Aalto University
School of Science
Master's Programme in Mathematics and Operations Research

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Discrete-event simulation of an automated guided vehicle system in a Finnish hospital

Master's Thesis
Espoo, May 27, 2022

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ABSTRACT OF MASTER'S THESIS

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Oulu University Hospital (OUH) is considering a partial replacement of a human-based material transportation system with an automated guided vehicle system (AGVS) in the interior parts of the hospital. Before the investment decision is made, however, it is useful to evaluate the feasibility of the superseding system. The research objective of this thesis is to study the operational feasibility of the proposed AGVS at OUH. Feasibility is studied through a discrete-event simulation model (DES) by analyzing system performance in 22 system configurations that differ in input data and parameters.

The conclusion of the results is that the proposed AGVS is operationally feasible in fleet sizes in the range of 26-32 vehicles. The feasible range is bound from below by delivery time requirements and it is bound from above by elevator waiting time requirements. The results also show how sensitive model output is to certain type of input changes. The sensitivity information and other findings presented in this thesis can be useful in possible further design of the system.

Keywords:	discrete-event simulation, automated guided vehicle, logistics, hospital
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DIPLOMITYÖN TIIVISTELMÄ

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Oulun yliopistollinen sairaala (OYS) pohtii ihmistyövoimaan perustuvan materiaalin kuljetusjärjestelmän osittaista korvaamista automaattitrukkijärjestelmällä sairaalan sisätiloissa. Ennen päätöstä järjestelmäinvestoinnista, on kuitenkin hyödyllistä arvioida korvaavan järjestelmän käyttökelpoisuutta. Tämän työn tavoitteena on tutkia ehdotetun automaattitrukkijärjestelmän operatiivista käyttökelpoisuutta OYS:ssa. Käyttökelpoisuutta tutkitaan tapahtumapohjaisella simulointimallilla analysoimalla järjestelmän suorituskykyä 22 järjestelmäkonfiguraatiolla, joiden syötetiedot ja parametrit eroavat toisistaan.

Johtopäätös tuloksista on, että ehdotettu automaattitrukkijärjestelmä on operatiivisesti käyttökelpoinen, kun trukkien määrä on 26-32. Käyttökelpoista määrää rajoittaa alhaalta toimitusaikavaatimukset ja ylhäältä sitä rajoittaa hissin odotusaikavaatimukset. Tuloksista selviää myös, kuinka herkästi mallin tulosteet muuttuvat tietyntyyppisillä muutoksilla syötteissä. Näistä herkkyystiedoista ja muista tämän työn tuloksista voi olla hyötyä mahdollisessa tarkemmassa järjestelmän suunnittelussa.

Asiasanat:	tapahtumapohjainen simulointi, automaattitrukki, logistiikka, sairaala
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The collaboration with the health care specialists at Oulu University Hospital was instrumental during the simulation study concerning the topic of this thesis. I would also like to acknowledge my colleagues at EP-Logistics and the company in general. The opportunities to create meaningful simulations of real-world systems have allowed me to learn the tools and knowledge essential for writing about the topic.

Espoo, May 27, 2022

Aleksi Pasanen

Abbreviations and acronyms

AGV	automated guided vehicle
AGVS	automated guided vehicle system
DES	discrete-event simulation
FIFO	First In, First Out
MABS	Multi-agent based simulation
OUH	Oulu University Hospital

Contents

Chapter 1

Introduction

The facilities of Oulu University Hospital (OUH) are at the end of their lifetime, which is why Northern Ostrobothnia Hospital District launched the Future Hospital 2030 program in 2012. The objective of the renewal program is to improve productivity and treatment effectiveness and to update the facilities of Oulu University Hospital to respond to the needs of the future. Future requirements must be supported by the logistics systems as well. The renovation project presents an opportunity to consider alternative material handling systems because the new facilities can be designed to support these systems. (Northern Ostrobothnia Hospital District, 2019)

Today, many types of material are transported by logistic workers in the interior parts of the hospital. The workers mostly operate towing tractors but some items must be delivered by hand. An automated guided vehicle system (AGVS) transporting material inside the hospital could reduce the need for towing tractors and improve delivery performance within the hospital. It is important to study if such a system is useful before it is invested in. Therefore, the feasibility of an AGVS at OUH is studied in this thesis.

1.1 Research objective

The research objective of this thesis is to study the operational feasibility of the proposed automated guided vehicle system for internal logistics at Oulu University Hospital. The purpose of the study is to ensure that the system is able to handle realistic loads. Feasibility is studied through a discrete-event simulation (DES) model by analyzing system performance in different system configurations. This involves sensitivity analysis on various system parameters and seeking the feasible fleet size range.

The simulation model used in this feasibility study is specifically built to represent the proposed system. Therefore, the principles of the model built for the research problem are thoroughly explained. Likewise, the theory on discrete-event simulation that is discussed in this thesis focuses on model building.

1.2 Existing approaches

Since the first automated guided vehicles (AGV) were deployed in a hospital in 1988, many studies have analyzed the feasibility of AGV systems in other health care facilities (Kirschling et al., 2009). A generic answer to the problem does not exist because facilities are different in a number of ways. The possible vehicle path topologies depend greatly on the size and layout of the facility. Financials and company policies also impose requirements and constraints, which may not apply at another site. Therefore, each facility must be evaluated individually.

Many methods to study AGVS feasibility have been employed. Naturally, simple systems can be studied using analytic methods. According to Ilić (1994), fleet size in simple cases can be estimated based on hourly round trips that vehicles make. However, even a manufacturing plant system can potentially be studied using analytic methods. Ji and Xia (2010) propose an approximate analytic method for minimizing the required fleet size in a steady state manufacturing system. Some AGV systems do not have a clear steady state, though. For example, hospitals may have a varying load throughout the day with different types of items being transported at different times. This behavior is further discussed in Chapter 3. Complexity like that is one of the reasons why simulation based methods are typically used in AGVS studies.

Discrete-event simulation appears to be the most prominent simulation-based approach used to study AGV systems. Rossetti and Selandari (2000) studied the feasibility of replacing a human-based delivery system with an AGVS at The University of Virginia Hospital. Based on the results of their DES models, the vehicles would significantly improve delivery variability at the expense of slightly worse average performance and elevator waiting times. Other simulation approaches have been presented in literature as well. For instance, Lawrence Henesey1 and Persson (2009) evaluated the efficiency of an AGVS at a container terminal through a multi-agent based simulation (MABS) model. They find that MABS allows fine granular control of entities, which can be useful in situations that involve different types of vehicles and the coordination of their activities is essential.

The feasibility of an AGVS can also be shown through optimization. For example, Kasilingam (1991) proposes an integer programming model to minimize the total system cost. Simulation-based optimization is also a valid approach in designing of an AGVS based on Gosavi and Grasman's (2009) research.

In addition to mathematical modeling studies, the feasibility of AGV systems has been evaluated using empirical methods. The feasibility of an AGVS for medication delivery at The University of Wisconsin Hospital and Clinics was determined using a pilot system with two vehicles. The decision not to expand the pilot system was based on data collected during a 125-day pilot phase. The collected data included technical and performance observations as well as surveys, which measured the delivery quality perceived by the staff. (Kirschling et al., 2009)

1.3 Structure of the thesis

The structure of the thesis is as follows. In Chapter 2, the principles of building a DES model are discussed. The problem setting and automated guided vehicles systems are discussed in Chapter 3 and the principles of the simulation model built for the research problem are explained in Chapter 4. In Chapter 5, the simulation scenarios are presented and their results are analyzed. Chapter 6 summarizes the findings and presents conclusions of the thesis as a whole.

Chapter 2

Building a discrete-event simulation model

Building a DES model is a challenging task. For the best results, it is important to understand both the problem setting and the intricacies of the simulation method. This thesis has an emphasis on the model building part in a simulation study. Therefore, this chapter discusses principles of building a DES model. The same principles are applied on the model presented in Chapter 4. The first section of this chapter describes the overall process of building DES models. The rest of the sections drill down to individual parts of this process.

2.1 Model building process

The steps and the flow of a typical model building process are visualized in Figure 2.1. As the flow chart shows, model building is an iterative process. The simulation expert is required to constantly evaluate the work done until the model is considered an adequate representation of the system. (Law, 2013)

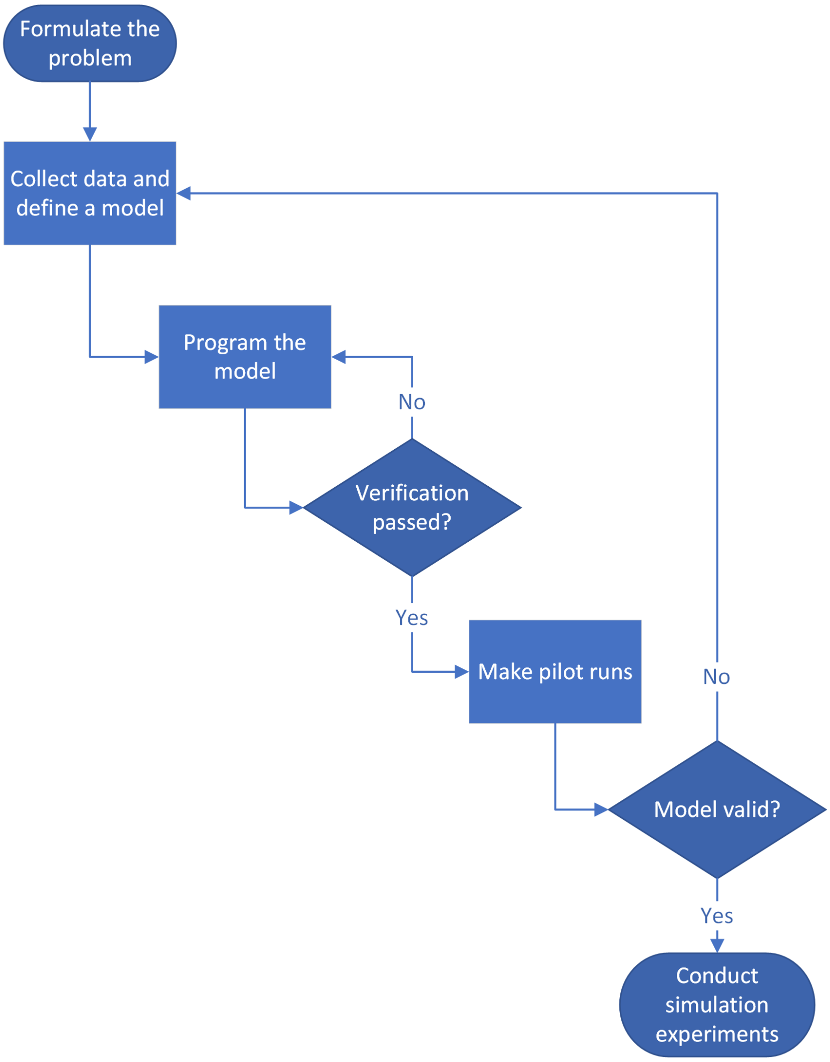


Figure 2.1: Steps in a simulation model building process based on Law's (2013) steps in a simulation study.

After the problem is formulated sufficiently, the first step in model construction is data collection and model definition. The purpose of the first step is to decide which parts of the system are modeled and how they are modeled considering the objectives of the study. Ideally, all the data is obtained before programming the computer model has started. In practice, however, programming may have to be done in parallel with data collection to save time or cost because of challenges in obtaining some information quickly enough. It may also be difficult to predict all the types of data that should be collected before hand. (Law, 2013)

The defined model is computerized using a programming language or a simulation software. The programmed model is verified to ensure it matches the conceptual model. The verified model is then used to make pilot runs whose purpose is to provide data for model validation. (Law, 2013)

Ideally, the model is complete before simulation experiments are conducted. However, results from production runs can generate new ideas and cause changes in requirements. Thus, the model may have to be revised even after simulation experiments have begun.

2.2 Modeling stochastics

Systems often include elements that are inherently stochastic. Analytic methods can be employed to analyze the output of simple stochastic systems. However, if the system has many stochastic elements with different characteristics, analytic models can be difficult to construct. Discrete event simulation is a powerful tool for analyzing such systems numerically.

It can be challenging to choose which elements should be modeled as random distributions. Selecting the distributions and their parameters correctly is important for valid results. If the system exists, the distributions can possibly be inferred experimentally. Sometimes the system being analyzed does not exist. For example, feasibility studies are often conducted before investment decisions. In such cases, prior information about similar systems can be used. Another approach sometimes employed is the use of informed guesses from experts in the field. (Law, 2013)

2.3 Verification

The purpose of verification is to ensure that the model is programmed correctly and the behavior is in accordance with the conceptual model (Law, 2013). There are many applicable methods for verifying a simulation model. The methods include model review by an expert, output reasonability testing and debugging. These techniques are similar to what is used in software verification and in fact, many software verification techniques apply for simulation model verification. Verification is made easier by including assertions and logging in the program.

2.4 Validation

The purpose of validation is to ensure that the model represents the actual system with the required accuracy. There are many decision-making approaches for determining whether a simulation model is valid. It is highly subjective which approach is the best for a particular situation. A frequently used approach is that the development team validates the model itself during development. If the users of the model are not part of the development team, they can also be involved with the developers in determining the validity. Alternatively, an independent third party can be tasked with making the decision whether the model is valid. Involving people outside the development team improves model credibility, though it may increase project cost. (Sargent, 2011, p. 184-185)

There are many techniques to evaluate the validity of the model and the data used by the model. If the system exists, it may be possible to compare the output of the model to the output of the actual system. Other available valid models, such as analytic models, can also be compared to the simulation model. While animation and graphical measures are often used in model verification, they can also assist in validation. Graphics can be especially powerful when validation is required from parties that are not involved in the technical part of the study. Other validation techniques include tracing individual entities in the system, empirical assumption validation, output consistency evaluation and historical data validation. (Sargent, 2011, p. 186-188)

Since every simulation model is only an approximation of the actual system, there is always a certain level of uncertainty in model validity. The members of the simulation project decide the required confidence level for the model validity and choose the used validation approach and techniques accordingly. The validity confidence level must be taken into account when the simulation results are interpreted and presented.

2.5 ProModel

Various tools can be used for building DES models. These include general purpose languages and simulation software. In this thesis, the simulation model of the AGV system is developed using ProModel 2018 software. ProModel provides facilities for building discrete-event simulations. The tools are specifically designed to assist in modeling manufacturing and logistics systems. Simple systems can be modeled entirely by combining parts from the set of included modeling elements. The user can also write custom functionality using a fairly simple built-in programming language. Complex logic can also be included by invoking external subroutines written in a general purpose language such as C++. (ProModel Corporation, 2019)

ProModel can read external data from Excel spreadsheets, SQL databases and ASCII files. The user can observe the system state through animation while the simulation is running. The data collected during simulation runs can be analyzed, compared and visualized using the included Output Viewer. ProModel is also capable of exporting results to Excel spreadsheets for advanced analysis. Additional data can be written to files during simulation runs using the built-in programming language. (ProModel Corporation, 2019)

Ideally, the simulation tool does not affect modeling decisions. The capabilities of simulation tools are not the same for all simulation tasks, however. In practice, the model is designed in a way that enables efficient development of a reasonably accurate model using the tools available. Therefore, tool selection is a compromise between cost, development time, and model accuracy. The simulation model presented in this thesis is designed using the elements and methods typical in ProModel simulations. Thus, the nomenclature is also similar to what is used in the software.

Chapter 3

Automated guided vehicle system in a hospital

An automated guided vehicle is a self-driving vehicle used in material handling. AGVs are often used to transport material in industrial buildings, such as manufacturing plants and warehouses. But AGVs have uses outside industry, too. For example, this thesis considers the use of these vehicles in a health care facility. AGV systems and equipment are discussed in this chapter. The operational environment is also described.

3.1 Automated guided vehicles

There are many types of automated guided vehicles available and the suitable type depends on the application and the transported material. A distinctive difference between AGV types is the method of material storage during transportation (Tzafestas, 2013, Section 15.2). For example, AGVs in a warehouse may transport pallets directly, while another application requires items to be stored inside a container during transportation (Ferrara et al., 2014). The assumption is that the preferred method of material storage during transportation at OUH is to use carts. There is an example of an AGV designed for transporting carts in Figure 3.1. The cart in the example is closed but open carts are used as well. The suitable cart type depends on the stored material. For instance, certain pharmaceuticals may require closed carts with locks to prevent unauthorized access to the substances.

