MASTER

Decision support tool to estimate personnel capacity requirements for the performance of baggage handling system

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Decision support tool to estimate personnel capacity requirements for the performance of baggage handling system

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Abstract

This master graduation report presents a decision support tool for the estimation of the personnel requirements for the maintenance of baggage handling systems at an airport. Firstly, a generic conceptual model is designed to develop a flexible simulation for the maintenance activities. This simulation allows assessing the effects of scheduling strategies and worker deployment on the ability to meet the customer performance requirements of baggage handling systems and evaluating the impact of various staffing levels on service efficiency. Secondly, a greedy algorithm based on the minimization of the total costs subject to performance constraints is implemented to permit systematic evaluations of system performance with many different team configurations and find a local optimal solution. Finally, the decision support tool is built by integrating the simulation and the stochastic optimization. The tool is designed to be user-friendly and as flexible as possible to be used for the maintenance of different baggage handling systems.

Keywords

Baggage handling systems, Decision support tool, Discrete event simulation, Maintenance, Manpower deployment, Multi-skilled environment, Stochastic optimization, Time-varying workload, Vanderlande Industries, Worker requirements

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The report you are about to read is the result of six months of research performed at Vanderlande Industries, as well as the end of the double master degree I did in Operations Management and Logistics between Eindhoven University of Technology and Grenoble-INP.

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Executive Summary

This report is the result of a Master graduation project at Vanderlande Industries. Vanderlande is dedicated to improving customers' business processes by providing automated material handling systems. Due to increasing complexity and scale of systems, VI offers site-based service contracts with a maintenance team that ensures the daily support and the continuous improvement of their system for the best performance. Failures cannot be avoided completely but the availability of the baggage handling system can be increased and maintenance costs reduced by proper estimation of labour requirements. An effective staffing of the maintenance team will help reducing the staffing and downtime costs as well as increasing the efficiency of the equipment. The lack of a user friendly and flexible way to calculate team size motivated the creation of a new tool adaptable to various airport configurations for estimating maintenance worker requirements. The performance represented by the availability of the system and the response times for failures depends on several factors which are: a time-varying arrival rate of failures, a multi-skilled environment and the travel time between the different areas of the airport. To provide insight into the effects of maintenance staffing strategies, the following research question has been investigated during this master thesis project:

> *Determine the right number of workers with the right skills at the right place at the right moment to realise the required performance for the baggage handling system of any airport.*

In order to develop a conceptual model taking into account these characteristics, the most appropriate methods have been selected by combining findings of an extensive literature study. The architecture of the model was influenced by the goal of building a generic and reusable model to consider different baggage handling system topology, failure volume levels and team parameters. Our objective was to be able to use the model as a research tool to evaluate the performance of different maintenance teams. This model takes into account of non stationarities in both failure location and failure frequency during the day as well as the difference in skills of the workers. The goal is to minimize total costs under a set of constraints on the quality of service. The decisions to be made are how many employees of each skill group to have in the airport as a function of time and space.

As the service level cannot be easily computed, a discrete event simulation program has been developed to evaluate the performance of a baggage handling systems under a given team configuration, i.e. given values of the decisions variables. This simulation model has been conceived with JAVA for a flexible evaluation of the performance of baggage handling system and maintenance activities at any airport. The model implementation accurately represents the initial conceptual model (verification) and recreates with satisfactory accuracy the real system (validation). The simulation allows evaluating different staffing plans under different input configurations to manage and understand the impacts of staff on both performance efficiency and the customer experience.

The simulation algorithm is then embedded in an optimization procedure to find the worker requirements. To resolve this staffing problem, the day is divided into fixed periods and one simply decides the number of workers of each skill group for each shift period and for each potential location. Optimization is difficult since it involves multiple scheduling and dispatching of workers to different shifts and locations, while minimizing cost and maintaining good customer service. A greedy algorithm was developed to find a near optimal solution. This combination of a simulation model and heuristic search routine permitted a degree of model realism not available with deterministic algorithms.

Finally, we designed the decision support tool that integrates the simulation model and the greedy procedure under an Excel interface which allows user friendliness. The graphical user interface as well as the explanations of the tool during different presentations improves user satisfaction and adoption of the model. Combining a mathematical formalization of the staffing problem of VI, consistent with the state of the art and a tool with appropriateness, ease of access and face validity allows satisfying both researchers and engineers.

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Abbreviations

BHS: Baggage Handling System

BPI: Business Process Intelligence

[redacted]

IID: Independent and Identically Distributed

NHPP: Non Homogeneous Poisson Process

PLC: Programmable Logic Controller

RMR: Revisions, Modifications and Retrofits

VI: Vanderlande Industries

List of Definitions

Term	Description	Reference
Business Process Intelligence	Software for gathering, storing and analysing data and providing information to help users make better decisions	Vanderlande Industries
Corrective Maintenance	Maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function	(SS-EN 13306, 2001)
Critical failure	Failure that needs to be repaired immediately because the BHS is not anymore able to provide the throughput of baggage on which VI and the airport agreed on	Vanderlande Industries
Downtime	Period of time between the occurrence of a failure and the restoration of operational readiness	FEM 9.221
Failure	Termination of the ability of an item to perform a required function	(SS-EN 13306, 2001)
Maintenance	Combination of all technical, administrative, and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function	(SS-EN 13306, 2001)
Preventive maintenance	Maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item	(SS-EN 13306, 2001)
Repair time	Time period during which the installation is repaired	FEM 9.221
Response time	Period between the time VI knows that a failure occurs and the start of the repair of the failure	Vanderlande Industries
Technical Availability	A system is technically available when it can meet the throughput where VI and its customer agreed on. A system is unavailable when due to technical failure the system cannot meet the throughput where VI and its customer have agreed on	Vanderlande Industries
Waiting time	Period between the occurrence of the failure and the start of search for fault by appropriate personnel	Vanderlande Industries

Chapter 1
Introduction & Problem identification

In this chapter, the organization Vanderlande Industries B.V. will be outlined in general terms, as well as the Service Development department in which this project has been done. That elaboration will increase the understanding of the reader for the situations that Vanderlande Industries is dealing with in its daily business. Furthermore, the global project motivation will be discussed in order to define the research objectives of this thesis.

1.1. Vanderlande Industries

1.1.1. History

Vanderlande Industries (VI) provides automated material handling systems and services. The company was founded in 1949 and nowadays employs around 2000 employees spread over customer centers and site based service contracts around the world. VI has customer centers in 12 different countries. The headquarters is located in Veghel.

VI supports customers worldwide in improving their competitive position by designing, implementing, and servicing automated material handling systems. The mission of the company is "*To support our customers in continuous improving their competitiveness by providing best-in-class automated material handling solutions*" (Vanderlande Industries, 2011). These customers demand high performance against minimal costs.

1.1.2. Organization

VI is divided into four business units:

- Baggage Handling: Baggage handling systems (BHS) at airports, from check-in through sorting, screening to baggage claim
- Distribution: Automated logistic solutions in warehouses and distribution centers
- Express Parcel & Postal: Automated systems to support the delivery of parcels and documents on time and in perfect condition
- Services: A full range of services to ensure lifetime reliability of logistic operations and systems.

The division of turnover between the different business areas is presented in Figure 1.1.

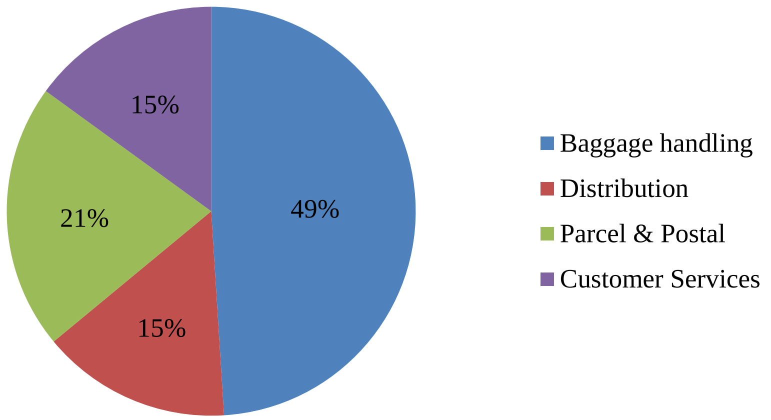


Figure 1.1: Division of turnover of VI, average over 2006-2011 – Source: Vanderlande Industries

1.1.3. Service Development

Over the years services have become more important. VI started as an equipment supplier and has evolved into delivering total solutions for customers. VI systems are used in a continuous way and need quick intervention to reduce downtime. To reach the objective of availability required by the customer, VI provides permanent on-site maintenance services for its customers. The main responsibility of the business unit Services is the development of new service activities, the support of customer centres and the supply of spare parts. [redacted] – Figure 1.2.

[redacted]

Figure 1.2: Total sales for Services – *Source: Vanderlande Industries*

[redacted]

1.2. Project Motivation

VI offers an assortment of different service contracts from a hotline support to a full service contract (Appendix A). These contracts define the responsibilities of VI for maintenance service. A typical service contract is built on the standard offerings of VI which can be tailor-made in order to meet the demands of the customer. This study focuses on Site Based Service Contracts since there is a need to explore and understand how the size of an on-site maintenance team influences the performance of the VI system.

For Site Based Service Contracts, VI is responsible for all maintenance activities on the baggage handling system. As failures cannot be completely avoided, an on-site team is located at the customer. System errors have to be solved within a time span as specified in the service contract. VI is responsible for keeping the availability up to a target level such that the customer can focus on its core business activities.

With the increasing complexity of the systems and the increasing customer demand of performance, the site-based contracts are more and more important for the service department. VI has therefore more and more responsibilities at the airports. On-site teams of VI are in charge of the daily support and the continuous improvement of their system to ensure the best performance.

A wide part of maintenance activities of on-site teams are initiated by failures of the system. As the failures arrive randomly over time, the workload is hard to predict. Because of this uncertainty, the allocation of labour resources over time is an important problem. An inadequate team size can cause serious problems for the company. On the one hand, an insufficient number of available employees can lead to service levels below the requirement of the customer mentioned in the contract. A loss of performance can result on penalties and a risk of reputational damage for VI. On the other hand, staffing too many employees increases the costs of the services and may result on the loss of contracts. Determining the number of employees is an important subject for VI because labour is expensive: about [redacted] of maintenance costs were due to direct labour cost for [redacted] airport (Franssen, 2006). Therefore a good forecast of the maintenance team size with an adapted model for VI is substantial.

Determining maintenance worker requirements for customers of VI is not easy as different factors can influence the performance. Due to the diversity of failures that can occur on VI systems, the failures can require different set of skills in order to resolve the problem. Maintenance team staffing has to take into account the set of required skills to be able to repair the system as soon as possible. Moreover, an on-site team size has to face the variation of the failure arrival rate over the time. Finally, the size of the airport can result in important distance to bridge between two locations where failures occur. By managing the starting point of workers, one can influence the reactivity of the workers.

As VI managers do not have a generic method to determine on-site team sizes, there is a need to help VI to develop their knowledge for staffing the maintenance team size of their customers which require on-site services. It will help VI managers to justify and explain to the customer the size of the maintenance team VI suggests during the negotiation of new contracts.

1.3. Research Objectives

1.3.1. Research Question

A key element in achieving a good performance level for Vanderlande is the elaboration of efficient maintenance team where employees are present at the right place, in the right quantity and exactly when needed. Therefore we need to develop a mathematical model that quantifies the influence of multi-skilled team size with respect to the process performances of baggage handling systems and find the appropriate staffing (size and organization) that fulfil the customer requirements. Based on these considerations, the following research question is defined:

> *Determine the right number of workers with the right skills at the right place at the right moment to realise the required performance for the baggage handling system of any airport.*

1.3.2. Deliverables

Before this graduation project, there was no appropriate method for the systematic determination of the worker requirements for the maintenance of BHS during the service contract phase. Therefore, VI asked to build a tool which can either determine the necessary worker requirements for a given service level or calculate the performance that the airport can expect with a given team size considering the features of the airport, the characteristics of failures and the available skill set of the workers. The aim was to elaborate a suitably parameterized and instruments tool to support knowledge acquisition about team size. It had to be flexible enough to accommodate the inputs to suit with any airport.

This tool aims at helping the maintenance contract manager to understand the impacts of staff on performance of BHS and to determine the labour requirements during the negotiation of a new contract. It could be a decision tool for the manager on site to determine the number of maintenance workers they require to meet the performance level.

1.3.3. Research Methodology

We started by field observations and interviews with the maintenance managers and maintenance workers at different airports and in the headquarters of VI to understand the work process and to collect information about the staffing and the scheduling processes. Data on the failures were gathered and analysed using database records. A literature study was done to identify the relevant way to deal with the problem. The tool was designed to look like a calculator tool with the possibility to fill the missing inputs. A flexible simulation program was implemented to evaluate the influence of the staffing on the performance level of the baggage handling system, i.e. the quantitative requirement (number of staff) and qualitative requirement (skills of the staff). The simulation collects statistics for performance measures like response time, availability of BHS and worker utilization. This simulation can be used for making sensitivity analysis and evaluating different scenarios. To evaluate quickly as many scenarios as possible, we built an optimization procedure which embeds the simulation. This procedure is able to find the worker requirements with their skills per daily shift and their start location within the airport that fulfils the performance constraints required by the customer - Figure 1.3. The interface of the final tool that includes the simulation and the optimization was designed to be user friendly. A technical and user manual were provided with the tool as well as some useful information recovered from the maintenance managers of different airports that can be used as benchmark values for the estimation of worker requirements of new systems. A case study was finally presented to the potential users to explain how the tool can be used.

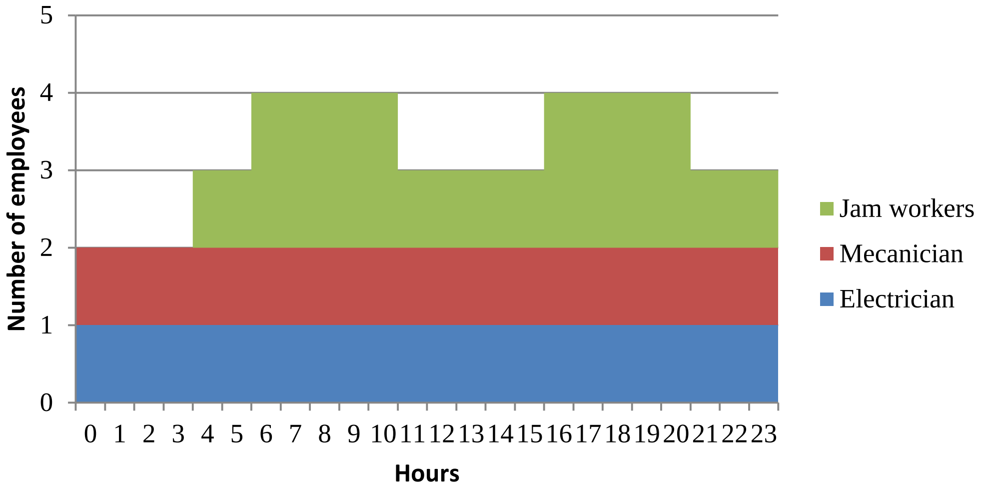


Figure 1.3: Example of a required output of the tool: Number of workers depending on the hour of the day

1.4. Thesis Outline

This thesis is organized as follows:

- Chapter 1 has presented a brief introduction to the company as well as the project motivation and the research objectives and methodology.
- Chapter 2 describes the problem and highlights the key points related the staffing of maintenance team.
- Chapter 3 reviews some of the important literature on team staffing. We particularly present a literature review on staffing issues that includes the main difficulties of our problem.
- Chapter 4 explains the model that is used by the tool as well as a description of the framework under which the tool was developed.
- Chapter 5 provides a detailed description of the simulation model
- Chapter 6 presents how the simulation was embedded in the optimization procedure to determine a near-optimal team configuration.
- Chapter 7 describes the integration of the simulation and optimization procedure in the decision support tool.
- Section 8 summarizes the results of this research and it suggests some extensions of the tool as well as recommendations for Vanderlande Industries.

Chapter 2
Problem Analysis

In this graduation project, we focus on baggage handling systems within airports. In this chapter, we familiarize the reader with the baggage handling systems, its maintenance, its performance and its costs and we point out the key elements of the maintenance team staffing for managers within VI. Section 2.1 describes the baggage handling systems which are studied and the requirements in maintenance of this kind of systems. In Section 2.2, the main performance criteria are presented. Finally, the costs at stake are highlighted in Section 2.3.

2.1. Baggage Handling System and its maintenance

2.1.1. BHS and airport topology

A baggage handling system generally provides the control, screening and handling of incoming baggage. A certain route is followed from the check-in to the airplane and from the airplane unloading to the passenger. This route consists of several steps and a simple scheme of the classic process flow is presented in Figure 2.1. When bags enter the system by the check-in desks, they go into a screening process to determine if they are safe or not. Then they can be stored if the bag comes too early or sorted between the different make-up areas to load them in the plane. When bags enter the system through the plane unloading area, they can be transported to the claim carrousels if the airport is the final destination or they can be routed to the screening process for baggage in transfer. The Appendix B gives a more detailed description of the process steps for the interested reader. The process flow can be adapted to the requirement of the airport. For instance, the airports do not always require a storage area.

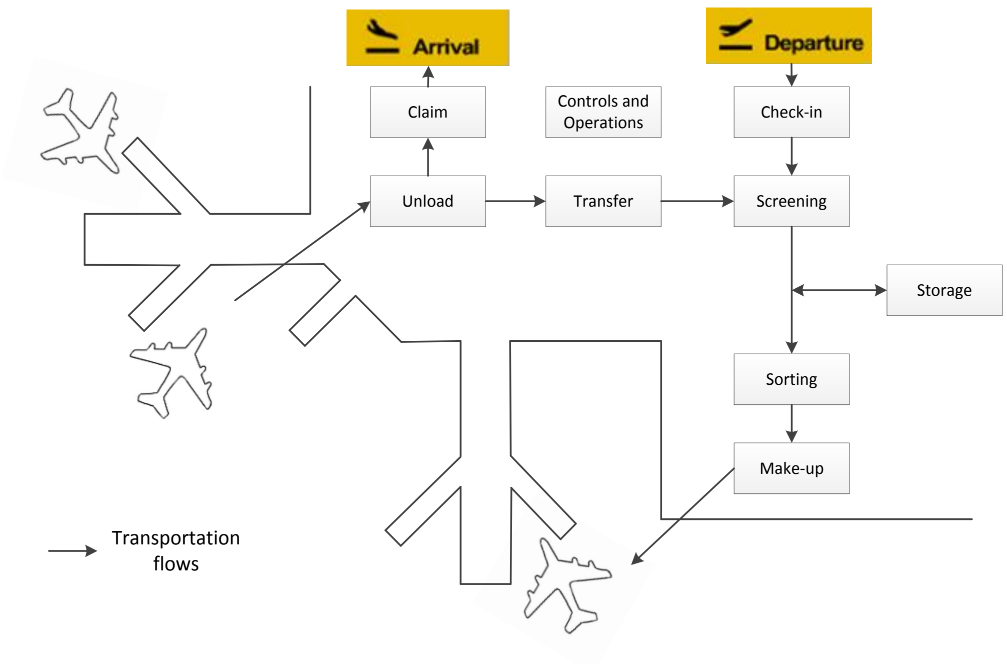


Figure 2.1: Baggage Handling Process Flows – *Source: Vanderlande Industries*

The topology of the airport has an influence on the maintenance activities. As the baggage handling system has to carry bags from the check-in desks in the passenger area to the plane, it results that the time to bridge two areas of the BHS can be important at the airport. For instance, for some airports, two areas of the system can be separated by 300 meters which results in an approximate travel time of 3 minutes. If an employee has to travel between these two areas to deal with a failure within 30 seconds, the travel time becomes a significant factor. The layout of the system is therefore an important parameter to consider for the staffing of maintenance team. Moreover, regulations can also have an influence on the travel time of the employee. The problem stems from the safety procedure that each employee has to respect to reach the BHS floor. For instance, if the employee is in the check-in area, he has to go through the security check to arrive in the basement of the airport where the BHS is which results in long travel times.

2.1.2. Classification of failures of a BHS

VI is responsible for two kinds of maintenance actions at the airports:

- Corrective maintenance: maintenance which caused by a failure. VI has to deal with corrective maintenance during operational hours of the airport, 7 days per week.
- Preventive maintenance: maintenance which is prior to a failure. Preventive maintenance is carried out to make a component less vulnerable to causal influences, by restoring the quality to an acceptable level. The preventive maintenance can be done in parallel of the corrective maintenance or during airport closing hours. In this graduation project, the preventive maintenance is not taken into account.

Different types of failure may occur on baggage handling system (Figure 2.2): technical failures or failures related to baggage. The technical failures are considered in different master theses done within VI in order to describe the corrective maintenance activities for their model (Vlasblom (2009), Stein (2009)). Stadhouters (2011) conducted a FMEA on early baggage storage and gave different potential causes of technical failures. The same analysis is made by Stein for four pieces of equipment. The time between two technical failures is generally given in operational hours.

Failures related to bags (customer failures) are sometimes mentioned in these master theses, however they are not considered in the models. These customer failures are caused either by the transportation of baggage (jam, loss of follow up, bags too closed) or operational failures (emergency stop). The customer failures occur when the conditions of use of the BHS that VI advises to the customer (an airport) are not met. Wrong bags (oversized, with wheels or with straps) must not go on the BHS. The check-in operators must sort the baggage between bags which can go in VI system and the “special” baggage (too big or too fragile). If the bag enters in VI system and it is too big or too tall (detection with cells), a security system stops the belt in order to remove the bag.

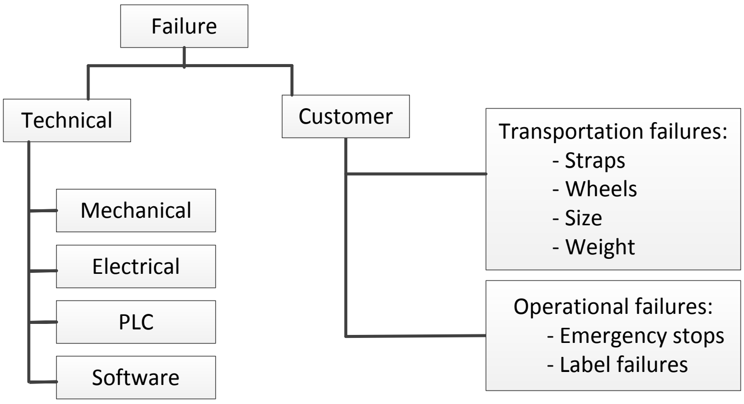


Figure 2.2: Different causes of failures at the airports

The distribution of the failures between customer and technical failures is directly related to the technology of the equipment of the BHS. Each airport uses different equipment depending on its needs. By experience, VI knows that if baggage is directly put on the conveyor belt, they can expect more customer failures than a technology that transports baggage within carts or tubs. Due to qualitative feedback of airports, VI managers know that there are far more customer failures than technical failures. The type of equipment is chosen as a function of the airport requirements.

Although VI is not responsible for customer failures, the maintenance team of VI has to solve both technical and customer failures. As pointed out in Figure 2.3, the technical failures require high level skills whereas customer failures can require either high level skills if the customer failure has damaged a piece of equipment or low level skills if not. At the airport, the technicians should be able to deal with both types of failure whereas jam workers just deal with failures that do not damage the equipment.

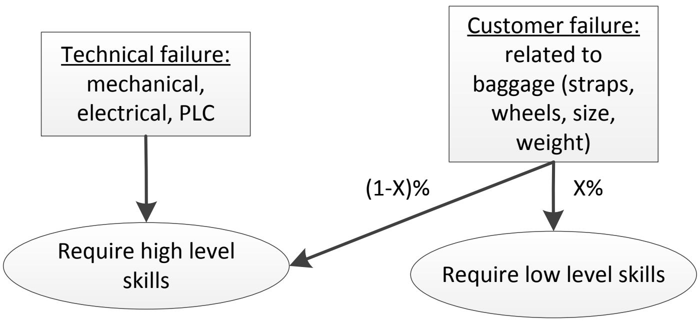


Figure 2.3: Different types of failures at the airports
X is airport-dependent and represents the percentage of customer failures that require low level skills. For example, this percentage reaches [redacted] based on the experience of the maintenance manager of the airport

Due to the diversity of maintenance activities, VI requires workers with high level skills in each of these fields:

- Electro-mechanic: engines, motor unit, sensors
- Automation and command: material and software
- Electricity: electric distribution, power supply
- Hydraulic, pneumatic

A technician can be multi-skilled and an expert in each of these different fields. The jams do not request a high level skill and some basic skills of electro technology are sufficient. Because of the high number of customer failures that are just jams, VI has to find a compromise between the amounts of skilled workers and jam workers. Staffing the maintenance team with too many skilled workers would cost a lot: the salary is higher than that of jam workers and VI has to maintain the knowledge in each field of each worker which is very expensive. However, a sufficient number of skilled workers is required to deal with all the failures which require high level skills to fulfil the service level requirement of the customer. At the moment, VI always requires two technicians to be on-site at any time for any airport due to safety considerations in principle.

Finally, the rules of priority to intervene on failures are defined by the airport and VI as a function of the criticality of the process area. A failure is critical and need to be repaired immediately when the BHS is not anymore able to provide the throughput of baggage on which VI and the airport agree on. When VI builds its system with redundancy, some failures are not required to repair immediately. For example, a failure on a check-in desk is rarely critical as there are many redundant check-in desks in the airport.

2.1.3. Demand for corrective maintenance over time

The arrival rate of interventions can change significantly throughout the day. A typical intervention demand profile over a 24-hour period is displayed in Figure 2.4. It highlights the morning and late afternoon peak hours. This pattern is explained by the increase of customer failures during peak hours. As we explained previously, the customer failures are caused by wrong bags in the system. During peak hours, more bags enter in the system and the probability to have a wrong bag increases. That is because the check-in operators are under pressure during peak hours due to the increasing number of passengers. Therefore, there is a clear relation between the amount of baggage going through the system and the amount of operational failures. In Appendix F, we point out that similar peaks can be observed for baggage flows during the week (peak in the weekend) and during the year (peaks during scholar holidays). The period of the week or the year can also influence the daily pattern. For instance, people are more disposed to travel very early or in late hours for a tourist trip during the holidays. It results that the peak hours are less pronounced.

According to managers of airport, this relation is not verified for technical failures which are very scarce events when we consider a day horizon. The amount of technical failures is not related to the amount of bags but related to the operational hours of the system. On a day horizon, they occur with a constant rate.

