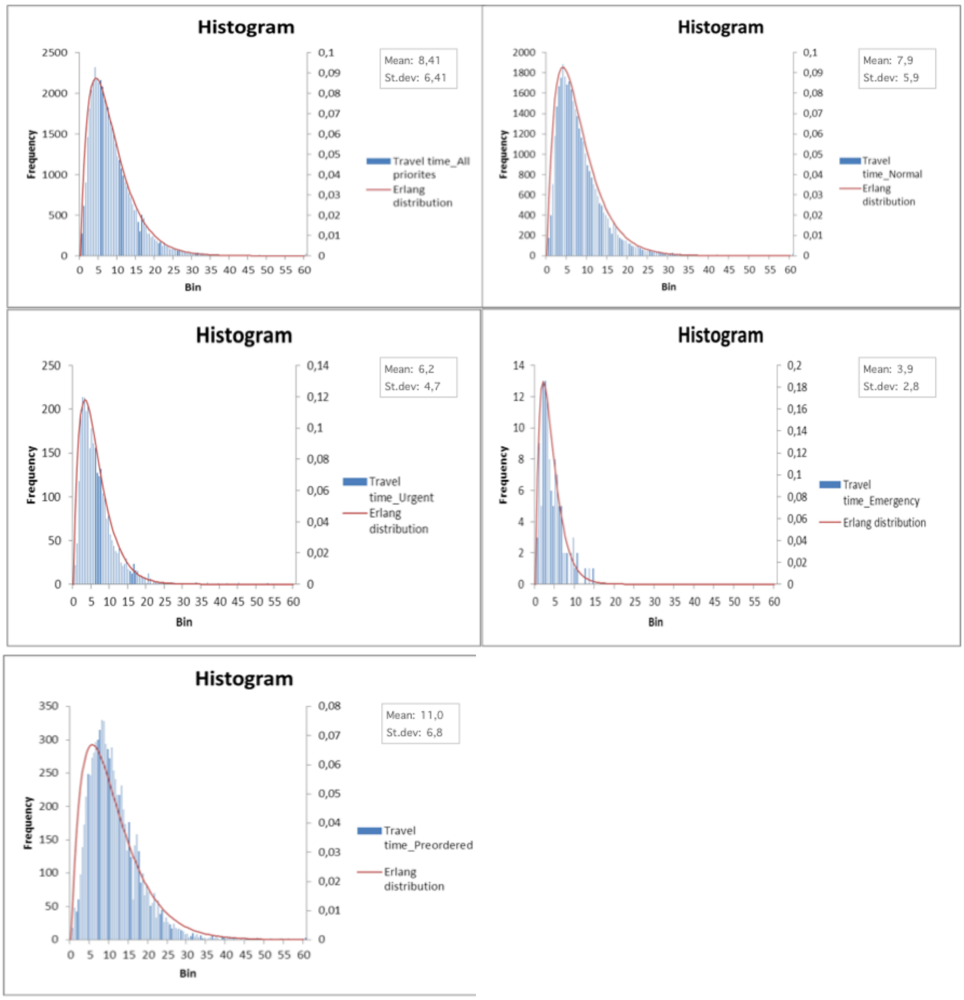
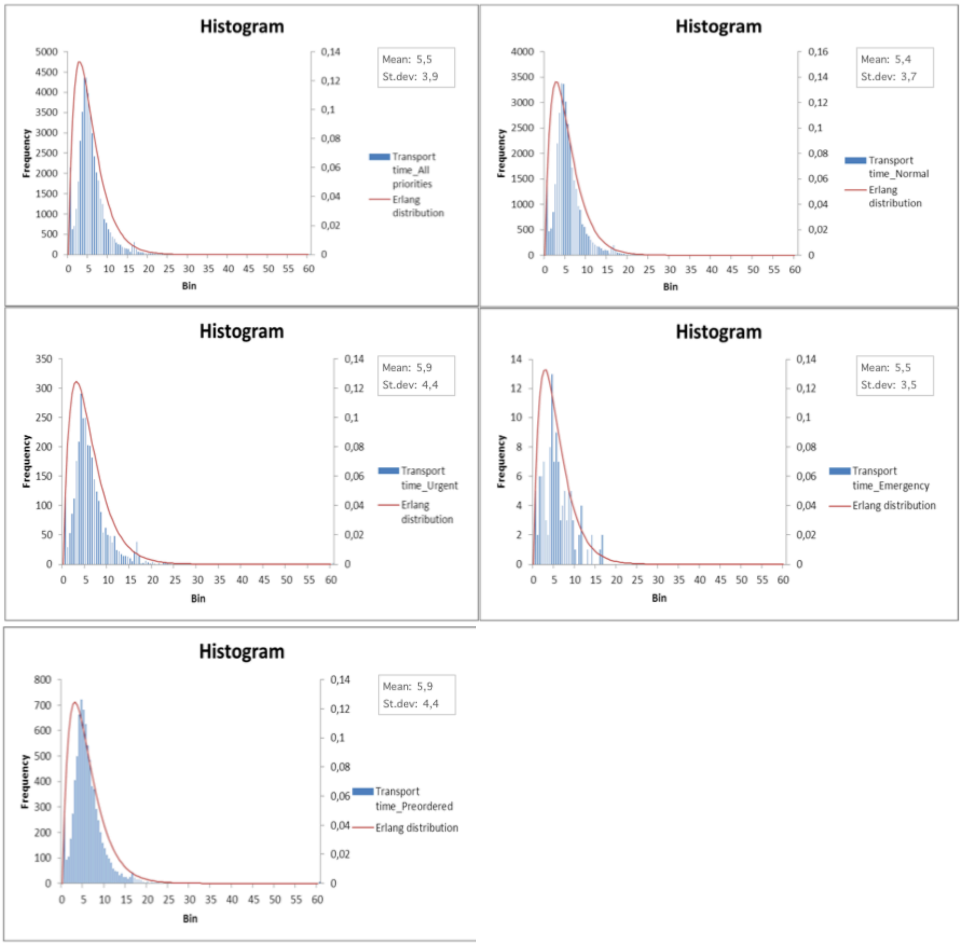