Figure 3.1: An automated guided vehicle transporting a cart and another vehicle traveling empty at Päijänne Tavastia Central Hospital in 2010. The image is cropped from the original picture taken by Petri Niemi (2010). Copyright permission is granted by EP-Logistics Ltd.

A basic automated guided vehicle system consists of a number of vehicles, a route network, a system controller and system users. The system users schedule material transport orders and handle exceptional situations, such as vehicles getting stuck. The controller allocates vehicles to tasks issued by the users. Additionally, the AGVS can be integrated with other material handling systems, such as elevator groups or automated storage systems (Ferrara et al., 2014). Many facilities also require doors to be electrified and integrated in the system so that AGVs can pass through them.

3.2 Oulu University Hospital

Oulu University Hospital is a university hospital part of the Northern Ostrobothnia Hospital District. Its layout is shown in Figure 3.2. The proposed automated guided vehicle system handles material in the four adjacent buildings shown in the layout. Buildings A and B have 12 floors. Some of the floors in these two buildings contain wards for patient care. Material required in every floor of building A and B are supplied from support services in building D and pharmacy in building C. These are located in the lowest floor. The support services include food terminal, laundry terminal, medical aid maintenance and waste depot. The material transported via these locations are discussed in the next section.

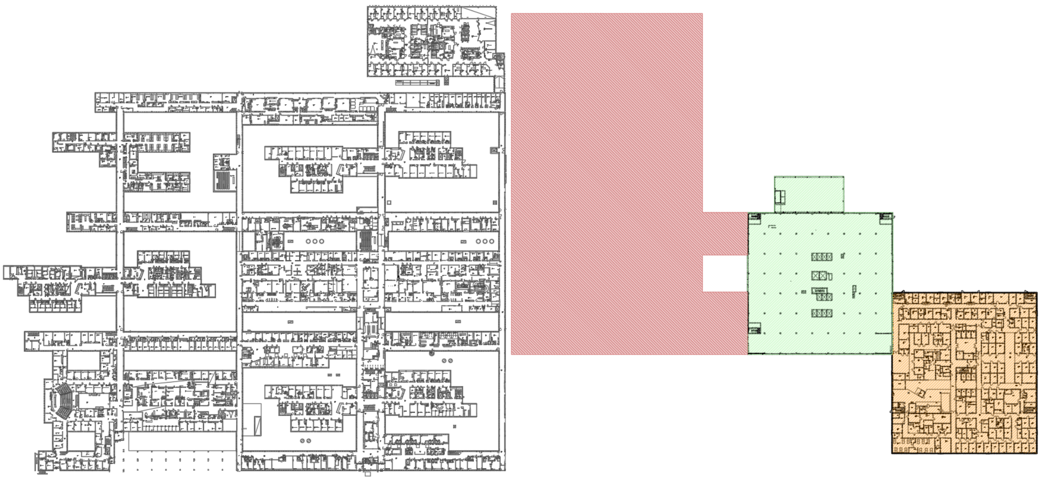


Figure 3.2: Layout of Oulu University Hospital. The four distinct buildings are A(yellow), B(green), C(red) and D buildings from right to left.

3.3 Transported material

The materials that are planned to be handled by the AGVS are food, laundry, warehouse inventory, medical aids, pharmaceuticals and waste. All of these are stored in carts during transportation, which means that AGVs do not directly handle the items inside the carts. Packing and unpacking of carts is performed by the staff.

Certain types of items must be delivered at designated times of the day. For example, breakfast is delivered in the morning, lunch at noon and dinner late afternoon. The allowed window for food deliveries can be fairly short, between one to two hours. Figure 3.3 presents the estimated daily number of carts moved by item type. As shown in the figure, food deliveries constitute a major part of the total daily logistics. They are expected to cause a noticeable spike in the AGV system load unless some other deliveries are scheduled outside food shipment delivery windows. For example, waste are scheduled for delivery after office hours in the baseline load that is used in most of the simulation scenarios studied in this thesis.

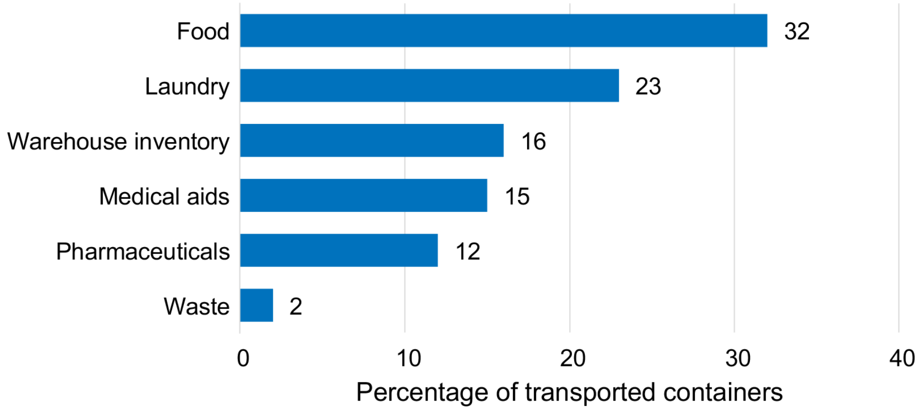


Figure 3.3: The estimated distribution of carts transported by item type. Both inbound and outbound deliveries are included. For example, the percentage of laundry carts includes both clean and dirty laundry.

3.4 Feasibility of the system

The proposed AGVS may assist in fulfilling the needs of Oulu University Hospital in the future. It is thus important to study if this type of system can handle the required loads at the hospital. As stated in the Introduction, the objective of this thesis is to study the feasibility of the proposed system. Since the system does not exist, its performance cannot be studied experimentally. The proposed system is also too complex to study analytically within a reasonable amount of time. Hence it is analyzed using a discrete-event simulation model. Multiple scenarios with different system configurations are simulated and their output are analyzed. The principles of the simulation model are discussed in the next chapter and the results are presented in Chapter 5.

Chapter 4

Simulation model of the automated guided vehicle system

Chapter 2 discusses the key parts of building a discrete-event simulation models. The same principles are used for constructing the model detailed in this chapter. However, the model is built and run using ProModel software, which is why modeling decisions are affected by what is possible and typical in ProModel simulations.

The overview of the model is presented in Section 4.1. Control logic and the elements that comprise the system are discussed in Section 4.2. Finally, Section 4.3 explains how the model is verified and validated.

4.1 Model overview

The model representing the proposed AGVS at OUH is a stochastic discrete-event simulation model. The model reads input data, takes parameters and running the model results in an output report containing statistics collected during the execution. The overview of the inputs and outputs of the model are shown in Figure 4.1.

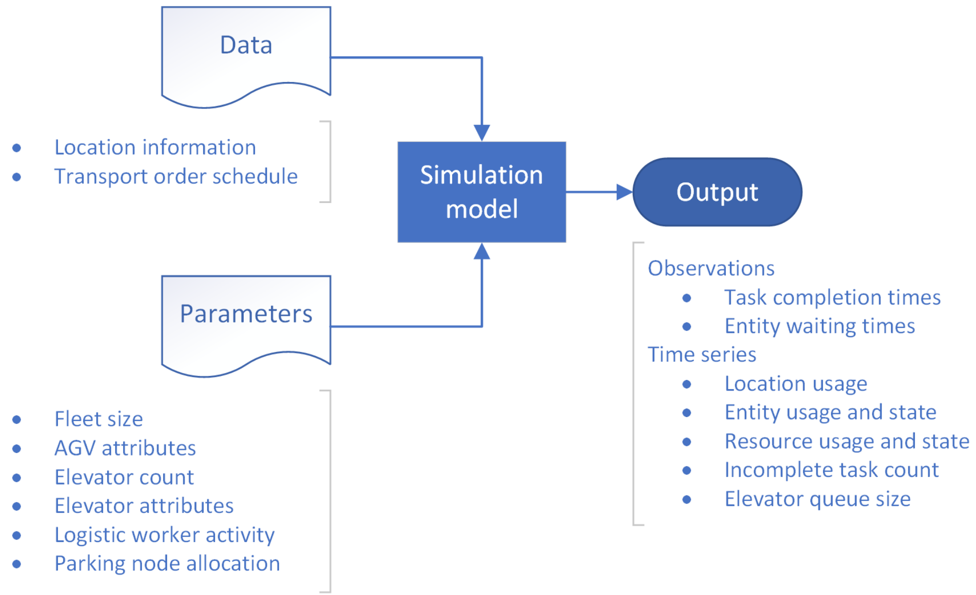


Figure 4.1: Overview of model inputs and outputs.

The model reads input data from external Excel sheets. This includes location information and a transport order schedule, which represents the typical daily workload concerning the AGVS. The system behavior and physical attributes can be adjusted using a number of parameters. For instance, the fleet size parameter determines the number of AGVs, which affects delivery capacity.

Running the model simulates a scenario that is defined by model input. Each scenario represents a potential configuration and daily workload of the system. The flow of a scenario is shown in Figure 4.2. Each scenario consists of a number of replication runs. Since the order and the number of events at the hospital vary daily, each replication is a possible realization of events in one single day. Therefore, multiple replications improve statistical significance of the results.

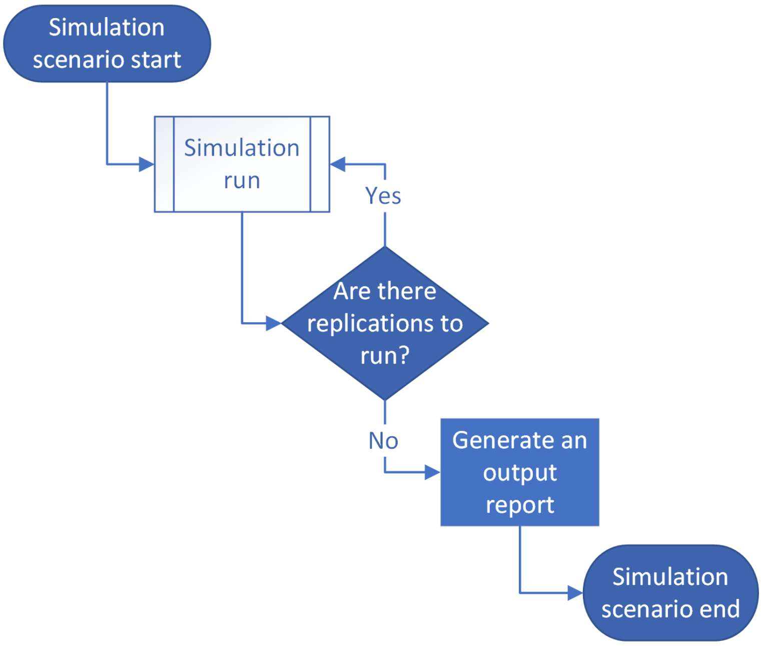


Figure 4.2: Flow of a simulation scenario in the AVGS model.

At the end of the scenario simulation, an output report is generated. The report contains all the data collected in the replication runs. The data includes observation based measurements and time series of select variables. The report also provides statistical quantities. For example, the average cart delivery time over the replications is included in the report.

Some simulation models end the simulation run based on system state. In this model, however, every replication begins at 2.00 and ends at 2.00 the next day. What happens during the run is illustrated in Figure 4.3. In the beginning, the model is initialized using input data and parameters. The initialization procedure also generates system controller entities that manage system state. Once the initialization is done, the system controllers begin generating carts and logistic workers. These physical entities are transported from one location to another. Once 24 hours of simulation time has passed, the model saves collected statistics and the run ends.

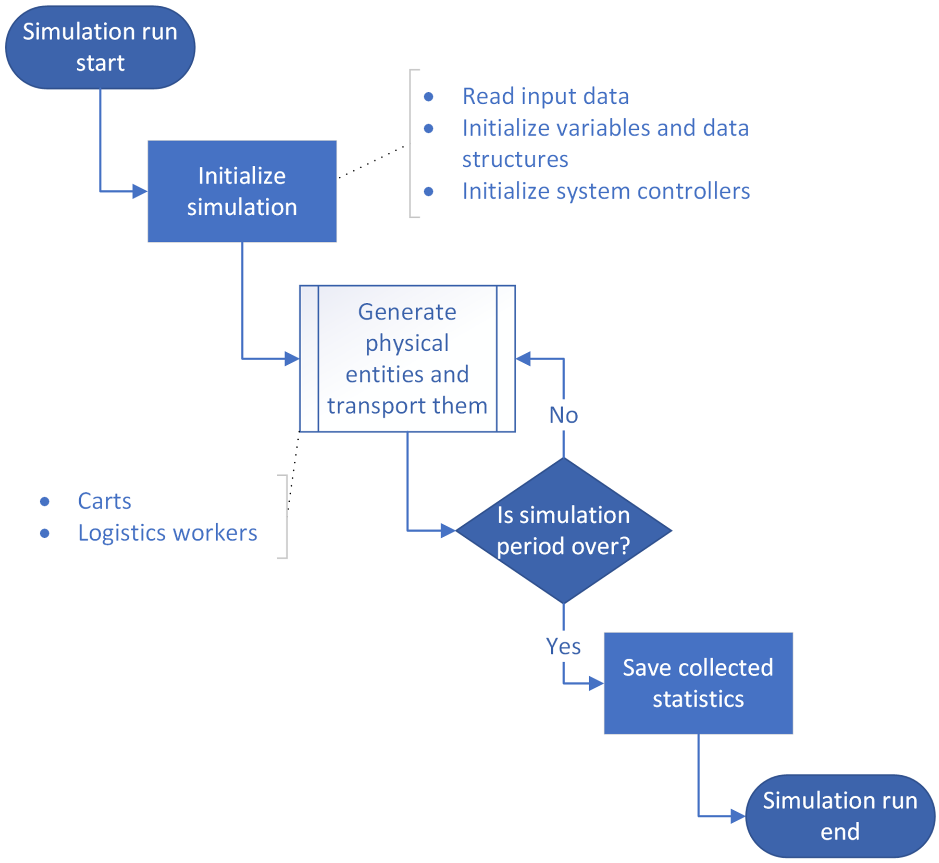


Figure 4.3: Flow of a replication run in the AGVS model.

As described above, the model transports carts and logistic workers between locations and tracks how well this is performed using observation and time series based variables. The lifetime of transported entities begins with their creation. Once created and placed to a source location, the next available resource collects the entity and starts its transportation. The resource transports the entity through a path network to the destination, after which the entity leaves the system. For example, AGV resources transport carts between cart processing locations through a network approximating the physical topology of the hospital. The next section describes the transported entities in more detail and discusses the parts of the model that are involved in their processing.

4.2 Model structure

4.2.1 Entities

Every object that requires processing is modeled as an entity. Entities trigger processes when they enter locations and can use resources to perform work and move between locations. They do not necessarily exist in the system for the whole duration of the simulation. An entity created in the system always arrives to a location, which triggers the initial processing. The processing can include work performed on the entity or waiting, for instance. Once the processing at the location is complete, the entity can be routed to another location. The entity can exit the system if further routing is not necessary. (ProModel Corporation, 2018)

While entities are naturally suited for modeling physical objects such as carts transported by AGVs, they can also represent abstract objects like system controllers that manage system state. For example, controllers can generate other entities or send information to other parts of the system. The model in this thesis includes both physical and abstract entities.

Material is stored inside carts for transportation using AGVs at OUH. Carts are modeled as entities, which are processed at the locations they visit. A newly created cart is placed to a location and it is given a list of destinations to visit. The creation triggers a search for an available AGV that would transport the cart through the destinations. Once the cart arrives at the final destination, the AGV drops it off and the cart exits the system.

There can be multiple types of carts available at the hospital. Some items, such as pharmaceuticals, may have to be transported in closed and locked containers, while other items only require open containers. However, the model considers all carts equal, because the effect of cart type is considered negligible. It is also assumed that there are always enough applicable carts available at the locations they are generated at. Cart generation logic is discussed in Section 4.2.5.

The model animation shows carts as long as the they exist in the system. As shown in Figure 4.4, a cart waiting for a pickup is displayed as a grey box. Once a vehicle picks it up, the vehicle is shown transporting the cart.

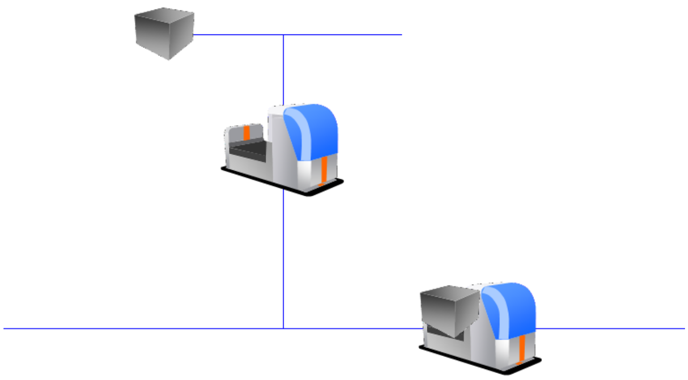


Figure 4.4: An empty AGV (the left one) traveling to pick up a cart in pharmacy and a full AGV (the right one) traveling to drop off another cart to its destination during a simulation run.