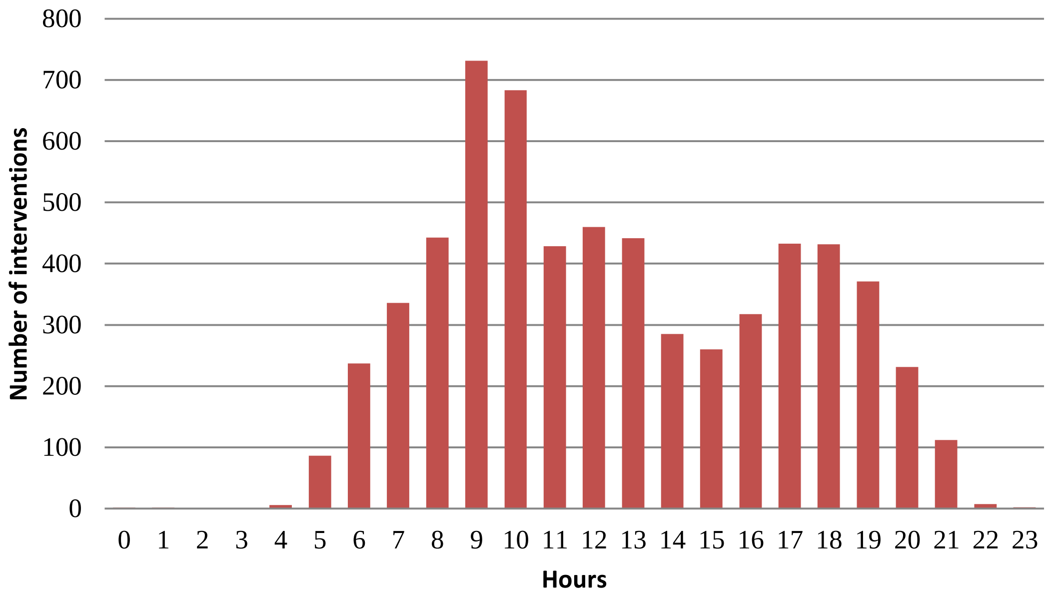


Figure 2.4: Example of non-homogeneous arrival of failures during a day: Mean number of interventions per hour of the day in [redacted] airport (March 2011 - March 2012)

The variations in the arrival rate of incoming failures are an important issue when determining the worker requirements. When an important demand is expected, more people are expected. However, it is important to consider that during low arrival rates, the airport does not require lots of workers and reduction of team size is possible to reduce costs. It results that the worker requirements may vary during the day or the year.

2.2. Baggage Handling System performance

Service level agreements are contracts set up between VI and their customers. Each on-site management team is responsible to define the performance indicators with the customer. For instance, one can find in Appendix D the service performance criteria on which VI managers and [redacted] airport agreed. In that case, VI has to pay penalties if they do not respect the service level agreements.

Each airport has its own performance indicators depending on the equipment and the requirements they have. However, all the performance criteria deal with downtime, availability or/and response time. Our model has to consider the difference of performance indicators between airports by providing different values in relation to availability and response time.

The availability has already been considered in a number of master theses at Vanderlande (Vlasblom (2009), Stein (2009)). Vlasblom defines: “A system is available when it can meet the throughput on which VI and its customer agreed on. A system is unavailable when due to failure the system cannot meet the throughput where VI and its customer have agreed on”. It means that every time a critical failure occurs, the downtime caused by this failure affect the availability. The definition of availability may differ per contract as the customer and VI are always discussing who is responsible of the failure. We will consider this definition as a standard to develop our model.

Figure 2.5 shows that the duration of the downtime can be decomposed in different periods: the notification time, the waiting time, the travel time and the repair time. In his project, Vlasblom (2009) also refers to a mean logistic delay time in order to consider an eventual shortage of spare parts or tools in the airport. We are not interested in the logistic delay time in this project as we focus on team size and we consider that spare parts and tools are always available. The process of an intervention for corrective action during opening hours can be seen in the Appendix E.

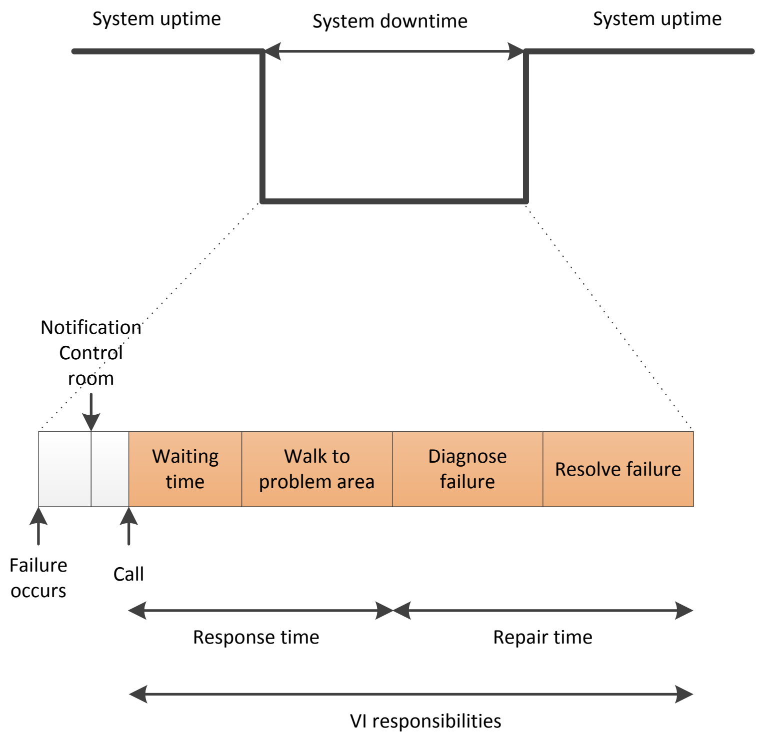


Figure 2.5: The composition of downtime

Team size clearly influences the availability of the system and the response times. By increasing the number of available workers, the waiting time decreases. By choosing relevant starting positions for maintenance workers, we can also decrease the travel time. Finally, by increasing the number of skilled workers, the waiting time of both technical and customer failures decreases while increasing the number of jam workers just decreases the waiting time for jams. Of course, increasing the number of workers is expensive and a good trade-off between performance requirements and maintenance labour costs must be found.

2.3. Classification of costs of a BHS

In 2006, Franssen did a life cycle cost analysis for baggage handling systems of VI. Within the Cost Breakdown Structure (complete overview in Appendix C), we focus on maintenance costs and downtime costs: the maintenance costs are all the necessary costs to keep or restore the system in a functioning state and the downtime costs represent the costs incurred for system unavailability. The classification of costs made by Franssen describes the maintenance costs as follows:

- **Labour costs:** all personnel costs occupied with maintaining the system. One distinguishes between direct and indirect labour. The direct labour concerns the service engineers which keep the system running and the indirect labour represents the administration work, i.e. work planning, preparation and process improvements.
- **RMR:** costs related to small systems extensions or systems adjustments
- **Spare parts:** cost of handling, stock keeping of spare parts and the cost of spare part itself
- **Subcontractors:** these are related to maintenance of equipment which VI does not produce itself

The Cost Breakdown Structure of [redacted] airport presented in Franssen's project establishes that the direct labour costs represent [redacted] of the total life cycle cost and [redacted] of the maintenance costs. As already mentioned in Chapter 1, these percentages point out the importance of labour cost in the life cycle cost of a BHS. Moreover, downtime costs can be considered as a direct consequence of a understaffing of the maintenance team as downtimes are the net result of failures. System unavailability will cause operational losses, which translates itself for a BHS into delayed baggage. It results in expensive delays and passenger dissatisfaction.

2.4. Summary

The analysis of the problem provides the motivation and the information to support the development of the decision support tool suggested in this thesis. It also points out three important characteristics that must be taken into account in the staffing of maintenance team for baggage handling systems at the airport which are:

- The arrival rate of failures follows a non-stationary process during the day. We expect the shape of the worker requirement profile to be similar to the expected failure profile with more employees required during peak hours. The influence of this pattern has to be taken into account in the modelling part to find the relevant worker requirements.
- Different types of failure exist at an airport and they require different skill levels. As a skilful employee is more expensive than a low level skill employee, we can expect that a trade-off between high level skills employee and low level skills employees can result in a reduction of the staffing costs.
- The time to bridge two areas of the system at the airport is important. A good allocation of worker within the airport should result in an increase of the performance.

In the next chapter we review the existing academic literature relevant to the staffing issue and the three key points just highlighted.

Chapter 3
Literature Review

This literature study explains the principles that are available in literature about the topic of team staffing and it describes the most appropriate methods. The review does not specifically focus on team staffing related to maintenance problem. Indeed, the call center business is also a relevant area where the number of workers has an important impact on the service level. Nurse or ambulance staffing is also widely studied and lots of similarities can be found between maintenance and healthcare studies. Section 3.1 presents the staffing problem and its objective. Then, the three important characteristics of our staffing problem highlighted in Chapter 2 are addressed in detail. In the Section 3.2, we deal with staffing in a context of time-varying workload. In Section 3.3, we review how researchers include a multi-skilled environment in the staffing problem. Section 3.4 tackles the problem of location allocation for the improvement of the service level.

3.1. Staffing problem

The task of determining the right people in the right places at the right time in order to provide a good service level refers to workforce management. In workforce management, the staffing problem is generally presented as a step of a four-step procedure (Buffa et al. (1976), Mason et al. (1998), Koole et al. (2008)):

- **Step 1 – Workload forecasting:** this step determines the underlying demand for service or future amount of work. The planning horizon is usually broken into short periods that are typically between 15 minutes and 1 hour long for call centers. We forecast period-by-period demand rates.
- **Step 2 – Worker requirements/ Staffing:** this step aims to convert the forecasted amount of work into the number of employees required with their skills. It seeks to determine the minimum number of agents needed during each period to ensure satisfactory customer service level. For call centers, the service level is typically in terms of customer waiting times. We expect the shape of the employee profile to be similar to the expected failure profile.
- **Step 3 – Shift scheduling:** the goal to achieve in this step is to select staff shifts in a set of permissible shifts that cover the worker requirements. This step aims to determine the number of employees to work in each permissible shift.
- **Step 4 - Rostering:** in this final step, we construct tours of shifts. The workers are assigned to shifts based on the schedule generated in step 3.

This report focuses on the step 2, i.e. to convert the workload into the number of employees required at each skill level. It is important to find a good match between the predicted workload and the scheduled workforce. An inadequately sized workforce can lead to low service levels or unnecessary high staffing costs (Koole et al. (2008)). Minimizing the number of employees is an important subject because labour is expensive. Therefore, staffing methods need to bring substantial cost reductions and good service level. As viewed previously, the allocation of workers over the space cannot be neglected and we can expect that this allocation has an influence on the worker requirements over the time.

Several models were suggested for maintenance staffing without tackling all the features of our problem. Basker et al. (1977), Paz et al. (1994) considered staffing at average demand levels without consideration of workforce skills whereas Al-Zubaidi and Christer (1997) or Safaei et al. (2012) included the problem of varying workload without dealing with workforce capabilities. Agnihothri and Mishra (2004) considered difference in skills between workers and travel time to go to the failure location without taking into account a fluctuating failure pattern. Chu and Lin (1993) or Tang et al. (2007) took into account the distribution of failures over the space but not over the time. The simulation is the method of resolution used by all these authors to deal with the problem of team staffing. The use of simulation is explained by the increasing complexity of systems under study and the requirement from the managers to get a better insight of their maintenance activities (Paz et al., 1994). However, as optimization can be difficult to implement with simulation due to the large number of possible solutions, optimization techniques like linear programming are often used to complete the staffing problem (Safaei et al. (2012), Jordan et al. (2004)).

The relationship between failure arrival rate and employee requirement is usually complex as many factors must be taken into account. In the case of the airport, the availability of the baggage handling system depends on several factors which are: the time-varying failure arrival rate, the multi-skilled environment and the travel time between the different areas of the airport. These characteristics make the system difficult to analyse with analytical methods and simulation seems an appropriate tool to model the maintenance activities of BHS.

We need to find the worker requirements for different skills over the time and over the space, i.e. to allocate the right number of people with the right skills at the right time and the right place. As pointed out previously, none of the authors dealing with maintenance issues consider these three key points. They are generally approached separately in the literature: staffing people over time, staffing people with different skills and staffing people over the space. Therefore, in the next sections, we focus on these three important characteristics.

3.2. Time-varying workload and staffing issue

Most articles about maintenance staffing consider a constant arrival rate during the day. This hypothesis cannot be applied for our case. The arrival rate of failures on the BHS is closely related to the number of baggage that is accepted in the system. As the departure of planes is generally planned to satisfy the demand, it is not surprising to identify some peak hours on the arrival rate of baggage and the arrival of failures. It results that the demand in work orders for maintenance team varies with the hour of the day.

Labour allocation over the time is typically a problem that call centers must deal with. As for airports, the arrival pattern of call centers changes over the course of the day. If over short periods of time, minute-by-minute for example, there is significant stochastic variability in the number of arriving calls, over longer periods of time – the course of the day – the variability can be predicted if we know arrival trend or seasonal patterns (Koole et al. (2003)). To attempt the required service level for each hour of the day, managers vary the number of available employees to face to the variability. For staffing call centers, engineers can assume constant arrival rates during each half-hour to obtain a piecewise constant arrival rate function and use standard model like the M/M/N (Erlang C) queueing model to estimate stationary system performance of each interval. This practice assumes that the system achieves a steady state relatively quickly within each interval. This assumption was made by Hueter and Swart (1998) to determine the optimal labour hours required to provide desired customer service and the optimal allocation of labour in different job categories to minimize labour cost with simulation and optimization.

In their study, Oostrum et al. (2008) considered that emergency patients arrive according to a Poisson distribution, which was modelled time-dependent. For each hour of the night, they defined an inter-arrival times representing the mean number of patients arriving in a particular hour. This assumption of time-arrival rate is often used for the staffing of hospital teams. Centeno et al. (2003) consider also an exponential distribution with different inter-arrival times per 3 hours. Kumar and Kapur (1989) also defined an arrival pattern that followed a Poisson distribution with a unique arrival mean for each hour. Thanks to one-way analysis of variance, he confirmed that the mean number of admissions by hour were not significantly different by day of week. Finally, Isken and Ward (2005) detailed a technique for generating arrivals which follow a non-homogeneous Poisson arrival processes. They allocated a fixed percentage of a day's total weekly arrival rate of patients for each hour of the week. Law (2007) presented two algorithms to generate a non-stationary Poisson process. The first one known as thinning has been proposed by Lewis and Shedler (1969). These authors used simulation to deal with the problem. In their article, Mason et al. (1998) also implemented a simulation system embedded in an optimization heuristic search to staff customs staff for each 15 minute period of each day in New Zealand with a greedy sequential descent heuristic.

As well as the arrival rate varies during the course of the day, Koole et al. (2003) pointed out that it can change with the seasonality, the holidays, the day of the week or with special events (day-off, historical day…). As seen in the previous chapter, the arrival rates of failures at the airport are influenced by these different factors. The worker requirements must be adapted as a function of the season or special events. For example, Safaei et al. (2012) determined the optimal size of external workforce under different weather situations. In function of the weather forecasting, the company managers can then adapt the size of the teams based on their calculations. Franzese et al. (2006) also treated the problem into two patterns, humid and dry seasons, in order to deal with seasonality effect on energy supplier maintenance team in Brasil. Maintenance managers of VI may specify certain days as special and increase or decrease anticipated baggage volumes accordingly.

3.3. Skills and staffing issue

There are several approaches for staffing a team in a multi-skill context.

The first one that can be described is to implement a single pool of workers. Each employee is cross-trained and can offer service in each ability that can be required by the activities. For the baggage handling system, it means that the employee is able to deal with technical failure (electrical, mechanical) and operational failures. It can also be viewed as a system that handles a single type of failure. This strategy is used by Tang et al. (2007), Al-Zubaidi and Christer (1997), Basker et al. (1977), Safaei et al. (2012), Koole et al. (2008). This kind of strategy leads to high labour cost due to the multi-skill employees. Koole (2008) also points out the possible difficulty to find these multi-skilled people in case of a large number of skills.

The second strategy is to staff a separate pool of workers for each skill. In this case, the complete team is seen as several smaller teams operating in parallel. In the maintenance context, this situation corresponds to a team with several subgroups like electricians, mechanical technicians or jam workers. In their article, Agnihothri and Mishra (2004) firstly simulate this case with dedicated queues for each failure before introducing cross-training of workers.

In between, one might partition skills into separate subgroups with common skills. For example, in call centers, some employees speak English and French whereas other ones speak just English. In maintenance paper, the term cross-training is used to present this situation. As pointed out by Jordan et al. (2004), cross-training allows that underutilized multi-skilled workers can help the overload workers whereas underutilized uni-skilled workers cannot offer help. For instance, at the airport, jam workers cannot repair a mechanical failure when all the mechanical technicians are busy whereas mechanical technicians can deal with a jam if necessary. The first two strategies are special cases of cross training: the first one implies that all the employees are cross-trained for every skill while in the second one, no cross-training is allowed (Figure 3.1). Jordan et al. (2004) compare these three strategies with 5 different types of skill and Agnihothri and Mishra (2004) also test 17 different cross-training strategies including the possibility that the secondary skill does not imply maximum efficiency level. Koole et al. (2003) presented a simple method for staffing in multi-skill call centers via a local search algorithm.

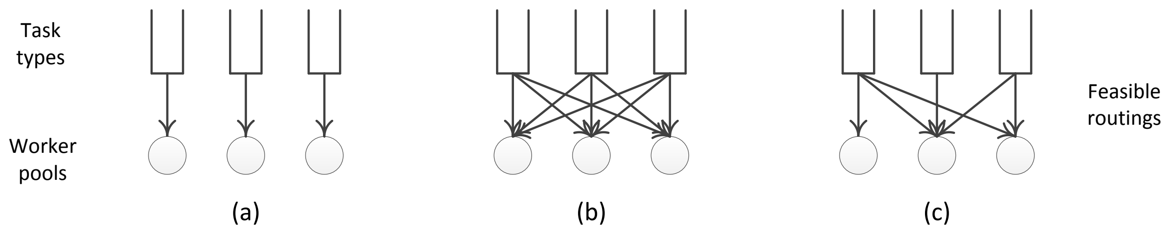


Figure 3.1: Comparison of cross-training strategies:
(a) no cross-training, (b) total cross-training, (c) partial cross training

Cross-training is a more flexible strategy but it involves a decision about the routing. Jordan et al. (2004) assume that the routing is made by assigning the task to the worker with the primary training for that task and reserving the more flexible workers for specific failures. This assumption can be selected for airport. If a jam occurs, the jam worker will be sent to the location of the failure to deal with it. However, this implies that the type of failure is known in advance. Agnihothri and Mishra (2004) tackle this problem by including a probability of mismatch in their model, i.e. the probability that the worker send on the failure location has not the right skills required to repair the failed equipment.

3.4. Deployment and staffing issue

Travel times are generally not considered in the model of the articles about maintenance within plant. However this assumption does not hold for the maintenance of BHS. As explained in the Chapter 2, jam workers may travel during 2 minutes to finally deal with a jam in 30 seconds. To improve the performance of the maintenance team size, we are faced with the decision of how to position employees throughout the airport to respond quickly to failure occurrence. Employee deployment strategies are one approach that may allow reducing response times. A good allocation can even cause a reduction of the worker requirements.

We face the problem of allocating a fixed number of employees among a set of areas. As this problem is not very tackled in maintenance literature, we had a look at the literature about strongly stochastic routing systems such as emergency services (police, fire fighting or ambulances) to get a better insight of allocation problem. In this kind of problem, no requests are known in advance to the day of operation. We focus only on static deployments, in the sense where employees return to their assigned locations whenever they are available to serve a failure (Restrepo, 2008). This is in contrast with dynamic deployment where entities can be directed to different locations throughout their shifts. The allocation problem we face is a static and probabilistic problem.

The models for deployment of Emergency Services Vehicles start generally by the definition of a zone structure in order to define a mathematical graph. The zone structure is often formed based on the convenience of the model builder (demand, geographical constraints) or the data collection system. These zones may take on any shape and all calls from a zone originate in the center. All travel to and from the zone is measured from the zone center point. Data is collected and aggregated at the zone level to define a graph with zones as nodes (Goldberg et al., 1990a).

When measuring the performance of a routing system, multiple objectives can be chosen. Some elements are almost always relevant to consider when defining the objective: the costs and the service levels. The costs are generally defined by the size of the fleet of vehicles and can also include the driving or depreciation costs (Larsen et al., 2007). The costs are indirectly minimized through a minimization of the number of vehicles needed or a minimization of total distance. The service level offered to the customers is in contrast to the objective of minimizing the costs. The quality of an emergency system is often measured by the actual perceived response time to maximize the customer satisfaction. In the case of the ambulance, the performance level is preferably chosen to reduce as much morbidity and mortality as possible. The emergency service providers accept to respond to a certain percentage of demands within a specified time period. A better allocation of emergencies vehicles can help reduce response times and improve the service level or reduce the operation costs (Haghani and Yang, 2007). The allocation problem deals with emergency vehicle location problems with two decisions: the location of fixed position vehicle stations and the number of vehicles of different types. Routing and dispatching policies can be also a topic of study.

Plenty of models have been developed to solve allocation problems. They can be grouped into different categories: deterministic, queuing and simulation (Goldberg et al., 1990a). We discuss the first two briefly and then focus on simulation:

- Deterministic models (Fitzsimmons and Srikar, 1982) like:
    - Set covering models which seek to minimize the number of facilities needed to cover the service area within a particular response time
    - Maximal covering models which seek to maximize the demand covered by a given number of facilities within a particular response time
    - P-center models that seek to minimize the maximum weighted travel time from a set of p facilities to all nodes.
    - P-median models that seek to minimize the weighted average travel times from the nearest of p facilities to all nodes

  In these approaches, the assumptions are very restrictive: for example, they do not consider that a vehicle can be busy or they assume that the demands are deterministic (Goldberg, 2004). Brotcorne, et al. (2003) study the development of ambulance location and relocation models proposed during the past three decades.

- Queueing models: The most well-known queuing approach for locating multiple emergency facilities is the hypercube model Larson and Odoni (1980). Its major strength is the ability to evaluate cooperation between vehicles while its weaknesses include assumptions of an exponentially distributed service time and computational difficulties for problems with many vehicles (Goldberg et al. (1990a)). Several improvements of this model have been proposed.

Savas (1969) describes a simulation model of the New York City ambulance service to compare different ambulance location pattern. The model suggested that locating ambulances near demand areas, rather than near hospitals, would increase performance. To reduce travel time and minimize response times, Swoveland et al. (1973) introduced a technique that combines simulation and probabilistic model to determine ambulance locations in Vancouver. Based on historical data, they determined the percentage of ambulance calls by area. Then, they used simulation to determine the probabilities that the emergency occur when q ambulances are already busy. These probabilities are used in a K-median model and a Branch-and-Bound algorithm to find the location of each ambulance. Fitzsimmons and Srikar (1982) use a location search routine and a simulation model to find based locations in Austin.

Goldberg et al. (1990a) developed a simulation model for evaluating a set of emergency vehicle base locations and validate another faster less detailed model. Repede and Bernardo (1994) combined the application of an integer linear programming with a simulation module to provide an assessment of the proposed solutions. They applied a set covering model to find the initial information to achieve a certain service level. The output of this deterministic model is then used as input data for a simulation model to obtain coverage and response time for each demand point. This simulation allows determining if satisfactory results were achieved. Maxwell et al. (2009a) formulate a simulation model of Emergency Medical Service operations to evaluate the performance of a given allocation policy. Henderson and Mason (2005) discuss a simulation and developed a decision support tool. They studied how many ambulances should be employed and where should they be stationed and different dispatching rules.

3.5. Summary

The above review demonstrates that it can be very difficult to estimate maintenance staffing needs using analytical models due to the time dependent nature of failure arrivals, the different employee skills and the location allocation within the airport that influence the performance of the system. Simulation is well suited to model these complexities. Moreover, simulation is a common and efficient tool to deal with team staffing as analytic models fail to model all the complexity of the problem. It allows evaluating its performance and comparing either difference of team configurations or dispatching policies. These models help determine base locations and employee scheduling rules.

This literature review shows that the complexities of our problem are well studied separately. But, to the best of our knowledge, no research includes all the components of our problem, i.e. determining the number of workers with their skills over the time and over the space. The model that we develop in this graduation project tries to combine these three parameters which represent the activities of maintenance at the airport.

Chapter 4
Model Development

In this chapter, we describe the conceptual model used to build the tool for Vanderlande Industries. The objective of this tool is to determine the minimum number of employees with their skills and their location that are required to reach the required availability for the baggage handling system at any airport. As the daily pattern of failures is very fluctuating, the model presented in this report will focus on the daily activities to estimate as good as possible the worker requirements for one day. This model has been designed to be generic, flexible for different baggage handling systems and reusable for application to different daily configurations during the year (difference in volume or in demand pattern). By using the tool with the features of these different daily configurations, the managers will obtain relevant information about the variation of staffing during the year.

The description of the model, including its parameters and its underlying assumptions are given in Section 4.1. Section 4.2 presents the performance outputs of the model that are evaluated by simulation. The optimization objective is defined in the section 4.3.

4.1. Model parameters and Assumptions

A model is developed to represent the system and maintenance activities described in Chapter 2. The main problem to model maintenance activities during operational hours at any airport is that the baggage handling system and service contracts are customized. The model structure must make easy to model different BHS topology, failure volume levels or failure service parameters as well as different teams. To build a model for the maintenance activities related to BHS, it is necessary to know the topology of the BHS within the airport (Section 4.1.1), the characteristics of the failures on the BHS (Section 4.1.2) and the team on site (Section 4.1.3). The additional assumptions about the failure management policies are presented in Section 4.1.4.

4.1.1. BHS topology

The baggage handling system may be divided in n ($\in \mathbb{N}$) different areas and be abstracted as a graph with n nodes. The failures are *assumed* to happen at nodes only and the properties of each area can be obtained through the aggregation of the information. This assumption is reasonable when the segment of baggage handling system is detailed enough. The set of locations is denoted by $A = \{1, 2,..., n\}$. The shortest travel time t_{ij} from node i to node j of the graph is *assumed* known and considered constant: this assumption is made to simplify the problem. This time can be considered between the central points of each area. The travel time matrix may not be symmetric even if it is generally the case in practice. Figure 4.1 gives an example of such a graph. The user defines as many areas as the modelling of the airport requires.

