The development of a decision support model for the picking, staging, combining and loading activities in the grocery distribution warehouse of a large fast moving consumer goods retailer

Werner Willem van Niekerk

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Author	van Niekerk, WW
Student number	12079619
Supervisor/s	Joubert, JW
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Executive summary

The Pick 'n Pay grocery warehouse situated at the Longmeadow *distribution centre (DC)* has 10 790 stock keeping units that are received from 123 vendors and are distributed to 421 stores located in several provinces as well as three neighbouring countries. The stock keeping units which are referred to as *delivery units (DUs)* are picked into *handling units (HUs)* (rolltainers used to transport DUs) and staged in staging lanes. Loading staff load the staged HUs onto *transport units (TUs)*. The TUs then deliver the stock to various Pick 'n Pay stores. This process is referred to as the *outbound process*.

The two concerns currently experienced by the outbound process is an excessive number of dropped HUs (HUs that are not loaded onto their planned TUs) and excessive TU loading times.

It was determined that a decision support model was required to provide insight on how to reduce dropped HUs and TU loading times. A Literature review was performed to investigate *agent based simulation (ABS)*, *system dynamics (SD)* and *discrete event simulation (DES)* as possible simulation techniques. Tako and Robinson (2012) determined that DES was most frequently used within the supply chain environment to assist in making tactical and operational decisions. It was determined that a DES model would be used in this project. AnyLogic was selected as the simulation software as this software provides the functionality required for a DES model.

The simulation model was developed by simulating the outbound process's picking/staging, combining and loading events. Data captured between the 1st of May 2017 and the 30th of June 2017 was used to develop the simulation model. Key measures were identified against which the simulation model was validated. These measures included the number of DUs per HU after loading, loading time per TU, number of HUs staged, combined, dropped and loaded per shift and the number of TUs loaded per shift. After comparing the data generated for each measure from 100 simulation runs to the observed data with distribution plots and 99% confidence intervals it was concluded that the developed simulation model was a valid representation of the outbound process.

It was determined that high levels of congestion in the staging lanes contribute to the excessive number of dropped HUs and TU loading times. Two scenarios were identified which could reduce staging lane congestion namely the increase in the number of stores with night-time receiving and the distribution of weekly volumes. The two identified scenarios were evaluated with the developed simulation model using data captured between the 1st of August 2017 and the 31st of August 2017. The effectiveness of the models were determined by evaluating the number of HUs dropped per shift, loading time per TU,the number of HUs per TU, the number of HUs in the staging lanes and the flow of HUs into and out of the staging lanes. It was concluded that both scenarios could reduce the number of HUs dropped per shift. The scenarios did not indicate a significant reduction in TU loading times but did produce an increase in the HUs per TU and loading rate per HU. The scenario proposing an increase in the number of stores with night-time receiving was selected as the most suitable solution as this solution was the most effective in reducing the number of dropped HUs and increasing the loading rate per HU.

Contents

List of Figures

List of Tables

Acronyms

ABS agent based simulation

BTU bulk transport unit

DC distribution centre

DES discrete event simulation

DU delivery unit

FMCG fast moving consumer goods

HU handling unit

KPI key performance indicator

SD system dynamics

TU transport unit

Chapter 1

Introduction

Have you ever stood in a Pick 'n Pay store and thought about the supply chain that filled those shelves with the variety of products that you, so conveniently, pick into your shopping basket? Considering that the grocery warehouse situated at the Pick 'n Pay Longmeadow *distribution centre (DC)* has 10 790 stock keeping units (articles with unique identification codes) that are received from 123 vendors and are distributed to 421 stores located in several provinces, as well as three neighbouring countries, it is nothing short of remarkable. Although Pick 'n Pay has several DCs across South Africa, this report focuses on the grocery warehouse situated at Longmeadow business estate.