The logistic elevators at OUH lift AGVs and logistic workers. The AGVs are modeled as resources that transport carts. However, ProModel does not support resource transportation using other resources. Therefore, transporting AGV resources using elevators is not possible. That is why elevator transportation for AGVs is tracked using dummy AGV entities, which are created whenever AGV resources request a lift to another floor. The logic used for generating these dummy entities is discussed in Section 4.2.5.

Since some items cannot be transported by AGVs alone, the effect of logistic workers is also considered. AGVs and logistic workers share the same freight elevators for inter-floor transportation, which can increase the delivery time for AGVs. Other effects from workers are considered insignificant. Logistic workers are modeled as entities similar to dummy AGVs because their sole purpose is to model their elevator usage. The workers are lifted by elevators essentially in the same way as AGVs although workers are able to enter and exit the elevator faster than AGVs. Figure 4.5 shows how AGVs and workers using elevators can be identified in the animation while the simulation is running.

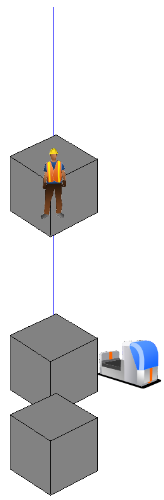


Figure 4.5: A logistic worker being lifted by an elevator and an AGV entering another elevator during a simulation run. The grey cubes model elevator resources.

To initialize the simulation, a system controller entity arrives in the system the moment the simulation run is initiated. Its arrival begins the initialization process, which sets up the initial system state. At the end of the initialization phase, the system controller creates two elevator controllers, one for building A and one for building B. Once the initialization phase is complete, the role of the system controller is to generate carts for AGVs to pick up while the elevator controllers generate elevator freight entities. Entity generation logic and other control policies are explained in Section 4.2.5.

4.2.2 Locations

Locations represent areas that entities can be processed or stored at (ProModel Corporation, 2018). The areas that AGVs pick up and drop off carts in are represented by cart processing locations in the model. There is also an elevator lobby location in immediate proximity to both elevator groups in buildings A and B on each floor. Since there are 12 floors in both buildings, there are 24 elevator lobbies in total. AGVs and logistic workers enter and exit elevators through these elevator lobbies.

Since the model includes controller entities, there is an abstract location that does not represent any physical location in the hospital. This abstract location is simply required for the creation and processing of the controller entities. The controller entities enter the location on simulation initialization.

It is assumed that the new buildings in the hospital can be designed to accommodate the spatial requirements of the system. Therefore, all locations in the model have unlimited maximum capacity for holding carts waiting to be picked up.

4.2.3 Resources

Resources model equipment that transports entities or performs operations on them (ProModel Corporation, 2018). There are two types of resources in the model, automated guided vehicles and elevators. The AGVs are responsible for picking up, transporting and dropping off carts. Elevators lift AGVs and logistic workers between floors in buildings A and B. One elevator resource represents an elevator cab and the associated shaft.

A moving AGV can either be transporting a cart or travel empty. The carried weight can affect vehicle speed in the real system. In this model, though, the vehicles are assumed to travel at a constant velocity at all times. This is considered accurate enough for a feasibility study because the objective is not to optimize the absolute performance of an existing system. Velocity and acceleration also depend on the AGV model and manufacturer. Similarly, the total weight of logistic workers and their freight can vary greatly because they might be walking or driving a towing tractor. Even though elevator acceleration depends on the lifted weight, the effect of lifted weight on elevator travel time is considered small. That is why velocity and acceleration of elevators are assumed constant as well.

ProModel supports static and dynamic resources. Static resources do not visibly move during the simulation run because they are not assigned to any path network. Once assigned to a path network, the resource becomes dynamic and can move along the network. All resources in the model are dynamic because AGV and elevator motion is modeled using path networks, as described in the next section. (ProModel Corporation, 2018)

4.2.4 Networks

The resources in the model travel between locations to transport entities. AGVs transport carts between processing locations while elevators lift AGVs and logistic workers in buildings A and B. Resource movement is modeled using path networks, which consist of nodes and path segments between the nodes. Resources assigned to the network travel along the path segments, which can be either uni-directional or bi-directional. Interfacing path nodes with locations also allows the resources to pick up and drop off entities at the locations assigned to the nodes. (ProModel Corporation, 2018)

Using a path network simplifies modeling resource movement because ProModel is capable of calculating optimal paths through the network. Resource control can also be automated using built-in rules for resource and entity selection, which are discussed in Section 4.2.5. Furthermore, the animation shows resources moving in the network, which can be used in model verification and validation. The model includes an AGV path network and two elevator shaft networks.

The AGV resources in the model are assigned to a single path network that is connected to all cart processing locations. The network, parking nodes and cart processing locations are shown in Figure 4.6. The bulk of the network is located on the corridors of the lowest floor. All cart processing locations in buildings C and D interface with the network on the lowest floor. The network also extends to logistic lobbies on all 12 floors in buildings A and B. Therefore, the AGVs sent from support services must travel through the lowest elevator lobbies to reach higher floors.

There are two nodes dedicated to vehicle parking on the lowest floor. One of them is located near support service locations in building D and the other one is located in building C. Idle AGVs park at these nodes. The parking logic is discussed in Section 4.2.5.

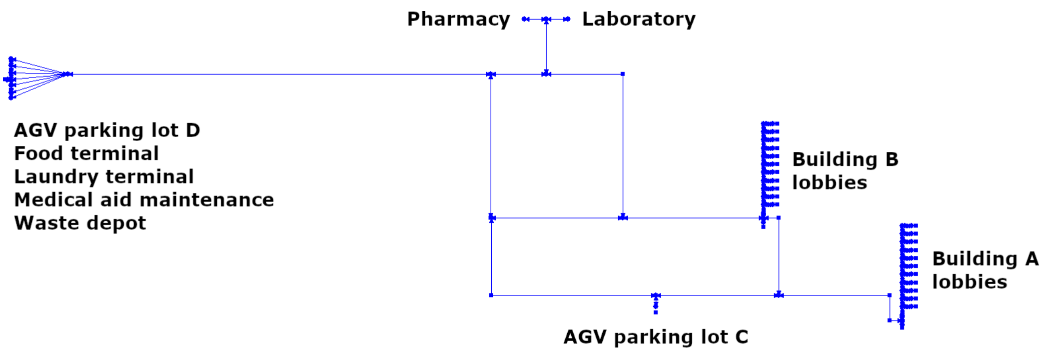


Figure 4.6: Network of paths that AGVs can travel on, parking nodes and locations that interface with the network. The dots represent nodes, which connect path segments.

A single unified path network enables sending AGV resources from any location to another. Each path segment is also specified with a distance, which allows vehicle selection for carts based on distance along the network. ProModel calculates optimal paths between nodes using these distances. Since the unified network connects all cart processing locations, the locations on different floors are also connected via the network.

In an automated guided vehicle system with fixed guide-paths, a deadlock may occur when two or more vehicles try to occupy the same space at the same time. However, the AGVs in this system are assumed to be free-ranging, meaning that they can select the appropriate route freely to reach their destination. Such AGVs constantly scan their surroundings, which allows them to go around obstacles and pass other vehicles. Therefore, deadlock situations are considered unlikely in practice. The free-ranging behavior is modeled using bidirectional path segments. Most of the paths used by the vehicles are wide enough for bidirectional traffic at the hospital, which is why the entire AGV path network is bidirectional for simplicity.

AGVs and logistic workers move between floors using elevators in the system at OUH. The elevators are resources that transport entities, which is why elevator shafts are modeled using path networks that the elevators can move on. There are two elevator groups at OUH, one in building A and another in building B. Thus, the model has two path networks representing elevator shafts. While each elevator requires its own elevator shaft in practice, controlling an elevator group is simpler using only one path network because the built-in resource and entity selection rules in ProModel can only be used within a single network. The used control rules are discussed in Section 4.2.5.

Figure 4.7 shows one of the path networks modeling an elevator shaft and an elevator resource assigned to it. There are also nodes that interface with elevator lobbies on each floor. The floor heights are identical in both networks.

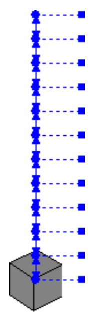


Figure 4.7: Elevator shaft and an elevator cab on the lowest floor. Freight entities enter and exit the elevators through the nodes on the right column.

4.2.5 Control

The system model consists of multiple integrated subsystems. AGVs transport material between locations and elevators enable the vehicles to switch floors. Additionally, logistic workers share elevators with AGVs, which affects AGVS performance. This section discusses control policies that model the behavior of these subsystems.

A typical automated guided vehicle system dispatches vehicles based on either a predefined schedule or transport orders issued on the fly. Modern systems are capable of mixing both types of dispatching rules. In a purely schedule based approach, an AGV begins a task at a designated time and visits all cart processing locations defined in the task. At each location, the AGV can wait for a cart to be transported up to a maximum waiting time. The vehicle continues to the next cart processing location after the maximum waiting time has passed. (Deery, 1997)

The schedule based approach can be useful for recurring deliveries. However, the approach also forces staff to adhere to the schedule. An AGV executing a scheduled task route will drive empty if the staff fail to supply carts in time at the locations the vehicle visits. A transport order based approach is more adaptive in this regard. Flexible vehicle dispatching is one of the AGV system requirements at OUH so that the staff can focus on the substance of their work as well as possible. Consequently, the vehicle dispatching process in the simulation model is based on transport orders that are generated on demand.

The simulation model takes a table of transport orders for one day as input. Each transport order represents demand for a number of carts to send from one location to another. Since the time of demand for containers will not be static every day, uncertainty in the order creation time is modeled by setting a possible order time interval for each order. For example, an allowed range for a breakfast transport order time might be from 6.00 to 7.00. A simplified example of a transport order table is shown in Table 4.1. Even though multiple containers can be included in a single order, each container is assumed independent of the other containers. Thus, batching multiple containers for similar deliveries merely simplifies the creation and management of the table. Containers and their order times are not truly independent in practice, though. For example, system users may order multiple containers to be transported at the same time to cover a large demand. The modeling inaccuracy is considered small, however.

Using the transport order schedule, the simulation model generates a detailed task schedule during the initialization of each simulation run. Since an AGV is capable of transporting no more than one container at a time, the model creates a task for each container in every transport order. As the containers are assumed mutually independent, the actual order time for each task is generated independently from uniform distribution $U(a, b)$, where a is the minimum order time of the task and b is the maximum order time.

For instance, $(a, b) = (6\text{ h}, 7\text{ h})$ for order number 1 in Table 4.1. A simplified example of a generated task schedule is shown in Table 4.2.

Table 4.1: An example of a container transport order schedule input to the simulation.

Order number	Order time interval	Number of carts	Source location	Target location
1	6.00-7.00	2	Food hub	Building A, floor 2
2	10.00-11.00	2	Food hub	Building A, floor 5
3	7.00-10.00	1	Building A, floor 3	Warehouse
4	11.00-16.30	1	Pharmacy	Building B, floor 6

Table 4.2: A possible realization of a container transport order schedule as defined in Table 4.1.

Order number	Task number	Order time	Source location	Target location
1	1	6.26	Food hub	Building A, floor 2
1	2	6.14	Food hub	Building A, floor 2
2	3	10.31	Food hub	Building A, floor 5
2	4	10.59	Food hub	Building A, floor 5
3	5	7.01	Building A, floor 3	Warehouse
4	6	11.00	Pharmacy	Building B, floor 6

Once a task is ordered in the simulation model, a cart is placed at the source location and the AGV controller needs to bind a vehicle to the task.

However, a vehicle cannot be assigned immediately at order time, if there are no vehicles available. Therefore, the cart is always placed in a FIFO queue. This means that the controller sends the next available vehicle to pick up the cart that has been waiting the longest. If there are multiple vehicles available, the controller selects the closest one. The metric used to calculate the distance is the smallest travel distance through the vehicle path network.

Using the simple FIFO queue method for cart selection eliminates some opportunities to optimize travel time. On the other hand, selecting always the cart closest to a vehicle could cause an extremely high waiting time for some carts. This cannot happen if there is always at least one vehicle immediately available and the elevators have enough lifting capacity. However, it is possible that all vehicles are in use during busy hours if the fleet is not overly large. Therefore, a FIFO queue is a safer choice.

An AGV without a task to execute must move to a parking lot. Otherwise, high volume locations might become filled with idling vehicles. Idle time is also an opportunity to charge the batteries at the parking lots. Since AGV movement is modeled using a path network in ProModel software, parking strategy can be modeled using a park search logic. Park search logic selects the parking node based on the current location of the AGV and free space in the parking nodes. (ProModel Corporation, 2018)

Each parking location has a maximum number of AGV slots. For simplicity, the total number of available slots is set equal to AGV fleet size. This allows all vehicles to park at the same time. It also equalizes the number of vehicles between the two parking nodes to some extent. Consider the case that there are 20 vehicles in the system and both parking nodes can hold 10 each. If parking node C is already full with 10 vehicles, other idling vehicles must travel to parking node D.

Once a vehicle completes its current task and no cart is waiting for pickup, the vehicle is released from further work and becomes idle. Parking node selection is primarily determined by the location the vehicle is released at. However, the desired parking location can be full, in which case the other parking node is selected. Park search logic in the model uses a static table that defines the primary node and the secondary for each possible release location. The release locations and parking node priorities are listed in Table 4.3.

For minimized immediate empty driving after becoming idle, the AGV should move to the closest parking station if possible. This is why idle vehicles are primarily forwarded to the closest parking node from most of the cart processing locations. The exceptions are pharmacy and laboratory, whose closest parking node is in building C. However, the difference between the distance from parking node C and D to these two locations is only 14 %.

Table 4.3: Park search table used to select the parking node for idle AGVs.

AGV release location	Primary parking node	Secondary parking node
Food terminal	D	C
Warehouse	D	C
Laundry terminal	D	C
Waste depot	D	C
Medical aid maintenance	D	C
Pharmacy	D	C
Laboratory	D	C
Building A locations	C	D
Building B locations	C	D

Parking node C already takes idle AGVs primarily from 24 cart processing locations in buildings A and B when there are only 36 processing locations in total. Therefore, the primary parking node for pharmacy and laboratory are in building D.

AGVs use elevators to move between floors in buildings A and B. There are four cargo elevators in both buildings and the AGVs can access the four elevators from a logistics lobby on each floor. Integration of elevators to an AGVS typically requires that the elevator can occupy only one AGV at a time and other freight cannot be carried at the same time. The elevator control logic in the model was built around this assumption. This assumption enables the use of a simple control policy. As explained in Figure 4.8, the elevator logic in the simulation model is as follows:

1. A load arrives in source floor lobby and it is placed to a waiting queue.

2. Once the load is the first in the waiting queue, the system selects the first available elevator to carry the load. If there are multiple available elevators, the elevator that is closest to the source floor is selected.

3. The load waits in the lobby until the selected elevator arrives at the source floor.

4. The load moves inside the elevator and the elevator carries it to the target floor.

5. Once the load has arrived to the target floor and left the elevator, the elevator is freed for the next load in the waiting queue.