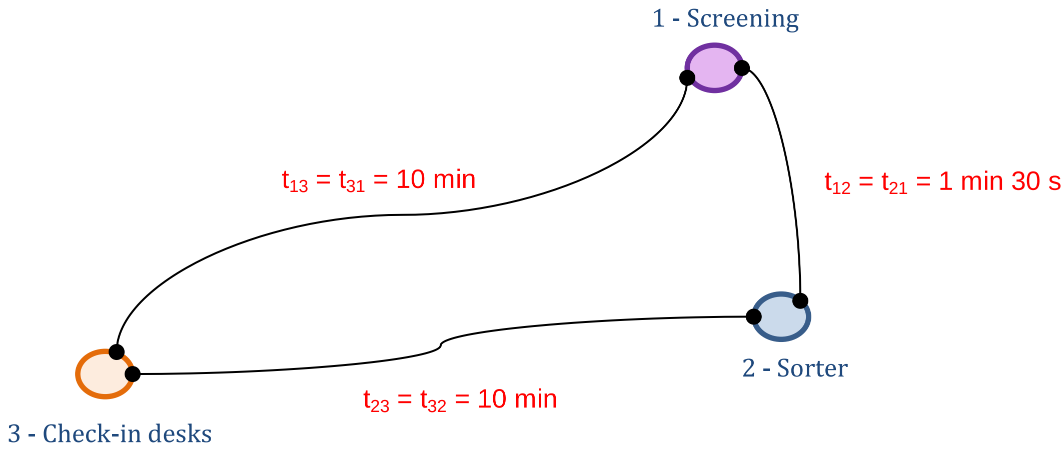


Figure 4.1: Example of the type of graph considered in this model (n=3).
The average travel times are given in minutes.

4.1.2. Failure characteristics

We *assume* that the expected amount of failures is F_{total}. Failures are classified into 2 causes: F_{cust} denotes the number of customer failures whereas F_{tech} denotes the number of technical failures. The parameter p_{cust} that is the percentage of total failures that are customer failures allows estimating $F_{cust} = p_{cust} * F_{total}$ and $F_{tech} = (1- p_{cust}) * F_{total}$. This parameter is introduced because it is often used and well-known by the airport managers and the managers of VI. The maintenance team of VI has to repair both technical and customer failures.

Customer failure arrival processes depend on time and area. Customer failure arrival is *assumed* to follow a nonhomogeneous Poisson process (NHPP) at each area. A definition of the NHPP can be found in Appendix G. Law and Kelton (2000) explained that the NHPP has been used frequently to model such time-dependent random arrivals. Lin et al. (2002) used it to generate failures for a simulation model for field service. Moreover, the arrival of passengers at check-in desk is usually approximate with this distribution (Koopman, 1972). Let λ_{at}^{cust} denotes the constant arrival rate for area a ($\in$ A) and hour t ($\in \{0,\ldots,24\}$ as we consider a daily horizon). The rate function depends on the time period so that the arrival rates change between peak and off-peak hours. The hour is chosen as a time index because it is the time index used by airport manager to gather data. We *assume* that customer failures are distributed independently during the day and the probability that a failure occurs during the hour t is denoted by p_t^{temp}. Customer failure arrival processes at different areas are independent. The probability that a customer failure occur at area a is denoted p_a^{cust}.
Finally, $\lambda_{at}^{cust} = F_{cust} * p_t^{temp} * p_a^{cust}$.

Based on airport manager opinion, the arrival rate of technical of failures does not depend on time. We *assume* that technical failure occurrences follow a Poisson Process with a constant failure rate λ_a^{tech}, i.e. failure occurs independently and the time between directly consecutive failures follows an exponential distribution with parameter λ_a^{tech}. This *assumption* of independent Poisson processes is justified when component failures do not lead to additional failures of other components in the same equipment. In general this is true at the airport as the number of machines is sufficiently large at each area. Technical failure arrival processes at different areas are independent and the probability that a technical failure occurs at area a is equal to p_a^{tech}.

Finally, $\lambda_a^{tech} = F_{tech} * \frac{1}{h} * p_a^{tech}$, where h denotes the operational hours of the airport.

Figure 4.2 summaries the assumptions we did about failure arrival processes.

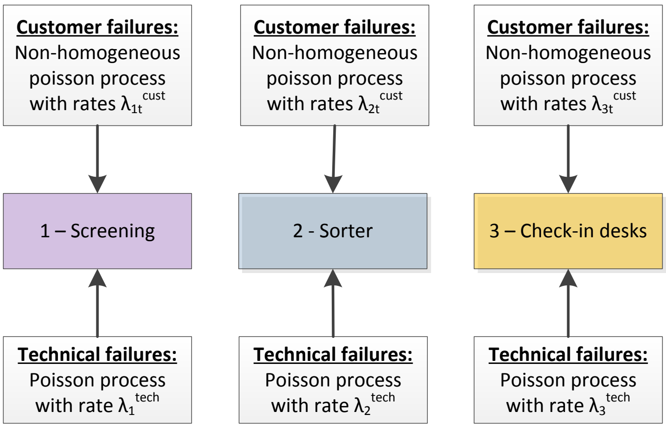


Figure 4.2: Schematic diagram of an example for the failure arrival processes

When a failure occurs at area a, it has a probability p_a^{crit} to be critical. This probability is independent on the cause of the failures. This assumption is realistic because the criticality of the failure depends on the equipment on which it occurs. If the piece of equipment on which the failure occurs is not redundant, the failure will be critical independently of its cause. A critical failure has a high priority. High priority jobs have non-preemptive priority over low priority jobs. That is, a high priority job can move ahead of all the low priority jobs waiting in the queue, but low priority jobs in service are not interrupted by high priority jobs.

The technical failures always require high level skills, i.e. a technician intervention whereas a customer failure may require either low level skills, i.e. a jam worker intervention, if the customer failure has not damaged the piece of equipment with a probability p_{jam}^{cust} or high level skills if it has damaged the equipment with a probability $p_{tech}^{cust} = 1 - p_{jam}^{cust}$. Figure 4.3, which is a simplification of Figure 2.3, illustrates this assumption.

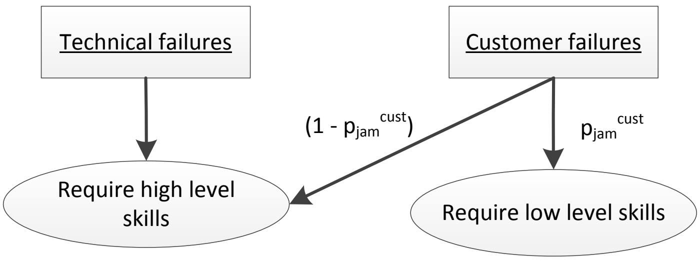


Figure 4.3: Assumption on the different types of failures

Both failures that require high level skills and failures requiring low level skills intervention have a repair time that we *assume* to follow a Gamma distribution. This distribution is often used in maintenance papers (Pegden, Shannon and Sadowski, 1995). Moreover, its parameters k (shape parameter) and θ (scale parameter) can be easily estimated with the mode *m*, the average *E [x]* and the minimum repair time *a* (Appendix H). The parameters are different for high level skills intervention and low level interventions as the time to undo a jam is generally much lower than the time to repair a technical failure. These parameters are considered as an input for the model as they can differ for each airport. This method was chosen for practical reasons: the mode, the average and the minimum are parameters well-known by the airport managers. The distribution can be adapted to any airport without strong knowledge about statistics and probabilities.

Whenever possible, statistical tests should be performed to assure that the real distribution indeed suits a Gamma distribution; if not, other theoretical or empirical distributions should be considered. However, in our case, the data were not enough detailed to determine technical and operational failure distributions for both repair time and process arrival. Moreover, we elaborate a general model for any airport. A specific distribution based on an analysis of data from one airport cannot be generalized for any airport. If only aggregate data, such as monthly mean arrival rate per hour, is available, then use of the Poisson process model is a convenient approach which seems intuitively reasonable. All these parameters about failures can be driven by a combination of historical data and expert judgment.

4.1.3. Team Configuration

The maintenance team within the airport can be composed of 2 types of workers: technicians or jam workers. This set of skills is denoted by S, where S = {technician, jam worker} with the index s. Technician can handle both failures requiring low level skills and high level skills whereas jam workers can just intervene for failures requiring low level skills. The cost for using different type of staff is different. Usually technicians are more expensive than jam workers.

We *assume* that each failure needs one and only one employee to be repaired and that every technician is able to repair any type of failure with the same efficiency. These assumptions are done to simplify the problem because it is possible during real activities that failures requiring high level skills are handled with two people or that the technician does not have the relevant skills (electrical, mechanical, PLC issues). According to airport managers, this situation is very seldom. This assumption results in an underestimate of the worker requirements.

An employee works in a shift. A shift has a start time and a length. There are m shifts. The set of shifts is denoted by I, where I = {1,…,m} with the index i. Employees are available 100% of the shift. No break time is built into the model. In real life, maintenance employee breaks are not scheduled; they occur whenever the employee gets free, and senses there is time to take a break. At the end of a shift, if an employee is busy, he has to finish what he is doing before leaving.

Every employee is assumed to have a “home” area, i.e. an area at which the employee will be at the beginning of his shift. These designated areas define a static allocation policy. The employees can be allocated at n_p potential start locations ($n_p \in \mathbb{N}$ and $n_p \leq n$). This set of potential worker start areas is denoted by $K \subset A$ and the index is k.

Employees can do preventive maintenance when they are free: every time a failure occurs, we assume they give up the preventive maintenance for the corrective maintenance. Moreover, the preventive maintenance is done at the location to which they are assigned at the beginning of the day. For location at which nobody is allocated, the preventive maintenance may be done during closing hours.

There are three parameters that define the profile of a worker: location (i.e. area), capability (i.e. skill) and availability (i.e. shift). The team has $x_{s,k}^{i}$ workers with skill s located at location k during shift i.

4.1.4. Failure management policy

The following rules were made to model the activities within the airport:

- **Priority rules:** the critical failures have to be repaired first. Then, for two failures with the same criticality, the technicians always repair the failures that require high level skills intervention first. Finally, for two failures with the same priority and that require the same skills, the rule of First Come First Served is applied.
- **Assignment rules:** Jam workers are first assigned to jams; if no jam workers are available, a technician is assigned to the jam. If two people with the required skills for the failure are available, the idle employee with the shortest expected travel time to the failure location is dispatched. Finally, if two people with the required skills and with the same travel time are available, the employee with the lowest utilization is sent to repair the failure. When a failure is assigned to the employee, the information about the location and the type of failure is known, resulting in no error in dispatching. We assume no pre-emption, i.e. if an employee works on a jam or technical failure, (s)he will first finish this before starting a new task job. Moreover, the employee is cannot rerouted when (s)he is walking to the failure location.
- **End of failure rules:** After having repaired a failure, if a failure is waiting for repair and the worker has the skills to handle it, (s)he goes directly from his current location to the location of the new failure. If there are no failures waiting for repair in the system, the worker will go back to his base location. At the airport, this assumption generally holds: when an employee has nothing to do anymore, (s)he generally prefers to go back where (s)he used to be (for example the control room to discuss with the other employees). Moreover, each employee is wearing a walkie-talkie and can be informed in real time. However we assume that the employee cannot be rerouted when (s)he is walking back to the base location.

4.2. Performance evaluation

In this section, the performance criteria that allow evaluating and comparing team configurations with each other are described.

As mentioned in Chapter 2, one of the performance level on which Vanderlande is evaluated by the airport and directly related to the maintenance activities of the team is the response time.

The response time is composed of the travel time plus a possible waiting time. The agreement on response times generally mentions a threshold for the fraction of failures for which a worker arrives on failure scene within a specified time limit: "β percent of the failures should have a response time of T minutes or less". The specific value of T may vary depending on the airport and with the type of failures. Critical failures should have lower T values. We chose two time limits that were taken as 5 minutes and 15 minutes in our model as they are the most common values in the contracts.

The second performance that has to be an output of the model is the availability of equipment. The response time could have been sufficient to evaluate the team configuration but the availability is the most common performance required by the customer and the manager of VI wanted an estimation of it. In VI contracts, a system is available when it can meet the baggage throughput where VI and its customer agreed on. As calculations for availability may be different between airports, we introduce a standard definition that we agreed with the managers of VI: only the occurrence of a critical failure affects availability. The calculation of the availability for each area is then made based on the downtime due to critical failures.

We assume that the downtime is decomposed in three different periods (Figure 4.4): the waiting time (period between stoppage of machine and start of consideration of the failure by personnel), the travel time from the location of the employee when the failure occurs and the location of this failure and the repair time (time needed to correct fault and restore serviceability). Due to SCADA software which indicates the piece of equipment down on a screen, we assume that the location of the failure is known as soon as the failure occurs. Some video cameras allow knowing in advance whether the failure requires a high or a low level skill. This is why we do not include time for diagnosis or to find the location of the failure. Furthermore, we assume that VI knows immediately the information after the occurrence of the failure (the notification time and the diagnosis time in Figure 2.5 is ignored).

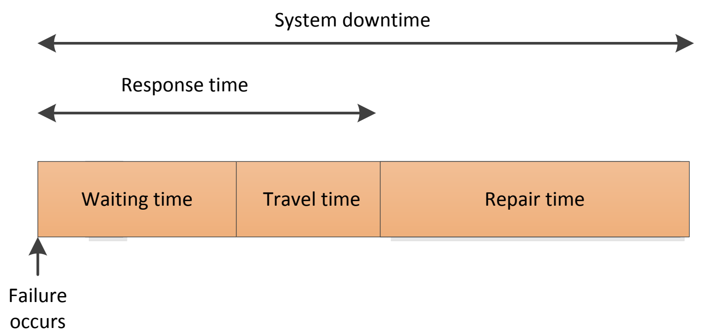


Figure 4.4: The composition of downtime and response time with the assumptions

The utilization of each employee is also essential to avoid that an employee complains because of a high workload. Based on the utilization of employees for unexpected failures, the hours of preventive maintenance that may be done in parallel can be calculated.

Availability, response time and utilization depend on the staffing over time and over the space. Reducing the staffing over a given period can increase the waiting time and thus reduce the service level in terms of availability and response time. A good allocation of workers reduces the travel time. When there are more people in the team, the workload can be distributed between the different workers and the utilization is therefore also affected by the team size.

We want to determine the performance level for the above three criteria for the BHS with a given team. As discussed in Chapter 3, simulation is especially useful to measure performance in systems that are so complex they cannot be described by analytical queuing models. Moreover, this model introduces some priority in the routing of the repairing of the failures and the evaluation of performance level that can be estimated easily with simulation. This model is used in the following part to build a simulation tool. It is true that the simulation is not able to compute an optimal solution, but it allows obtaining a satisfactory solution under the requirements of decision makers.

4.3. Worker requirement estimation

We want to determine the number of employees in each operational period to meet maintenance requirements due to unexpected failures on the baggage handling system at the airport. This has to be done by an optimization technique that is concerned with finding the best possible answer to a problem.

There are many possible optimization goals as pointed out in the literature research (Chapter 3). The first possible optimization could be to maximize the performance. However, the maximization of the performance can cause large teams and very high costs and the company context enforces to consider costs as the true objective. The goal is to achieve an acceptable balance between maximizing performance and minimizing staffing costs. Because a trade-off exists, the total cost of the system will be minimized under constraints of performance. If failures are answered and repaired quickly, then this will lead to better performance outcomes and customer satisfaction.

This is why we consider the minimization of the staffing and downtime costs under customer performance constraints. Downtime costs are included in the model to let the possibility to the users to use them. Of course, if they are not interested in downtime costs, these ones can be put equal to 0. It has to be said that the objective function as well as the performance constraints can take several other similar forms to suit the company's business goals that evolve over time.

The optimization model can be written as follows:

Notations:

n denotes the number of areas

A denotes the set of areas A = {1, 2,..., n} with the index a.

n_p denotes the number of potential start areas

K denotes the set potential area at which employees can be allocated: $K \subseteq A$ and index k

S denotes the set of skills, S = {Technician, Jam Worker} with the index s

m denotes the number of shifts

I denotes the set of shifts I = {1, …, m} with the index i

Decisions variables:

$x^i_{s,k}$: the number of employees with skill s allocated to area k during shift i

x: the vector of decisions variables: $x = \{x^i_{s,k}\}$, $i \in \{1, \dots, m\}$, $k \in \{1, \dots, n_p\}$, $s \in$ {Technician, Jam Worker}

Parameters:

β^{15}_c: minimal percentage of critical failures to repair with a response time below 15 min

β^{5}_c: minimal percentage of critical failures to repair with a response time below 5 min

β^{15}_{nc}: minimal percentage of non critical failures to repair with a response time below 15 min

U: maximal allowed utilization of an employee during one shift

M_s: hours of preventive maintenance to be done by employee with skill s per day

c_s: hourly cost of an employee with skill s

f_c^{15}: fine for a critical failure with a response time more than 15 minutes

f_c^{5}: fine for a critical failure with a response time more than 5 minutes

f_{nc}^{15}: fine for a non critical failure with a response time more than 15 minutes

h_i: number of hours in shift i

Variables (determined by simulation):

$F_c^{15}(x)$ = amount of critical failure with a response time less than 15 minutes per day

$F_c^{5}(x)$ = amount of critical failure with a response time less than 5 minutes per day

$F_{nc}^{15}(x)$ = amount of non critical failure with a response time less than 15 minutes per day

$g_s(x)$ = possible hours of preventive maintenance by employee with skill s

$u_{isk}(x)$ = average utilization of employees with skill s allocated to area k during shift i

We define:

Staffing costs: $c_{staff}(x) = \sum_{i,s} (c_s * h_i) \sum_k x_{s,k}^i$

Downtime costs: $c_{down}(x) = F_c^{15}(x) * f_c^{15} + F_c^{5}(x) * f_c^{5} + F_{nc}^{15}(x) * f_{nc}^{15}$

Hence, our optimization problem P is as follows:

(P) Minimize $(c_{staff}(x) + c_{down}(x))$

Subject to:

- $\frac{F_c^{15}(x)}{F} \geq \beta_c^{15}$
- $\frac{F_c^{5}(x)}{F} \geq \beta_c^{5}$
- $\frac{F_{nc}^{15}(x)}{F} \geq \beta_{nc}^{15}$
- $u_{isk}(x) \leq U$ for all i, s, k,
- $g_s(x) > M_s$ for all s,
- $x \geq 0$, and integer

The service levels involved in the constraints and in the cost function must be estimated by simulation. The main problem with a manual approach to find worker requirements is the complexity arising from the different combinations of skill, shift and area data. To find an optimal solution, one must embed the simulation model in a search routine to test different staffing designs.

4.4. Summary

The architecture of the model was influenced by the goal of building a generic, reusable model. The model structure makes it easy to model different BHS configurations, failure volume levels and team parameters. Our objective was to be able to use it as a research tool to evaluate different maintenance teams with performance criteria often used at the airport: the response times, the availability of the system and the utilization of the workers. This model takes into account of non stationarities in both failure location and failure frequency during the day. These non-stationarities in demand as well as the difference in skills of the workers affect system performance.

We will design the decision support tool by integrating simulation with optimization. The complexity of the system requires that we develop a simulation program to evaluate the performance of a given staffing configuration for any airport. Simulation configurations are particular settings of the decision variables, which are the number of employees with a certain skill. The optimization procedure will use the simulation program to seek the optimal or near optimal staffing configuration that minimize the total costs under performance constraints.

The following steps had to be completed:

- The simulation program is presented in Chapter 5.
- An optimization procedure is designed in Chapter 6.
- The tool development is finally explained in Chapter 7.

Chapter 5
Simulation Study

A simulation model is necessary to evaluate the level of performance that can be reached with a given team configuration. It allows understanding the impacts of staff on service level. This chapter starts with the description of the simulation model. Then the different elements of the simulation are described in section 5.2. We pursue with the logic that makes the interaction between these elements in section 5.3. We investigate the number of replications necessary to get significant results in section 5.4. The details on the verification and validation of the simulation models are given in section 7.4 and 7.5, respectively.

5.1. Simulation Modelling

Our simulation model is:

- Stochastic, i.e. is has inputs and outputs which are random variables;
- Dynamic, i.e. there is a time dimension and the state changes over time
- Discrete, i.e. the system depicted by the simulation changes at discrete points in time

As said previously, the simulation depicts the maintenance activities for the BHS at the airport. The time unit in our simulation study is minute. The airport is modelled according to the specifications given in Chapter 4. The inputs given by the user with the interface are considered to develop the simulation.

The simulation avoids simplifying assumptions that are otherwise needed to obtain performance measure predictions using other methods. Perhaps the biggest advantage of simulation is that it is easy to explain as a decision tool to managers so that after they understand the model they can use it for new baggage handling system/airport combinations.

JAVA is utilized for the simulation modelling because it allows greater programming flexibility than simulation software like Arena or Enterprise Dynamics and does not require buying an expensive license. This type of simulation is generally more time-consuming to implement but the run time of the simulation can be less.

5.2. Elements of the simulation study

The main elements of the simulation study are entities, random number generators, events and performance measures.

5.2.1. Entities

For each entity of the system, we defined an object in JAVA. These entities are:

- Failures: a failure is described by its attributes which are its cause (technical or customer), its consequence (high level skill intervention, low level skill intervention), its location, the parameters of its repair time distribution, its priority. Failure events are then described by keeping track of the hour of occurrence, the repair starting time or the end of the repairing.

The simulation allows determining when a failure occurs, when someone starts to repair it and when it is repaired (Code in Appendix I.a).

- Employees: every employee is assumed to have one skill level (low or high), a “home” base (the area to which (s)he returns after finishing to repair a failure), the starting hour of his/her shift and the ending hour of his/her shift. Throughout the simulation, the location and status of each employee is tracked; the status of the employee is either “off duty”, “free” or “busy” (Code in Appendix I.b).
- Team: The team is the set of all the employees for the day simulated (Code in Appendix I.c).
- Queues: there are two queues: one for failures that require high level skills and another one for failures that can be handled with low level skills. The jam workers pick failures from the jam queue whereas the technicians can pick failures from both queues. While the queue for technical failure still contains critical failures, the technicians have to pick these critical technical failures. It there are critical jams and no critical technical failure, the technician can pick the critical jam. If there is no critical failure anymore, the technician picks failure from the queue of high level skills failures. The priority rule for failures within the queue is firstly the criticality and then First in First Out. The simulation model considers employees as servers and the failures as customers (Code in Appendix I.d).
- Sources: there are two sources: one for technical failures and one for customer failures. The first source creates failures according to the Poisson distribution whereas the second source creates failures according to a non-homogeneous Poisson distribution. When a failure is created by one of the two sources, we attribute its features, i.e. its area, its consequence (high level skill intervention, low level skill intervention) and its criticality. Then the failure is put in the appropriate queue depending on the skill level required (Code in Appendix I.e).
- Airport: the airport is defined by the network of areas and the two sources. It contains the information about the spatial distribution of failures, the travel time matrix and the priority probabilities (Code in Appendix I.f).

5.2.2. Events

As mentioned previously, this simulation is a discrete event simulation. It means that just few events are considered and the time clock just move from an event occurrence time to another one.

The different events considered are:

- The events related to the failures:
  - A failure occurs
  - A failure is being repaired
  - A failure is repaired
- The events related to employee of VI:
  - The employee is on duty
  - An employee starts travelling to the location of a failure
  - The employee arrives at the area of the failure and starts repairing
  - The employee is free
  - The employee is off duty

5.2.3. Random number generators

The algorithms and the Java codes of the random number generators are described in Appendix J.

5.2.4. Performance

The simulation allows knowing exactly the downtime caused by each failure. We therefore know exactly the downtime caused by critical failures that allows calculating the customer and technical availabilities. We can also count the amount of failures that overlap the response time thresholds of 5 and 15 minutes and compute the percentage of failures that fulfilled the requirement of 5 or 15 minute response time. Moreover, we know exactly when a worker is busy or not and the utilization can be calculated based on the statistics tracked by the simulation.

Finally the outputs of the simulation are:

- The percentages of critical failures with response times more than 5 minutes and 15 minutes
- The percentages of non-critical failures with response times more than 5 minutes and 15 minutes
- The availability of each area
- The utilization of each worker

The simulation is therefore able to estimate accurately the performance that a team configuration $\{x_{ij}^k\}$ can handle.

5.3. Explanation of the simulation logic

The simulation is driven by the events. In each simulation point, the program updates the failure and employee information.

Figure 5.1 shows the flowchart of the general procedure (the subroutines with a colour are detailed afterwards). The simulator processor begins by reading the input statements and initializing variables. The processor then begins execution of the simulation by generating the whole list of failures for the whole day considering their time of occurrence and the duration of the repair. Then, the simulation run occurs, i.e. the employees of the team are assigned to repair the failures generated for the day following the rules presented in the model. At the end of the simulation run, the statistics are published. A test is then made to check if the number of runs is sufficient to have significant results. If more runs are necessary, the program returns to the initialization routine and another simulation run is executed. The code can be found in Appendix K.a.

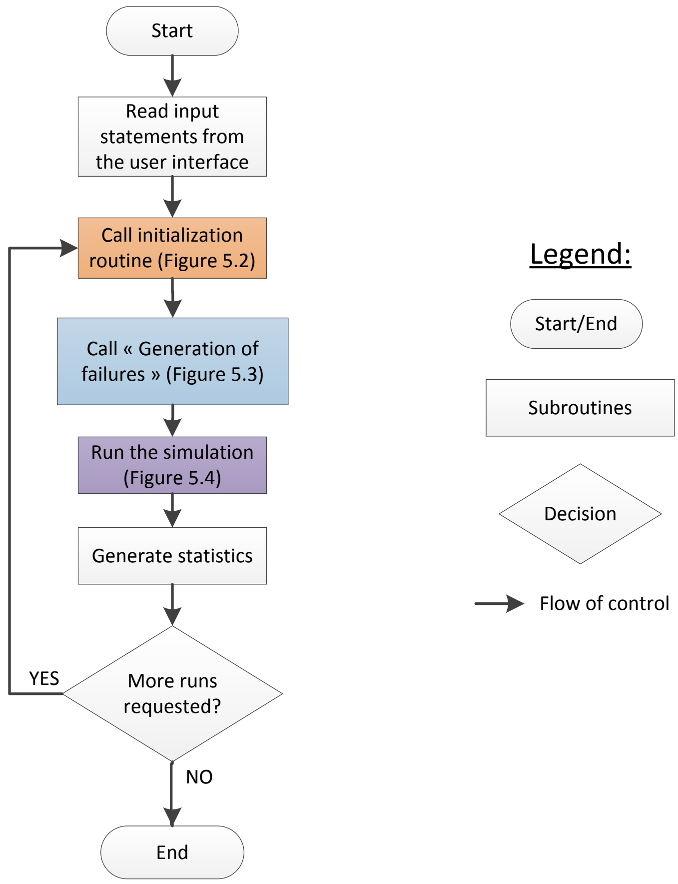


Figure 5.1: Total overview of the logic for simulation

Figure 5.2 shows the flowchart that represents the initialization routine of the simulation model (orange subroutine in Figure 5.1) which specifies initial conditions for the simulation. It involves creating entities that represent the airport configuration like the areas and the travel time matrix. Then the sources are defined by collecting the information about the theoretical distributions for failure arrival processes and repair time. Finally, this routine initializes the team with the different employees with their skills, their working hours and their initial location. The code can be found in Appendix K.b.