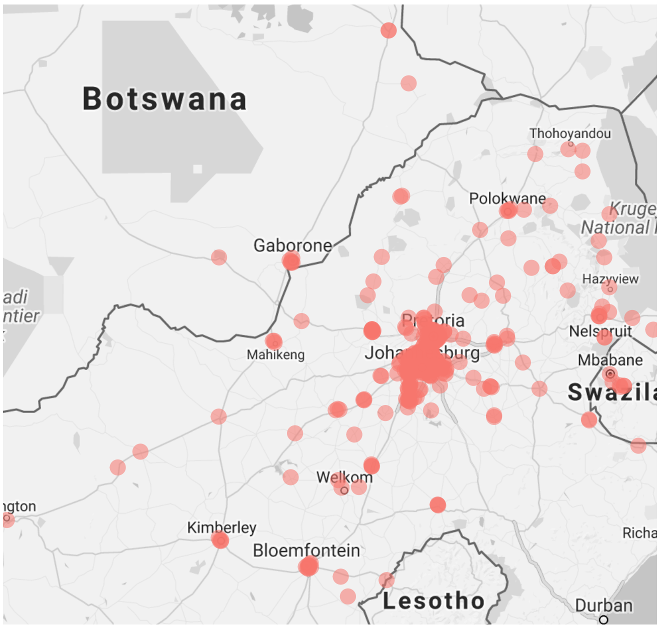

Figure 1.1: Location plot of Pick 'n Pay stores serviced by the grocery warehouse at Longmeadow DC.

This introductory chapter provides a detailed description of the operations responsible for the delivery of stock to the respective Pick 'n Pay stores. The current constricting factors are discussed and a methodology is defined, which forms the base of the developed solution.

1.1 Operational overview

Three different units are referred to in this report: delivery units, handling units and transport units. To clarify the different units, consider the following analogy. When shopping in a Pick 'n Pay store the products on the shelves, whether individual or grouped items, are known as *delivery units*. The trolley used to transport the selected delivery units is a *handling unit*. The vehicle used for delivering handling units containing delivery units home, from Pick 'n Pay, is known as a *transport unit*.

Figure 1.2 is a basic illustration of the outbound supply chain of the Pick 'n Pay grocery warehouse.

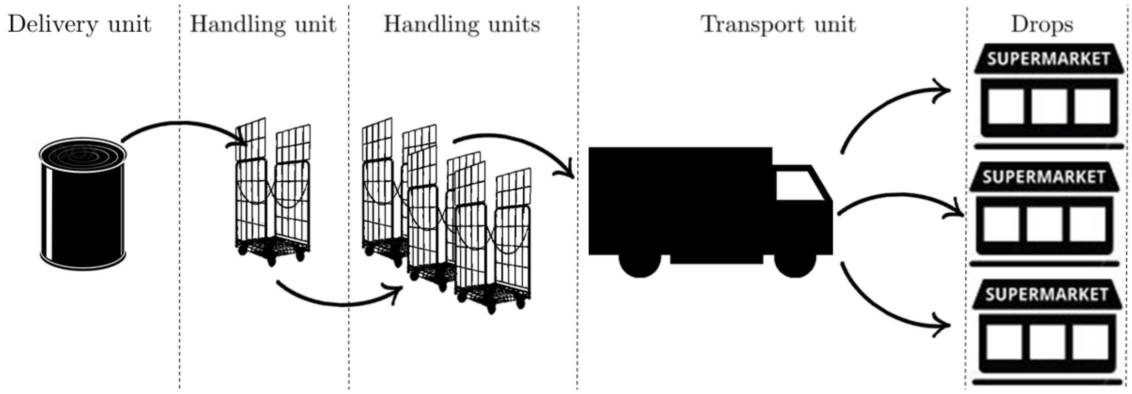

Figure 1.2: Basic illustration of the outbound supply chain.

Multiple delivery units (DUs) are packed in a handling unit (HU). Multiple HUs are loaded onto a transport unit (TU). A TU delivers the HUs during a trip to one drop (delivery to a store) or multiple drops.

1.1.1 Outbound paper process

Pick 'n Pay stores order DUs in SAP, the enterprise resource planning tool used at Pick 'n Pay's distribution centre. SAP contains master data regarding the volume and weight of different DUs.

SAP allocates picking tasks to the ordered DUs. A bin packing algorithm uses the master data as an input and assigns the picking tasks to newly generated HUs, theoretically filling the HUs. The objective function of the algorithm is to minimise the total amount of HUs used and ensure that the DUs placed in the HUs are stacked from heaviest to lightest to attempt to minimise stock damage. The algorithm also ensures that HUs only contain DUs that have the same store destination.

SAP contains a consolidated order file. Each file entry has a picking task allocated to a DU which is linked to an HU number. Each file entry also states the store destination of each HU and the date that the store requires the stock by. The file is imported in Plato, vehicle routing software that solves a vehicle routing problem. The objective function of the vehicle routing algorithm is to minimise total transportation costs by taking into consideration the number of HUs, store destinations, store locations, nominated delivery days of each store, available vehicles and vehicles' HU capacities.