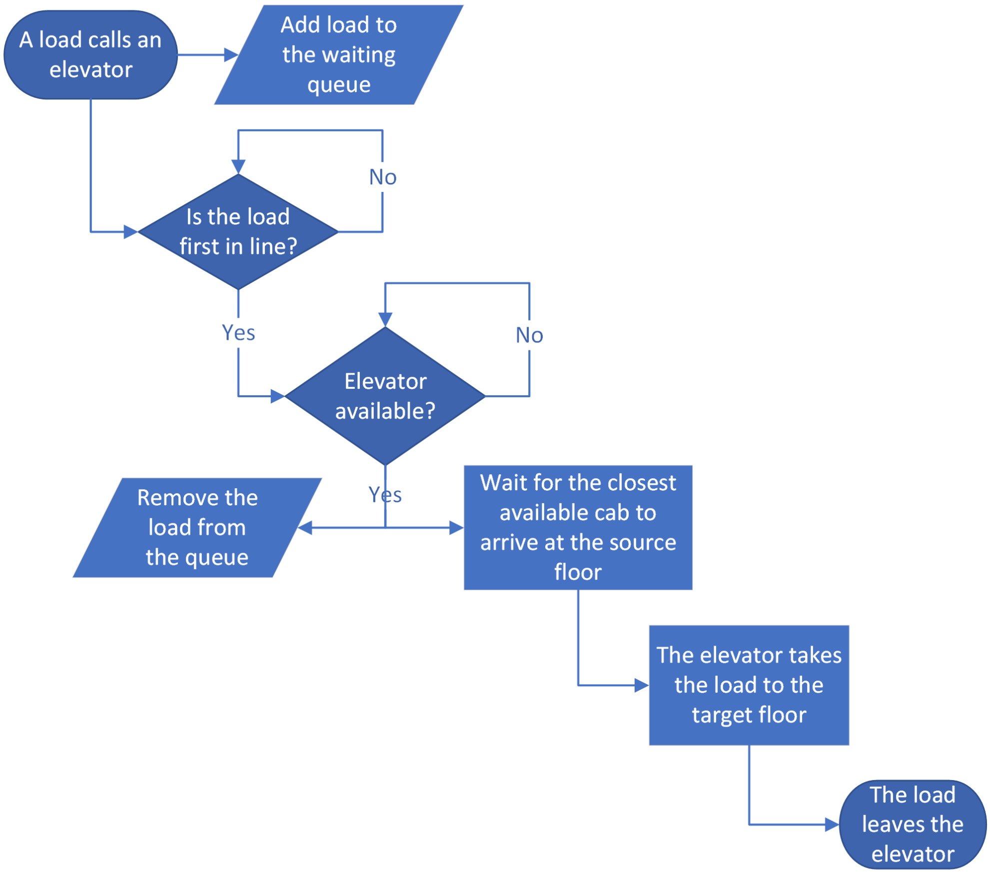


Figure 4.8: Elevator waiting and transfer process for a single load.

As explained above, the loads in the waiting queue are selected using FIFO logic. The logic can sometimes work counter-intuitively. Once a load has left the elevator at its target floor, the elevator could have an opportunity to pick up another load at the same floor to reduce empty driving. Because of the FIFO logic, however, the system respects the waiting queue and moves the available elevator to the floor with the next load in line. On the other hand, this way the queuing and elevator selection logic can be modeled with the built-in facilities in ProModel. Using the included resource and path network tools reduces the possibility of errors and makes the the logic easy to understand. The results in Chapter 5 show that the simple elevator control logic is sufficient for modeling this particular system.

AGVs run on battery power, which is why available system capacity is limited while any vehicles are charging. However, logistics activity at OUH is mainly set during daytime, between 6.00 and 22.00. Most of the logistics activity occurs during office hours with peak activity around midday as shown in Figure 4.9. Therefore, the batteries can be fully charged during the night. AGVs are also likely to require intermittent charging during the day.

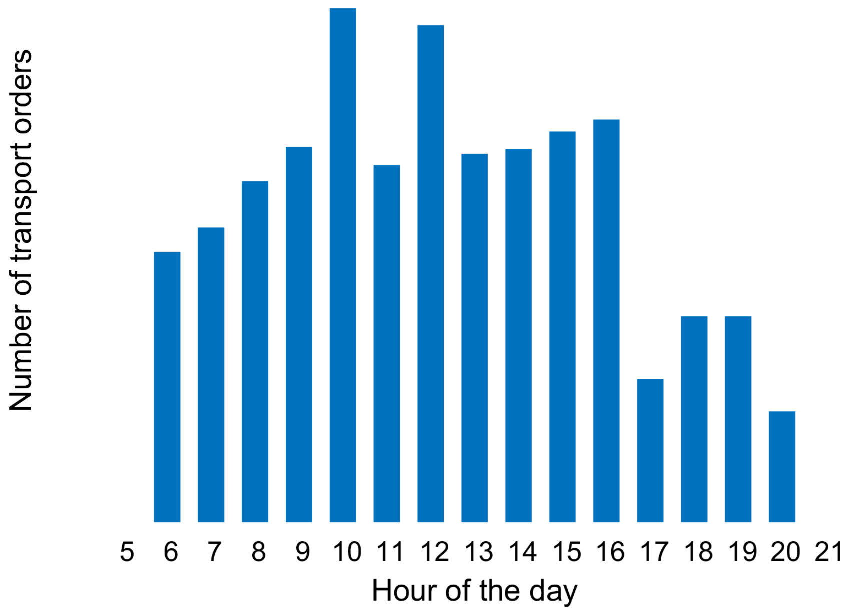


Figure 4.9: Distribution of the expected number of transport orders by the hour of the day.

The system load distribution is not entirely flat during the day, as seen in Figure 4.9. Thus, a system that can handle peak loads has some vehicles parking most of the time. This provides opportunities to charge during the day. If the fleet size is insufficient, the system capacity is fully utilized for longer periods. The vehicles may require charging during these periods, in which case the system capacity is also reduced.

McHaney (1995) explains that including battery constraints in AGVS simulations may not be necessary in systems with low vehicle utilization. Figure 4.9 shows that the AGVS at OUH is used only 16 hours per day and the highest load is concentrated at midday. Since delivery times must not grow too long during peak load hours, the fleet must be large enough to fulfil this requirement. A realistic fleet size thus enables vehicles to have ample idle time to charge outside peak load. Consequently, the effect of charging in delivery performance is considered small and charging is not taken into account in the simulation model. Still, the effect of this decision in the results is considered in Chapter 5.

4.3 Model verification and validation

The simulation model is verified mainly by checking the collected output values. Checking involves analyzing whether the output values fall within expected ranges. The program code is also verified using a debugger by monitoring system state at run-time. Various constraint checks are placed in the code as well. The checks enforce proper behavior by stopping the program when constraints are violated. Animation shown by ProModel also helps to verify that resources and entities are moved and processed in a seemingly correct way. This is also used for validating the model.

In addition to animation, the model is validated by testing the plausibility of the output. This is tested using both realistic and unlikely input. Individual entities and resources are also traced in the system to ensure correct logic. Moreover, the model is accepted by the hospital staff involved in the simulation project.

Chapter 5

Results and analysis

As stated in the first chapter, the objective of this thesis is to study the feasibility of the proposed AGVS at OUH. The feasibility is studied through a discrete-event simulation model, which is described in Chapter 4. Different scenarios are evaluated by running the simulation using different input parameter sets. To obtain information about system feasibility from key aspects, a total number of 22 scenarios are studied in this thesis. The results of the simulation runs are presented and analyzed in this chapter.

Section 5.1 of this chapter presents the model input that are varied across scenarios and discusses what type of output data is analyzed. The analysis begins with a baseline scenario in Section 5.2. Then, sensitivity analysis on a few input parameters is performed in Section 5.3. Sensitivity is analyzed by varying each parameter across a number of scenarios. Some of the parameters, such as vehicle velocity, simply represent physical qualities of the system. Sensitivity analysis on these parameters provides information on the uncertainty of the results. Other inputs affect the control of the system. That is why the capacity ratio between the two possible parking nodes is varied and the best ratio is used for determining the feasible fleet size in Section 5.4. Finally, Section 5.5 summarizes all the obtained results.

5.1 Methods

5.1.1 Common parameters

As discussed in Chapter 4, the model contains stochastic elements. The stochastic elements in the model are modeled by random distributions. The distributions and their arguments used in all studied scenarios are shown in Table 5.1.

Table 5.1: Model parameter distributions and distribution argument values used in all scenarios.

Parameter	Distribution (unit)
Cart pickup time	$\mathcal{N}(30, 5^2)$ (s)
Cart drop-off time	$\mathcal{N}(30, 5^2)$ (s)
Elevator enter time (AGV)	$\mathcal{N}(10, 2^2)$ (s)
Elevator enter time (logistic worker)	$\mathcal{N}(5, 2^2)$ (s)

Because of stochastic elements in the model, each simulation run must consist of multiple replications to obtain reliable statistics. Computing resources set the limit on how many replications can be run in a reasonable time. The number of replications also affects the size of the output data, which in turn influences the computational time during data analysis. All scenarios in this thesis are run using 200 replications for a good balance between computational time and result accuracy. Each replication runs for 24 hours in simulation time. The simulation clock begins at 2.00 and ends at 2.00 on the next day.

5.1.2 Input variation

Feasibility of the proposed AGVS is studied by analyzing system performance under different simulation scenarios. The scenarios are distinguished by different input to the model. The key aspects are analyzed by varying the following parameters

- AGV fleet size
- AGV velocity
- Mean logistic worker inter-arrival time (building A)
- Mean logistic worker inter-arrival time (building B)
- Number of elevators
- Parking node C and D capacity ratio.

The effect of a parameter is studied by comparing two or more scenarios, in which the parameter of interest is different with all other parameters being the same.

AGV fleet size affects the maximum capacity of the system directly, which is why it is arguably the most important parameter of interest. However, the overall capacity is potentially limited by the lifting capacity of elevators because the vehicles must use them to travel between floors. Therefore, it is also important to study whether the lifting capacity is sufficient. The usable lifting capacity for AGVs is affected by logistic workers who also use the same elevators. A higher logistic worker activity is simulated with shorter worker inter-arrival times.

AGV velocity depends on the chosen vehicle model and this thesis does not assume the use of a specific model. Therefore, the sensitivity of velocity is analyzed. Parking node capacity allocation may also affect system performance. Different ratios are evaluated and the best ratio found is used for estimating the feasible fleet size.

The simulation model takes a transport order schedule as input in addition to the parameters. The baseline schedule presented in the next section represents the typical daily schedule and workload at the hospital for the transported material considered in this thesis. It is possible that some days are more demanding, however, which is why the effect of a more challenging schedule with the same total workload is studied in Section 5.3.4.

5.1.3 Output analysis

System feasibility in each scenario is studied by analyzing system performance through the collected output data. The output data is presented in the form of performance indicators. The most important performance indicators are cart delivery time and the number of incomplete cart deliveries. Large delivery times indicate an insufficient system capacity. Spikes in system load are studied through timeseries of the number of incomplete deliveries.

Elevator waiting time, elevator queue size and elevator resource usage are used to analyze if the performance is limited by an insufficient lifting capacity. A high system load can cause carts to accumulate at their source locations. Thus, the number of carts waiting for pickup at processing locations is also used in the analysis.

The system is considered feasible, if all the following criteria are met

- The average cart delivery time is 20 min at most and the 90th percentile is 30 min at most
- The average number of carts waiting for pickup in any one location in building A and B is 5 at most at any single time of day

- The average number of carts waiting for pickup in any one location in building C is 15 at most at any single time of day
- The average elevator waiting time is 30 s at most and the 90th percentile is 60 s at most
- The 90th percentile of the largest elevator queue size of all elevator lobbies is 5 at most at any single time of day

5.2 Baseline scenario

5.2.1 Input

The first simulation scenario is run using baseline input. The baseline parameter values are shown in table 5.2. In the following sections of this chapter, only the parameters that differ from the baseline are presented. Thus, the parameter values that are not explicitly specified in other scenarios are equal to their baseline values.

Table 5.2: Baseline values of parameters that are varied across the studied scenarios.

Parameter	Value
AGV fleet size	10
Number of elevators (building A)	4
Number of elevators (building B)	4
AGV velocity	1.00 m/s
Mean logistic worker inter-arrival time (building A)	120 s
Mean logistic worker inter-arrival time (building B)	111 s
Parking node C and D capacity ratio	0:100

The transport order schedule used in the baseline scenario is characterized by the distribution shown in Figure 5.1. The first carts are sent after 6.00 in the morning and the last transport orders are created by 21.00. The highest order counts occur between hours 10 and 11. Transport orders for lunch carts account for approximately half of this demand. Lunch time also causes another busy hour between 12-13, because empty lunch carts are sent back to food terminal around that time. Dinner is served at around 16-17, which is why it is the third busiest hour. The expected number of created orders drops rapidly after 17.00, which marks the end of office hours. Mainly only less urgent items, such as waste, are transported after office hours.

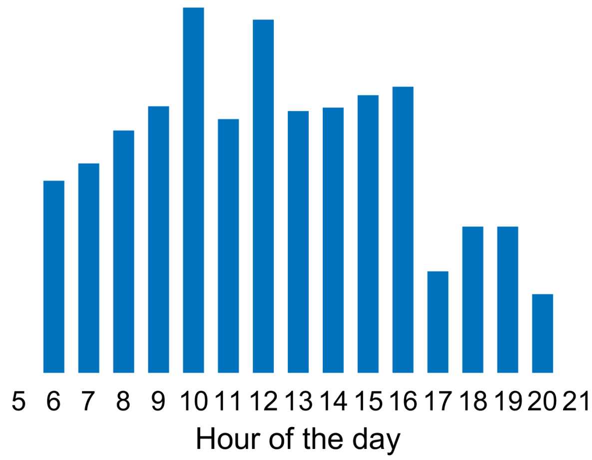


Figure 5.1: The expected number of sent carts by the hour of the day in the baseline input schedule of transport orders.

The baseline transport order schedule is used in all but one of the studied scenarios. Section 5.3.4 analyzes a scenario with a different schedule using the same total workload. The results obtained from running the model using the baseline input are analyzed next.

5.2.2 Output

The system in the baseline scenario cannot cope with the load caused by the transport order schedule. It is evident from Figure 5.2, which shows the distribution of the time it takes to deliver a cart to its destination from the moment it is sent. On average, it takes around 5.5 h to deliver the cart, which is unacceptably high. 10 % of carts take more than 10 h to deliver based on the 90th percentile. Thus, the system in the baseline scenario is not feasible.

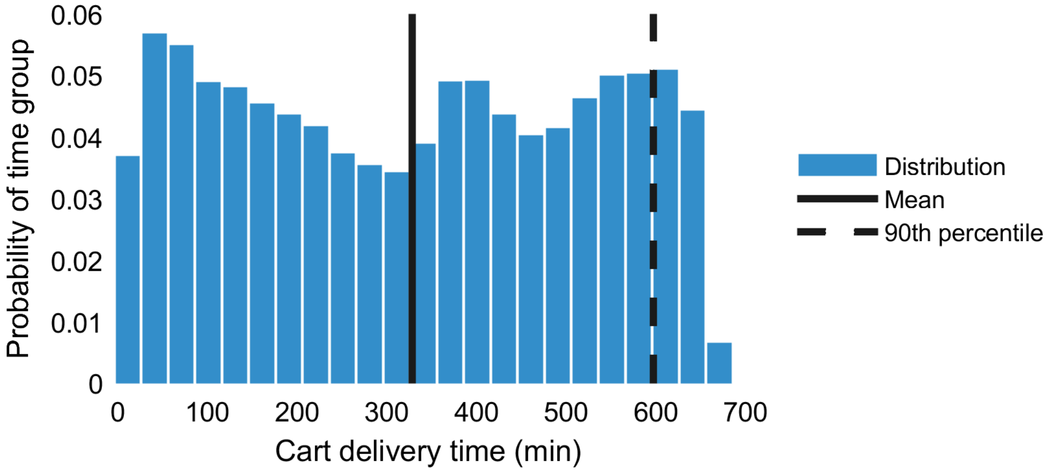


Figure 5.2: Distribution of cart delivery time in the baseline scenario.

Figure 5.3 shows that the reason for poor performance is insufficient system capacity. The mean transport order backlog increases steadily the moment the first orders are created. The backlog begins to clear after 19.00 but it is not resolved completely before the simulation period ends. This results in carts spending almost all of their time waiting for pickup at their source locations, as shown in Figure 5.4.

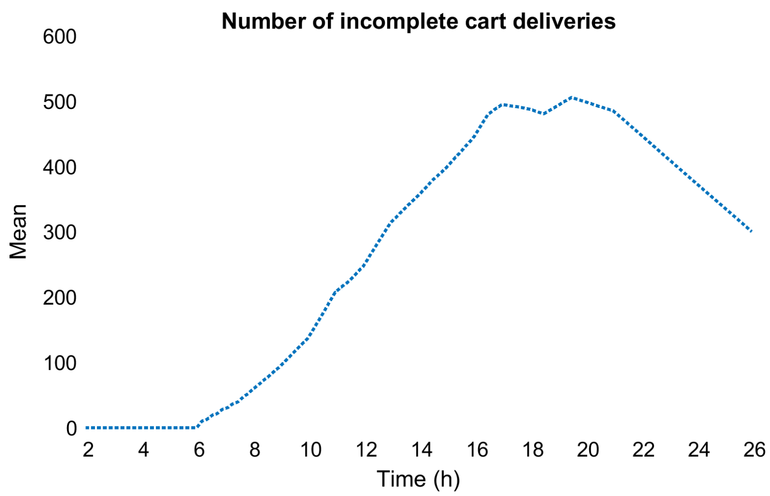


Figure 5.3: Mean number of incomplete cart deliveries over time in the baseline scenario.