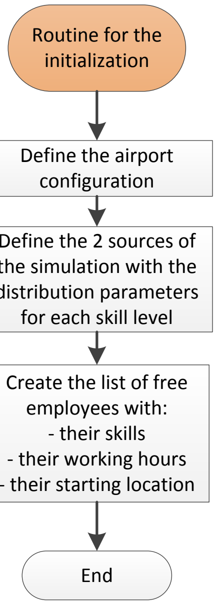


Figure 5.2: The initialization routine

We now consider the logic associated with the generation of the list of failures for the whole day. Figure 5.3 displays the flow chart that outlines the logic for this routine (blue subroutine in Figure 5.1). It creates the failures for both technical and customer failures. When the failure is created, the routine also determines its location thanks to the spatial distributions, the level of skills required and its criticality. The failures are created and put in a list while the time is not greater than or equal to the ending time of the simulation. When all repair requests are created, the main routine will start running the model. The code can be found in Appendix K.c.

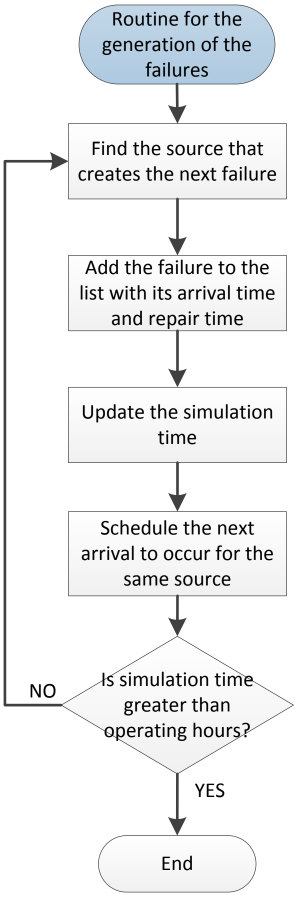


Figure 5.3: The logic associated with the generation of a set of failures

Figure 5.4 shows the flow chart of the simulation scheduler of the events, i.e. the simulation run itself (purple subroutine in Figure 5.1). At each simulation time point (failure status change, employee status change, or an incremental time point), the scheduler module makes decision about the procedure that have to be called. So it is the key module of the operation, receiving and processing all failures and controlling all activities of the employees. The code can be found in Appendix K.d.

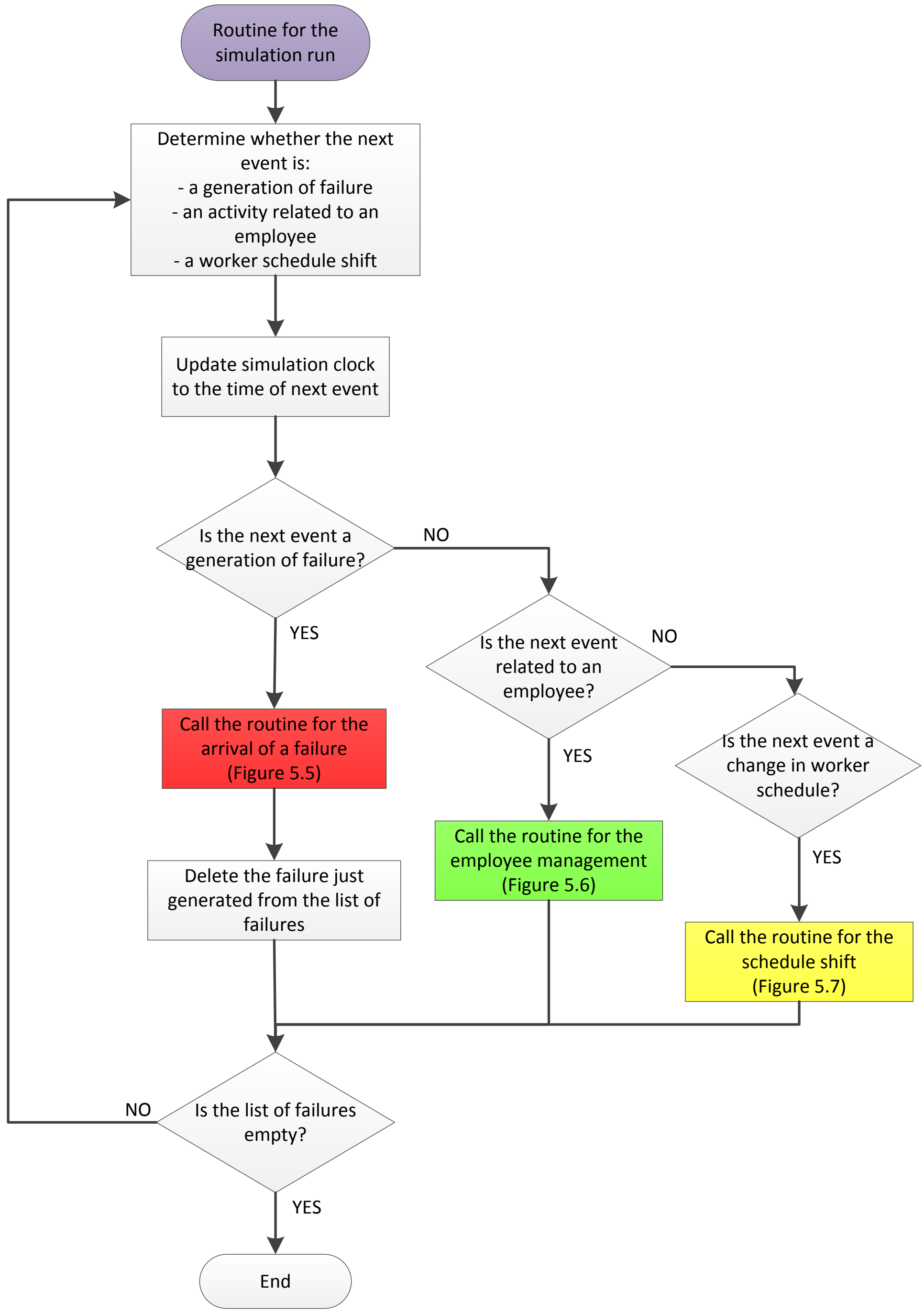


Figure 5.4: The logic associated with the scheduler of events

Figure 5.5 shows the flow chart of the routine to deal with a new failure arrival (red subroutine in Figure 5.4). If any available employee fulfils the requirements to handle this failure, the failure is added to the relevant queue (high level skills intervention or low level skills intervention). Otherwise, the procedure assigns the failure to an employee according to the assignment strategy assumed in the model and the next event of the employee is updated with the travel time and repair time. The code can be found in Appendix K.d.

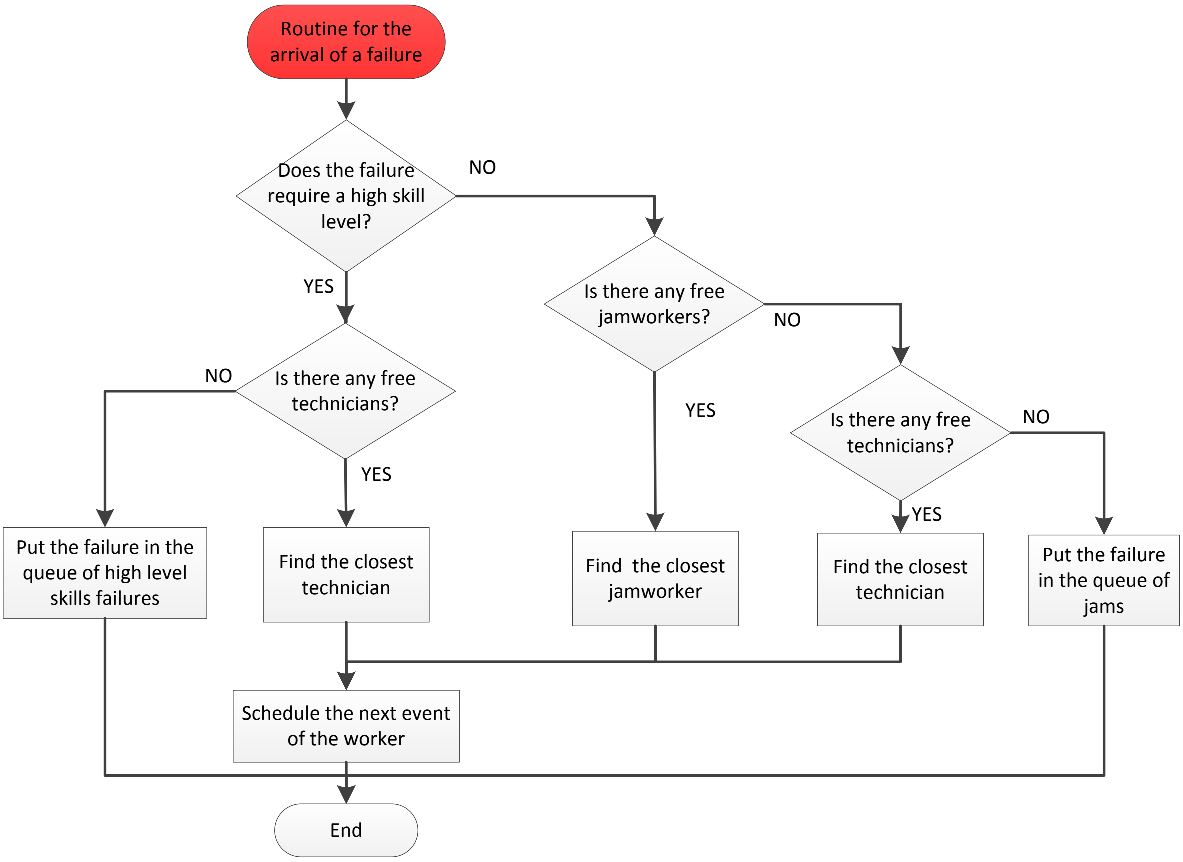


Figure 5.5: The logic associated with the arrival of a failure

In Figure 5.6, the logic associated to the employee events is presented via a flowchart (green subroutine in Figure 5.4). This procedure starts sorting the queues by priority. Then it identifies the status of the worker to know the actions that have to be done. If the worker is busy, it means that the worker has just finished with the repair of the failure and has to be set free. If the worker is free, it means that a failure has been assigned to him and he must find it in the relevant queue. The code can be found in Appendix K.e.

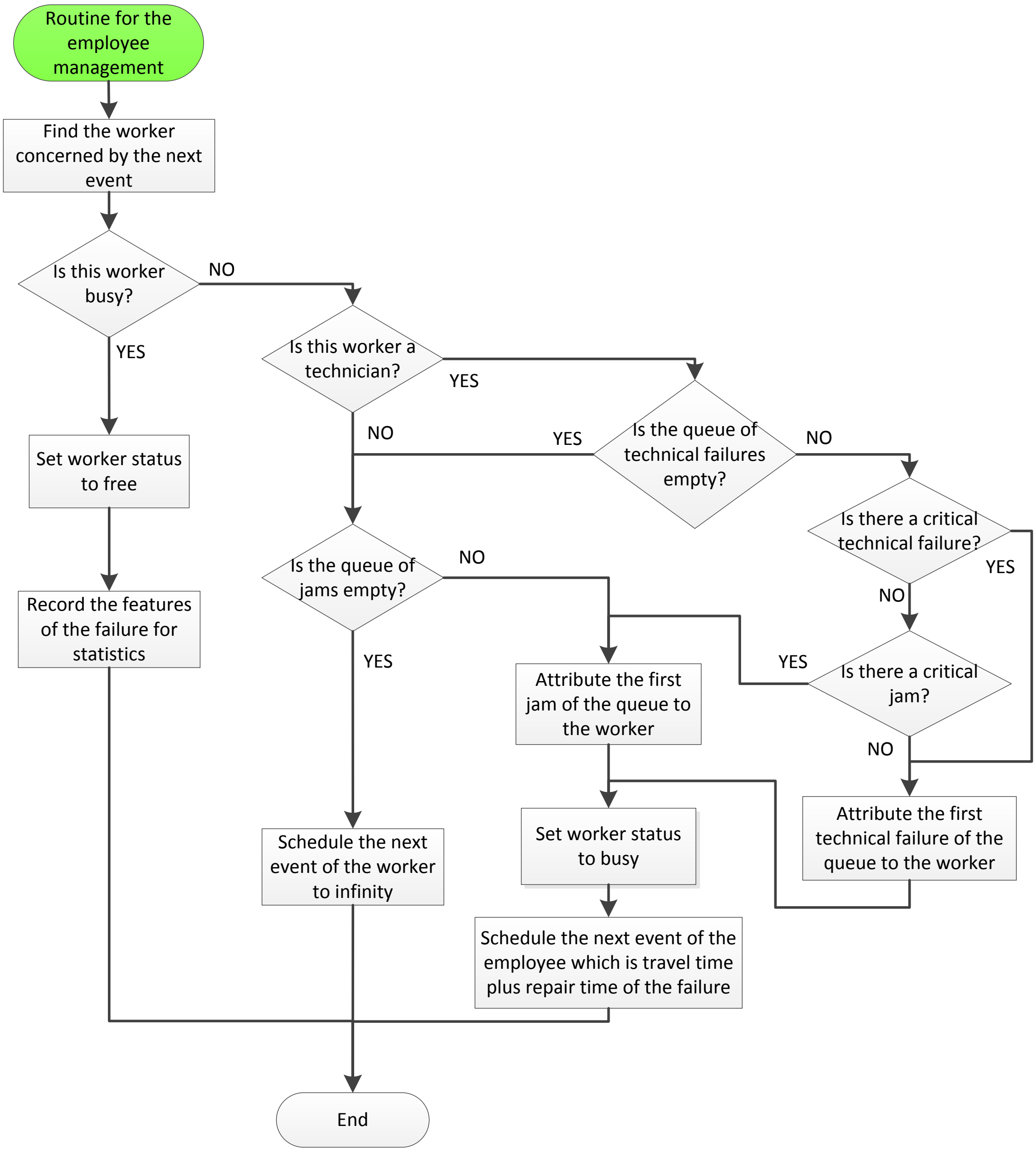


Figure 5.6: The logic associated with the management of an employee of the maintenance team

The flowchart of Figure 5.7 shows the logic associated to a shift event (yellow subroutine in Figure 5.4). The shift event is either the beginning of a shift or its end. In case of the beginning, the presence status of the employee concerned by the shift event is set on free. For the end of a shift, this status is set on “off duty”. The code can be found in Appendix K.f.

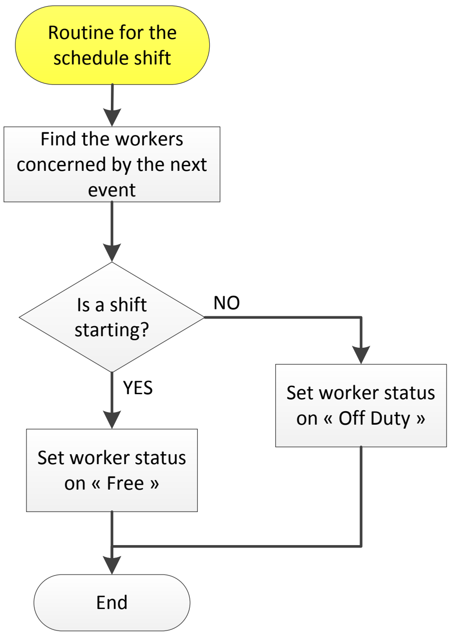


Figure 5.7: The logic associated with a schedule shift event

5.4. Simulation Run Parameter: Number of replications

One simulation run is a computer-based statistical sampling experiment, i.e. the simulation of one day of maintenance activities. Each run only produces a realization of a set of random variables, which may be far from the true system characteristics. To ensure an appropriate statistical analysis from simulation results, a number of simulation replications are necessary. The number of replications required depends on the specified precision, degree of confidence and sample variance.

We want to determine the number of replications necessary for a given set of inputs in order to have a good precision of the output value. We decided that a precision of ε = ±0,5% is required with a 95% confidence interval in order to get a good estimation of the output. The simulation gives different outputs. We first present the approach for one output denoted f. According to the law of large numbers, for N independent replications of the simulation (N higher than 30), we know that:

$$\varepsilon = t_\alpha \sqrt{\frac{V(f)}{N}}$$

with N the number of replications,
V(f) the variance of the output f considered,
and t_α the only positive number such as a standard normal distribution satisfies:

$$P(Y \epsilon [-t_\alpha, +t_\alpha]) = 1 - \alpha$$

As the value of V(f) is unknown, we use the simulation to estimate $V(f)_{estim.}$ that denotes the variance of the output f estimated by simulation (Fleury et al., 2007):

$$V(f)_{estim.} = \frac{1}{N}\sum_{i=0}^{N}(f(w_i) - S_N(f))^2$$

with $f(w_i)$ the value of the output f at the replication i and $S_N(f) = \frac{1}{N}\sum_{i=0}^{N} f(w_i)$

In the program, after each replication, the variance of the output is updated. The number of replications is sufficient when the following condition is fulfilled:

$$\varepsilon > t_\alpha \sqrt{\frac{V(f)_{estim.}}{N}} \qquad \text{with } t_\alpha = 1{,}96 \text{ for a 95\% confidence interval}$$

As we have different outputs, this method is used for each output of the simulation. The number of replications is sufficient when all the outputs follow the above condition.

Figure 5.8 shows an example of one of the output for which the precision varies when we increase the number of replications. For this example, it requires 316 replications to reach a precision of ±0,5%. Figure 5.9 shows how the value of this output varies for the same simulation. We can see high fluctuations before a steady-state is reached. The output falls in a range of ±0,5% of the final value for 316 replications.

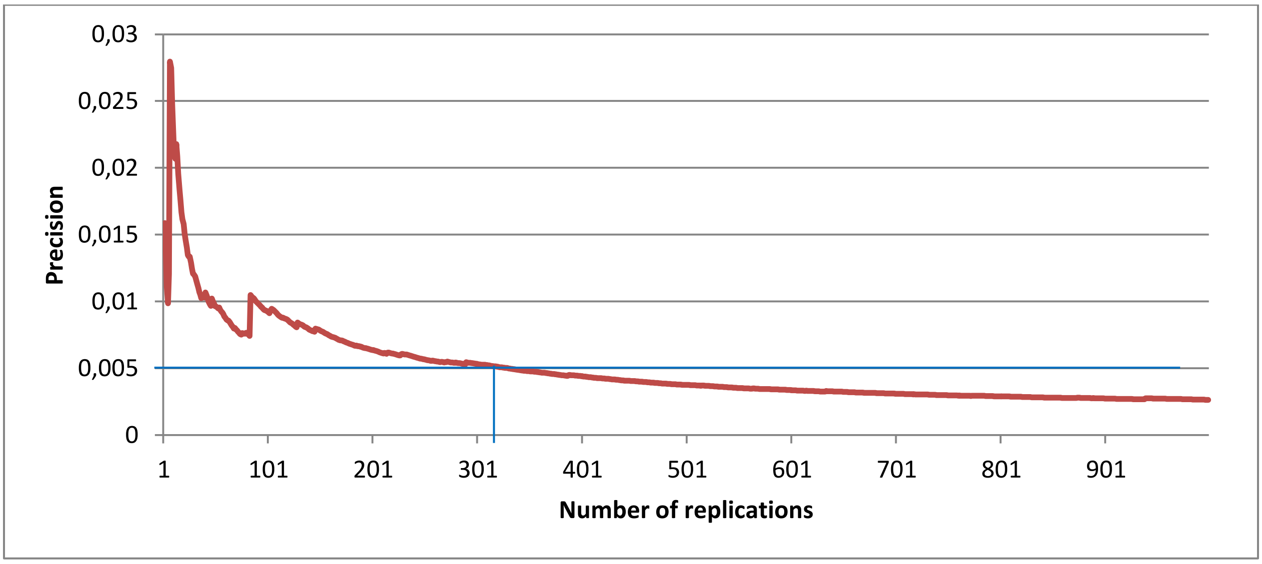


Figure 5.8: Precision of the simulation as a function of the number of replications: the number of replications is sufficient when the precision is below 0,005 (blue lines), i.e. when the output is known with a precision of ±0,5% with a 95% confidence interval

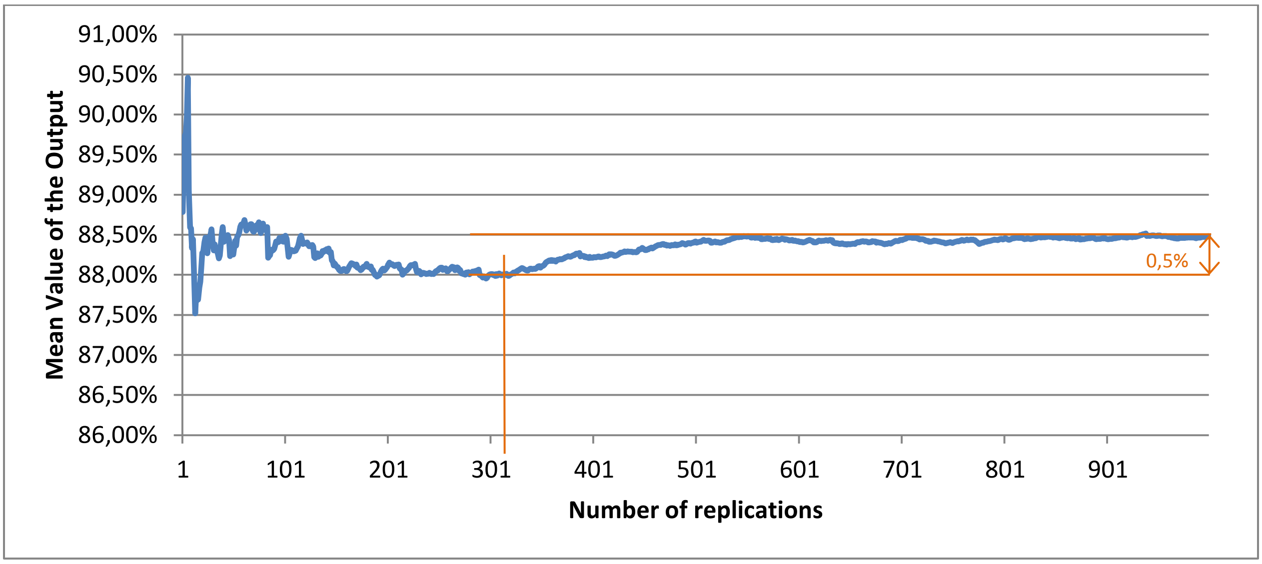


Figure 5.9: Value of the output as a function of the number of replications: above 316 replications, the mean value of the output stays in an interval of ±0,5% of the final value

5.5. Verification of the simulation model

Verification is concerned with determining whether the conceptual simulation model (model assumptions) has been correctly translated into a computer "program", i.e., debugging a large-scale simulation program (Law and Kelton, 2000). The model has been debugged, following an iterative procedure, for finding and eliminating all the bugs due to model translation (translation from the conceptual model to the analogic model, or, in other words, to the computerized model). To ensure that the conceptual model is reflected accurately in the computer code, the model was divided into segments. Then each segment was coded and the output was carefully examined for reasonableness. The combination of the segments as a whole was checked at the end.

To be sure that the final simulation model is doing what we expect, we did two final verifications. The first one was to take very simple inputs for which we can calculate the output of the simulation with mathematical formulas. The second one was to do an input analysis to check if the behaviour of the output of the simulation is the one we expect. We run the simulation under a variety of settings of the input parameters, and check to see that the output is reasonable.

5.5.1. Mathematical formulas

The model was run under simplifying assumptions for which its true characteristics are known or can easily be computed.

One could first run the general model with one area, a homogeneous Poisson Process, only one type of failure and one technician. The resulting model is known as the M/M/1 queue and has known transient and steady state characteristics. Then, by increasing the number of employees, the resulting model should correspond to the M/M/c queue. By comparing the analytical results and the simulation results, we can conclude that the simulation logic works as expected since the waiting times for the failures and the utilization of workers are equal.

A third test of the program can be achieved by running the general with one area, a homogeneous Poisson Process, one type of failures and m employees. The resulting model can be compared with the calculations of non-preemptive priorities in a M/M/m system. The analytical calculations of this configuration are described in Larson and Odoni (1980) pages 239-240. In our model, the failures with the highest priorities are the critical failures whereas the non-critical failures have the lowest priority. The results are presented in Table 1.

	Analytical	Simulation
Critical failures	10,2 min	10,5 min
Non critical failures	36,6 min	37,1 min

Table 1: Comparison of the expected service time from analytical calculations and simulation

The simulation estimates are quite close to the theoretical values, which gives increased confidence in the program.

5.5.2. Input analysis

For the verification of the simulation program, we did many different input analyses. By changing inputs values, we check that the outputs of the simulation go as expected. As many parameters are considered in this model, all the analyses are not presented. We just report ones we made for the expected amount of failures. All the parameters stay fixed except the total amount of failures F_{total}. A discrete graph is displayed in Figure 5.10 with the values of the percentages of failures that overlap the threshold for 5 different values of F_{total}. We can see that the 4 performance measures decrease as a function of the expected amount of failures per day. By increasing the number of failures without increasing the team size, the workers are less available and the failures wait longer in the queue for an intervention. This phenomenon increases for more than 190 failures (higher slope) because the workers are less and less available and the failures which results on longer waiting times increase faster. Figure 5.11 shows the discrete evaluation of the worker utilizations for the same values of F_{total}. Increasing the number of failures results on a rise of the worker utilization because the workload is higher.