Each HU imported in Plato is allocated a designated drop number linked to a trip number. Plato's output is a list of trip numbers and a trip schedule containing the planned trip departure, planned store arrival time(s), planned DC return time, number of drops and the destination(s), allocated HUs and the TU registration number responsible for executing the trip. This trip schedule is then imported in SAP.

Figure 1.3 illustrates the paper process from receiving an order to generating a transport schedule.

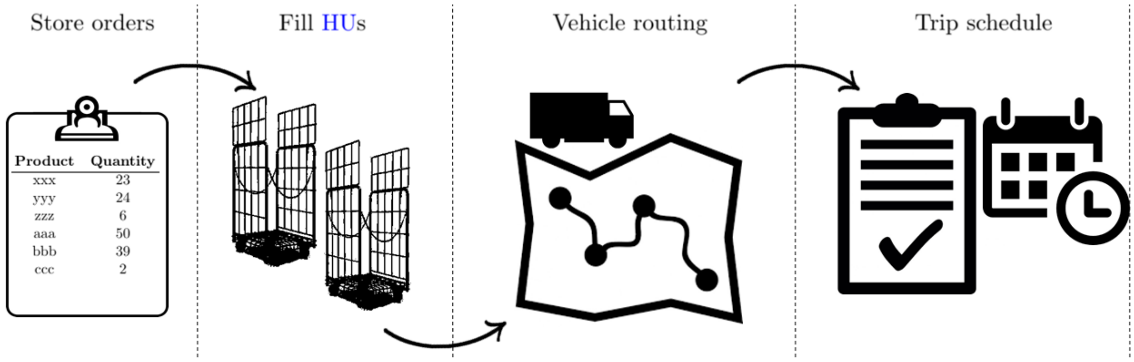

Figure 1.3: Illustration of the paper process once store orders are received.

The bin packing and vehicle routing problems are referred to above; the investigation of these problems are not included in this project's scope. The master data of the DUs' volumes, an input to the bin packing algorithm, was however evaluated regarding accuracy and availability and is discussed in Chapter 3. For more information regarding the bin packing and vehicle routing problems, refer to article Maarouf et al. (2008) and article Golden et al. (2008).

1.1.2 Outbound physical process

Warehouse *picking waves* are released at fixed times during the day. SAP determines the picking wave in which certain picking tasks should be released. This ensures that HUs are picked and loaded on time, allowing the vehicles to despatch as stated on the trip schedule. Once the picking wave has been released, picking staff receive picking tasks from SAP via an advanced material technology wrist pad. Each staff member receives three HUs to pick at a time as this is the maximum amount of HUs that fit onto a bulk transport unit (BTU). Each picking task states:

- The DUs that need to be picked.
- The bin locations where the DUs could be located within the warehouse.
- The sequence in which DUs should be placed into the HUs.
- The staging lanes in which the completed HUs should be placed.

Completed HUs are placed in staging lanes in front of the outbound dock doors to await being loaded into TUs. There are 98 staging lanes. Each staging lane represents a single Pick 'n Pay store during a picking wave; lanes could represent multiple stores on different days, but only represent a single store at a time. The completed HUs are not always full as a result of incorrect or absent DU volume master data causing the bin packing algorithm to inefficiently pack the HU. Staging lane staff combine HUs that have been incompletely filled.

Loading tasks are issued manually by printing a loading sheet for a trip and handing it to a loading staff member. The loading sheet provides the trip number, HU numbers with associated staging lane locations, as well as the dock door where the TU responsible for executing the trip is docked. A loading sheet is issued for a trip once the HUs of the corresponding trip have been staged and the TU has been docked for loading.

Figure 1.4 illustrates the physical process from the release of a picking wave to the loading of a TU.