Figure 25 Distribution of transport times for the different priorites



11.3 Program Code of the Simulation Model

```
SIMULATE 1

aiat2 FUNCTION v$clock,D
60 10.6
120 13.2
180 17.3
240 22.7
300 29.8
360 30.7
420 25.4
480 14.2
540 3
600 1.8
660 1.7
720 2.2
780 1.9
840 1.4
900 1.5
```

```
960 1.7
1020 1.9
1080 2.3
1140 3
1200 3
1260 2.3
1320 3.7
1380 7.3
1440 7.8
aiat3 FUNCTION v$clock,D
120 120
240 120
360 120
480 12
600 4
720 5.4
840 3.9
960 11.7
1080 23
1200 27.9
1320 54.5
1440 120
aiat4 FUNCTION v$clock,D
240 170
480 148.9
720 17.6
960 15.7
1200 43.2
1440 73.9
cap FUNCTION v$clock,D
30 2
60 2
90 2
120 2
150 2
180 2
210 2
240 2
270 2
300 2
330 2
360 2
390 2
420 2
450 5
480 11
510 12
540 12
570 13
600 13
630 13
660 9
690 9
720 10
750 11
780 13
810 13
840 13
870 13
900 16
930 9
960 9
990 8
```

```
1020 7
1050 6
1080 6
1110 6
1140 6
1170 6
1200 6
1230 7
1260 7
1290 7
1320 9
1350 3
1380 3
1410 2
1440 2
DispC CAPACITY
QTABLE Rec2,0,5,10
QTABLE Rec3,0,5,10
QTABLE Rec4,0,5,6
QTABLE Rec5,0,5,4
clock VALUEOF cl-1440*fn$int(cl/1440)
      GENERATE FN$aiat2*FN$xpdis    ! IAT Normal jobs
      LET+ x$jobs2,1    ! Calculating nb of incomming jobs
      GOTO canc2,0.03   ! probability of cancellations
      LET PRIORITY=1
      ENTER DispC ! Dispatching center
      ARRIVE Rec2
      LET p$rect2=cl
      ADVANCE 0.25,0.1
again2      LET x$cap=fn$cap
      LET p$porter=MIN,F,1,x$cap
      IF p$porter=U,wait2
      SEIZE avail,L
      LEAVE DispC
      SEIZE p$porter,Q
      ARRIVE Travt2
      ADVANCE 7.92*FN$rlng2   ! Travel time
      DEPART Travt2
      GOTO abort2,0.02  ! probability of aborted order
      DEPART Rec2
      ARRIVE Trant2
      ADVANCE 5.39*FN$rlng2   ! Transport time
      DEPART Trant2
      RELEASE p$porter
      SEIZE avail,L
      LET+ x$comp2,1    ! Calc completed Normal jobs
      TERMINATE
abort2      LET+ x$bom2,1     ! (Loc: -7,+1)
      RELEASE p$porter
      SEIZE avail,L
      TERMINATE
canc2 LET+ x$canc2,1    ! (Loc: -18,+0)
      TERMINATE
wait2 RELEASE avail     ! (Loc: +7,+0)
      LET p$wait2=cl-p$rect2
      IF p$wait2>25,inc2
retur2      WAITIF avail=NU
      GOTO again2
inc2  LET PRIORITY=2    ! (Loc: -1,+1)
      GOTO retur2

      GENERATE FN$aiat3*FN$rlng2    ! IAT Preordered jobs
      LET+ x$jobs3,1    ! Calculating nb of incomming jobs
```

```
      GOTO canc3,0.09    ! probability of cancellations
      LET PRIORITY=0
      ENTER DispC ! Dispatching center
      ARRIVE Assign
      ARRIVE Rec3
      LET p$rect3=cl