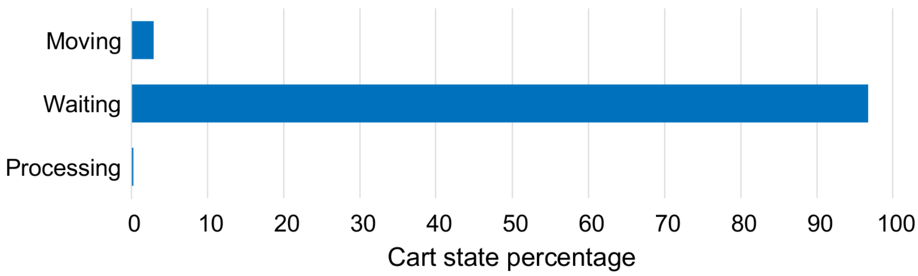


Figure 5.4: Mean cart entity state in the baseline scenario.

Distribution of the elevator waiting time is shown in Figure 5.5. On average, AGVs and logistic workers must wait only 4.4 s for the elevator to arrive at the source floor. 90 % of the waiting times are below 19 s. Waiting times are fast, which indicates that elevator lifting capacity is not the reason for the poor system performance in the baseline scenario.

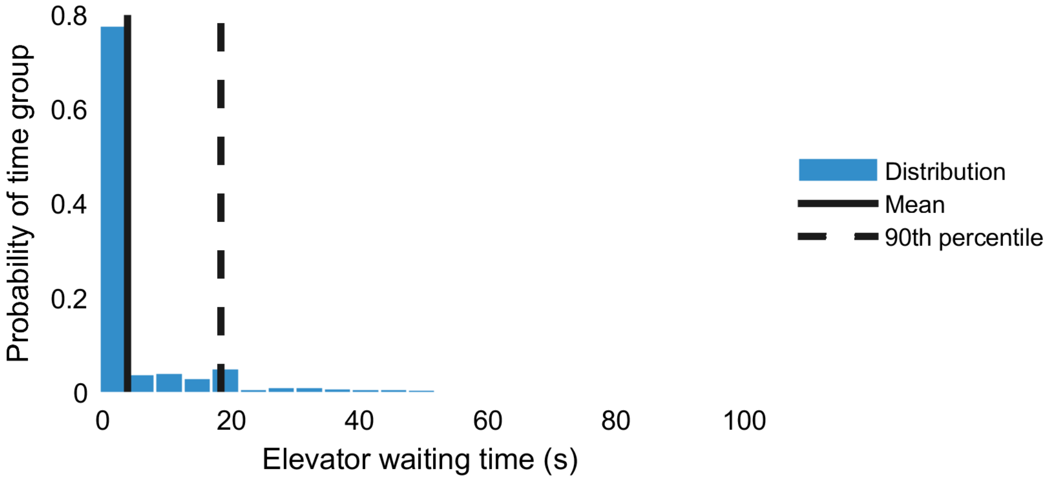


Figure 5.5: Distribution of elevator waiting time in the baseline scenario. Both elevator groups in buildings A and B are taken into account in this distribution.

As shown in Figure 5.6, all the vehicles are in use almost immediately after the first carts are sent. This indicates that a larger fleet would improve system capacity. The next section indeed shows that performance can be increased considerably by adding more vehicles in the system.

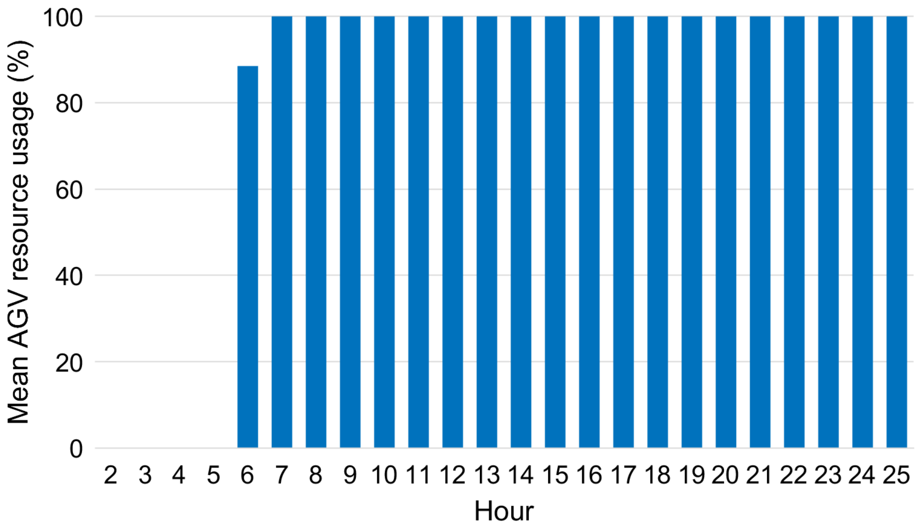


Figure 5.6: Mean hourly AGV usage in the baseline scenario.

5.3 Sensitivity analysis

5.3.1 Fleet size

The baseline scenario results indicate that 10 AGVs does not provide enough resources to handle the daily demand at the hospital. Since a fleet size of 10 vehicles is clearly unfeasible, it is not sensible to analyze input sensitivity using this size. Therefore, the realistic range on the fleet size is sought roughly in this section. This allows using realistic fleet sizes in further analysis of the system. AGV fleet size is also the most important system parameter because it affects delivery capacity directly. Thus, it is useful to understand how the system behaves when the number of vehicles changes.

To study the effect of fleet size, the baseline size of 10 is incremented by 10 in four scenarios. This results in five scenarios to compare. Parameters other than AGV fleet size are kept constant across these scenarios. The used fleet sizes during these runs are shown in Table 5.3.

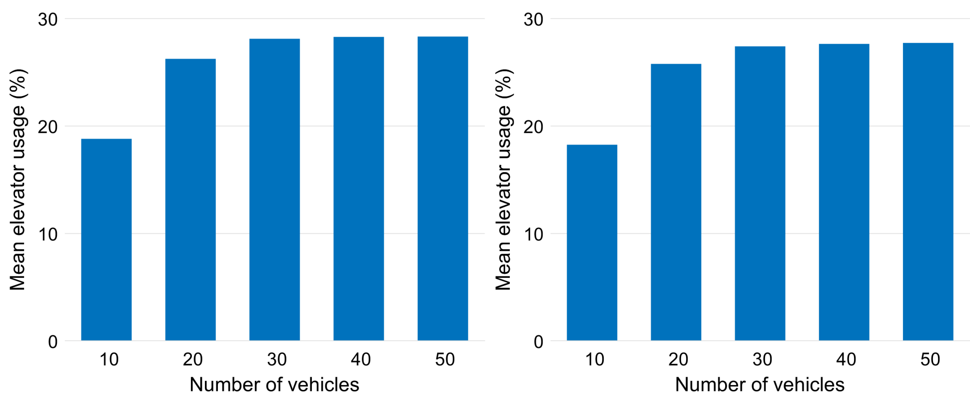
The AGVs travel between floors using elevators in buildings A and B. These elevators potentially constitute a bottleneck that limits the ability of the vehicles to efficiently deliver carts around the hospital. Increasing the fleet size can also increase elevator usage, which is why it is important to study whether the lifting capacity can accommodate the needs of the AGVS.

Figure 5.7 shows that the average elevator usage relative to the number of elevators increases as vehicles are added to the system. In the 10-vehicle

Table 5.3: Varied parameter values in baseline scenario and scenarios 2-5.

Parameter	Scenario				
	Baseline	2	3	4	5
AGV fleet size	10	20	30	40	50

configuration, the usage is low because a part of the transport orders are not completed before the simulation period ends. If the 10-vehicle case is ignored, the usage still grows as fleet size is increased. This makes sense, because more vehicles can make it more likely that more elevators are in use at the same time. As desribed in Chapter 4, the first load in the elevator queue always uses the next available elevator when all elevators are in use. If fewer elevators are in use at the same time, an elevator closer to the calling site can be selected, which decreases traveling time and thus, elevator usage is decreased. The usage grows asymptotically with fleet size, which is why it is approximately the same in 30 and 50 vehicle configurations. The differences between the usage percentages in buildings A and B are small, though elevators in building A exhibit slightly higher use overall.



(a) Building A (b) Building B

Figure 5.7: Mean total elevator resource usage in buildings A and B against AGV fleet size.

Adding more vehicles beyond 30 does not increase mean elevator usage considerably because the mean number of AGVs in use does not increase either. This is evidenced by Figure 5.8 showing the absolute AGV usage against the fleet size. AGV usage is actually lower in 40 and 50 vehicle configurations compared to a 30 vehicle configuration. The reason is that a larger vehicle pool provides better chances for the system controller to select vehicles closer to carts waiting for pickup. This reduces traveling time to pickup locations. Lower absolute AGV usage in the baseline scenario is caused by the small number of 10 vehicles in the system.

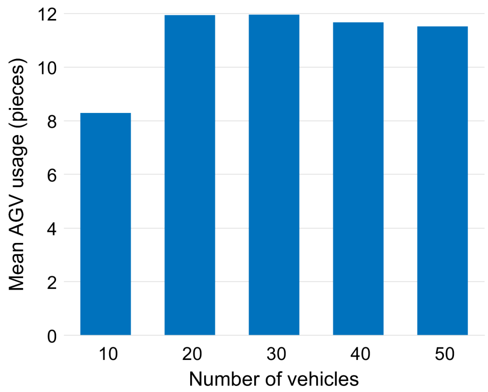


Figure 5.8: Mean total AGV usage against fleet size.

The simulation model tracks the time AGVs and logistic workers must wait after arriving at the elevator lobby until they can begin to enter the elevator. Figure 5.9 illustrates the differences between waiting times in the first five scenarios with mean and 90th percentile values. Increased elevator usage translates to higher waiting times. While 10 vehicles result in an average waiting time of around 4 s, the average is around 20 s in a 50 vehicle configuration. Ignoring 10 % of the worst occurrences, the maximum waiting time is 65 s in building A and 60 s in building B. The effect of fleet size on elevator waiting time is analyzed in Section 5.4 in more detail.

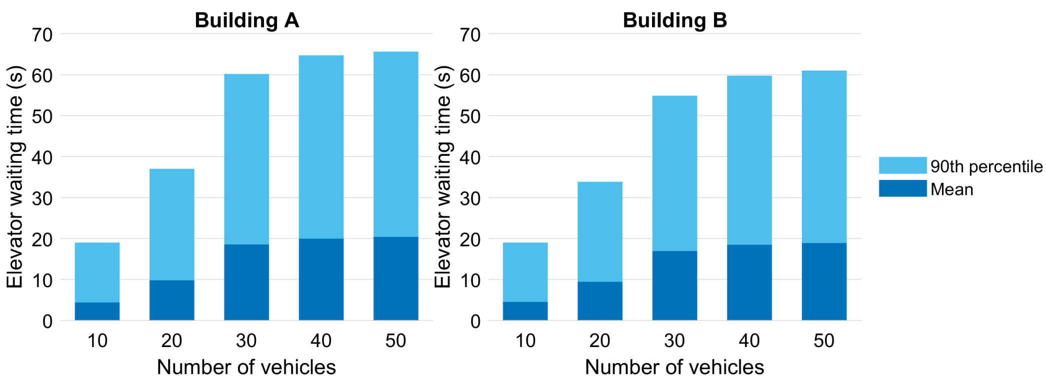


Figure 5.9: Mean and 90th percentile of elevator waiting time in buildings A and B.

The simulation model collects time series of elevator queue sizes on each floor in buildings A and B during simulation. The queue lengths include both AGVs and logistic workers. The time series are used to calculate the largest queue size at each time point in both buildings. Figure 5.10 shows the average time series of the largest per-floor queue size in three scenarios. It shows that increasing the fleet size also increases elevator queue sizes. However, on average, the largest queue size stays reasonable throughout the simulation period even with a 50 vehicle configuration.

90th percentile of the largest queue size in a 50 vehicle configuration is shown in Figure 5.11. Using 50 vehicles, the queue size is 3 at most if 10 % of the largest values are ignored. Elevator lobbies at the hospital could accommodate even larger queues but the results show that such queues are rare.

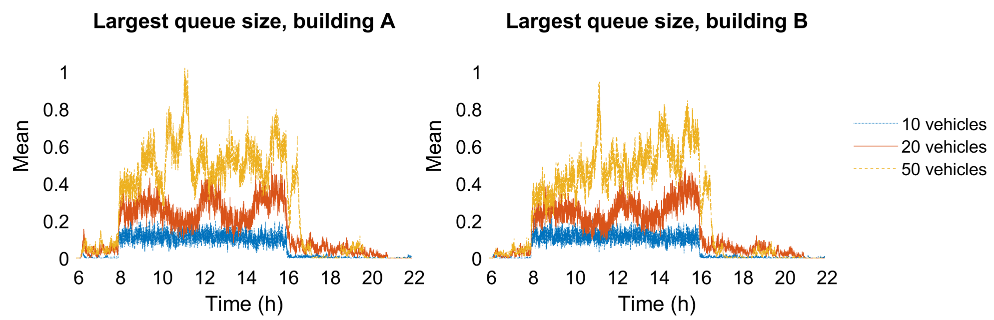


Figure 5.10: Mean of the largest elevator queue size by time in buildings A and B for three fleet sizes.

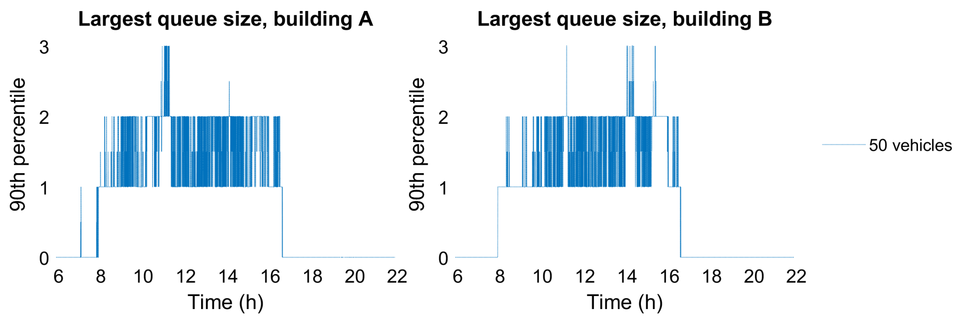


Figure 5.11: 90th percentile of the largest elevator queue size by time in buildings A and B when fleet size is 50.

The number of AGVs in the system affects system performance greatly. Insufficient capacity causes a quick buildup of order backlog on average, as seen in Figure 5.12. Using 10 AGVs, carts accumulate in source locations in a considerably faster rate than the vehicles can deliver them. The first tasks are created at 6.00, after which the order backlog begins to rise immediately, ultimately reaching a size of around 500 tasks on average by 19.30. Even though the last transport orders are created by 21.00, the drop in demand is not enough to resolve the backlog before the end of the simulation period.

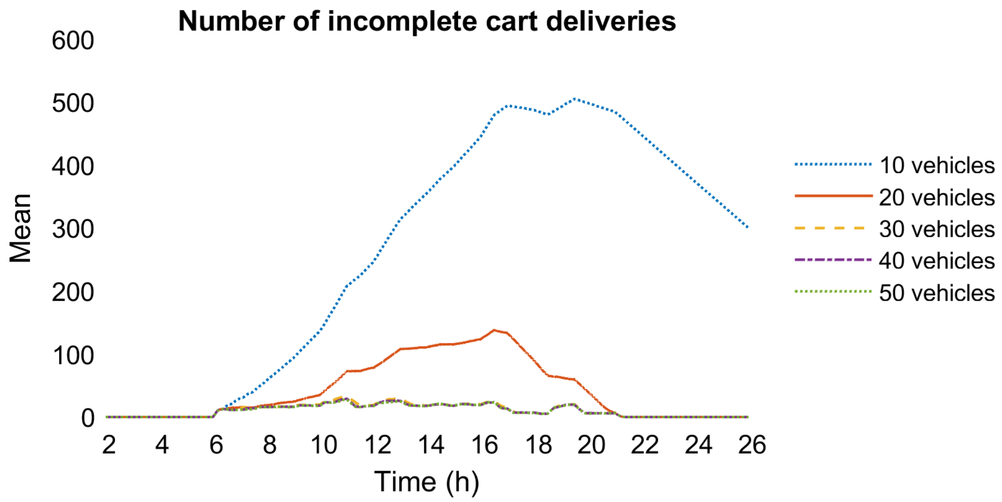


Figure 5.12: Number of incomplete AGV tasks against simulation time averaged over the replications. Each line represents the average replication in a scenario. See Figure 5.13 for a zoomed view of the curves from scenarios with 30 or more vehicles.