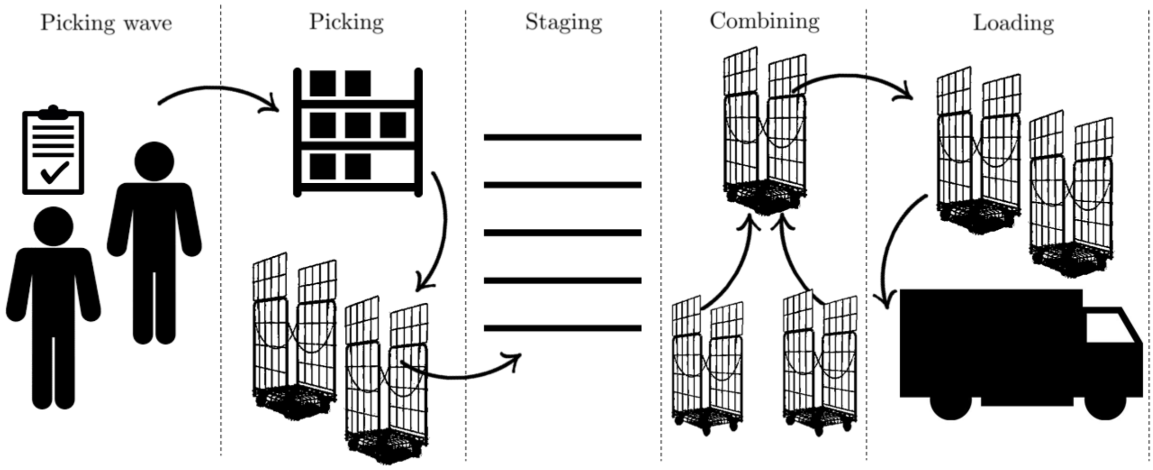

Figure 1.4: Illustration of the physical process of executing received store orders.

This report focusses on the picking, staging, combining and loading processes at the Pick 'n Pay grocery warehouse at Longmeadow business estate and is referred to as the *outbound process*.

1.2 Research question

The concerns currently limiting the responsiveness of the outbound process are excessive TU loading times and HUs not being loaded onto the TUs (dropped HUs). Figure 1.5 illustrates the frequency histogram of 2773 recorded TU loading times at the end of February 2017. 86% of the TUs loaded exceeded the current loading time *key performance indicator (KPI)* of 35 minutes.

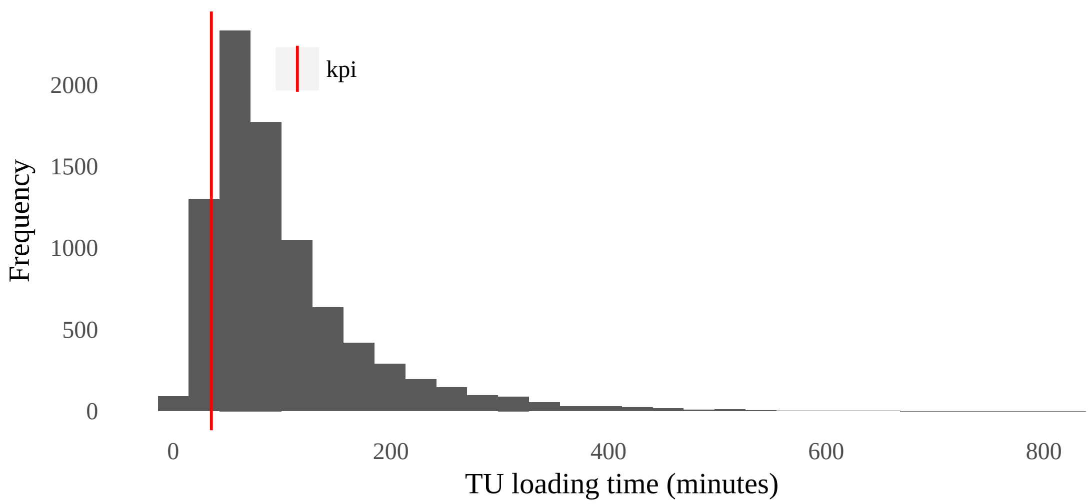

Figure 1.5: Illustration of excessive vehicle loading time.

Figure 1.6 illustrates the number of loaded and dropped HUs in a single twelve-hour shift for 873 shifts.