      ADVANCE 0.25,0.1
again3      LET x$cap=fn$cap
      LET p$porter=MIN,F,1,x$cap
      IF p$porter=U,wait3
      SEIZE avail,L
      LEAVE DispC
      DEPART Assign
      SEIZE p$porter,Q
      ARRIVE Travt3
      ADVANCE 11*FN$rlng2      ! Travel time
      DEPART Travt3
      GOTO abort3,0.07  ! probability of aborted order
      ARRIVE Trant3
      ADVANCE 5.91*FN$rlng2    ! Transport time
      DEPART Trant3
      RELEASE p$porter
      DEPART Rec3
      SEIZE avail,L
      LET+ x$comp3,1    ! Calc completed Preordered jobs
      TERMINATE
abort3      LET+ x$bom3,1      ! (Loc: -7,+1)
      RELEASE p$porter
      SEIZE avail,L
      TERMINATE
canc3 LET+ x$canc3,1    ! (Loc: -20,+0)
      TERMINATE
wait3 RELEASE avail     ! (Loc: +8,+0)
      LET p$wait3=cl-p$rect3
      IF p$wait3>20,inc3
retur3      WAITIF avail=NU
      GOTO again3
inc3  LET PRIORITY=3    ! (Loc: -1,+1)
      GOTO retur3

      GENERATE FN$aiat4*FN$xpdis    ! IAT Urgent jobs
      LET+ x$jobs4,1    ! Calculating nb of incomming jobs
      GOTO canc4,0.03   ! probability of cancellations
      LET PRIORITY=2
      ENTER DispC ! Dispatching center
      ARRIVE Rec4
      LET p$rect4=cl
      ADVANCE 0.25,0.1
again4      LET x$cap=fn$cap
      LET p$porter=MIN,F,1,x$cap
      IF p$porter=U,wait4
      SEIZE avail,L
      LEAVE DispC
      SEIZE p$porter,Q
      DEPART Rec4
      ARRIVE Travt4
      ADVANCE 6.23*FN$rlng2   ! Travel time
      DEPART Travt4
      GOTO abort4,0.02  ! probability of aborted order
      ARRIVE Trant4
      ADVANCE 5.9*FN$rlng2    ! Transport time
      DEPART Trant4
      RELEASE p$porter
```

```
      SEIZE avail,L
      LET+ x$comp4,1    ! Calculating completed Urgent jobs
      TERMINATE
abort4      LET+ x$bom4,1     ! (Loc: -6,+1)
      RELEASE p$porter
      SEIZE avail,L
      TERMINATE
canc4 LET+ x$canc4,1    ! (Loc: -19,+0)
      TERMINATE
wait4 RELEASE avail     ! (Loc: +7,+0)
      LET p$wait4=cl-p$rect4
      IF p$wait4>15,inc4
retur4      WAITIF avail=NU
      GOTO again4
inc4  LET PRIORITY=3    ! (Loc: -1,+1)
      GOTO retur4

      GENERATE 720*FN$xpdis   ! IAT Emergency jobs
      LET+ x$jobs5,1    ! Calculating nb of incomming jobs
      GOTO canc5,0.05   ! probability of cancellations
      LET PRIORITY=4
      ENTER DispC ! Dispatching center
      ARRIVE Rec5
      LET p$rect5=cl
      ADVANCE 0.25,0.1
again5      LET x$cap=fn$cap
      LET p$porter=MIN,F,1,x$cap
      IF p$porter=U,wait5
      SEIZE avail,L
      LEAVE DispC