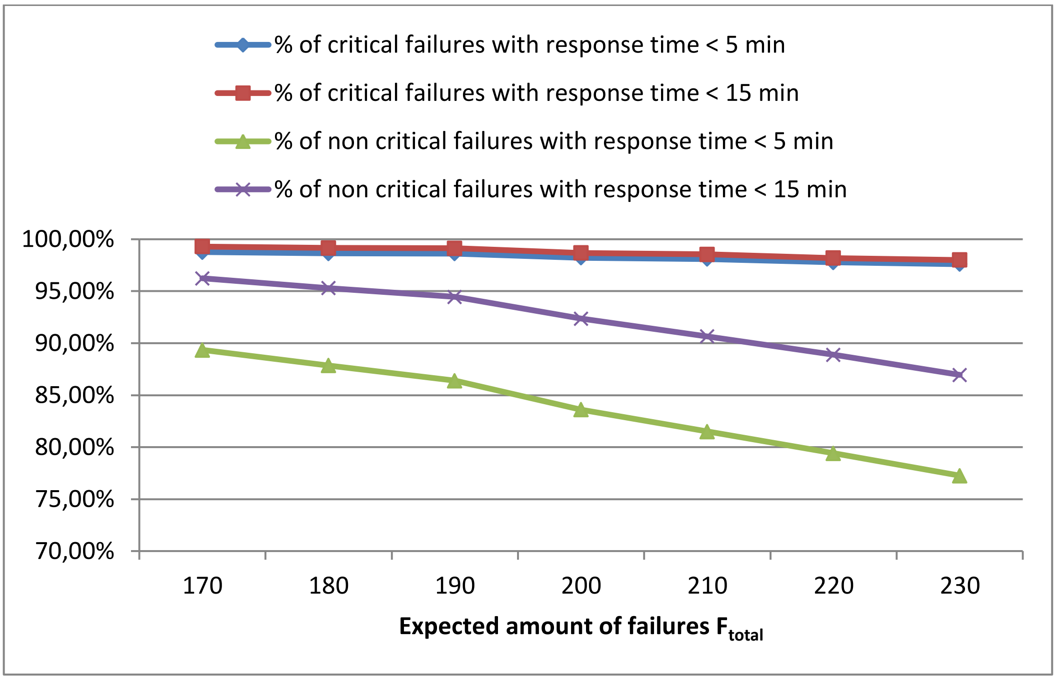


Figure 5.10: Value of the outputs related to the response time as a function of the expected daily amount of failures: when we increase F_{total}, the percentage of failures with a response time under the threshold decreases when the worker requirements remain the same

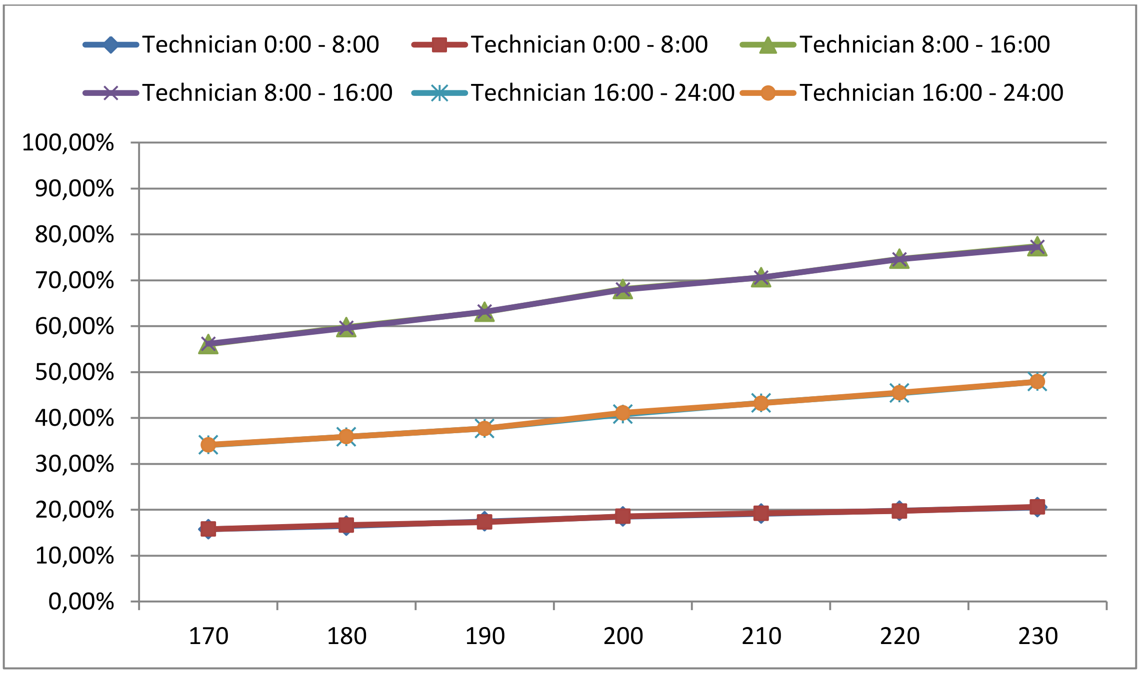


Figure 5.11: Value of the utilization of each worker of the team as a function of the expected daily amount of failures: when we increase F_{total}, the utilization of the workers increases as the workload is higher

With all the other input analyses, we concluded that, in its domain of application, the model implementation accurately represents the initial conceptual model.

5.6. Validation of the simulation model

Validation of the simulation model is the major step in gaining user acceptance. The model validity refers to its ability to predict output and to make decisions that will work as predicted in the actual system. According to Law and Kelton (2000), the validation of simulation models is questioning that the assumptions underlying the conceptual model are correct and they reasonably represent the problem for a given purpose. The simulation model was validated by showing that the model had "face validity" (reasonable to the user) and "technical validity" (assumptions were not far from reality) as suggested by Goldberg et al. (1990a). This simulation validation focused on the assumptions made to model the maintenance activities of the airport, i.e. the assumptions about the behaviour of maintenance team like dispatching assumptions or the assumptions about the generation of failures like the non-homogeneous Poisson distribution.

5.6.1. Face validity

In simulation, the first goal of the simulation modeller is to construct a model that appears reasonable on its face to model users and others who are knowledgeable about the real system being simulated (Law and Kelton, 2000). If these experts feel the model is adequate, then it has face validity.

Within VI, People familiar with staffing are maintenance managers at the airports and people who are used to staff team for new contracts. The correctness of the conceptual model was discussed in detail in several meetings. These discussions were made in the light of the observations provided by a case study and the knowledge of similar cases. Input-output relationship was found reasonable.

Two case studies were done during this master graduation to check the validity of the model. We applied the model to the airport of [redacted] and the airport [redacted]. The parameters were chosen based on either data analysis or on manager field experience. The managers of each airport recognized the value of the simulation outputs as really representative of the reality. Different input parameters and team configurations were tested to represent the seasonal fluctuations. The case study of [redacted] airport is presented in Chapter 7. These two experiments gave good face validity to the model. The simulation model represented well what happens at the airports. It turned out that the outputs estimated by the model are generally similar to the estimates made from observations. Of course, the simulation outputs depend on the input parameters chosen by the users. It means that applying the model to another airport requires selecting with caution the input parameters. A wrong selection of input parameters introduces obviously some biases on the outputs. Chapter 7 will present the way to recover relevant data to use this simulation tool. Before using the simulation, the user must check that the assumptions made for this model are fulfilled with the airport under study. These assumptions were gathered in the user manual. The face validation is a step that must be completed by the user every time he uses it for a new system and the input parameters have to be selected by discussing with people who know very well the system.

5.6.2. Technical validity

We particularly focused our attention on the generation of the failures. To ensure that the conceptual model assumptions reflect accurately what happens at the airport, we compared the simulation outputs of a trace-driven simulation and the ones given by the simulation with the assumptions made in the model. We used a complete list of failures for the month of March from [redacted] airport to characterize the failures with their actual location, their repair time and their actual time of occurrence. It allowed comparing the model outputs with a trace-driven generation of failures and a generation based on theoretical distributions. The same team was chosen for the two experiments to compare utilization.

The assumptions seem not far from reality as the outputs of both simulations are very close to each other, i.e. the generations of failures through the simulation generators or using the list of failures are similar. The results can be seen in Table 2.

	Data-driven	With distributions
Mean Time in Queue	0,48205853	0,3856119
Mean Time in System	6,18286989	6,28301715
Mean Time to Repair	5,70081135	6,26740524
Mean Time Between Failures	36,9408401	36,619056
Nb of failures per day	36	37
Utilization of worker 1	2%	2%
Utilization of worker 2	3%	2%
Utilization of worker 3	6%	8%
Utilization of worker 4	6%	8%
Utilization of worker 5	4%	5%
Utilization of worker 6	4%	4%
Utilization of worker 7	18%	21%
Utilization of worker 8	17%	14%
Time for Preventive Maintenance for Technicians	45,9612634	45,8153596
Time for Preventive Maintenance for Jam Workers	6,55144265	6,52934493

Table 2: Comparison of the outputs with a simulation based on the generation of failures with assumed distributions and a data-driven simulation

We can conclude that the assumptions on the distributions made for the generation of the failures cannot be rejected.

5.7. Computation times

The time to generate results with the sufficient number of runs is about one second. This computation time can increase with the value of parameters. For instance, the computation time as a function of the expected amount of failures per day is drawn in Figure 5.12. We notice that the computation time increases with this amount of failures. An increase of this input means that the number of failures to generate is larger and the number of iterations for the generation of failures increases what explains the increase of the computation time.

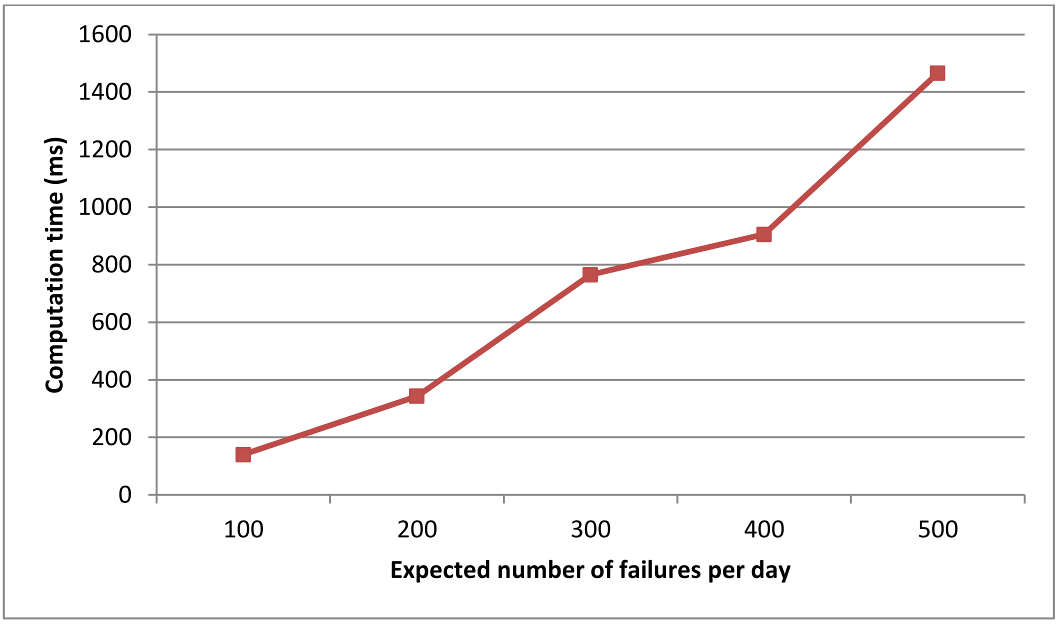


Figure 5.12: Computation time as a function of the expected number of failures generated per day. When F_{total} increases, the number of failures to be generated increases which results on the rise of the computation time

5.8. Summary

This simulation model has been conceived with JAVA for a flexible evaluation of the performance of baggage handling system and maintenance activities at any airport. The model implementation accurately represents the initial conceptual model (verification) and recreates with satisfactory accuracy the real system (validation).

Throughout this graduation project, we worked closely with people who are intimately familiar with the system to represent the maintenance activities as they occur at the airport. The interaction with the managers had been done on a regular basis in order that the completed model will be employed in the decision making process to determine team staffing. The system was observed at two airports to make the overview of the problem as general as possible. Validation did not invalidate our conceptual model. However, for each use of the simulation program, the user must make sure that the assumptions written in the user manual are met. The inputs must be relevant and they have to be discussed with maintenance managers. The outputs of the simulation should be checked with people conversant with the BHS studied.

While this simulation model provided detail about the dynamics of the operation and functioned as a convenient "what-if" evaluator of proposed operational changes, it did little in terms of telling us what assignment of workers is best. This is why we develop a procedure to solve this problem embedding the simulation problem in a greedy procedure. This procedure is presented in Chapter 6.

Chapter 6
Simulation Optimization Study

The simulation program allows evaluating the performance of any team configuration. By testing different configurations, the managers of VI want to assign the right number of employees with the right skills at the right time in order to meet the customer performance requirements and to minimize costs. To help them to find a good team configuration, the simulation program may be embedded in a search routine to evaluate as many different values of decision variables as possible and to select an efficient and effective solution. This chapter starts with a brief introduction to simulation optimization in Section 6.1. Then we explain the optimization model used in this study in Section 6.2 and present the greedy algorithm chosen to find an optimal or sub-optimal team in Section 6.3. Finally, some results are presented in section 6.4.

6.1. Introduction to Simulation Optimization

Simulation optimization is defined as an optimization where the performance measure is the output of a simulation model and the problem setting includes the common optimization elements, namely decision variables, objective function and constraints. Simulation optimization goes further than a simple evaluation of performance with the simulation which is often insufficient.

Law and Kelton (2000) indicated that the goal of an optimization procedure "is to orchestrate the simulation configurations, so that a system configuration is eventually obtained that provides an optimal or near optimal solution". Simulation configurations are particular settings of the decision variables.

It is possible to separate optimization procedure from simulation model. The optimization procedure uses the outputs of the simulation model to evaluate the results of decision variables that were entered into the simulation model as inputs. According to both this evaluation and the evaluation of past results, the optimization procedure decides on a new set of values for decision variables as inputs to the simulation model. This relationship can be seen in Figure 6.1. The optimization procedure executes a search in which the successively generated values of decision variables result in changing evaluations. Not all these evaluations are improving; however the procedure seeks for a highly efficient path to the best solutions. This process continues until a terminating criterion is reached such as an optimal solution found or a computation time limit.

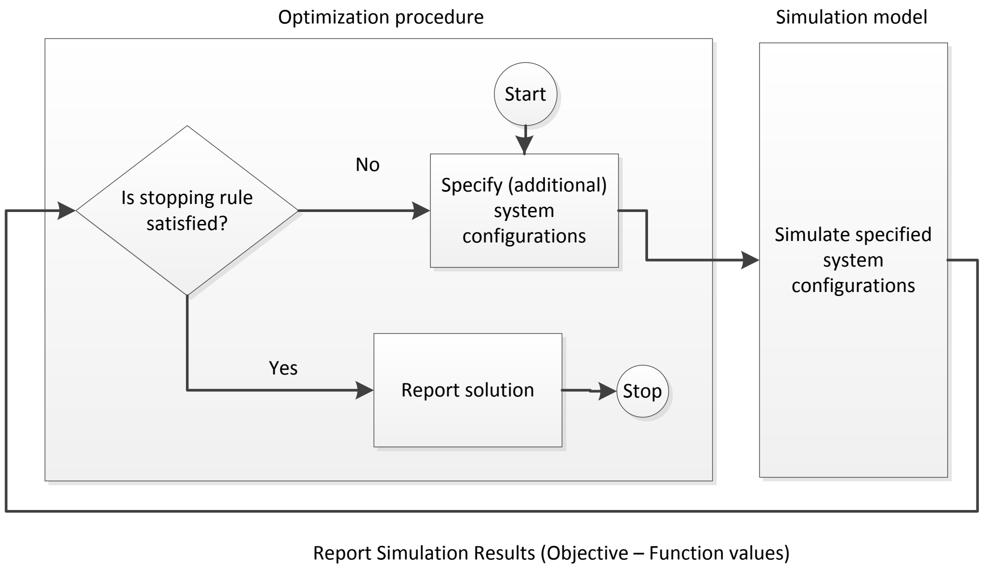


Figure 6.1: Interaction between optimization procedure and simulation model
Source Law and Kelton, 2000

6.2. The Simulation Optimization problem

The optimization problem is the problem (P) presented in Chapter 4. It aims to minimize the total costs subject to performance constraints and employee utilization constraints. The service levels involved in the constraints and in the cost function must be estimated by simulation. The main problem with a manual approach to find worker requirements is the complexity arising from the different combinations of skill, shift and area. To find an optimal solution, one must embed the simulation model in a search routine to test different staffing designs.

Optimization is difficult since it involves multiple scheduling and dispatching of workers with different skills to different locations, while minimizing cost and maintaining good customer service. Using complete enumeration implies too long duration for finding a solution. The combinations of possible solutions to evaluate are too large to compute by brute force. In Chapter 5, we show that the simulation can be equal to 1 second. Evaluating 1000 configurations already results in 1000 seconds, i.e. 17 minutes. The combinatorial nature of the problem means that it is difficult to come up with an optimal or near-optimal solution. Allocation problems are already NP-complete problems, i.e. the size of the solution space of locating m employees in n areas is exponential in n*m. Because of the complex combinatorial nature of these problems, we need to use meta-heuristic search methods. VI managers expect a good quality solution and not obviously the optimal one to have a first insight on staffing that fulfils the performance constraints with not too high costs. This is why a pseudo optimization is developed in the next section to evaluate as many solutions as possible to come with a feasible and good team configuration. We will simulate a number of different team configurations with the simulation output statistics from one configuration being used to determine the next configuration to be simulated. This procedure will be continued until a system design is obtained that meets our performance requirements and a local minimum.

6.3. The Simulation Optimization procedure: Greedy algorithm

We want to find the solution that yields the best performance and that minimizes total costs over possible team configurations. Several algorithms are available in the literature including genetic algorithm, simulated annealing or taboo search to find a global minimum. As the number of possible solutions to the problem is too large to be evaluated, we chose a simple local search method to reach a relatively short computation time. One of the drawbacks of local or greedy searches is that the quality of solutions may not be as good as those from alternative meta-heuristics (taboo search, simulated annealing, and evolutionary algorithms) but the greedy procedure generally finds a good solution in a reasonable number of steps. Koole and van der Sluis (2003) developed a local search algorithm for a call center staffing problem with a global service level constraint that results in good results. In their study of the maximal covering allocation model which is an NP-hard combinational problem, Xia et al (2009) tried various heuristics to solve it. They compared the performance through computation experiments and conclude that the greedy algorithm falls a little bit behind the other algorithms, but it is still remarkably faster than the others. Since we aim at giving a first insight in the optimal worker requirements to the managers of VI, we used a greedy algorithm to generate a first solution to the staffing problem in relatively short computation times. The managers will then be able to modify this first staffing to change few parameters and test different close staffing configurations with the simulation.

The basic idea of the local search is to move from solution to solution by applying local changes until an optimal solution that fulfils the performance constraints is found. For the greedy algorithm, the choice is made on local optimal improvement. At each step, we move to the solution that makes the better improvement to minimize total costs.

Instead of solving problem (P) on pages 25-26, we consider a closely related problem (Q) which is the Lagrangian relaxation of (P), i.e. we include the constraints in the cost function by considering very high values for the costs related to the constraints. The high value allows that the total cost of unmet goals is minimized firstly. The optimization procedure will first seek for a feasible solution that fulfils the constraints before looking for the local optimal solution in the space of feasible solutions.

Let c_{const} denote the constraint cost:

$$c_{const}(x) = L * \left(\left(\beta_c^{15} - \frac{F_c^{15}(x)}{F}\right) y_c^{15} + \left(\beta_c^{5} - \frac{F_c^{5}(x)}{F}\right) y_c^{5} + \left(\beta_{nc}^{15} - \frac{F_{nc}^{15}(x)}{F}\right) y_{nc}^{15} + \sum_{i,s,k} (u_{isk}(x) - U) y_{isk} + \sum_{s} \left(M_s - g_s(x)\right) y_s \right)$$

With,

$$y_c^{15}(x) = \begin{cases} 1 \text{ if } \beta_c^{15} > \dfrac{F_c^{15}(x)}{F} \\ 0 \text{ else} \end{cases}$$

$$y_c^{5}(x) = \begin{cases} 1 \text{ if } \beta_c^{5} > \dfrac{F_c^{5}(x)}{F} \\ 0 \text{ else} \end{cases}$$

$$y_{nc}^{15}(x) = \begin{cases} 1 \text{ if } \beta_{nc}^{15} > \dfrac{F_c^{15}(x)}{F} \\ 0 \text{ else} \end{cases}$$

$$y_{isk}(x) = \begin{cases} 1 \text{ if } U \leq u_{isk}(x) \\ 0 \text{ else} \end{cases}$$

$$y_s(x) = \begin{cases} 1 \text{ if } M_s \geq g_s(x) \\ 0 \text{ else} \end{cases}$$

Then:

(Q) Minimize $(c_{staff}(x) + c_{down}(x) + c_{const}(x))$

Subject to:

- $x \geq 0$, and integer

As explained in the literature review, staffing aims to convert the forecasted workload into the number of employees required with their skills. It seeks to determine the minimum number of workers needed during each period to ensure satisfactory customer service level. For call centers, the period to determine the worker requirements is generally 1 hour. In the case of the maintenance at airport, this period length is not suitable as repair time of technical failures can be in order of 30 minutes. To determine the worker requirements for the maintenance team, the day is divided into fixed periods with duration equal to a divisor of 24 (8, 6, 4, 3 or 2 hours). This shift duration determines m, the number of potential shifts.

One can then develop the greedy algorithm that searches for feasible and locally optimal solutions in the large space of potential staffing plans. In essence the algorithm works as follows: at each stage, the algorithm selects a staffing plan among all the staffing plans possible when we increase by one the team size and runs a simulation to determine service level performance. The algorithm selects the more promising solution among the potential staffing plans depending on the results of the simulation. The algorithm terminates when the local minimum is reached. We detail this procedure in the following paragraph with Figure 6.2.

For each shift period, the greedy algorithm firstly adds a technician to the first period (Step 1 in Figure 6.2) and allocates the worker to the different potential locations (Step 2 in Figure 6.2). When all the possible locations were tested, the algorithm moves the skills from technician to jam worker (Step 3 in Figure 6.2) and continues to compute the performance for each location with the simulation (Step 4 in Figure 6.2). Then the second period is considered (Step 5 in Figure 6.2) and the process is repeated until all the shift periods are evaluated (Step 6 in Figure 6.2). The basic idea of the greedy algorithm is to select a potential configuration which does the best improvement with the lowest investment at each round, i.e. “best bang for the buck”. Thus, the solution selected is the one that makes a significant improvement to reduce the downtime and constraint costs when the team is increased with one worker with skill s at shift i and location k in comparison of the previous configuration.

This algorithm works well if the constraint and downtime cost functions are concave, i.e. if the best improvements with the lowest investment are non-increasing. No proof of such concavity is given but it seems reasonable to assume such a thing. Indeed, we would expect that the service level increases if we increase the number of employees in any given period and the more we increase the number of people, the less the improvement of the service level will be high as the service level is bounded. Therefore, the downtime constraints are concave. Koole (2003) explains that the service level in call center based on response time is only concave in the number of agents if the system is stable, i.e. assuming no abandonments occur. For our problem no abandonments are considered.

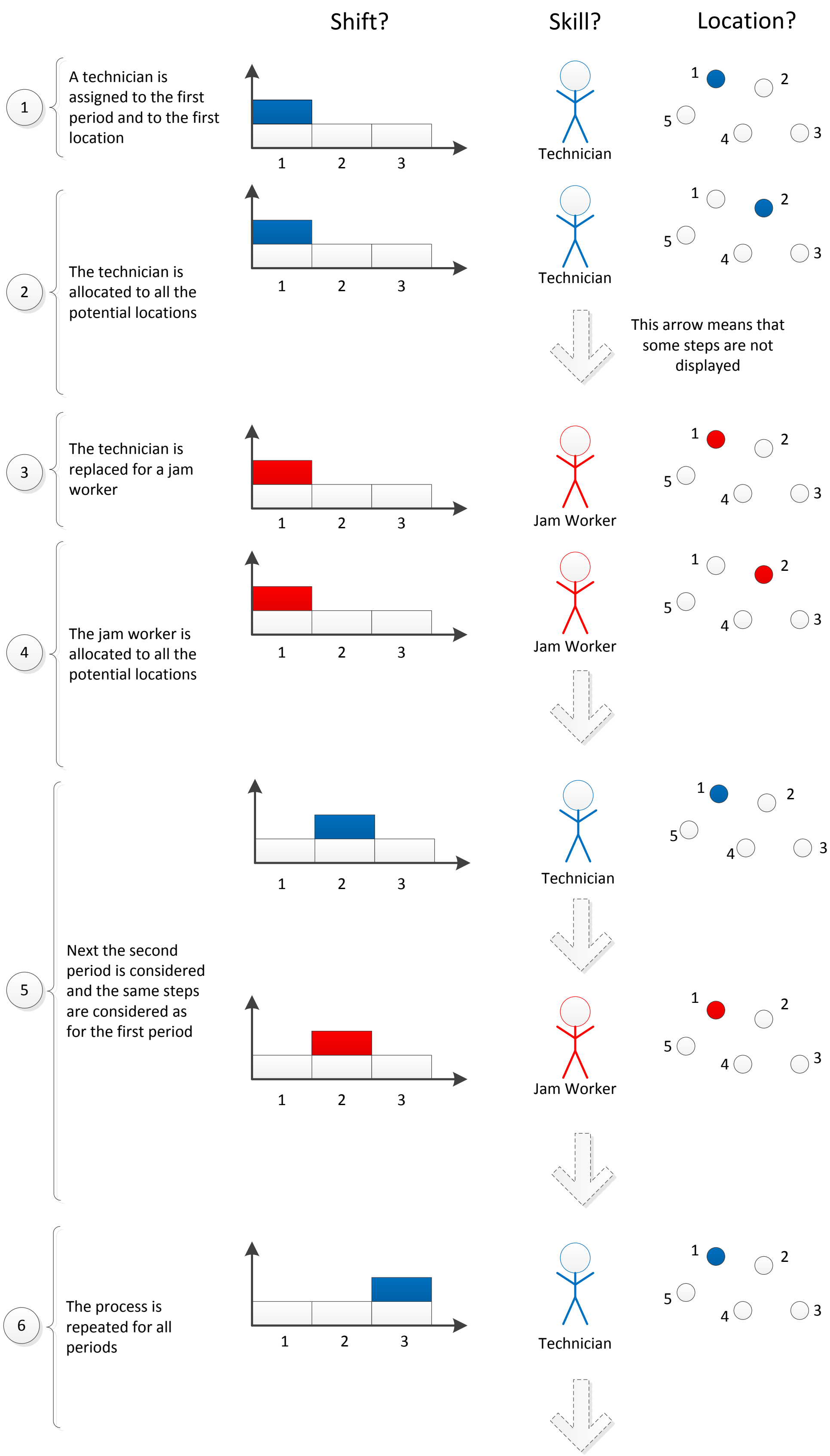


Figure 6.2: Possible solutions evaluated at each iteration of the greedy algorithm

The proposed procedure works with two algorithms: a first one to set up the initial team that must be composed of two technicians at any time for any airport due to safety considerations and the second one is the greedy search algorithm.

Algorithm I: *Initialization*

The optimization starts constructing an initial solution with the two technicians required on site at any time. This first algorithm must be used to set up the initial team. We start setting $x = 0$, i.e. all potential areas are empty, no employee is located. We first increase by one the number of technician for each shift. All the employees are allocated to the same location. We evaluate the total cost of each configuration when we move the employees at each potential starting location with the simulation. In each shift, the workers are finally allocated to the location that minimizes the total cost.

We again increase by one the amount of technicians for each shift to get the minimum amount of 2 employees per shift. To determine the initial allocation of this second employee, we keep the first employee at the location determined previously and we evaluate all the new configurations by allocating the second employee in each potential location. Again, the configuration that we keep is the one that minimizes the total cost.

Initialization

Step 1: Start with no employee is present: x = 0.

Step 2: We add a technician at each shift period i. We compute the performance by allocating the technician to each potential area k.

Step 3: Identify the area k* that minimizes $c_{down} + c_{const}$ and locate the technician for each shift i at area k*.

Step 4: If 2 technicians have been located at each shift, terminate the procedure. Otherwise, go to Step 2.