Compared to the baseline scenario, using 20 vehicles shows a similar accumulation of carts until the demand drops. The highest average number of incomplete cart deliveries is considerably smaller, however. Even though 20 vehicles is enough to resolve the average order backlog completely before the end of the simulation period, the system struggles to keep the backlog in check between hours 9-19.

Using 30 vehicles instead of 20 prevents the gradual increase in order backlog during hours 8-16. Further increases in fleet size show diminishing returns. The differences between 30, 40 and 50 vehicle configurations cannot be seen in Figure 5.12 because of the large accumulation of carts in the baseline scenario. Figure 5.13, on the other hand, shows these small differences with a comparison of only scenarios having at least 30 vehicles. There is a slight benefit from using 40 or more vehicles, which shows as lower peaks in the number of incomplete cart deliveries during the system load spikes at around 11.00, 13.00 and 16.00. 90th percentile also improves slightly during these load spikes, as shown in Figure 5.14.

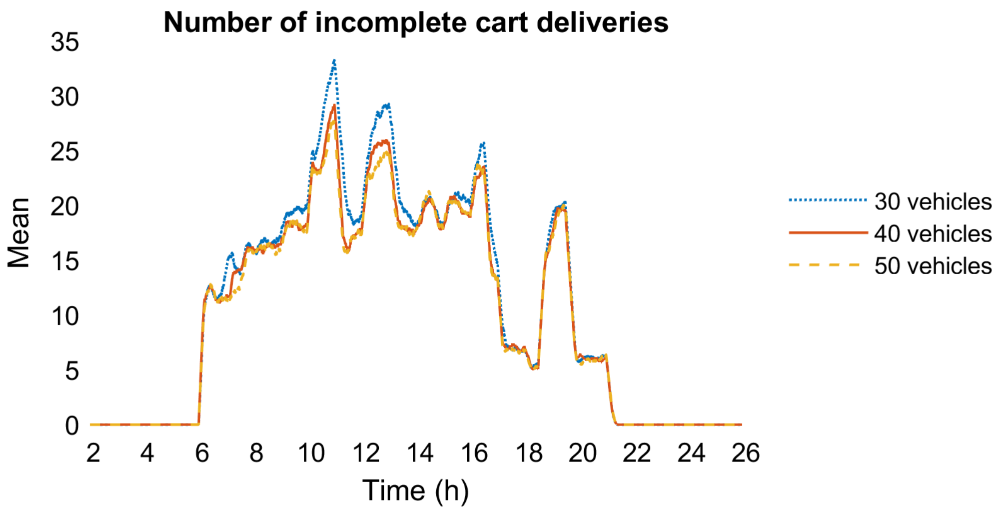


Figure 5.13: The average number of incomplete AGV tasks against simulation time for fleet sizes 30, 40 and 50.

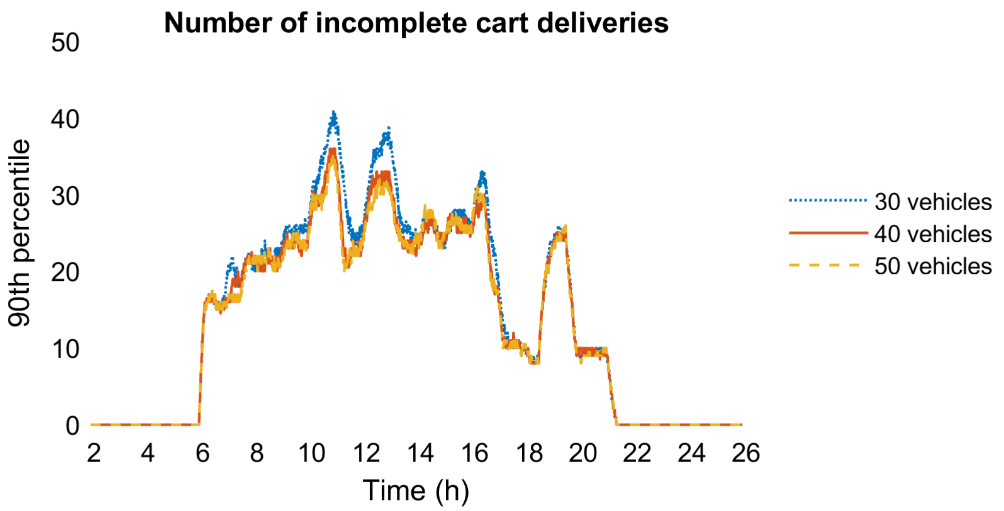


Figure 5.14: 90th percentile of the number of incomplete AGV tasks against simulation time for fleet sizes 30, 40 and 50.

Raising the fleet size from 30 to 40 is a 25 % increase in vehicle capacity. However, increases in capacity reduce the overall fleet usage, as shown in Figure 5.15. Therefore, it may be difficult to justify increasing the fleet size beyond 30 considering the small benefit that it provides during short peak loads.

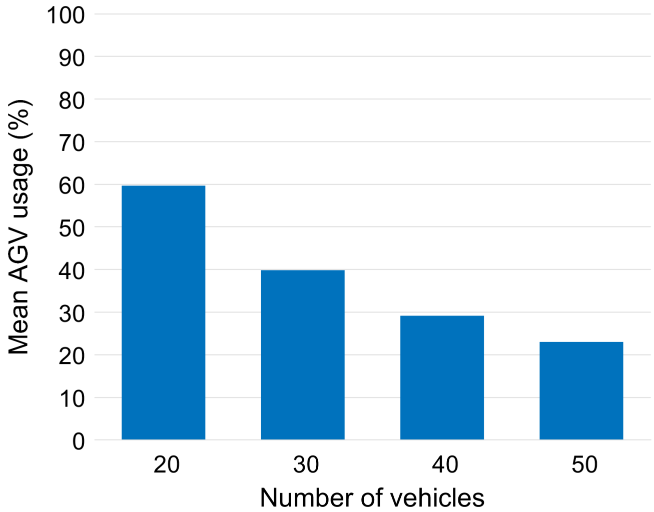


Figure 5.15: Mean relative AGV usage against fleet size.

An insufficient fleet size causes a gradual increase in the number of incomplete incomplete cart deliveries. This results in lengthy cart delivery times, which is evident in Table 5.4. Using 20 vehicles, the cart delivery time is over 60 minutes on average. This is a large improvement over the baseline result, although it is still unacceptably high. Adding 10 more vehicles to the system brings the mean delivery time down to an acceptable 15.6 min. Further increases in capacity provide only small overall decreases in delivery times through improved peak load performance. The difference in mean cart delivery time between 30 and 50 vehicle configurations is approximately 8 %.

It is important that there are not too many deliveries that take significantly longer to complete compared to a typical delivery. The box plot in Figure 5.16 shows the variation in the delivery time against AGV fleet size. Based on the figure, 25 % of cart deliveries take over 91.2 minutes to complete if the system has 20 vehicles. Increasing the capacity to 30 vehicles not only brings the median down but the variation is also considerably smaller. Using 30 vehicles, 50 % of delivery times fall between 12.3 and 18.5 minutes. Fleet sizes from 30 to 50 provide reasonable worse case delivery times.

Table 5.4: Mean cart delivery time in five systems employing AGV fleets of different size. The delivery time is rounded to three significant digits.

Fleet size	Mean cart delivery time (min)
10	332
20	62.3
30	15.6
40	14.6
50	14.4

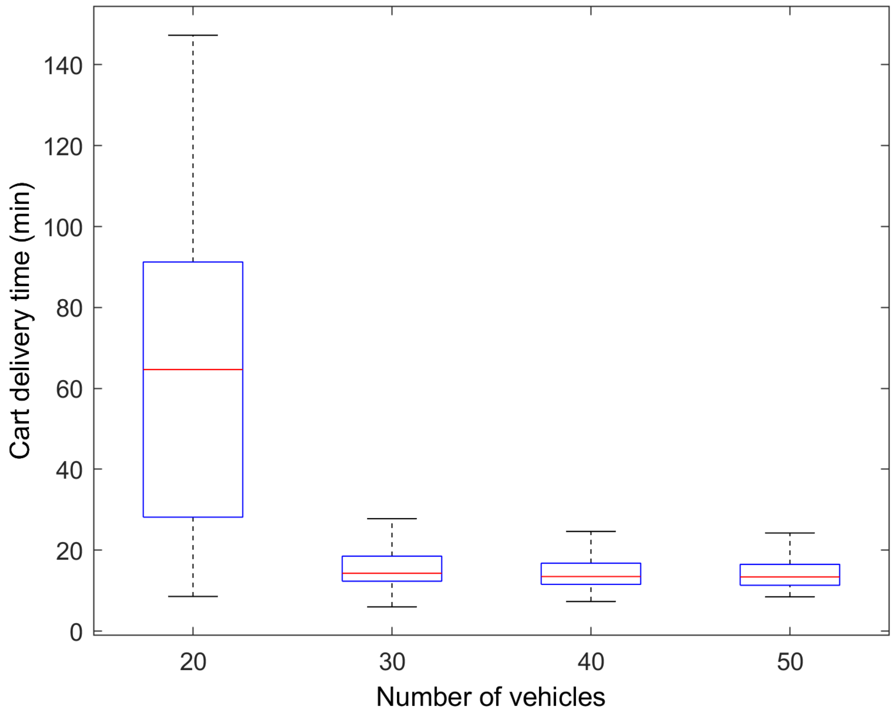


Figure 5.16: Box plot of cart delivery time against AGV fleet size. 50 % of observations are included within the blue boxes and the red horizontal lines in the middle are medians. The maximum length of the whiskers is 1.5 times the interquartile range.

5.3.2 Vehicle velocity

The AGV models applicable for hospital logistics are different from those used in many other applications, such as manufacturing. One of the differing characteristics is vehicle velocity. The simulation model in this thesis does not assume that a specific AGV model is used. Therefore, it is important to analyze how largely vehicle velocity affects system performance. The effect is analyzed by comparing two scenarios that use unequal velocities.

The baseline velocity used in the studied scenarios is 1.00 m/s. In this section, a scenario with vehicles traveling at the baseline velocity is compared to a scenario with 20 % slower vehicles. Values of the varied parameters are shown in Table 5.5.

Table 5.5: Parameter values different from the baseline in scenarios used to study the effect of AGV velocity.

Parameter	Baseline	Scenario 3	Scenario 6
Fleet size	10	30	30
AGV velocity (m/s)	1.0	1.0	0.80

Most carts are transported through the corridors between support services and the elevator lobby on the first floor in building A. It takes approximately 8 min for the AGV to travel this distance at the baseline velocity of 1.00 m/s. Based on the results in the previous section, this travel time is approximately half the cart delivery time in a 30-vehicle system. Thus, changes in vehicle speed are expected to affect delivery speed considerably.

As shown in Figure 5.17, decreasing vehicle velocity from 1.0 m/s to 0.80 m/s increases average cart delivery time from 16 min to 23 min when there are 30 vehicles in the system. The relative increase is 46 %. 90th percentile is increased from 22 min to 34 min, which is a 49 % increase. Thus, a velocity of 0.80 m/s cannot produce feasible delivery times in a 30-vehicle system. The system performance is rather sensitive to changes in vehicle velocity because decreasing velocity by 20 % increases delivery time by 46 % in this comparison. As was to be expected, traveling horizontal distances accounts for a major part of the delivery time. Figure 5.18 also shows the decline in system capacity when velocity is decreased by 20 % from the baseline. On average, there are many more undelivered carts during the peak load hours around midday.

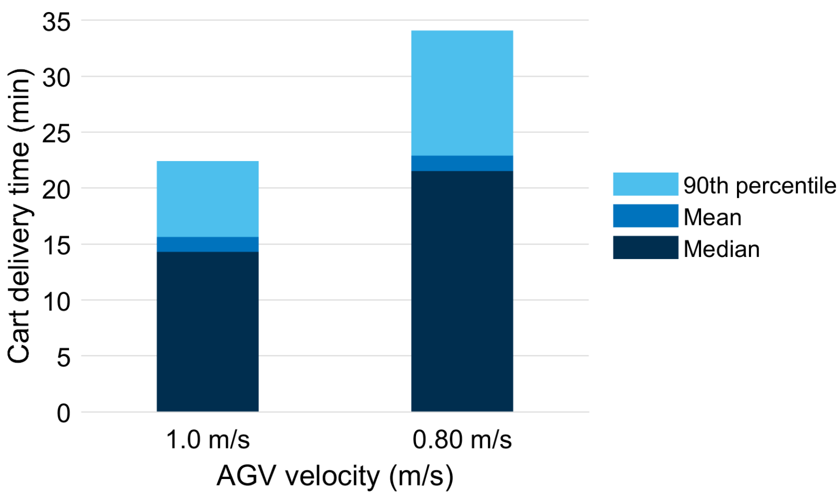


Figure 5.17: Cart delivery time statistics when AGV velocity is 1.0 m/s and when it is 0.80 m/s. The fleet size is 30 in both scenarios.

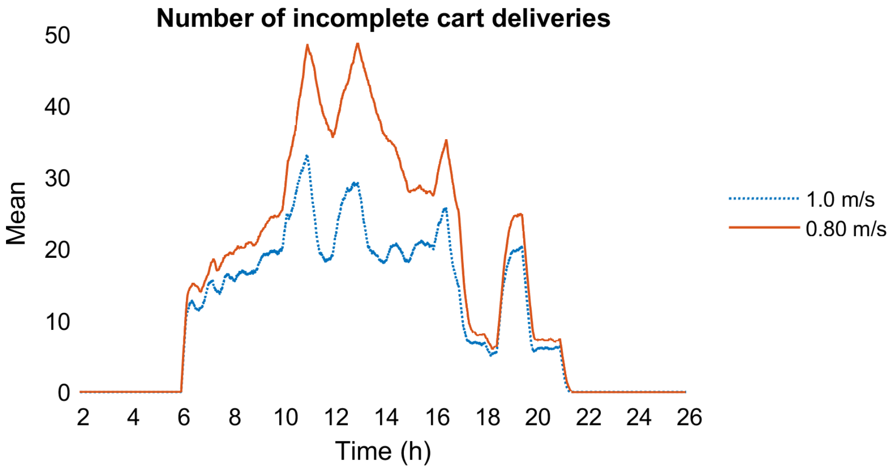


Figure 5.18: Number of incomplete cart deliveries over time when AGV velocity is 1.0 m/s and when it is 0.80 m/s. Fleet size is 30 in both scenarios.

5.3.3 Logistic workers

The AGVS is not the only material transportation system at the hospital. Some items are delivered by logistic workers who also use the same elevators. Therefore, it is important to study if an increase in logistic worker activity has adverse effects on AGVS performance. These effects and their impact are studied in this section. This analysis is carried out by comparing two scenarios, one of which has a 25 % higher logistic worker activity compared to baseline.

Logistic worker inter-arrival times to buildings A and B are modeled as exponential distributions with mean inter-arrival times as input parameters. One of the scenarios used for analysis in this section uses the baseline inter-arrival times. The mean inter-arrival times are 20 % lower in the other. Both scenarios use 30 AGVs. Table 5.6 shows the parameter value differences between the baseline and these two scenarios.

Table 5.6: Parameter values varied in scenarios used to study the effect of logistic worker activity.

Parameter	Scenario		
	Baseline	3	7
Fleet size	10	30	30
Mean worker inter-arrival time (building A) (s)	120	120	96.0
Mean worker inter-arrival time (building B) (s)	111	111	88.8

Figure 5.19 shows cart delivery time statistics when the mean inter-arrival times are at their baseline and when they are reduced by 20 %. The statistics show that the AGVS is not sensitive to changes in logistic worker arrival volume. The 20 % reduction in the mean inter-arrival time increases mean and median cart delivery time by approximately 1 %. Worst-case performance is affected slightly more but the increase in the 90th percentile is also small, about 2 %.