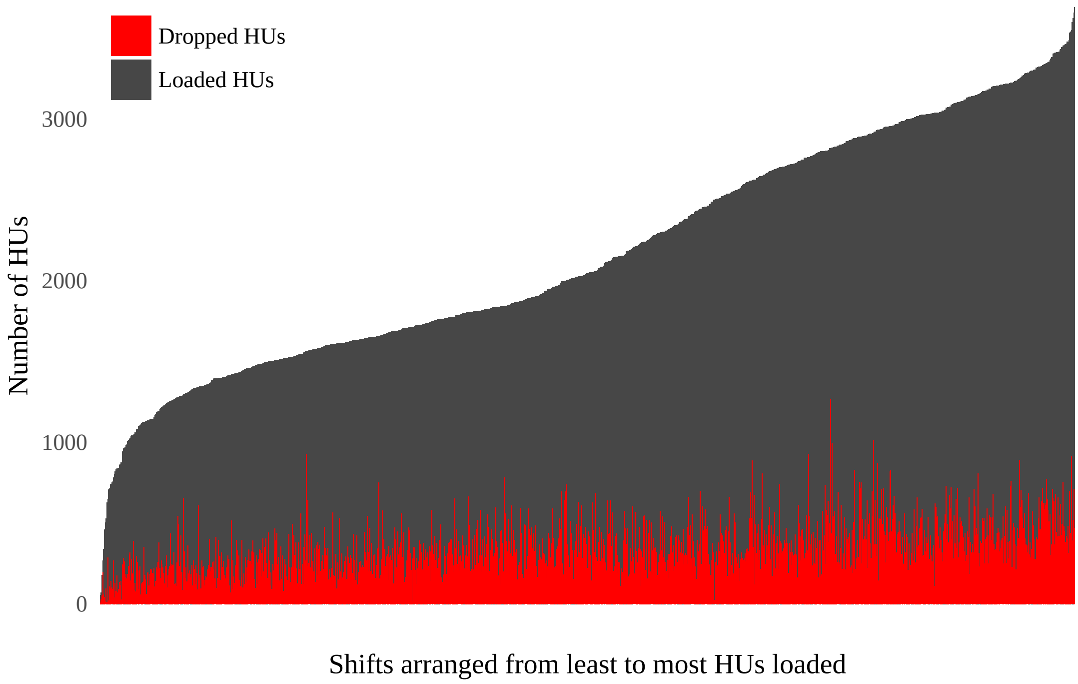

Figure 1.6: Illustration of the number of HUs loaded and the number of dropped HUs per shift for 873 shift, from the fewest HUs loaded to the most HUs loaded.

Pick 'n Pay does not own a vehicle fleet and outsources this supply chain requirement to a third party transport solution provider. A fixed cost is incurred per vehicle per month as well as a variable cost per kilometre travelled. The number of TUs required by Pick 'n Pay is revised every six months.

Excessive TU loading times and dropped HUs directly influence transportation costs. When a TU exceeds the required loading time it reduces the time that could be utilised to deliver HUs to stores and restricts the amount of trips that could be executed per day. Reduced trips per TU per day result in an increase in TUs required to deliver the planned HUs, therefore increasing fixed transportation costs.

The actual number of trips made per day are currently 1.7 times the planned number of trips made per day due to dropped HUs. Additional trips are required to deliver the dropped HUs to ensure that store orders are delivered, thus increasing the kilometres travelled and the variable transportation cost.

Employees responsible for loading reported that 87% of dropped HUs were dropped as the HUs could not be located in the staging lanes. Loaders spend unnecessary time locating HUs required for loading. Potential reasons for employees not locating the HUs required for loading include HUs not being staged in the right lanes, employees misplacing HUs after combining, and high levels of congestion in the staging lanes. Taking this into account the assumption could be made that the high number of dropped HUs could directly influence excessive TU loading times as loading staff spend unnecessary time searching for HUs.

1.3 Research design

This project provides a decision support model capable of representing the outbound process. The model was used in the investigation of operational improvement opportunities regarding TU loading times and dropped HUs. Two proposed solutions were developed; an increased number of stores with night-time receiving to increase the total number of TUs loaded during day shifts, and the adjustment of stores' nominated delivery days to distribute the total volume over the week to reduce volume spikes. Both solutions proposed aim to reduce congestion in the staging lanes. Each solution was evaluated by using the developed decision support model and potential impacts regarding the performance of the outbound process for each solution were determined and evaluated.

1.4 Research methodology

An operations research design was followed in this project (Manson, 2006). The design consists of gaining awareness of the problem, devising suggestions, developing solutions, evaluating the developed solutions, and making conclusions.