      SEIZE p$porter,Q
      DEPART Rec5
      ARRIVE Travt5
      ADVANCE 4.09*FN$rlng2   ! Travel time
      DEPART Travt5
      GOTO abort5,0.03  ! probability of aborted order
      ARRIVE Trant5
      ADVANCE 5.6*FN$rlng2    ! Transport time
      DEPART Trant5
      RELEASE p$porter
      SEIZE avail,L
      LET+ x$comp5,1    ! Calculating completed Emergency jobs
      TERMINATE
abort5      LET+ x$bom5,1     ! (Loc: -6,+1)
      RELEASE p$porter
      SEIZE avail,L
      TERMINATE
canc5 LET+ x$canc5,1    ! (Loc: -19,+0)
      TERMINATE
wait5 RELEASE avail     ! (Loc: +7,+0)
      WAITIF avail=NU
      GOTO again5

      GENERATE 30,,0
      SEIZE avail,L
      TERMINATE

      GENERATE 1440,,,,1      ! Print segment
      LET x$jobs=x$jobs2+x$jobs3+x$jobs4+x$jobs5
      LET x$comp=x$comp2+x$comp3+x$comp4+x$comp5
      LET x$canc=x$canc2+x$canc3+x$canc4+x$canc5
      LET x$bom=x$bom2+x$bom3+x$bom4+x$bom5
      PRINT 'Print output'
```

```
       PRINT '-------------------------------------'
       PRINT
       PRINT 'Total incoming jobs:',x$jobs
       PRINT 'Total completed jobs:',x$comp
       PRINT 'Total cancelled jobs:',x$canc
       PRINT 'Total aborted jobs:',x$bom
       PRINT
       PRINT 'Incoming Normal jobs:',x$jobs2
       PRINT 'Incoming Preordered jobs:',x$jobs3
       PRINT 'Incoming Urgent jobs:',x$jobs4
       PRINT 'Incoming Emergency jobs:',x$jobs5
       PRINT
       PRINT 'Completed Normal jobs:',x$comp2
       PRINT 'Completed preordered jobs:',x$comp3
       PRINT 'Completed Urgent jobs:',x$comp4
       PRINT 'Completed Emergency jobs:',x$comp5
       PRINT
       PRINT 'Cancelled Normal jobs:',x$canc2
       PRINT 'Cancelled Preordered jobs:',x$canc3
       PRINT 'Cancelled Urgent jobs:',x$canc4
       PRINT 'Cancelled Emergency jobs:',x$canc5
       PRINT
       PRINT 'Aborted Normal jobs:',x$bom2
       PRINT 'Aborted Preordered jobs:',x$bom3
       PRINT 'Aborted Urgent jobs:',x$bom4
       PRINT 'Aborted Emergency jobs:',x$bom5
       PRINT
       LET x$jobs=0
       LET x$jobs2=0
       LET x$jobs3=0
       LET x$jobs4=0
       LET x$jobs5=0
       LET x$comp=0
       LET x$comp2=0
       LET x$comp3=0
       LET x$comp4=0
       LET x$comp5=0
       LET x$canc=0
       LET x$canc2=0
       LET x$canc3=0
       LET x$canc4=0
       LET x$canc5=0
       LET x$bom=0
       LET x$bom2=0
       LET x$bom3=0
       LET x$bom4=0
       LET x$bom5=0
       TERMINATE

       GENERATE 1440*85
       TERMINATE 1

START 1
END
```