Figure 5.20 shows how the difference in the mean inter-arrival time between the two scenarios affects the number of incomplete cart deliveries by the time of the day. There are small differences in the mean numbers throughout the day. However, the differences are mostly indistinguishable, which is expected based on the small difference in mean cart delivery times.

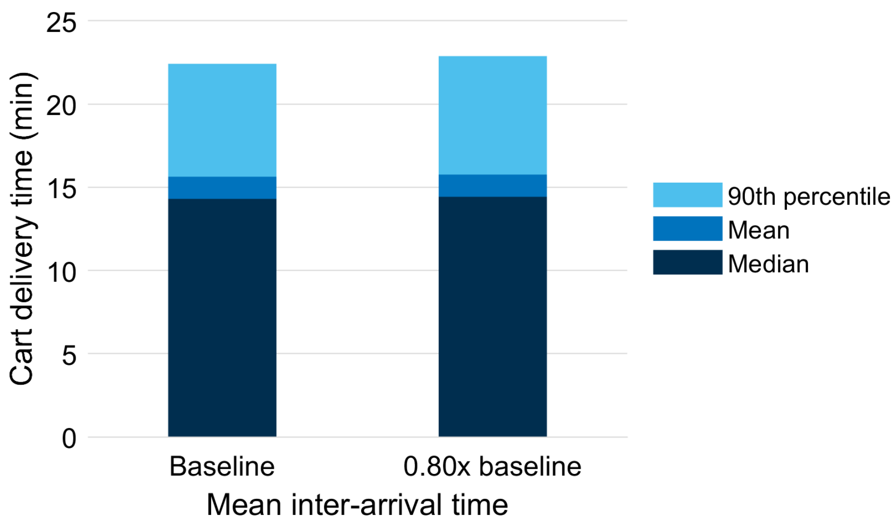


Figure 5.19: Cart delivery time statistics when mean logistic inter-arrival times in buildings A and B are equal to the baseline values and when they are reduced by 20 %. Fleet size is 30 in both scenarios.

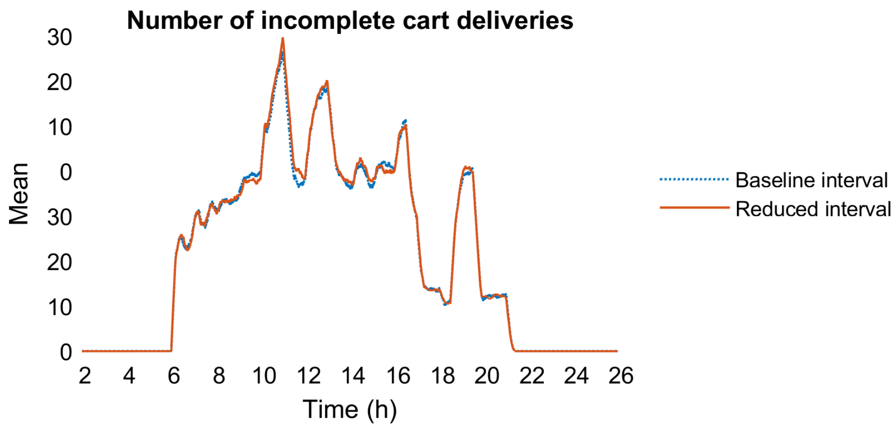
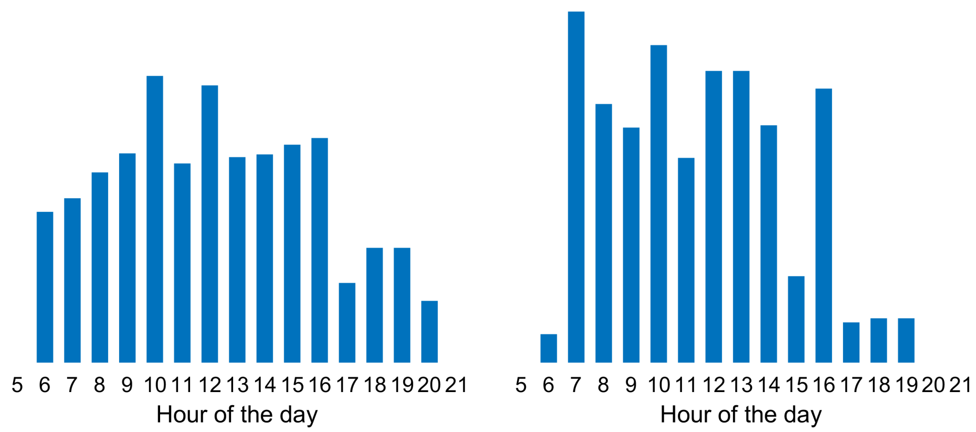


Figure 5.20: Cart delivery time statistics when mean logistic inter-arrival times in buildings A and B are equal to the baseline values and when they are reduced by 20 %. Fleet size is 30 in both scenarios.

5.3.4 Transport order schedule

As described in Chapter 4, the transport order schedule input to the simulation represents the daily demand for cart deliveries. The baseline schedule is assumed to represent this demand realistically. While the simulation model includes a degree of uncertainty in transport order times, the order time distribution is the same across simulation runs with a given input order schedule. Thus, it is important to study how a heavier schedule affects system performance. For example, if the system implementation plans indicate that it is impossible to maintain the assumed schedule in practice, it is useful to know how a heavier workload affects the system. The effect of such a schedule is studied in this section. The baseline schedule is referred to as "baseline schedule" and the heavier schedule as "heavy schedule".

The hypothesis is that the system performs worse if the total demand is distributed over a smaller period of time and if there are large variations in demand during this period. The transport order schedule is characterized by the distribution of the expected number of sent carts over time. The expected numbers of sent carts per hour in both baseline and heavy schedules are shown in Figure 5.21. The total number of sent carts are the same in both schedules but the load is less balanced in the heavy schedule. Highest load peaks are larger and the shape of the distribution is more narrow. In the baseline schedule, orders are created between hours 6 to 21. Whereas in the heavy schedule, only a small percentage of orders are created between hours 6 to 7 and the last orders are created before 20.00.



(a) Baseline schedule (b) Heavy schedule

Figure 5.21: Distribution of the expected number of sent carts by the hour of the day. Subfigure (a) shows the baseline distribution and the heavy distribution used in scenario 8 is shown in Subfigure (b).

Scenario 8 is run using the heavy schedule. It is compared to scenario 3, which is run with the baseline schedule but otherwise equal input. The differences to the baseline parameter values in these scenarios are shown in table 5.7.

Table 5.7: Parameter values different from baseline in scenarios 3 and 8, which are run with different transport order schedules. Baseline values are also shown.

Parameter	Baseline	Scenario 3	Scenario 8
Fleet size	10	30	30

The effect of the heavy schedule on cart delivery time compared to baseline schedule is shown in Figure 5.22. In comparison with the baseline, the heavy schedule results in higher cart delivery times. The increase in both the average and the 90th percentile is about 28 %. Even though the total number of transported carts are the same in both scenarios, concentrated workload and large variations in demand decrease system performance significantly. However, the heavy schedule allows sufficient performance, with an average delivery time of about 20 min and a 90th percentile of about 29 min. Typically, cart delivery time is under 20 min based on the median in the heavy schedule scenario.

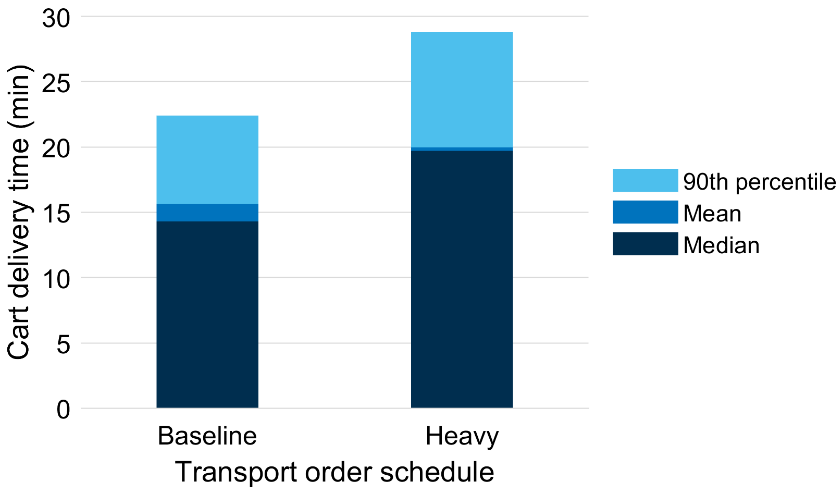


Figure 5.22: Cart delivery time statistics in the scenario using the baseline transport order schedule and another using the heavy schedule. Fleet size is 30 in both scenarios.

Figure 5.23 shows the mean number of incomplete cart deliveries over time in both scenarios compared in this section. The large variations in demand in the heavy schedule and the shorter window for deliveries throughout the day clearly increase the number of undelivered carts. Peak average is around 48 in the heavy scenario and in the baseline scenario it is about 33. Note that using the baseline schedule, most of the sent carts are assigned an AGV immediately on average, because there are 30 vehicles to select from. At around 11.00, there are a few carts waiting for vehicle assignment on average. In contrast, there are many more carts waiting for vehicle assignment in the heavy scenario. At the same peak load moment at 11.00, there are 48 undelivered carts on average. This means that there are 18 carts waiting for an AGV to be assigned to them.

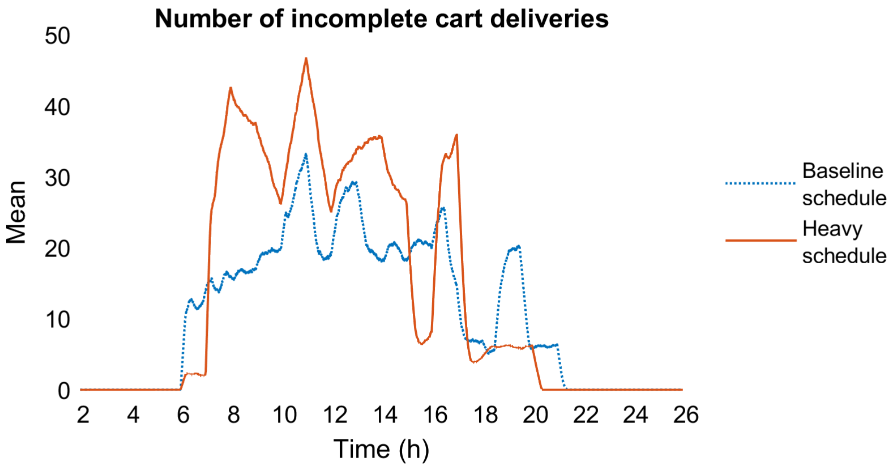


Figure 5.23: Mean number of incomplete cart deliveries over time with two different transport order schedules. AGV fleet size is 30 in both scenarios.

Based on the comparison between the baseline scenario and the heavy scenario, the distribution of the cart delivery demand affects system performance greatly. Balancing the total load over the day with as small variations as possible reduces delivery times significantly. A perfectly balanced load is unlikely to be possible in practice, though.

5.3.5 Number of elevators

There are four elevators dedicated to logistics in both elevator groups in buildings A and B at OUH. Under normal conditions, all elevators are in use. However, it is possible that some of them are down because of a breakdown or a scheduled maintenance, for instance. To evaluate the performance of the AGVS under a decreased elevator capacity, the simulation model is run using only three elevators per elevator group. This reduces the number of available elevators by 25 % compared to the baseline.

The differences in input parameters values in the compared scenarios are shown in table 5.8. Scenarios 9 and 10 are run using 25 vehicles. Scenario 9 uses 4 elevators per elevator group and scenario 10 has 3 of them. Scenario 11 is run with 30 vehicles and 3 elevators per group to analyze if increasing the fleet size can compensate for the reduced performance caused by the smaller lifting capacity.

Table 5.8: Parameter values different from baseline in scenarios 9, 10 and 11, which are run to analyze reduced elevator lifting capacity.

Parameter	Scenario			
	Baseline	9	10	11
Fleet size	10	25	25	30
Number of elevators (building A)	4	4	3	3
Number of elevators (building B)	4	4	3	3

Cart delivery times in the three scenarios compared in this section are shown in Figure 5.24. When there are 25 vehicles and 4 elevators per elevator group in the system, the average cart delivery time is approximately 20 min. Decreasing the number of elevators per group from 4 to 3 increases the average cart delivery time to 27 min. The 90th percentile increases from 31 min to 44 min. The decrease in lifting capacity decreases AGVS performance greatly. However, increasing the fleet size from 25 to 30 compensates for the reduced lifting capacity in terms of cart delivery time.

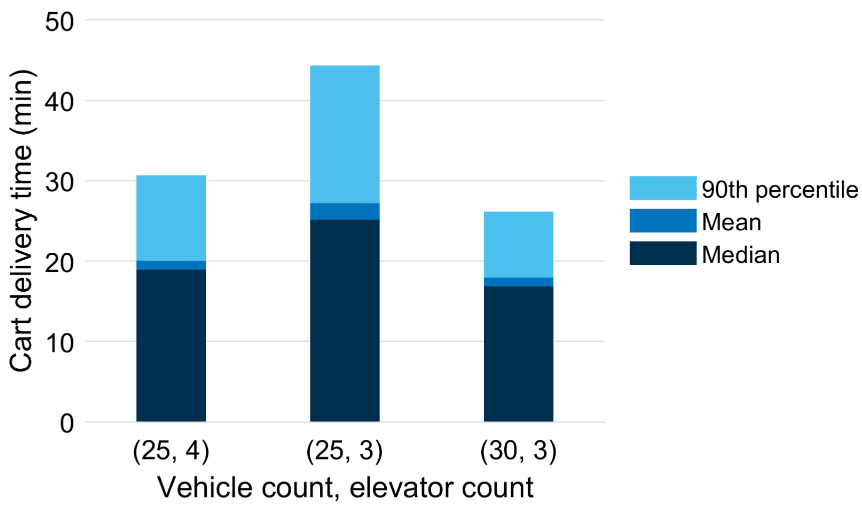


Figure 5.24: Cart delivery time statistics in scenarios with different fleet sizes and elevator group sizes.

Figure 5.25 presents the mean number of cart deliveries against the time of the day in the three considered scenarios. The figure shows that decreasing the lifting capacity by 25 % in a 25-vehicle system does not affect performance significantly during low load. For example, the mean number of incomplete deliveries are nearly equivalent between hours 6-10 in both 25-vehicle scenarios. However, the insufficiency in lifting capacity shows during high load situations. For example, without reduction in the number of elevators, a 25-vehicle system is able to resolve the transport order backlog faster in the hours after the high load spike at 13.00. In comparison with the 25-vehicle scenarios, the 30-vehicle scenario with reduced lifting capacity shows the best performance in terms of number of incomplete cart deliveries. Even with the reduced lifting capacity, the 30-vehicle scenario performs the best during high load in this regard.

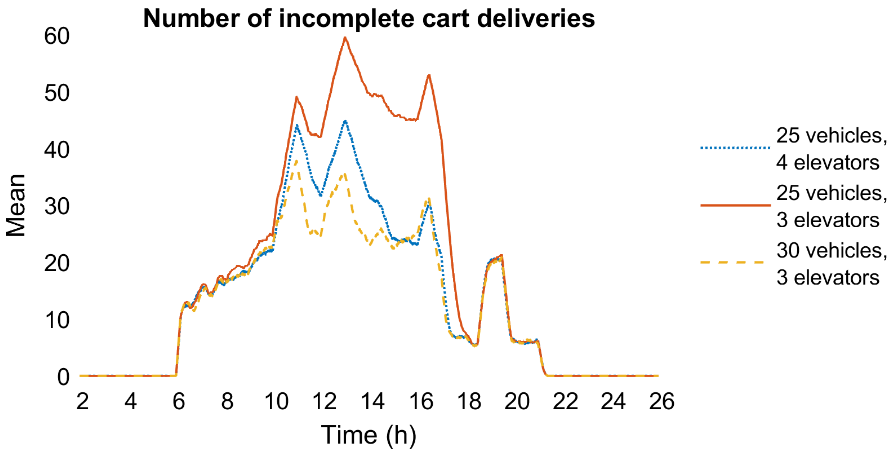


Figure 5.25: Mean number of incomplete cart deliveries over time in scenarios with different number of elevators and vehicles. The varied parameters in the scenarios are presented in the legend on the right.

While having 30 vehicles in the system compensates for the reduction in lifting capacity, elevator waiting times are long compared to the waiting times in the 25-vehicle systems. This is evident in Figure 5.26. The 90th percentile is as high as 190 s in the 30-vehicle configuration. AGVs do not mind waiting, but the long waiting time is not user friendly for the logistic workers using the same elevators. Worst case waiting times are also rather high in the scenarios with 25 vehicles and 3 elevators per group.