Algorithm II: *Greedy algorithm:*

Once the first algorithm applied, we can start the greedy procedure: for each shift, for each skill and for each potential location, we compute the decrease in $(c_{down} + c_{const})$ relative to the increase in staffing costs when $x^i_{s,k}$ would be increased by one unit. The increase in staffing costs c_{staff} equals C_s, while the change in $(c_{down} + c_{const})$ is evaluated by the simulation by making the difference between the new downtime cost and the downtime before the increase.

The decrease in $(c_{down} + c_{const})$ divided by the increase in c_{staff} is denoted by $\Delta^i_{s,k}$. The set of values (i,s,k) with the highest value for $\Delta^i_{s,k}$ is selected and the corresponding amount of employees $x^i_{s,k}$ is increased by one unit. The generation of new solutions is continued until a local solution is found, i.e. when we increase by one unit any $x^i_{s,k}$ the total costs do not decrease anymore. The formal procedure is described in the following algorithm.

Greedy algorithm

Step 1: Call algorithm 1 to set up the initial team

Step 2: Let x* the current team and $\varepsilon_{s,k}^{i}$ a new worker with skill s at shift i at location k.

$$\Delta_{s,k}^{i} = \frac{C_{down}(x^*) + C_{const}(x^*) - C_{down}(x^* + \varepsilon_{s,k}^{i}) - C_{const}(x^* + \varepsilon_{s,k}^{i})}{c_s} \text{ for all } s, i, k;$$

$$i^* = \text{argmax}\{\Delta_{s,k}^{i} : \ i \in I,\};$$

$$s^* = \text{argmax}\{\Delta_{s,k}^{i} : \ s \in S\};$$

$$k^* = \text{argmax}\{\Delta_{s,k}^{i} : \ k \in K\};$$

Step 3: $x^* = x^* + \varepsilon_{s^*,k^*}^{i^*}$. If 'stop criterion', then stop, else go to step 2.

The optimal team configuration is obtained for the set of $\{x_{s,k}^{i}\}$ that minimizes the total costs.

The influence of the position of the first workers can influence significantly the local optimal. This is why it is strongly unlikely to find the optimal solution. Moreover, it is well known that greedy algorithm does not in general produce an optimal solution, but nonetheless it may yield locally optimal solutions in a reasonable time.

6.4. Example

To illustrate this optimization procedure, we suggest an example with the following parameters:

- We optimize with 6 shifts of 4 hours
- The control room is the only location where the workers can be allocated
- Workers cannot be utilized more than U = 78%.
- **Staffing costs:**
    - Hourly cost of a jam worker: $c_{jamWorker} = 10$
    - Hourly cost of technician: $c_{tech} = 20$
- **Downtime costs:**
    - Fine for a critical failure with a response time more than 5 minutes: $f_c^5 = 10$
    - Fine for a critical failure with a response time more than 15 minutes: $f_c^{15} = 25$
    - Fine for a non-critical failure with a response time more than 15 minutes: $f_{nc}^{15} = 1$

The performance constraints selected are the following:

- Minimal percentage of critical failures to repair with a response time below 5 min: $\beta_c^5 = 95\%$
- Minimal percentage of critical failures to repair with a response time below 15 min: $\beta_c^{15} = 98\%$
- Minimal percentage of non-critical failures to repair with a response time below 15 min: $\beta_{nc}^{15} = 60\%$
- Minimum hours of preventive maintenance for technicians: $M_{tech} = 12$ hours
- Minimum hours of preventive maintenance for jam workers: $M_{jamWorker} = 10$ hours

In Figure 6.3, the team that we obtain by applying the optimization procedure to this problem is displayed. The initial team is composed of 12 technicians required during shift of 4 hours (blue part on the graph) to fulfil the safety constraints of two technicians per shift. We notice that the second algorithm increases the team with 3 jam workers (red part on the graph) between 8:00 – 12:00, 12:00 – 16:00 and 16:00 – 20:00 (shift 3, 4, and 5). This algorithm gives the worker requirements for 4 hour periods. Therefore, VI managers can then merge the worker requirements to do shifts.

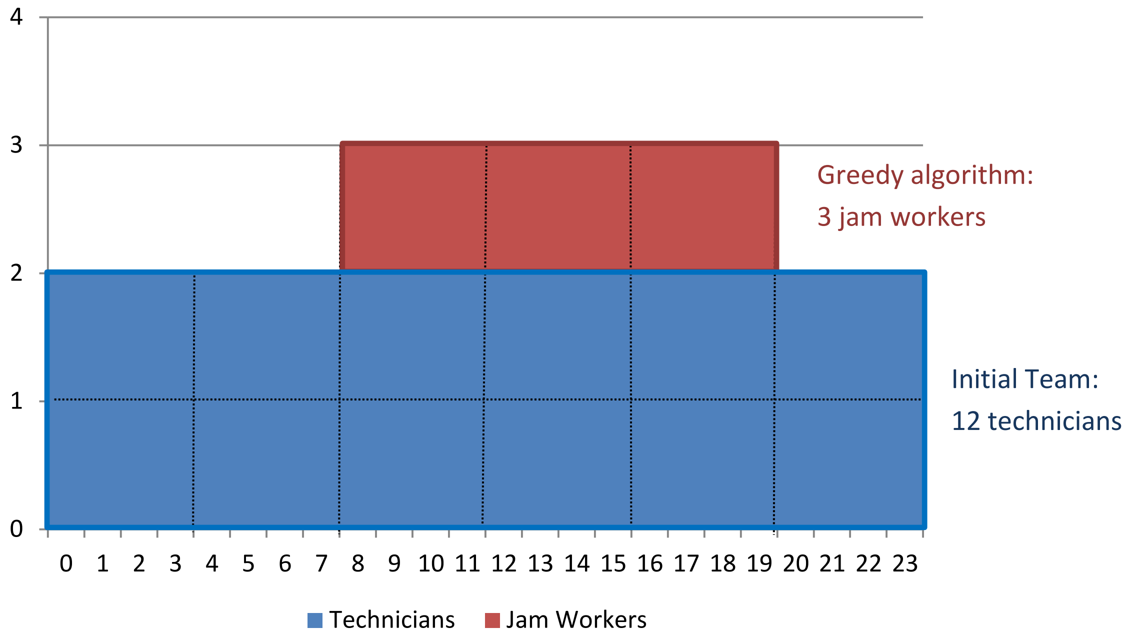


Figure 6.3: Worker requirements given by the optimization procedure that minimizes the total costs

We then draw how the different costs vary during the greedy algorithm, i.e. when we increase the amount of employees per period in Figure 6.4. We start with the 12 technicians from the initial team and the greedy algorithm is applied to add the other employees (in the figure, the greedy algorithm was run for additional steps to draw the curves). We notice that the downtime costs decrease when the greedy algorithm increases the number of people whereas the staffing costs increase. The staffing cost curve is linear because only jam workers were added. The downtime costs curve is concave and decreasing as there are more employees to repair failures and thus, fewer and fewer failures wait to be solved. The constraints costs become equal to 0, i.e. the constraints of problem P are satisfied, with 14 people.

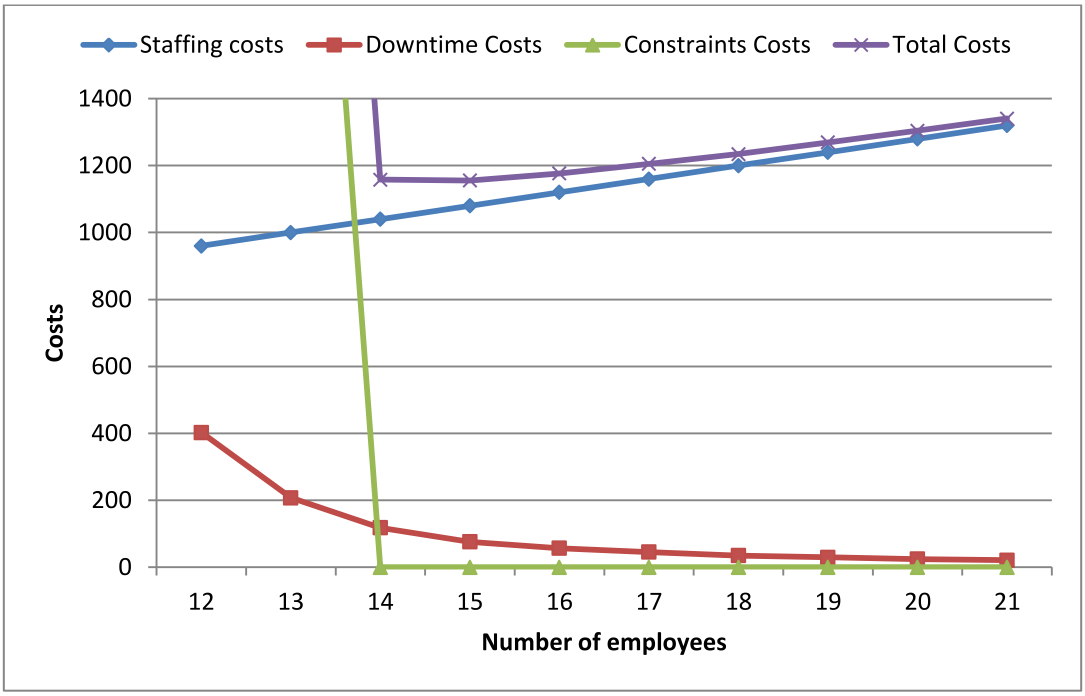


Figure 6.4: Cost optimization path during the greedy algorithm (second algorithm)

By enlarging this graph on the lowest point of the total cost curve (Figure 6.5), we can see that the minimum total costs are obtained with a team of 15 employees (12 technicians + 3 jam workers). This is the number of employees in Figure 6.3.

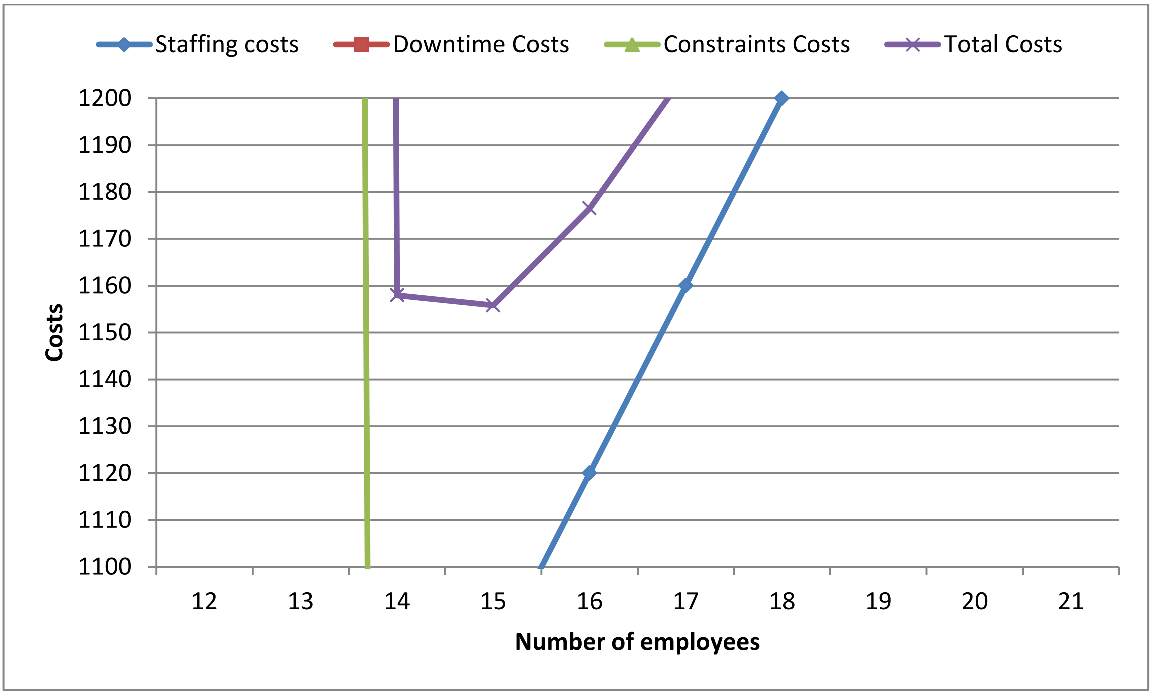


Figure 6.5: Zoom on the lowest point of the total cost curve

Finally, Figure 6.6 shows how the performance varies with the increase of the number of employees. The performance increases during the greedy algorithm as adding employees allows reducing the waiting time of failures.

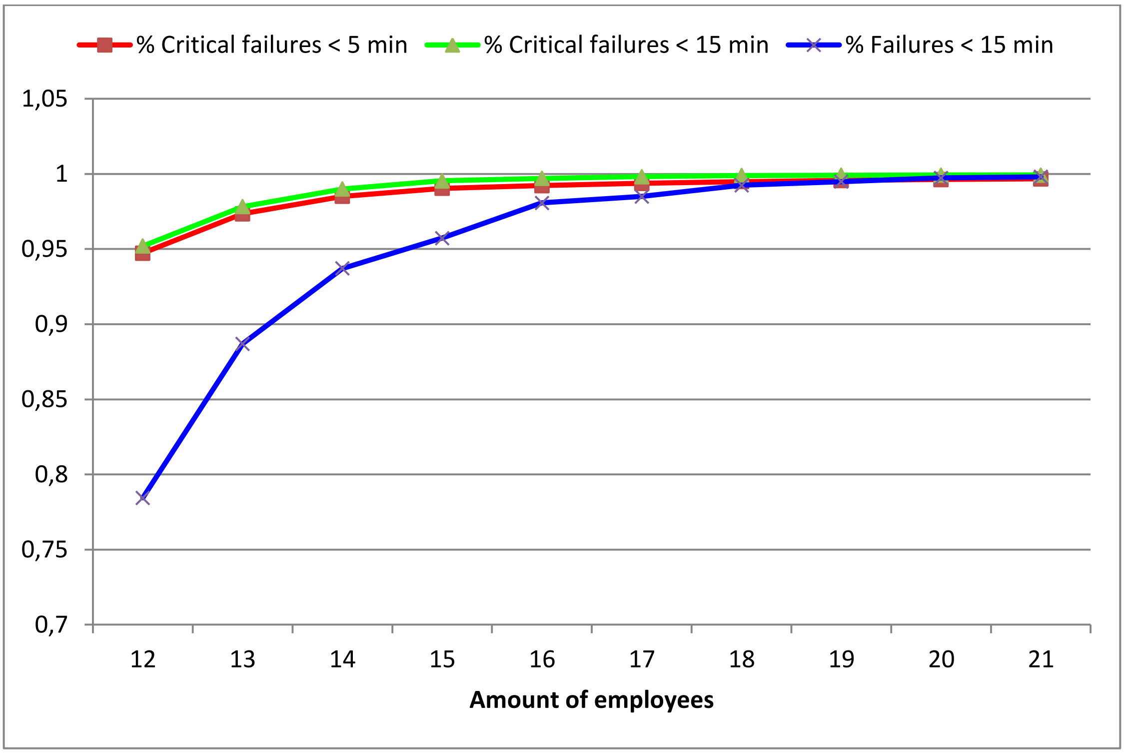


Figure 6.6: Performance optimization path during the greedy algorithm (second algorithm)

6.5. Computation times

The time to generate results with the greedy algorithm depends on the parameters selected for the optimization. We already noticed that the time of the simulation increases with the expected number of failures. However, in this section, we are interested in parameters that increase the number of solutions to evaluate for each iteration of the greedy algorithm, i.e. the number of shift m and the number of potential locations n_p. When we add an employee to the team with the greedy algorithm, there are 2 * n_p * m possibilities (2 is the number of skills). Thus, an increase of one of these two parameters implies a longer computation times.

This phenomenon is pointed out in Figure 6.7 with the graph of the computation time as a function of the shift period length. By decreasing this period, more solutions have to be tested at each iteration. Moreover, more iterations are necessary to reach the optimal solution as the shift are smaller. To cover a period of 8 hours with 2-hour periods, we need 4 iterations whereas we need only one for with 8-hour period. Thus, the computation time increases when we increase m, i.e. we reduce the period length.

Figure 6.8 displays the computation time as a function of the number of locations for different period length. As expected, an increase of the number of potential results in a growth of the computation times. For a given period length, the relation between computation time and number of potential locations is linear since the number of iterations does not change.

Figure 6.7: Computation time of the greedy algorithm as a function of the length of the shift period

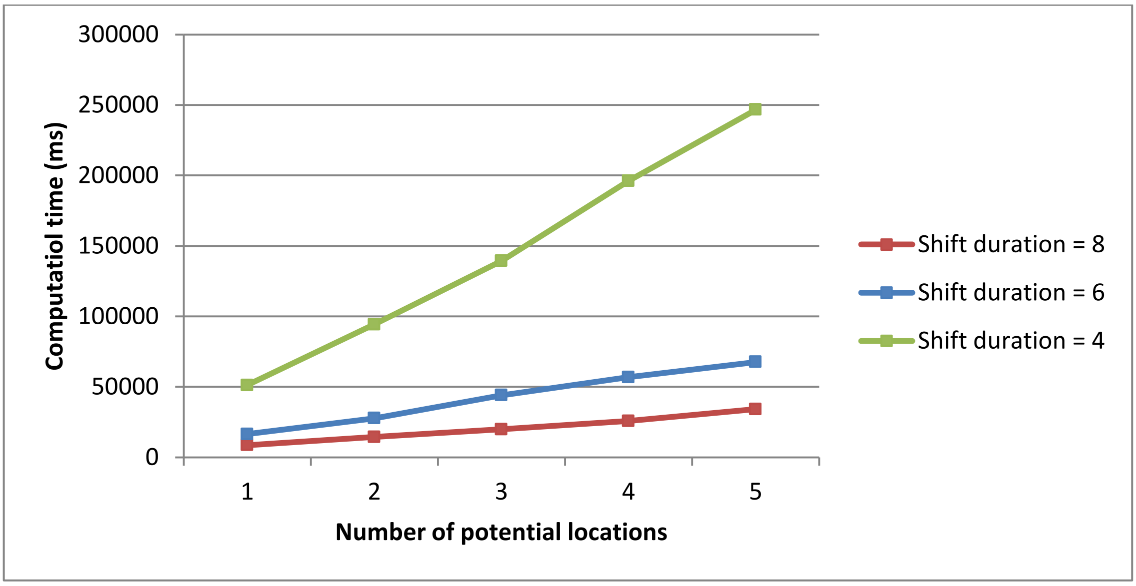


Figure 6.8: Computation time of the greedy algorithm as a function of the number of potential location and the length of the shift period

6.6. Summary

In this chapter, we provided a methodology that uses simulation combined with optimization to determine the optimal number of staff members required to achieve the availability requirements that minimize the staffing costs. A local search algorithm allowed evaluating alternative choices for decision-makers through ‘‘what-if” models. The procedure used to find the worker requirements per day involves a greedy algorithm and the simulation as a performance evaluator for a given team size.

The greedy algorithm might not always produce mathematically optimal solutions. However, it gives a good insight on how many people with which skills, the VI managers must ask for. This algorithm was made as generator of “what-if” analysis with a quick resolution. To find truly optimal values, we may face long computation time and having a near-optimal solution in shorter time was more useful in our context. Some advanced models that examine all the space solution could be developed but we consider our main contribution to be the development of a practical tool to make it useful for managers within VI. In Chapter 7, a decision support system is designed to help decision-makers to either evaluate different situations of staffing distribution or optimize the system for optimal staffing distribution. The decision support tool has to be designed in order that the user can modify the parameters of the model. An interface linkage between an Excel worksheet and Java simulation programming is therefore necessary.

Chapter 7
Decision Support Tool

A software tool has been developed that implements automatically the model described in this paper. The tool automatically builds the simulation model which determines the results based on the parameters specified by the user. This decision support system is designed to help decision makers at Vanderlande to either evaluate different situations of staffing with simulation or optimize the system for finding near-optimal staffing configurations with the optimization procedure. Managers at VI pay particular attention to the ease-of-use of the tool and the clearness to their customers. In this chapter, we first explain how the tool works and then, we present a case study to show how the inputs have to be filled.

7.1. Technical implementation

We constructed this decision support system by establishing an interface linkage between Excel worksheet and the simulation program. The input parameters must be filled by the user through different Excel sheets. Once the input data are entered, the user can click on a button to launch the procedure. A VBA program takes input data from Excel and writes them in text files in order that the Java program can read them. Then the VBA program launches the Java program via a batch file. This Java program performs the necessary simulation analysis or optimization procedure and produces the measure of performance for the current staffing distribution. When this is done, the Java program writes all the results in text files. Finally, the VBA program takes the control to display on Excel the results. This procedure was explained in a technical manual with both the assumptions of the model and the technical detailed of the program. Figure 7.1 summaries the previous explanations.

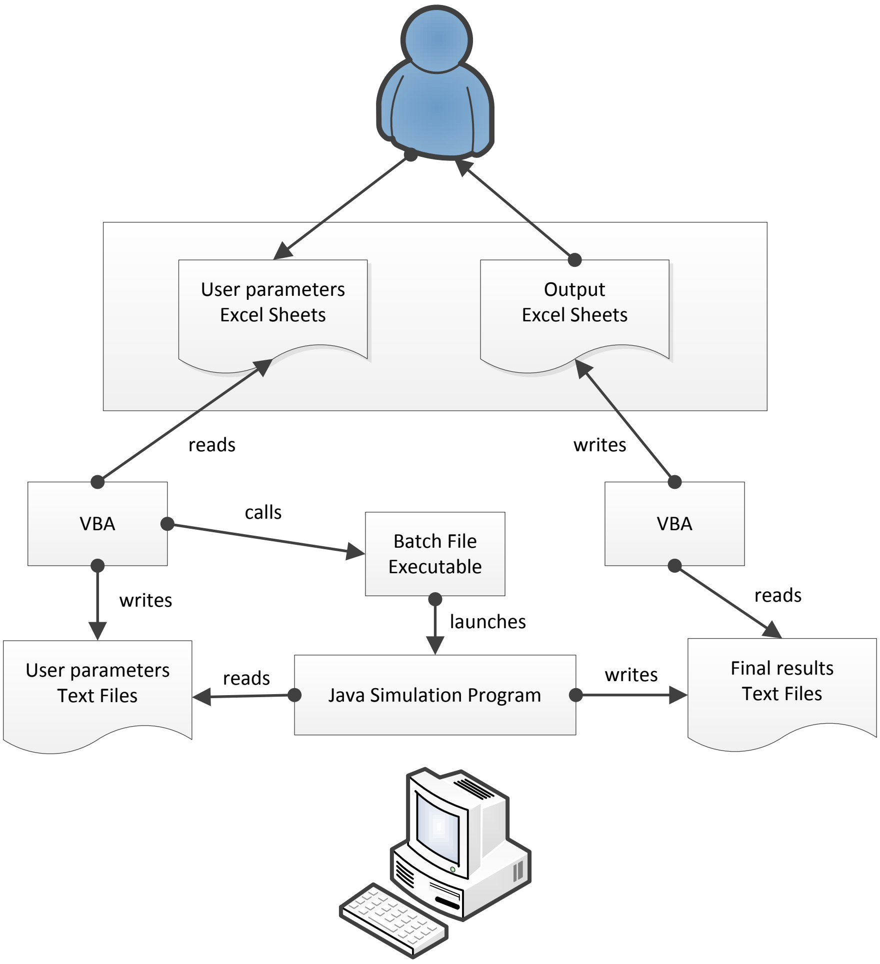


Figure 7.1: System Integration

The choice of this procedure was driven by the requirement of a user-friendly interface. Improvement of the interface between the end user and the computer model increases its chances of acceptance and use. Practitioners' understanding of the model and the meaning of its components was enhanced since the interface appropriately represents the relationship between the model and "reality". With a graphical interface, presentation quality was improved, providing an important persuasive tool and minimizing the need for formal user education. Another major benefit of an enhanced interface on Excel is the willingness to use it, and increased frequency of use as Excel is nowadays the main tool used by managers.

The problem of detailed simulation models made within Vanderlande is that they are very detailed to meet specific requirements. A model implemented to satisfy specific requests could not be applied to solve problems for another BHS which is different from the one considered. A generalized flexible simulation model allows analysing general problems of a BHS under different operative scenarios. This is why the focus of this work was to implement a flexible simulation model of the maintenance activities that can be easily modified to study BHS in any airport. The simulation model proposed in this thesis reproduces all the most important parameters of maintenance activities of the BHS.

Since each airport is different, the tool is flexible. It means that few inputs are mandatory to customize the tool for the considered airport. These inputs have been thought to be relatively easy to recover and the user is free to use parameters as he wants. Of course, the validity of the results is directly related to the quality of the input data. A trade-off has to be found between detailed data that can be time-consuming and lengthen the computation time and rough data that could affect the results.

The user supplies the input parameters through Excel sheets with the help of buttons for an intuitive use. Furthermore, a user manual was provided with the tool to ensure a good use of it. Firstly, information about the airport has to be filled to build the graph we use in the model. Therefore the number of areas and the travel time matrix are the parameters to fill in the first sheet with the probabilities that a failure occurs for each hour of the day. On a second sheet, the failure characteristics have to be informed: expected amount of technical and customer failures, percentage of customer failures that require technicians, spatial distribution for both customer and technical failures, the probability that a failure is critical for each area and the parameters of the repair time distribution.

If the user selects to do a simple simulation, he has to determine the number of workers required during the day and assign them to a shift and a location. If he selects the optimization part, the staffing costs, downtime costs, the performance constraints, the duration of the shift and the maximum utilization have to be filled.

7.2. Application of the tool in practice

We now illustrate how the tool can be used in practice via the case study of [redacted]. During this graduation project, two case studies [redacted] were done to compare the results obtained with the tool and the actual results. They were presented to maintenance managers of the airport for validation of the outputs as well as potential users of the tool to increase user acceptance. The tool was provided with a technical manual that explains the model, the code and the technical implementation and with a user manual to explain the user how to fill the parameters and to provide the assumptions underlying the model.

7.2.1. Determination of the Areas

Firstly, information about the topology of the airport has to be filled. The number of areas and the travel time matrix are the parameters to fill in the first sheet of the tool. The areas may be formed based on the convenience of the model builder or the data collection system. The airport is divided into a number of areas by grouping pieces of equipment together. By looking at the layout, we can already define critical locations at the airport. Both expected failure rates and travel times are also considered.

In Figure 7.2, the process flow layout is shown with the selection of the areas. One can see that the baggage handling system was divided in $n = 7$ areas. We grouped each sorter with their transportation belts which makes the relation between the main lines and the sorter. They are important in the process and require to be considered separately. Moreover, there is significant travel time between each sorter. The control room in which no failure occurs and which operates as a warehouse for spare parts was considered as an area because this is the location where the employees stay during their idle time. Finally, we define the check-in desks as an area. The check-in desks are not in the basement of the airport and a long travel time is observed to reach them.