11.4 Complete Tables from the Experiments

Table 25 Complete tables - experiments on variability

	Normal		Preordered		Urgent		Emergency		Grand Total	
Initial system	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Delay [1]	26,7	29,0	31,0	16,6	0,1	0,4	0,2	0,4	57,4	34,4
Percentage delay [2]	6,3 %	6,9 %	33,4 %	17,8 %	0,3 %	1,1 %	8,8 %	21,6 %	10,4 %	6,3 %
Variability Travel time										
Delay [1]	23,1	27,6	29,3	16,1	0,0	0,2	0,2	0,4	52,6	35,7
Percentage delay [2]	5,5 %	6,5 %	32,1 %	17,7 %	0,1 %	0 %	9,3 %	20,1 %	9,6 %	6,5 %
Expected diff. in delay [3]	-0,8 %	5,5 %	-1,9 %	18,8 %	-	-	-	-	-0,9 %	8,2 %
Confidence interval [4]	[-2,0%, 0,3%]		[-6,0% ,2,2%]		-		-		[-2,7%, 0,9%]	
Variability Aborted jobs										
Delay [1]	18,5	19,1	29,8	15,7	0,1	0,2	0,2	0,4	48,6	28,2
Percentage delay [2]	4,4 %	4,5 %	31,7 %	16,7 %	0,2 %	0,8 %	11,6 %	24,9 %	8,8 %	5,1 %
Expected diff. in delay [3]	-1,9 %	7,4 %	-1,3 %	21,0 %	-	-	-	-	-1,6 %	7,7 %
Confidence interval [4]	[-3,5%, -0,3%]		[-5,9% ,3,2%]		-		-		[-3,3%, 0,1%]	
Variability Travel time, Aborted jobs										
Delay [1]	16,0	18,8	27,2	15,9	0,1	0,2	0,1	0,3	43,4	25,5
Percentage delay [2]	3,8 %	4,5 %	28,3 %	16,5 %	0,2 %	0,8 %	5,8 %	19,0 %	7,9 %	4,6 %
Expected diff. in delay [3]	-2,5 %	7,7 %	-3,9 %	23,3 %	-	-	-	-	-2,5 %	7,2 %
Confidence interval [4]	[-4,2%, 0,9%]		[-8,9% ,1,1%]		-		-		[-4,1%, -1,0%]	

Note:
1: Mean and standard deviation for delay is calculated on the basis of outputs from 85 days, measured in number of jobs.
2: Percentage delay is calculate on the basis of Completed jobs and Delay
3: Expected difference in delay is expected delay in initial system minus expected delay in experiments
4: 95 % confidence interval, t-distribution with n-1 degrees of freedom