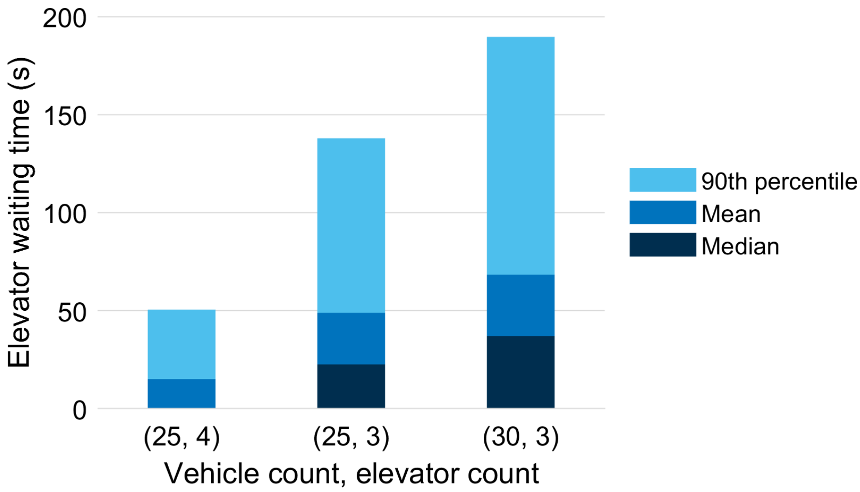


Figure 5.26: Elevator waiting time statistics in scenarios with different number of elevators and vehicles.

Figure 5.27 shows the 90th percentile of the largest elevator queue size in all the elevator lobbies in each building by time of the day. Like waiting times, elevator queues become longer if the lifting capacity is reduced by 25 %. The peak 90th percentile of the largest queue size is 6.5 in the 30-vehicle scenario. Such queue sizes should be taken into account in the elevator lobby design if the number of available elevators is often reduced. The 4-elevator scenario with 25 vehicles clearly performs the best in this regard. The momentary 90th percentile is 2 at most in that scenario.

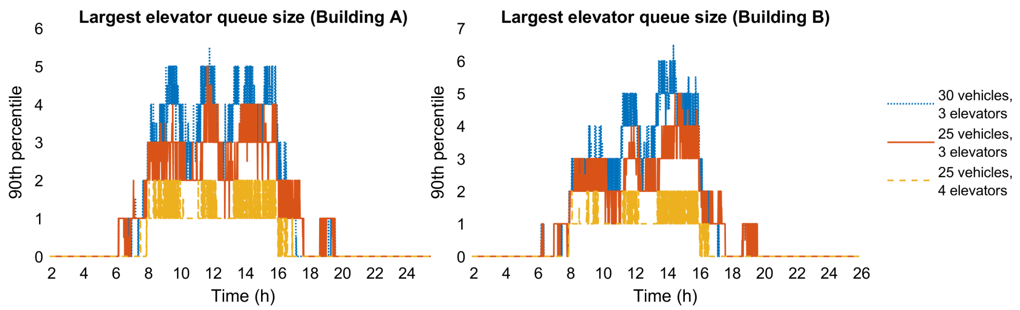


Figure 5.27: 90th percentile of the largest elevator queue size by time in buildings A and B. Both logistic workers and AGVs are included. The varied parameters in the compared scenarios are shown in the legend on the right.

It is possible that the long elevator waiting times and queue sizes in situations with reduced lifting capacity are caused by the simple elevator logic in the simulation model. An optimized algorithm would likely improve lifting throughput during periods of high elevator utilization. However, based on these results, keeping all 8 elevators functional is essential for the AGVS performance.

5.3.6 Parking node capacity

The simulation model has two possible nodes at which vehicles can park. The capacity ratio between parking node C and D is 0:100 in the baseline scenario and all scenarios analyzed in the previous sections. This ratio means that all vehicles park at node D. This section compares system performance in six scenarios. One of them uses the baseline parking node capacity ratio of 0:100. Other scenarios use varying ratios that make both parking nodes available. The differences in input parameter values in the scenarios compared in this section are shown in Table 5.9. All the scenarios are run using a fleet size of 25.

Table 5.9: Parameter values different from baseline in scenarios used to compare the effect of node capacity ratios between parking nodes C and D.

Parameter	Scenario					
	9	12	13	14	15	16
Fleet size	25	25	25	25	25	25
Parking node capacity ratio	0:100	10:90	20:80	40:60	50:50	60:40

The effect of parking node capacity ratio on cart delivery time is shown in figure 5.28. Using the baseline parking node capacity ratio between C and D nodes provides an average cart delivery time of 20 min. 90th percentile is 31 min. The five other system configurations, which allocate idling vehicles between both nodes in differing ratios, provide almost equivalent results. The largest delivery times are seen using 40:60 ratio. The smallest average and median are obtained with 10:90 ratio. However, 10:90 ratio provides the same 90th percentile as 0:100 ratio.

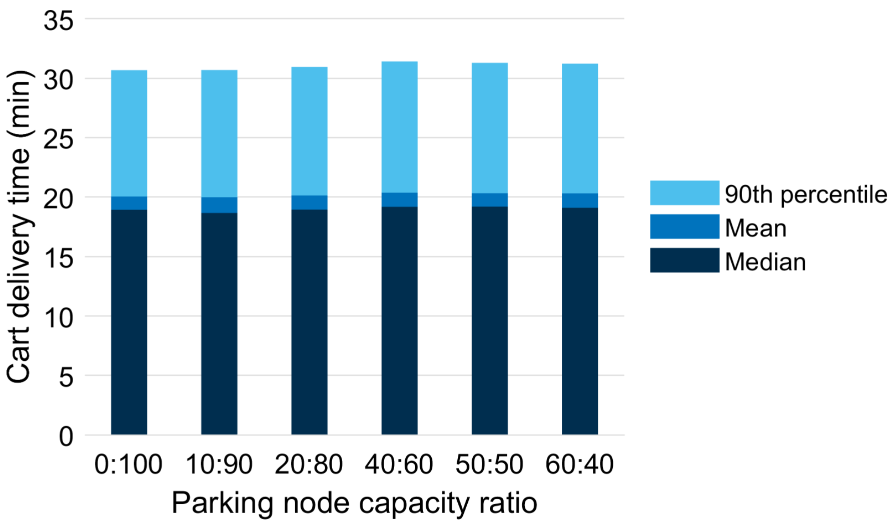


Figure 5.28: Cart delivery time statistics in scenarios with different parking node capacity ratios and otherwise equal input.

It appears that the system favors ratios, which allocate more vehicles to node D rather than to node C. However, allocating at least some part of the capacity to node C is better than not using it at all. The difference between the smallest and the largest average delivery time between the scenarios compared in this section is just under 2 %. Therefore, the choice of ratio is not important. Nevertheless, since the ratio of 10:90 provides the best results in this comparison, this ratio is also used in estimating the feasible fleet size in the next section.

5.4 Feasible fleet size

The results in Section 5.3.1 show that the AGV fleet size has a significant effect on system performance. Thus, the feasibility of the system is also affected and it is important to find the fleet size that allows feasible operation. The sizes studied in Section 5.3.1 are 10 apart from each other so the results cannot provide an exact feasible range. A more detailed analysis is thus necessary. The lower and upper bound of the feasible fleet size are presented in this section.

The minimum feasible fleet size is determined by comparing seven scenarios with all fleet sizes in range 24-30. The exact numbers are shown in Table 5.10. The results of the previous section show that out of the studied parking node ratios, a ratio of 10:90 between nodes C and D provides the best AGVS performance. Therefore, the scenarios studied in this section are also run with this ratio.

Table 5.10: Parameter values different from baseline in scenarios used to estimate the feasible fleet size.

Parameter	Scenario						
	12	17	18	19	20	21	22
Fleet size	25	24	26	27	28	29	30
Parking node capacity ratio	10:90	10:90	10:90	10:90	10:90	10:90	10:90

Running the seven scenarios with varying numbers of vehicles produces the cart delivery time statistics shown in Figure 5.29. 25 vehicles is enough to meet the requirement of 20 min for the average delivery time. However, the 90th percentile is slightly over the limit of 30 min. Using 26 vehicles instead drops the 90th percentile to 26 min. Therefore, the fleet size must be 26 at minimum for cart delivery times to be feasible.

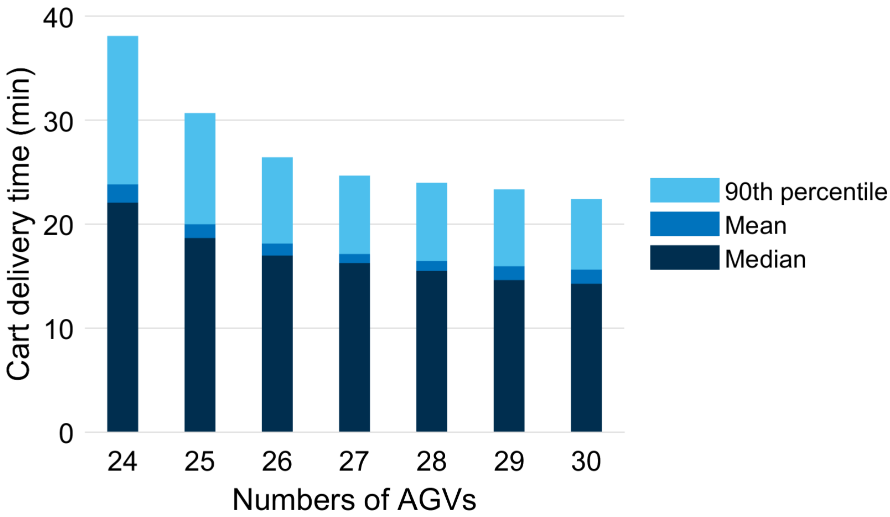


Figure 5.29: Cart delivery time statistics in scenarios with different fleet sizes. Parking node capacity ratio is 10:90 in all scenarios.

It would be sensible to think that the system would perform better the more vehicles are used. However, Figure 5.30 shows an increasing trend in the average elevator waiting time and the 90th percentile as the fleet size is increased. The results on waiting times in Section 5.3.1 also show the same trend even though the scenarios are run with slightly different parameters. The performance requirements dictate that the average elevator waiting time must be no more than 30 s and the 90th percentile must be 60 s or less for the system to be considered feasible. Figure 5.30 shows that fleet sizes larger than 32 violate the 90th percentile requirement.

Figure 5.30 shows that the median waiting time is exactly 0 in all cases. This is surprising but explainable. A median of 0 means that most of the time, a lifting request can be fulfilled using an elevator already on the same floor. This makes sense because all of the scheduled deliveries are either inbound or outbound from a first floor location. Also, the cart processing locations on upper floors are close to elevator lobbies so the AGVs can likely use the same elevator they arrived in to continue to their next location.

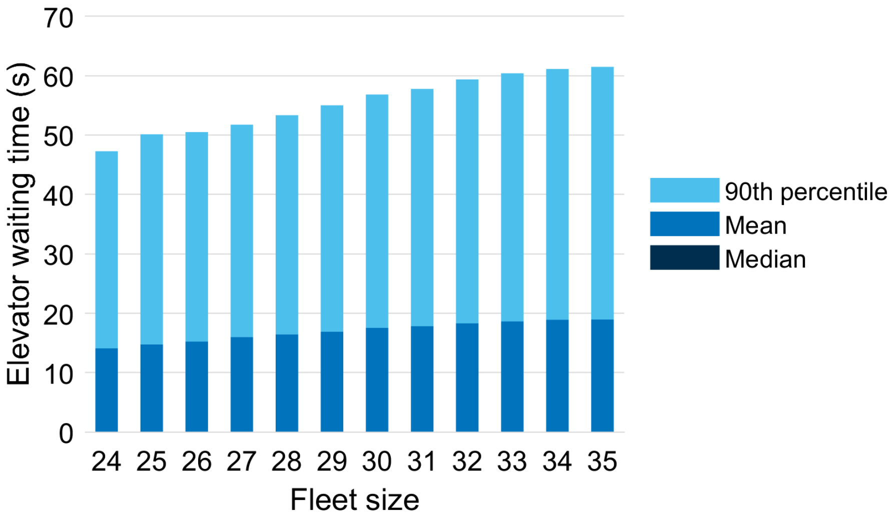


Figure 5.30: Elevator waiting time statistics in scenarios with different fleet sizes. Median is 0 in all scenarios.

Although adding more vehicles to the system improves delivery performance, elevator waiting times are increased as a result. Fortunately, the results in this section show that using a fleet size in range 26-32 allows all requirements to be fulfilled.

5.5 Summary

Based on the simulation results presented in this chapter, the proposed AGVS at OUH can operate feasibly. Feasible operation requires 26 vehicles at a minimum given that the used parameters apply. However, the results also show that elevator waiting times can become unfeasible if the fleet size is too large. Thus, the feasible fleet size is better expressed as a range rather than a lower bound. Based on the results, the feasible range is 26-32 vehicle.

The results show that cart delivery times decrease as more vehicles are added to the system. However, increasing the fleet size beyond the feasible range has diminishing returns. Increasing the fleet size from 20 to 30 decreases the average delivery time by 75 % while a fleet size increase from 30 to 50 decreases the average by a mere 9 %.

The optimal usage of the two available parking nodes was also evaluated in this chapter. This was done by varying the capacity ratio between the two possible parking nodes. The results show that the ratio has a minimal effect on system performance. The differences in delivery times are under

2 % between the studied ratios. The best performance is achieved when the capacity ratio between the parking nodes in buildings C and D is 10:90. Using only parking node D provides virtually the same performance, though.

The sensitivity to changes in input data was evaluated as well. The difference in performance was compared using two transport order schedules. One schedule was the baseline schedule and the other was a heavy schedule with larger load peaks and faster rate in delivery requests. Although systems in both configurations made the same deliveries during the simulation period, the heavy schedule caused delivery times to suffer by 28 %. Therefore, distributing the load evenly is crucial for the performance of the system.

The performance of the system can be greatly affected if parameter values representing physical qualities change. Increasing the frequency of logistic worker arrivals in the system by 20 % has almost an imperceptible effect. On the other hand, decreasing vehicle velocity by 20 % can increase the average delivery time by 46 %. Thus, the results are rather sensitive to the selected vehicle and the associated system. The feasible fleet size is largely affected, if the chosen system cannot attain the assumed average velocity of 1.0 m/s.

The sensitivity analysis also shows that the availability of the four elevators in each building are essential for the AGVS performance. Disabling one elevator in both buildings increases the average elevator waiting time by approximately 225 % in a 25-vehicle system. The average cart delivery time is also increased by 36 %, which can be compensated with a larger fleet, however. Compensating with a larger fleet causes an even higher load on the elevators but at least cart delivery time requirements would be satisfied.

Chapter 6

Conclusions

The objective of this thesis was to study the feasibility of the proposed automated guided vehicles system at Oulu University Hospital. The study was carried out by analyzing system performance through a discrete-event simulation model that represented the system. The simulation results show that feasible operation is possible. A fleet size of 26-32 vehicles allows feasible operation in all aspects considered in this thesis.

Although this thesis shows that technical feasibility of the system is attainable, financial aspects are not considered. Financial viability is also important to analyze before an investment decision is made. Fortunately, the results of this thesis can be used for evaluating the economics of the system. For example, the estimated feasible fleet size can be used for assessing the costs of the vehicle units.

Although the simulation model in the thesis is considered a reasonably accurate representation for the problem at hand, the results can be slightly biased. For example, the model does not take battery charge levels into account, although the omission is justified because of low vehicle utilization in this case. Moreover, the simulation model could be refined to take AGV breakdowns into account. There also exists some uncertainty in the results. Since the system performance is greatly affected by the vehicle velocity, the estimated feasible fleet size range is valid only if the chosen system can attain the assumed average velocity used in the simulations.

Further research on the topic could include optimization of the system. The control rules used in the thesis model are simple and not designed for the absolute best performance. Thus, it would be interesting to study how the lower bound on the feasible fleet size range could be decreased through optimized control logic in vehicle selection and dispatching rules. Optimization of the system design in general could be useful during implementation of the system and over its lifetime.

The results in this thesis apply only to single-load vehicles. Further research on the subject could include the use of multi-load vehicles and study their benefits in comparison to single-load vehicles. The performance of the system could also be compared to other types of material handling systems through similar simulation approaches. This could include financial viability analysis as well.

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