[redacted]

Figure 7.2: Definition of the areas: aggregation of pieces of equipment

Next the travel times t_{ij} are defined based on the experience of the maintenance manager and on the current distances which can be found via the layout. The graph in Figure 7.3 defines few travel times. We can notice that a travel time of 10 minutes is considered because of the time the employee must take to deal with the security controls. The information can be filled in the tool as shown in Figure 7.4.

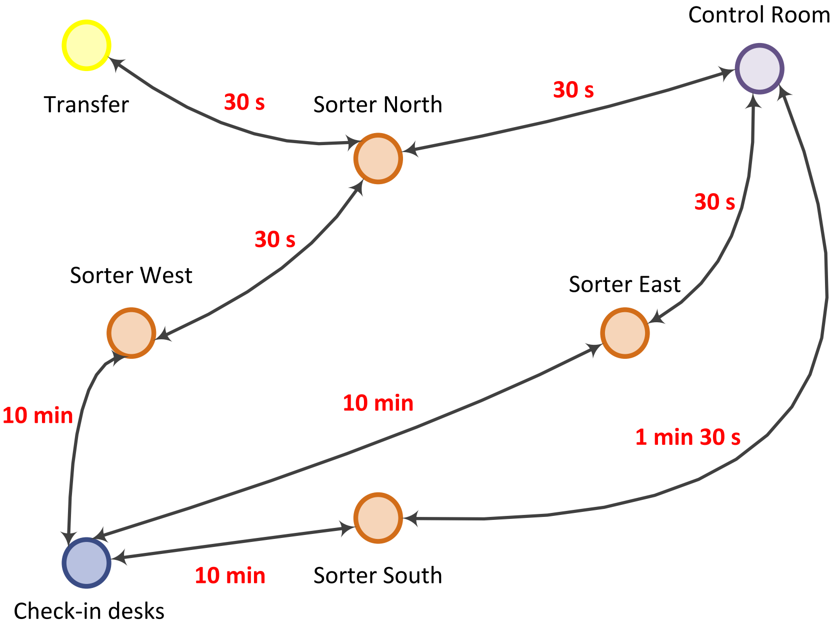


Figure 7.3: Definition of the travel times

Number of areas: 7

Travel time Matrix:

Name of the area		1	2	3	4	5	6	7
Control Room	1	0	0,5	1,5	1,5	0,5	1	10
Sorter North	2	0,5	0	0,5	1,5	0,5	0,5	10
Sorter West	3	1,5	0,5	0	0,5	1,5	0,5	10
Sorter South	4	1,5	1,5	0,5	0	0,5	1,5	10
Sorter East	5	0,5	0,5	1,5	0,5	0	1	10
Transfer	6	1	0,5	0,5	1,5	1	0	10
Check-in desks	7	10	10	10	10	10	10	0

Figure 7.4: Screenshot of the travel time matrix

7.2.2. Determination of the Failure Characteristics

We are first interested in the amount of failures expected during one day. Based on historical data for the months of March and April 2012, an average of F_{total} = 190 failures was observed. We pick this amount for a first use of the model. Then the probabilities that a failure occurs for each hour of the day (p_t^{temp}) are required. The user can indicate the amount of failures per hour since the calculations of the probabilities will be made automatically. The mean amount of interventions for each hour of the day was available for [redacted] airport for March and April 2012 (Figure 7.5).

Temporal Activity Pattern

Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Total
Amount of bags/failures																									0
Probabilities	0	0	0	0	0	0,019	0,037	0,06	0,077	0,104	0,098	0,059	0,067	0,068	0,044	0,04	0,05	0,081	0,08	0,069	0,037	0,01	0	0	1

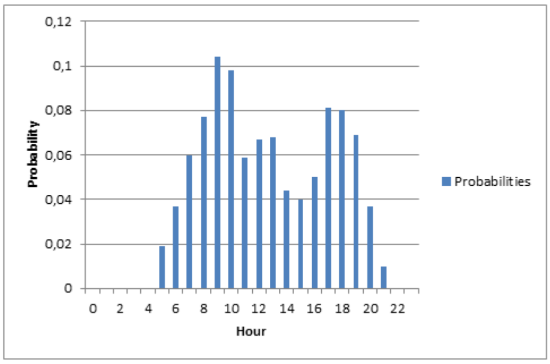
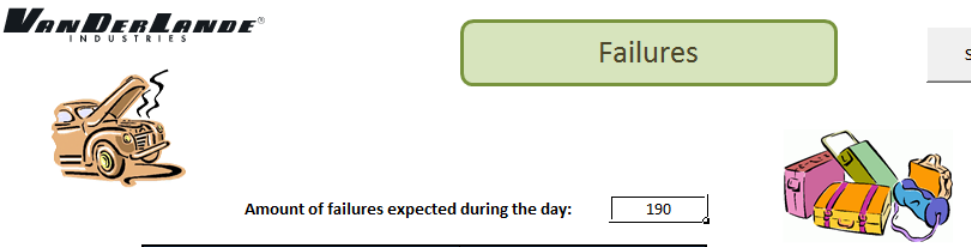


Figure 7.5: Screenshot of the temporal pattern of workload

Next the percentages of technical and customer failures are required as well as the percentage of customer failures that require high skill intervention (Figure 7.6). They can vary with the type of technology. For [redacted] airport, the maintenance manager reports that 99% of failures are customer failures (p_{cust} = 0,99) whereas the remaining 1% is due to technical failures. This trend is also observed in [redacted] airport. Moreover, 95% of failures related to baggage require a low skill intervention (p_{jam}^{cust} = 0,95).

During a maintenance manager forum, parameters were recovered from 21 sites and reported in a table. This table can be used for future studies on these sites. They can also be used as benchmark values for new systems on which data are not available. It gives a first insight of what can be the worker requirements for a new baggage handling system.



Cause		Consequence	
% of technical	1		
% of operational	99	% high level skills	5
		% low level skills	95

Figure 7.6: Screenshot of the failure features and the distribution of the failure types

The study continues with determining the spatial distribution for both customer and technical failures (p_a^{cust} and p_a^{tech}). In Figure 7.7, the values filled for [redacted] airport are represented. They are based on historical data for 2011. This information can also be filled based on the experience of managers. Maintenance managers typically have some valuable knowledge about demand patterns in space and time (e.g., “peak” time periods and intense geographical areas). The sum of both technical failures and customer failures should be 100%.

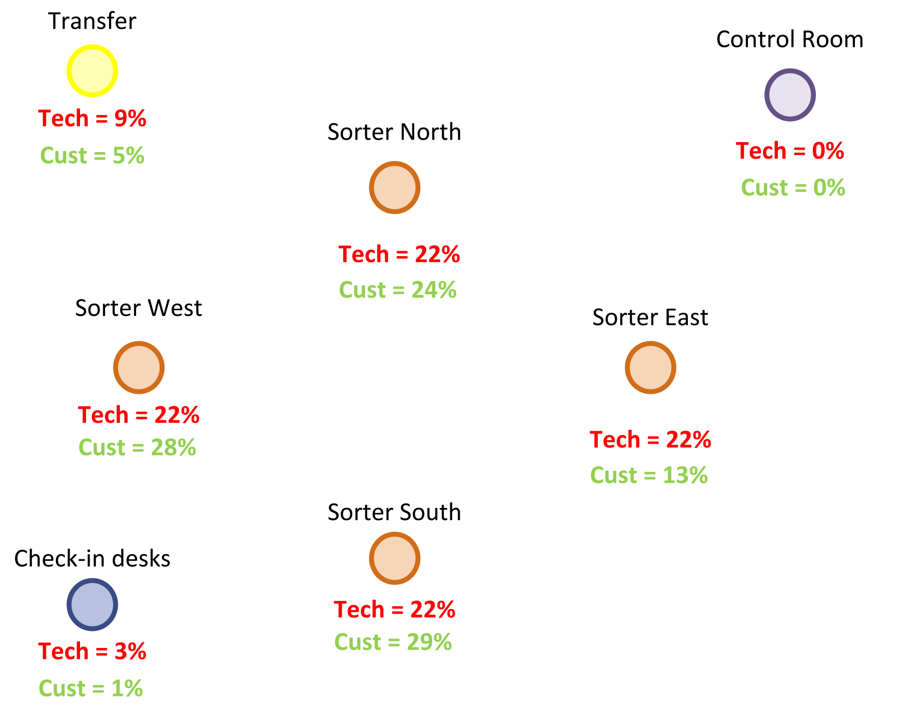


Figure 7.7: Spatial distribution of both technical and customer failures

The next parameters deal with the criticality of each area. The user must fill the percentage of critical failures for each area (p_a^{crit}). The data of [redacted] airport are shown in Figure 7.8.

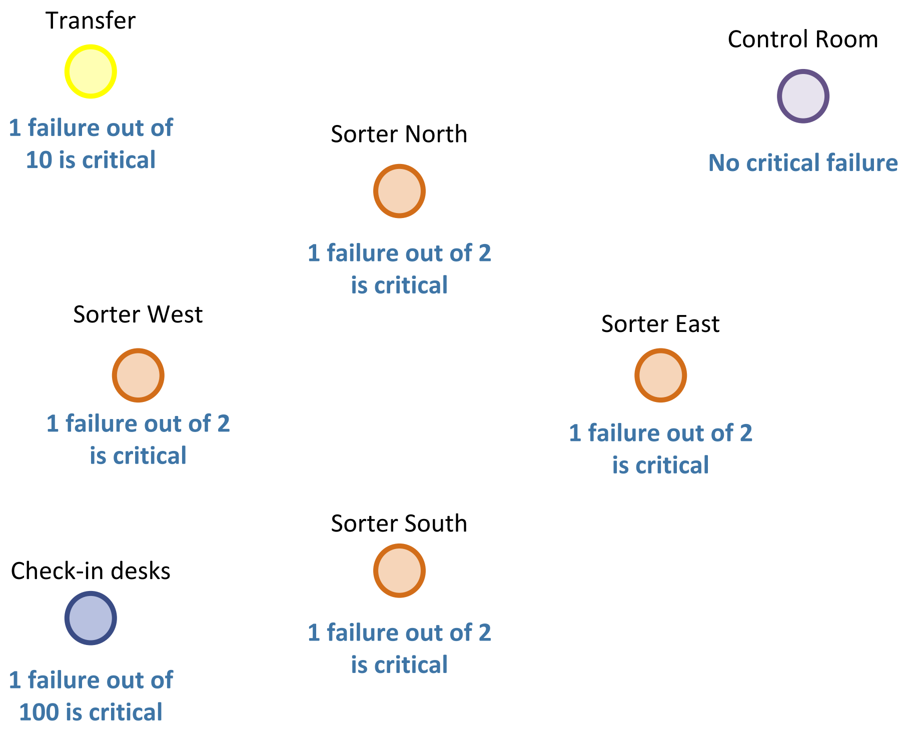


Figure 7.8: Definition of the criticality of each area

Finally, the parameters of the repair time distributions must be selected. To simplify the selection of the distribution, the method proposed by F.A. Lootsma (1989) has been implemented to determine easily the parameters of the gamma distribution based on the average E[x], the most likely time m and the minimum a (Figure 7.9). The probability density functions are displayed on the Excel sheet in order that the user may evaluate if it looks like to what they expect.

Repair time

Low level skills (jams)	
Minimum	2
Most Likely time	3
Mean	5,4

High level skills	
Minimum	10
Most Likely time	20
Mean	30

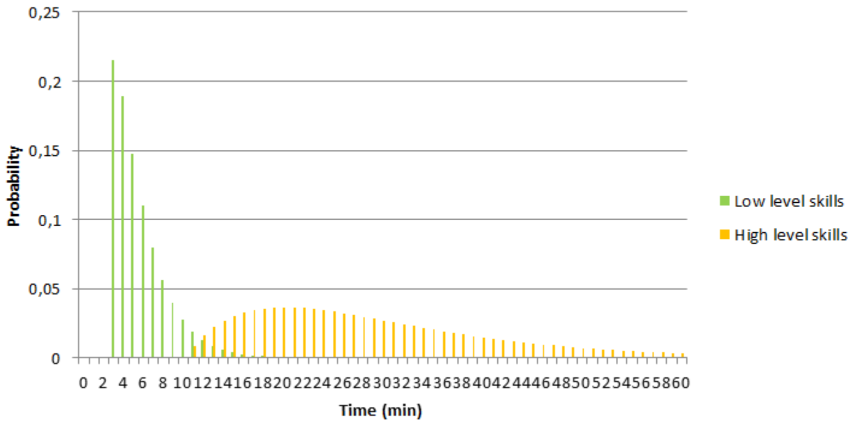
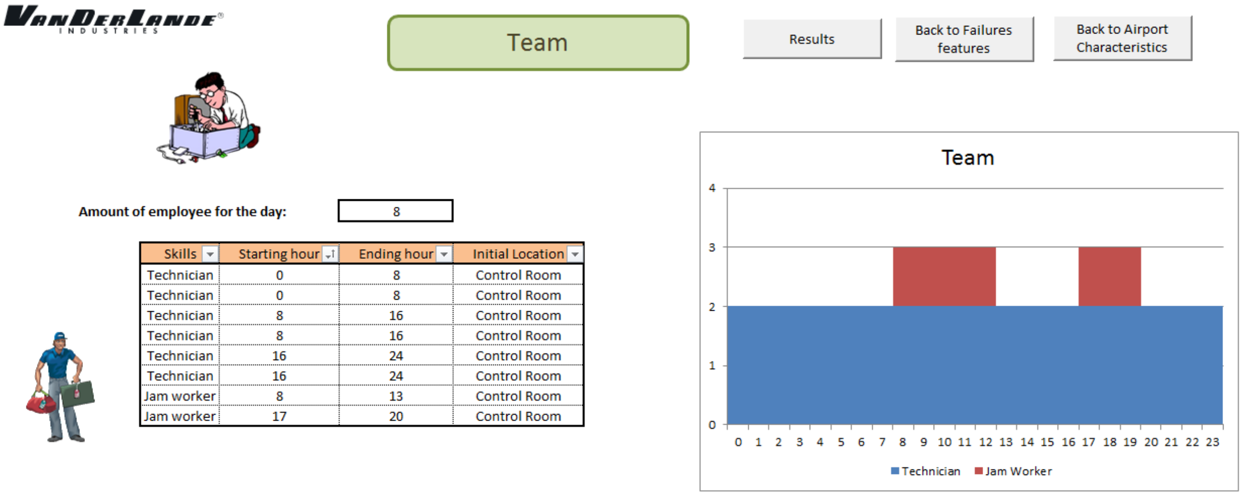


Figure 7.9: Determination of Gamma distribution thanks to the mode, the mean and the minimum

7.2.3. Evaluation of the Team Performance

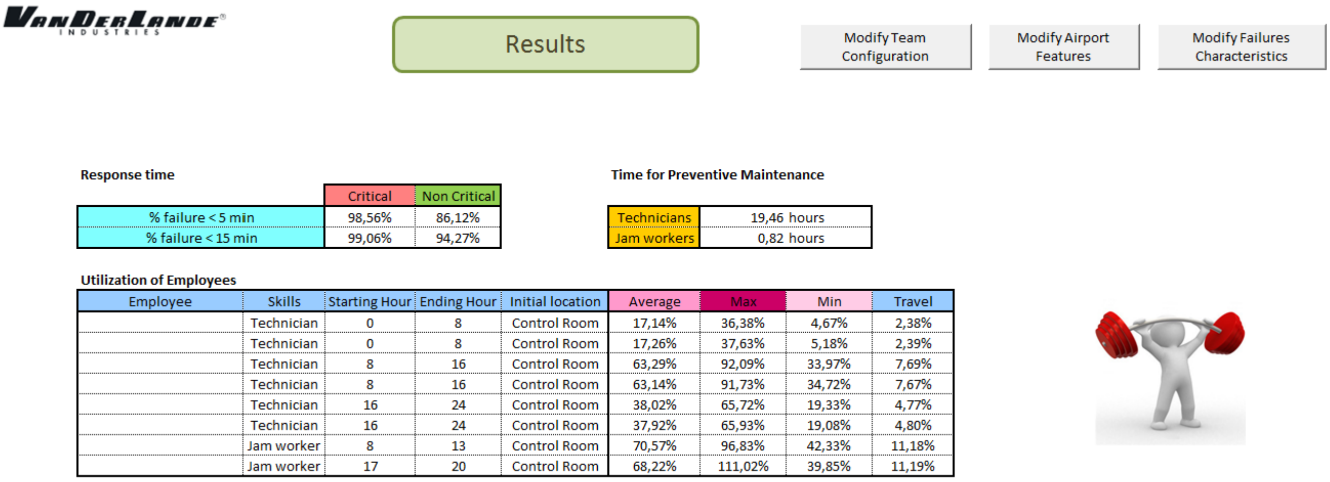
If the user selects to do a simple simulation, he has to determine the number of workers required during the day and for each shift (start hour and end hour) and the base location i.e. the decision variables $x^{i}_{s,k}$. In our study case, we apply the simulation with the actual team used by the airport manager when they expect 190 failures. This team is defined in Figure 7.10: on the left, the table allows the user to fill the inputs and on the right, the graph displays the worker requirements over the day which are updated with the inputs of the table.



Skills	Starting hour	Ending hour	Initial Location
Technician	0	8	Control Room
Technician	0	8	Control Room
Technician	8	16	Control Room
Technician	8	16	Control Room
Technician	16	24	Control Room
Technician	16	24	Control Room
Jam worker	8	13	Control Room
Jam worker	17	20	Control Room

Figure 7.10: Screenshot of the Excel sheet on which the user defines of the team configuration

By clicking on the "Results" button (Figure 7.10), the user launches the simulation with the information filled previously. The results are computed by the simulation and given in a new Excel sheet (Figure 7.11). The percentage of critical and non-critical failures with a response times below 5 or 15 minutes are given. The utilization of each employee is also presented with the maximum and minimum values for the different runs made during the simulation. Finally a simple calculation of the remaining time for preventive maintenance is done by considering that a worker cannot be busy more than 80% of his shift to avoid that an employee complains because of a high workload.



Response time

	Critical	Non Critical
% failure < 5 min	98,56%	86,12%
% failure < 15 min	99,06%	94,27%

Time for Preventive Maintenance

Technicians	19,46 hours
Jam workers	0,82 hours

Utilization of Employees

Employee	Skills	Starting Hour	Ending Hour	Initial location	Average	Max	Min	Travel
	Technician	0	8	Control Room	17,14%	36,38%	4,67%	2,38%
	Technician	0	8	Control Room	17,26%	37,63%	5,18%	2,39%
	Technician	8	16	Control Room	63,29%	92,09%	33,97%	7,69%
	Technician	8	16	Control Room	63,14%	91,73%	34,72%	7,67%
	Technician	16	24	Control Room	38,02%	65,72%	19,33%	4,77%
	Technician	16	24	Control Room	37,92%	65,93%	19,08%	4,80%
	Jam worker	8	13	Control Room	70,57%	96,83%	42,33%	11,18%
	Jam worker	17	20	Control Room	68,22%	111,02%	39,85%	11,19%

Figure 7.11: Screenshot of the result sheet for the simulation (1)

Then values about availabilities are given for both technical and customer failures (Figure 7.12). The calculations are based on the definition given in Chapter 4.

Technical Availability

Area	Average	Max	Min
Control Room	100,00%	100,00%	100,00%
Sorter North	99,81%	100,00%	94,30%
Sorter West	99,76%	100,00%	91,59%
Sorter South	99,77%	100,00%	93,03%
Sorter East	99,79%	100,00%	93,15%
Transfer	99,99%	100,00%	96,09%
Check-in desks	100,00%	100,00%	100,00%

Customer Availability

Area	Average	Max	Min
Control Room	100,00%	100,00%	100,00%
Sorter North	85,77%	95,66%	49,91%
Sorter West	82,71%	96,08%	61,19%
Sorter South	81,79%	92,91%	43,40%
Sorter East	92,39%	98,55%	75,35%
Transfer	99,37%	100,00%	92,88%
Check-in desks	99,97%	100,00%	96,47%

Figure 7.12: Screenshot of the result sheet for the simulation (2)

The values were considered as relevant by the manager of the airport. The calculations of the total availability of the system could be considered but they depend on the configuration of the systems. For example, for [redacted] airport, the four sorters can be considered as built in parallel as main lines make the link between them. In Chapter 5, we validate the dispatching assumptions and the distributions for the generation of the failures. By using the model for a new system, a validation has to be done to validate both the zone structure and the input parameters. The user must take care to compare the real value of performance (availability, response times) with the values obtained by the tool to validate the model. Unfortunately, we were building a model, so some errors and approximations were unavoidable. Therefore, the user has to ensure every time he uses the tool that the outputs seem valid by discussing with customers and including several people to evaluate the relevance of the results.

7.2.4. Optimization Study

If the user selects the optimization part, the staffing costs, downtime costs, the performance constraints, the duration of the shift and the maximum utilization have to be filled in (Figure 7.13).

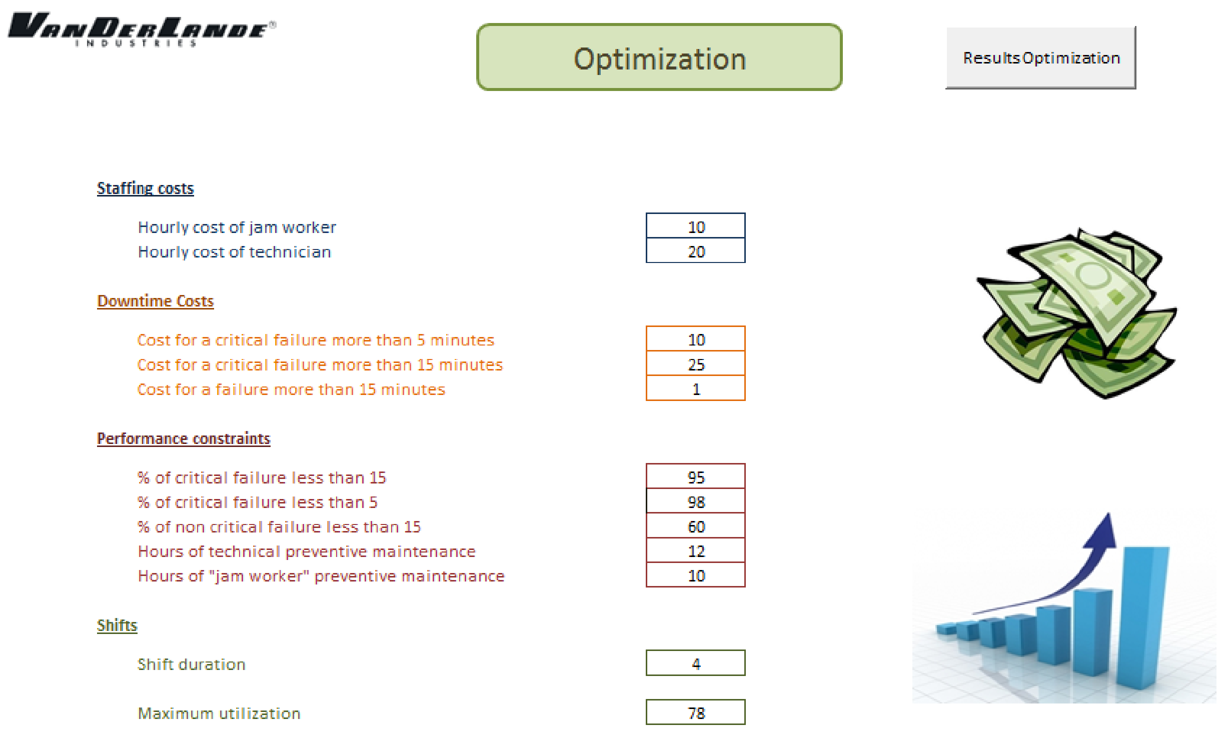


Figure 7.13: Screenshot of the sheet to fill the optimization parameters (1)

Moreover the potential areas at which employees can initially be assigned have to be informed by the user (Figure 7.14). In the case of [redacted] airport, all the workers are considered located in the repair room.

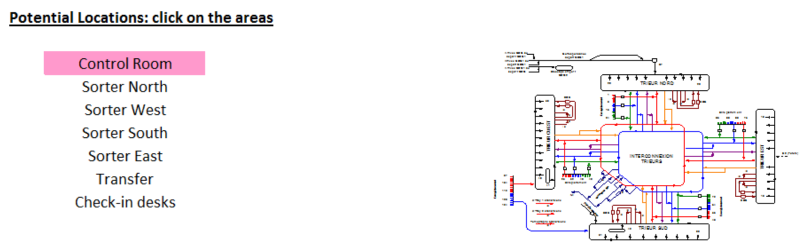


Figure 7.14: Screenshot of the sheet to fill the optimization parameters (2)

By launching the optimization, the proposed BHS is simulated with different team configurations to determine the team that fulfils the performance constraints and minimizes the total costs as given in Chapter 6.

The results are found very close to the actual team. Several configurations have been tested. This example is based on data from March to April 2012 but it can be extended to other months in order to define the strategy about the hiring of employees.

7.3. Summary

The lack of a satisfactory simulation model of maintenance activities motivated the creation of our new flexible simulation tool that can either simulate the maintenance activities for a given team configuration or give the team that minimizes total costs under performance constraints. It includes the common features of all BHS and, after an appropriate definition of the key parameters, is capable of describing maintenance activities on any BHS. All input data concerning BHS structures and related maintenance activities are supplied by means of guided menus.

Input values are required to use the tool as expected. A high importance was given to the user friendliness of this decision support tool. During this master graduation project, information was recovered with the maintenance managers of different sites to get a benchmark list. It allows the user playing with the tool for new systems by selecting values with comparison of other system. However, the quality of information and the precision of the data are important to expect relevant results from the tool. Using the tool with data from experience will not give better results that using the tool with actual data measured from the field. Moreover, there is necessarily a trade-off between the level of detail which could be represented by the system, and the computation requirements necessary to support the various location possibilities.

Chapter 8
Conclusions & Recommendations

This final chapter draws the conclusions in Section 8.1 and presents the recommendations in Section 8.2.

8.1. Conclusions

In this master thesis, a tool has been built, that evaluates the performance with given worker requirements and calculates the worker requirements under performance constraints to meet both researcher and practitioner requirements.

The model we developed is based on a mathematical formalization of the staffing problem of VI, consistent with the state of the art. We identified the main parameters of the problem and the underlying assumptions that we justified with practical reasons and data availability. The maintenance activities are represented using a simulation program to evaluate the performance of team configuration. Then this program was embedded in a greedy algorithm to find the worker requirements that minimize the total costs under performance constraints. By determining the number of workers with their skills over space and over the time, the procedure developed allows answering the research question:

> *Determine the right number of workers with the right skills at the right place at the right moment to realise the required performance for the baggage handling system of any airport.*

The tool is parameterizable to deal with different airport and failure characteristics. It is built in Excel, using straightforward, well-known parameters and an intuitive interface. The model can be used to simulate any airport configuration by adapting the parameters and the assumptions are based on the experience of the on-site maintenance managers to strengthen their relevance. The graphical user interface improved user satisfaction and adoption of the model. It can be used by VI managers to give insights of a maintenance team size required for a certain performance of the baggage handling on-site. Appropriateness, ease of access and face validity allows satisfying practitioners. Thus, the tool meets the engineering requirements of Vanderlande in terms of deliverables.