Table 26 Complete tables - experiments on capacity

	Normal		Preordered		Urgent		Emergency		Grand Total	
Initial system	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Delay [1]	26,7	29,0	31,0	16,6	0,1	0,4	0,2	0,4	57,4	34,4
Percentage delay [2]	6,3 %	6,9 %	33,4 %	17,8 %	0,3 %	1,1 %	8,8 %	21,6 %	10,4 %	6,3 %
Capacity +1										
Delay [1]	15,8	20,1	19,3	10,0	0,1	0,3	0,1	0,4	35,2	25,0
Percentage delay [2]	3,7 %	4,8 %	21,0 %	10,9 %	0,2 %	0,9 %	6,9 %	19,8 %	6,4 %	4,6 %
Expected diff. in delay [3]	-2,6 %	4,5 %	-12,8 %	16,6 %	-	-	-	-	-4,0 %	7,4 %
Confidence interval [4]	*[-3,6%, -1,6%]*		*[-16,4 ,-9,2%]*		-		-		*[-5,6%, -2,4%]*	
Capacity +2										
Delay [1]	8,0	8,6	12,1	6,7	0,1	0,3	0,1	0,3	20,3	13,0
Percentage delay [2]	1,9 %	2,0 %	12,9 %	7,2 %	0,3 %	1,1 %	7,0 %	18,3 %	3,7 %	2,4 %
Expected diff. in delay [3]	-4,4 %	6,0 %	-20,2 %	16,5 %	-	-	-	-	-6,7 %	6,4 %
Confidence interval [4]	[-5,7%, -3,1%]		[-23,8%, -16,6%]		-		-		[-8,1%, -5,4%]	
Capacity +3 Day shift										
Delay [1]	5,5	5,7	7,9	3,7	0,0	0,2	0,1	0,3	13,5	8,0
Percentage delay [2]	1,3 %	1,3 %	8,5 %	4,0 %	0,1 %	0,6 %	5,1 %	18,0 %	2,5 %	1,5 %
Expected diff. in delay [3]	-5,0 %	6,7 %	-24,7 %	17,5 %	-	-	-	-	-8,0 %	6,3 %
Confidence interval [4]	[-6,5%, -3,6%]		[-28,5% ,-21,0%]		-		-		[-9,3%, -6,6%]	
Capacity +3 Evening shift										
Delay [1]	4,9	5,2	8,0	4,4	0,2	0,5	0,2	0,4	13,2	7,9
Percentage delay [2]	1,2 %	1,2 %	8,8 %	4,8 %	0,5 %	1,4 %	7,9 %	18,8 %	2,4 %	1,4 %
Expected diff. in delay [3]	-5,2 %	6,6 %	-25,0 %	17,2 %	-	-	-	-	-8,1 %	6,2 %
Confidence interval [4]	[-6,6%, -3,7%]		[-28,7, -21,3%]		-		-		[-9,4%, -6,7%]	

Note:
1: Mean and standard deviation for delay is calculated on the basis of outputs from 85 days, measured in number of jobs.
2: Percentage delay is calculate on the basis of Completed jobs and Delay
3: Expected difference in delay is expected delay in initial system minus expected delay in experiments
4: 95 % confidence interval, t-distribution with n-1 degrees of freedom

Table 27 Complete tables - experiments on queuing discipline and reallocation of demand

	Normal		Preordered		Urgent		Emergency		Grand Total	
Initial system	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Delay [1]	26,7	29,0	31,0	16,6	0,1	0,4	0,2	0,4	57,4	34,4
Percentage delay [2]	6,3 %	6,9 %	33,4 %	17,8 %	0,3 %	1,1 %	8,8 %	21,6 %	10,4 %	6,3 %
Queue discipline FCFS										
Delay [1]	50,6	41,4	15,9	10,0	0,1	0,3	0,1	0,4	66,7	49,6
Percentage delay [2]	12,0 %	9,8 %	17,1 %	10,8 %	0,3 %	1,0 %	7,7 %	21,0 %	12,1 %	9,0 %
Expected diff. in delay [3]	5,7 %	7,1 %	-16,3 %	16,8 %	-	-	-	-	1,7 %	9,9 %
Confidence interval [4]	[4,1%, 7,2%]		[-19,9 ,-12,7%]		-		-		[-0,4%, 3,8%]	
Queue discipline Priority										
Delay [1]	60,2	47,2	5,0	2,3	0,1	0,4	0,2	0,4	65,4	47,7
Percentage delay [2]	14,3 %	11,2 %	5,4 %	2,5 %	0,2 %	1,2 %	8,8 %	23,1 %	11,9 %	8,7 %
Expected diff. in delay [3]	8,0 %	8,6 %	-28,2 %	17,7 %	-	-	-	-	1,5 %	9,5 %
Confidence interval [4]	[6,1%, 9,8%]		[-32,0%, -24,4%]		-		-		[-0,6%, 3,5%]	
Reallocation in demand										
Delay [1]	24,8	26,5	21,8	12,1	0,1	0,3	0,1	0,3	46,7	32,4
Percentage delay [2]	5,5 %	5,9 %	31,4 %	17,4 %	0,2 %	0,9 %	4,8 %	16,0 %	8,5 %	5,9 %
Expected diff. in delay [3]	-0,4 %	8,1 %	-13,3 %	30,0 %	-	-	-	-	-1,9 %	9,2 %
Confidence interval [4]	[-2,2%, 1,3%]		[-19,8 ,-6,9%]		-		-		[-3,9%, 0,1%]	

Note:
1: Mean and standard deviation for delay is calculated on the basis of outputs from 85 days, measured in number of jobs.
2: Percentage delay is calculate on the basis of Completed jobs and Delay
3: Expected difference in delay is expected delay in initial system minus expected delay in experiments
4: 95 % confidence interval, t-distribution with n-1 degrees of freedom

Table 28 Complete table of sensitivity analysis

	Normal		Preordered		Urgent		Emergency		Grand Total	
Initial system	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Delay [1]	26,7	29,0	31,0	16,6	0,1	0,4	0,2	0,4	57,4	34,4
Percentage delay [2]	6,3 %	6,9 %	33,4 %	17,8 %	0,3 %	1,1 %	8,8 %	21,6 %	10,4 %	6,3 %
Sensitivity analysis +5 %										
Delay [1]	37,4	35,2	42,2	17,5	0,2	0,4	0,1	0,4	79,9	40,8
Percentage delay [2]	8,4 %	7,9 %	43,2 %	17,9 %	0,4 %	1,2 %	6,4 %	18,2 %	13,8 %	7,0 %
Expected diff. in delay [3]	2,4 %	9,6 %	11,4 %	24,4 %	-	-	-	-	3,9 %	9,5 %
Confidence interval [4]	[0,3%, 4,5%]		[6,2%, 16,7%]		-		-		[1,8%, 5,9%]	
Sensitivity analysis +10 %										
Delay [1]	59,3	39,4	55,8	16,5	0,4	0,8	0,4	0,6	115,9	45,4
Percentage delay [2]	12,9 %	8,6 %	53,9 %	15,9 %	1,2 %	2,2 %	20,9 %	33,0 %	19,3 %	7,6 %
Expected diff. in delay [3]	7,1 %	10,4 %	23,9 %	22,0 %	-	-	-	-	9,7 %	8,6 %
Confidence interval [4]	[4,9%, 9,3%]		[19,2%, 28,7%]		-		-		[7,9%, 11,6%]	
Sensitivity analysis -5 %										
Delay [1]	14,6	16,3	20,5	10,9	0,1	0,4	0,2	0,4	35,4	22,6
Percentage delay [2]	3,7 %	4,1 %	23,0 %	12,2 %	0,4 %	1,2 %	8,3 %	19,6 %	6,8 %	4,3 %
Expected diff. in delay [3]	-3,0 %	8,3 %	-11,9 %	21,0 %	-	-	-	-	-4,2 %	7,6 %
Confidence interval [4]	[-4,8%, -1,2%]		[-16,4%, -7,4%]		-		-		[-5,9%, -2,6%]	
Sensitivity analysis -10 %										
Delay [1]	6,9	7,0	16,3	9,0	0,1	0,3	0,1	0,4	23,4	12,3
Percentage delay [2]	1,8 %	1,9 %	19,9 %	11,0 %	0,2 %	1,0 %	6,4 %	18,5 %	4,8 %	2,5 %
Expected diff. in delay [3]	-5,2 %	8,0 %	-17,8 %	23,3 %	-	-	-	-	-6,9 %	7,9 %
Confidence interval [4]	[-6,9%, -3,5%]		[-22,92%, -12,8%]		-		-		[-8,6%, -5,2%]	

Note:

1: Mean and standard deviation for delay is calculated on the basis of outputs from 85 days, measured in number of jobs.

2: Percentage delay is calculate on the basis of Completed jobs and Delay

3: Expected difference in delay is expected delay in initial system minus expected delay in experiments

4: 95 % confidence interval, t-distribution with n-1 degrees of freedom

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