8.2. Recommendations

In this section recommendations are given for using the tool as well as possible improvements of the model and future research opportunities.

Recommendations for using the tool

The tool is a decision support tool and like every tool and model, it is based on assumptions. The results are only as good as the underlying assumptions of the model. If the assumptions are not fulfilled, the model cannot be applied and the results too. The main assumptions are presented in the user manual and the complete model is presented in the technical manual. It is necessary to put results of the simulation into perspective of other results like personal calculations or previous team size on site and checking for the face validity of the results. Conducting a sensitivity analysis must also allow validating the output.

We developed a generic and flexible tool. As a consequence, the user must fill the input parameters that correspond to the airport under study. Some input values can be recovered with data processing and it is important to make use of the database as often as possible. The inputs may be validated by verifying with airport manager the relevance of the parameters chosen.

Improvements of the tool

We recognize several limitations and extra efforts may be made to relax the assumptions:

- In the model, we assumed that one employee is necessary for each failure. Maintenance managers at the airport criticize this assumption arguing that a technical intervention may require two employees as the required operations imply to transfer heavy parts. This could be introduced in the model.
- Efforts to improve the travel time model could be done. Firstly, it could be possible to introduce variability in the travel time. In the model, the failures are assumed to occur at the central point of the area. In reality, the walking time could be shorter or longer. A triangular distribution might be interesting to introduce to consider this variability. Moreover, we can expect that the travel time will certainly vary with the period of the day or with the criticality of the failures.
- Pre-emption could be introduced to better fit with what happens within the airport. If a critical failure occurs, employees generally stop what they do to solve the failure. This could be included in the model.
- We assume that employees cannot be rerouted when they are walking to go back to their “home” area. The simulation model could consider that the employee can be rerouted to another failure during this travel time since each employee wears a walkie-talkie.
- The model could introduce a regionalized response for each employee, i.e. each employee has a certain coverage area, which is represented by the portion of areas that can be reached by that employee within certain time limit. It would avoid sending an employee which is too far from the location of the failure.
- The thresholds of 5 and 15 minutes were taken to define the criteria on response time. These two values could be introduced as inputs of the tool.
- We assumed that the failures occur independently to use the Poisson distribution. If the assumption about the independence of the failures at the airport was well accepted at the airport, one person doubted about this assumption arguing that one failure at one location generally causes more failures at the same location. Other solutions could be tested.
- The first algorithm of the optimization procedure which gives the initial team assumes that two technicians are required for all the airports. If this is the case in principle, the tool could consider that this initial team can include more or less people.

We provided a technical document in which the model and all the assumptions are presented. This document was given to VI managers. In case of improvement of the tool with new assumptions, it is essential to maintain this document. Making the model’s assumptions explicit in a technical document is important because the model’s assumptions and input values determine whether the model is valid.

Finally, extra efforts could be necessary to improve the technical implementation of the tool. This was made with our knowledge about computing but more efficient methods should be found to make more reliable the interface between Java and Excel.

Future research opportunities

The optimization procedure should be improved by a stronger research study. We consider our main contribution to be the development of the model with the identification of the assumptions as well as the design of the practical tool to make it useful for managers within VI. Less time has been spent on the optimization procedure. As pointed in the literature review, the dispatching and scheduling problem are never combined to determine the worker requirements. An efficient algorithm like simulated annealing, genetic algorithm or tabu search could be designed to find a better solution based on the existing simulation program. The optimization problem could also introduce other downtime costs like availability costs if the availability goes under a certain threshold to suit the company's business goals that evolve over time.

In this graduation project, we developed a model that corresponds closely to the behaviour of employees at the airports. The simulation can be used to evaluate the best dispatch policies and study the influence of the dispatch rules on performance. Redeployment procedure can be an enhancement for the future. Due to the limited number of employees, whenever an employee is dispatched to a failure, it may leave a significant fraction of the system without proper coverage, e.g. the future failures will experience long waiting times because of the walking time. Therefore it is necessary to introduce more flexible dispatching strategies, such as to allow dispatched employees on route switch to a new emergency failure that is more critical (diversion) or to relocate the idle employees (relocation) in order to maintain a proper coverage for future demands. With the development of technology and the use of mobile phone at the airport, the decisions can be taken faster and allows this kind of redeployment procedure.

Another research opportunity is to have a look at relation between the number of bags in the system, the number of failures and the type of equipment should be found. Work can be done for the aggregation of the data for technical failures between the different airports. This work would allow getting more information about the occurrence of failures on the BHS for both technical and customer failures.

The tool has been built considering baggage handling systems. We do not have time to explore distribution systems or parcel & postal systems. A future research could study the extension of the tool to these systems.

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Appendices

Appendix A - Description of the assortment of different service contracts

- **No Service Contract:** VI is not responsible for doing maintenance on the system. Delivery of spare parts is still possible.
- **Support Service Contract:** A support service contract includes hotline availability, remote support and mobilization priority at a 24/7 basis. System inspections are also included in this contract. Vanderlande is just responsible for the operations and maintenance management.
- **Site-Based Contract:** VI is responsible for all maintenance activities (resources and tooling) on the system at all times. An on-site team is stationed on the premises of the customer. System errors have to be solved within a time span as specified in the service contract. VI is also responsible for keeping the availability up to a target level. Hence, the customer can focus on its core business activities.

Appendix B - Description of the process steps of baggage handling

1) Check-in

When people arrive with their bag in the airport, they start at the check-in. Check-in operators give a barcode to the bag. The baggage enters the BHS. If the baggage is Out-of-Gauge, i.e. too heavy or too large/small for the system, the baggage has to be handled separately. When the baggage goes behind the wall of the check-in, the passenger does not see this baggage before the arrival in the destination airport. The check-in operator has an influence on the behaviour of the system: if they accept bags which do not respect the system constraints, it can occur jams and downtime of the system.

2) Transportation

Within the baggage handling systems of VI bags have to be transported from one process to another process. VI sells different equipment to transport baggage:

- Transporting baggage loose or in totes on conveyor belts
- High speed transportation

All transportation solutions are a compromise between financial, technical and operational considerations in order to meet the required system availability, speed, throughput capacity and types of baggage or available space. The choice of equipment has a direct influence on the type and the amount of failures and the frequency of jams we can expect.

Figure B.1: Transportation solution with conveyor belt

3) Screening

After the check-in, the baggage has to be identified by scanners. Then it follows a multi-level screening for the security. An automatic system tries to scan the label in order that the computer identifies the bag. If the scan fails in the identification, the baggage is identified manually by a person. At the screening area baggage is screened for dangerous goods, like bombs. First a computer makes an X-ray of the baggage. Then it decides whether the baggage is safe or not. If the baggage is safe, it is sent further into the BHS, otherwise it will have to undertake more levels of screening: a person starts by looking at the X-ray that the computer made. If it is still not sure whether the baggage is safe or not, another more detailed scan is made. After rejection by this computer again a person will look at the more detailed picture. If the baggage fails at the last level of screening, it leaves the system and it is entrusted to custom authorities. By using this method of screening, the airport can ensure with high probability that baggage in the system is safe. However, screening machines are not VI equipment but VI has to integrate them in their process.

Figure B.2: Hold Baggage Screening

4) Early Bag Storage

For baggage which has been checked in early, a baggage storage system is necessary for temporary storage. This baggage can be retrieved from its temporary storage based on departure time or priority. Early Bag Storage is not always integrated in the process.

Figure B.3: Early Bag Storage

5) Sorting

Sorting is required for the distribution of the baggage between the different flights. There is several sorting equipment. Sorting can be done by vertical or horizontal diverters.

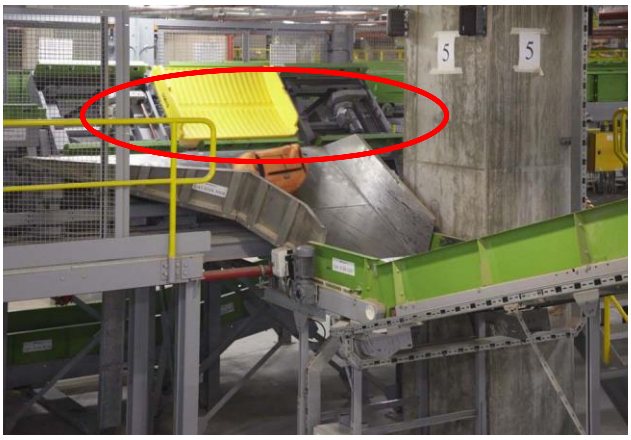


Figure B.4: Sorter

6) Make-up

Flight baggage can be gathered in chutes (location where the baggage leaves the system to be taken by an operator), on lateral belt conveyors or on carousels. Carousels are also used to transport or sort baggage for flight make-up. VI offers a choice of flat or tilted carousels, with several cladding options to match the requirements.

7) Transfer

All the transfer baggage is coming in from an airplane. This baggage has already a label. In the same way as with the baggage at check-in, Out-of-Gauge bags are sorted out and will not enter the BHS. The rest of the transfer baggage can go the same way as the check-in baggage. Transfer baggage is from arriving people who change at the airport to another plane.

8) Arrival

When the plane arrives, arrival baggage is unloaded manually or with a lifting tool onto the arrival reclaim carousel where passenger can recover their baggage. Transfer bags are unloaded manually or with the lifting aid on belt conveyors configured as unloading quays.

9) Controls

Operational control is the implementation of operating plans, monitoring day-to-day results, and taking corrective action when required to perform the baggage operation from check-in to make-up.

Integral control of baggage operation is delivered by Vanderlande Industries' software.

Appendix C - Breakdown costs structure for BHS proposed by Franssen (2006)

[redacted]

Appendix D - Description of the service level requirements within the contract [redacted]

To help the reader to understand the customer requirements, the case of [redacted] airport is presented. The VI management team in [redacted] and the customer [redacted] airport define different measures of performance level presented below. Not respecting these performance indicators causes some penalties to Vanderlande. The penalties are only applicable in case of technical failures of electromechanical or automatic nature. In the case of [redacted] airport contract, the indicators are:

- Number of delayed bags: threshold for 2012: 1,70 per 1000
- Availability of check-in desks: mean rate of availability for all the desks. The threshold is fixed to [redacted] for 2012. VI has to pay a penalty for each 0,1% under the threshold. A downtime of one of the sorters makes the associated check-in desk unavailable.
- Availability of chutes (make-up area): mean available time for all the chutes. The threshold is fixed to [redacted] for 2012.
- Availability of arrival equipment: mean available time for all the arrival conveyors. The threshold is fixed to [redacted] for 2012 and 2013. This indicator was equal to [redacted] between July 2010 and November 2010.
- Availability of lines HX1 and HX2: threshold of [redacted] of availability

[redacted].

Appendix E - Process of intervention for corrective maintenance actions

In a control room, two employees of [redacted] airport monitor the system with movie cameras and system measurements. As soon as the failure is detected by [redacted] airport, the control room employees call the VI team leader. The team leader takes the decision to send someone to the location of the failure by considering the kind of failure, the availability of people and the location of each person. After a repair, an analysis of the cause of the failure is done to enhance the system. This team leader has to respect the reactivity criteria set by the customer and take into account the priority specified by the airport in the control room. The process of intervention is presented in figure 9.

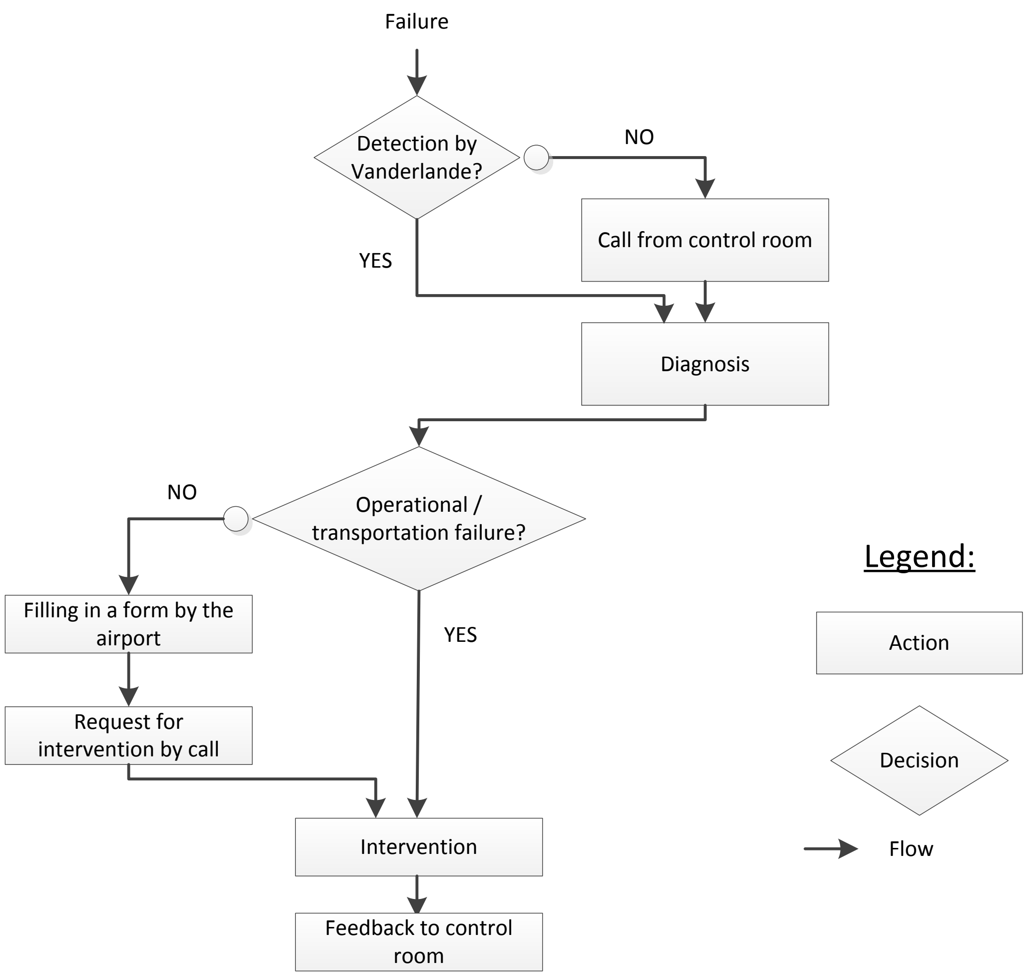


Figure E.1: The process of intervention for corrective maintenance

Appendix F - Variation of intervention rates at [redacted] airport

In Figure 1, we can see the fluctuations of the mean number of interventions per day during the week. Tuesday and Wednesday are known by all the employees as the days where there are not lots operations to do.

[redacted]

Figure F.1: Mean number of interventions per day of the week (March 2011 - March 2012)

Figure 2 points out the increase of traffic during Summer holidays. That causes the increase of interventions.

[redacted]

Figure F.2: Number of baggage and number of intervention per 1000 bags per month (March 2011 -March 2012)

Appendix G - Non stationary Poisson Processes

The following definition is given by Law and Kelton (2000), page 377:

Let $\lambda(t)$ denote the arrival rate of customers at time t.

The stochastic process $\{N(t),\ t \geq 0\}$ is said to be a nonhomogeneous Poisson Process with intensity function $\lambda(t)$ if:

1. $N(0) = 0$
2. $N(t + s) - N(t)$ is independent of $\{N(u), 0 \leq u \leq t\}$
3. For each t > 0, $N(t)$ has a Poisson distribution with mean $\Lambda(t) = \int_0^t \lambda(t)dt$

Appendix H – Estimation of the parameters of Gamma distribution with the minimum, the mode and the mean

The Gamma distribution is widely used for describing the distribution of times to repair failure. The probability density function of a gamma distribution is given by:

$$f(x) = \begin{cases} \frac{\theta^{-k}}{\Gamma(k)}(x-a)^{k-1}e^{-\frac{(x-a)}{\theta}} & \text{if } x \geq a \\ 0 & \text{else} \end{cases} \quad \text{where} \quad \Gamma(z) = \int_0^{\infty} t^{z-1}e^{-t}dt$$

where $k > 0$ is the shape parameter and $\theta > 0$ is the scale parameter and a the minimum

The probability density function for the Gamma distribution is shown in Figure H.1 for several different values of k and θ.

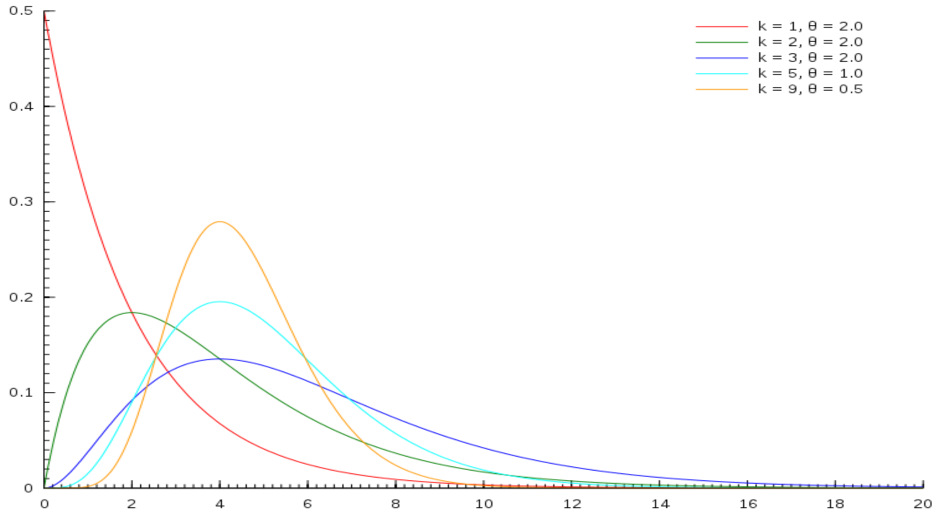


Figure H.1: For different values of k and θ the Gamma distribution takes different shapes (a = 0)

The mean is equal to:

$$E[x] = k\theta + a$$

For $k > 1$, the mode, i.e. the most likely value:

$$m = (k-1)\theta + a \qquad \text{for } k > 1$$

For repair time, the distribution is skewed to the right, i.e. the expectation is not below the most likely estimate $E[x] > m$ which is well accepted by the maintenance managers.

And we can therefore write k and θ as a function of E[x] and m:

$$\theta = E[x] - m > 0$$

$$k = \frac{E[x] - a}{E[x] - m} > 1$$

Finally, the parameters of the Gamma distribution can be easily estimated as a function of the mean E[x], the mode m and the minimum a which are well-known parameters by the maintenance managers and can be easily recovered.

Appendix I - Entities of the simulation

a) Java Code to define the object "Failure":

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

b) Java Code to define the object “Employee”:

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

c) Java Code to define the object "Team":

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

d) Java Code to define the object “Queue”:

[redacted]

[redacted]

e) Java Code to define the object "Source":

[redacted]

[redacted]

f) Java Code to define the object "Airport":

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

Appendix J – Random generators

a) Java code of Gamma generator

As assumed in Chapter 4, the repair time of failure is assumed to follow a Gamma distribution. The inputs of the Gamma distribution are the minimum a, the scale parameter $b > 0$ and the shape parameter $c > 0$. The density function is:

$$f(x) = \begin{cases} \frac{b^{-c}}{\Gamma(c)}(x-a)^{c-1}e^{-(x-a)/b} & \text{if } d \geq a \\ 0 & \text{else} \end{cases} \quad \text{where } \Gamma(z) = \int_0^\infty t^{z-1}e^{-t}dt$$

There are three algorithms (Law and Kelton, 2000), depending upon the value of the shape parameter *c*.

Case 1: c < 1

Let $\beta = 1 + c/e$.

(1) Generate $U1 \sim U(0, 1)$ and set $P = \beta U_1$.

If $P > 1$, go to step 3; otherwise, go to step 2.

(2) Set $Y = P^{1/c}$ and generate $U_2 \sim U(0, 1)$.

If $U_2 \leq e^{-Y}$, return $X = Y$; otherwise, go back to step 1.

(3) Set $Y = -\ln[(\beta - P)/c]$ and generate $U_2 \sim U(0, 1)$.

If $U_2 \leq Y^{c-1}$, return $X = Y$; otherwise, go back to step 1.

Case 2: c = 1

Return $X \sim$ exponential (a, b).

Case 3: c > 1

Let $\alpha = 1/\sqrt{2c-1}$, $\beta = c - \ln 4$, $q = c + 1/\alpha$, $\theta = 4.5$, and $d = 1 + \ln\theta$.

(1) Generate two IID uniform variates, $U_1 \sim U(0, 1)$ and $U_2 \sim U(0, 1)$.

(2) Set $V = \alpha \ln[U_1/(1 - U_1)]$, $Y = ce^V$, $Z = (U_1)^2 U2$, and $W = \beta + qV - Y$.

(3) If $W + d - \theta Z \geq 0$, return $X = Y$; otherwise, proceed to step 4.

(4) If $W \geq \ln Z$, return $X = Y$; otherwise, go back to step 1.

The Java code of this algorithm is presented below:

```
	void gamma( double a, double b, double c ) // a = minimum ; c = alpha ; b = 
lambda
	{
		assert( b > 0. && c > 0. );
		double A = 1. / Math.sqrt( 2. * c - 1. );
		double B = c - Math.log( 4. );
		double Q = c + 1. / A;
		double T = 4.5;
		double D = 1. + Math.log( T );
		double C = 1. + c / Math.exp(1);
		boolean condition = false;
		if ( c < 1. ) {
			while ( condition == false ) {
				double p = C * Math.random();
				if ( p > 1. ) {
					double y = -Math.log( ( C - p ) / c );
					if ( Math.random() <= Math.pow( y, c - 1. ) ){
						repairTime = a + b * y;
						condition = true;
					}
				}
				else {
```

```
                        double y = Math.pow( p, 1. / c );
                        if ( Math.random() <= Math.exp( -y ) ){
                            repairTime = a + b * y;
                            condition = true;
                        }
                    }
                }
            }
            else if ( c == 1.0 ) repairTime = a - b * Math.log(Math.random());
            else {
                while ( condition == false ) {
                    double p1 = Math.random();
                    double p2 = Math.random();
                    double v = A * Math.log( p1 / ( 1. - p1 ) );
                    double y = c * Math.exp( v );
                    double z = p1 * p1 * p2;
                    double w = B + Q * v - y;
                    if ( w + D - T * z >= 0. || w >= Math.log( z ) ){
                        repairTime = a + b * y;
                        condition = true;
                    }
                }
            }
        }
```

b) Java code of NNHP generator

The technical failures are generated following a Poisson process with rate λ. We generate time between failures with a generator of random number following an exponential distribution:

(1) Generate $U \sim U(0, 1)$
(2) Return $X = a - b \ln U$

The generation of the non-stationary Poisson process is less common and we used the method proposed by Lewis and Shedler (1979), known as thinning. For this algorithm, we consider λ^* = max $\lambda(t)$, the "peak" arrival rate. The principle of the algorithm is to generate "trial" arrivals at the (too-rapid) rate λ*. For a "trial" arrival at time t, we accept it as a "real" arrival with probability λ(t) / λ*. The algorithm is given as follows (Code in Appendix J.b).:

1. Set $t = t_i - 1$
2. Generate U_1, $U_2 \sim$ U (0,1) independently
3. Replace t by $t - (1 / \lambda^*) \ln U_1$
4. If $U_2 \leq \lambda(t) / \lambda^*$, set $t_i = t$ and stop; else go back to step 2 and go on

```
double NHPPGenerator(double date, double[] pattern){

    double max = 0;
    boolean find = false;

    for (int j = 0; j < pattern.length; j++){
        if (pattern[j] > max){ max = pattern[j]; }
    }

    while (find == false){
```

```
                    date = date - Math.log(Math.random()) / (max *
expectedNbFailures / 60);
                    int b = (int)(date / 60);

                    if (b >= pattern.length){ break; }
                    if (Math.random() < (pattern[b] / max)){
                          find = true;
                    }
              }
              return date;
       }
```

c) Java Code to determine failure characteristics

After we create a failure, its characteristics are attributed with the probability given as inputs. We use the spatial distribution to attribute the location to the failure and the probability to be critical to determine the urgency of the failure. The code is presented below:

```
       int determineLocation(){
              int location = 0;

              double[] frequenciesTable=new double [spatialDistribution.length+ 1];
              frequenciesTable[0] = 0;
              for (int i = 1; i <= spatialDistribution.length; i ++){
                    frequenciesTable[i] = frequenciesTable[i-1] +
spatialDistribution[i-1] / 100;
              }

              double p = Math.random();
              for ( int i = 0; i < spatialDistribution.length; i++ ){
                    if ( frequenciesTable[i] <= p && p < frequenciesTable[ i+1 ] ){
                          location = i;
                          break;
                    }
              }

              return location;
       }


       int determinePriority(int location){
              int priority = 0;

              if (Math.random() > tableAreas[location].criticality/100){
                    priority = 1;
              }

              return priority;
       }
```

Appendix K – Simulation logic

a) General Simulation Logic

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

b) Java Code of the initialization

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

c) Java Code of the generation of failures

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

d) Java Code of the simulation run

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

e) Java Code of the routine for the arrival of a failure

[redacted]

f) Java Code of the routine for the employee management

[redacted]

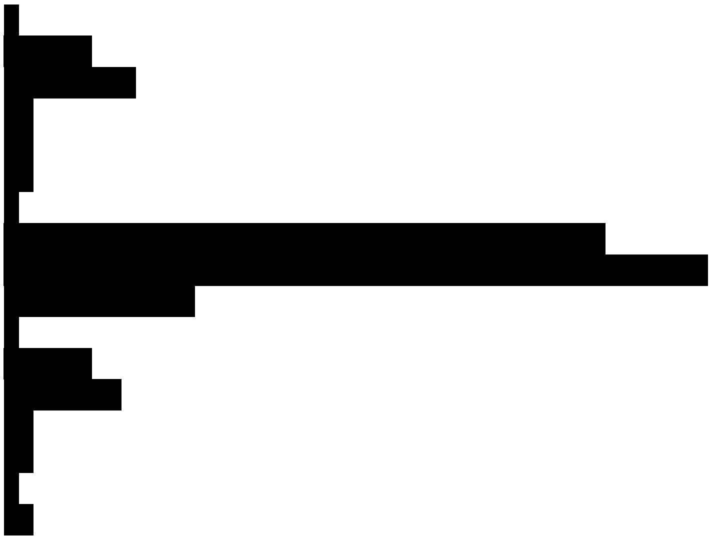
[redacted]

[redacted]

[redacted]

g) Java Code of the routine for the schedule shift

[redacted]



Appendix L – Optimization code

a) Java code of the initialization

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

b) Java code of the greedy algorithm

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]