The *problem* was investigated and is elaborated on in the research question (refer to section 1.2, Research question). Potential *suggestions* were devised by reviewing simulation literature, specifically within the supply chain environment; agent based simulation (ABS), system dynamics (SD) and discrete event simulation (DES) were investigated as possible simulation techniques as well as the software and validation techniques required. A DES simulation model of the outbound process was *developed* to address the identified problems. DU volume master data was reviewed and conclusions were made regarding the accuracy and availability of the data. Model validation was done by identifying key measures and comparing the simulation model's results to the real-life process under the same input conditions by using distribution plots and 99% confidence intervals. These measures include:

- DUs per HU after loading.
- Loading time per TU.
- HUs staged, combined, dropped and loaded per shift.
- Number of TUs loaded per shift.

Two scenarios that could potentially address the problems identified were determined. The two scenarios include an increased number of stores with night-time receiving to increase the total number of TUs loaded during day shifts, and the adjustment of stores' nominated delivery days to distribute the total volume over the week to reduce volume spikes. The developed simulation model was used to *evaluate* the scenarios. The model was validated by analysing key measures that represent the performance of the outbound process. These measures include:

- HUs staged and loaded per shift.
- Number of TUs loaded per shift.
- Loading time per TU.
- Mean number of HUs per TU.
- Mean number of HUs in the staging lanes.
- Flow of HUs into and out of the staging lanes.

Each scenario's results were evaluated and *conclusions* regarding possible improvement opportunities were stated.

1.5 Document structure

Chapter 2 provides a review of simulation literature that was used to determine this project's approach. A review of Pick n Pay's DUs' volume master data was conducted; recommended methods of improving the data's availability and accuracy is provided in Chapter 3. The decision support simulation model developed, including the data used in developing the simulation model, the model's functionality, model simplifications and model assumptions are elaborated on in Chapter 4. Chapter 5 stipulates the methods used to validate the simulation model and provides the validation's results. Two potential solutions were identified and analysed by using the simulation model; the results of each solution's implementation are included in Chapter 6. Conclusions and recommendations regarding the proposed solutions are presented in Chapter 7.

Chapter 2

Literature review

Due to the complex nature of the outbound process, it is challenging to assess the process while taking all variables into account. Two potential techniques capable of assessing the outbound process were determined, namely supply chain optimisation and supply chain simulation.

Ingalls (2014) depicts the difference between supply chain optimisation and supply chain simulation. Supply chain optimisation could be compared to a car dealer while supply chain simulation could be compared to a test drive. The car dealer owns a large variety of cars, but allows the customer to provide desired specifications such as the size and colour of the car. By taking the customer's specifications into account the car dealer could determine a suitable choice. Supply chain optimisation also takes user-defined constraints into consideration, reducing the total number of feasible solutions and therefore assisting the user in determining the most suitable solution. Once the dealer has determined a suitable car for the customer, the customer could request a test drive to experience the car first-hand before making a decision. Supply chain simulation also allows the user to experience the model in a real-life system before making a decision.

It was concluded that simulation could provide a risk-free design and test environment; this is beneficial as it allows users to gain insight on the system's variables and factors, identify problems and make informed decisions regarding potential process improvement opportunities. Simulation also allows the user to develop a model capable of accounting for variability, an important requisite considering the nature of the outbound process (Ingalls, 2013). Simulation was therefore selected as the technique that would be used to analyse the outbound process in this project.

2.1 Simulation

Three simulation methods namely *agent based simulation (ABS)*, *system dynamics (SD)* and *discrete event simulation (DES)* were investigated to determine which technique should be applied in this project.

ABS decentralises a system into its basic components, allowing each component to be represented by a collection of agents and their environments. Each agent's behaviour is programmed individually and the system's properties are defined by the system's agent interactions with their environments (Kasaie and Kelton, 2015). ABS is an ideal approach when a system's agents' behaviour define the system. The outbound process is not defined by agents; a picking wave in the outbound process for example is released and triggers pickers to start placing delivery units (DUs) in handling units (HUs), concluding that the movement of a DU into an HU and an HU to a staging lane is initiated by the system.

$$\text{Stock}(t) = \text{Stock}(t_0) + \int_{t_0}^{t} \Big[\text{Inflows}(s) - \text{Outflows}(s)\Big] ds \qquad (2.1)$$

Figure 2.1: Representation of stocks and flows (Kunc, 2016).

SD represents the relationship between various system components over time and captures the dynamic aspects of the system by making use of elements such as stock (the number of agents in a system that increases due to inflows and decreases due to outflows), feedback loops (controlling the movement of stock by changing variables in the system in an effort to achieve a certain goal or to stabilise the system) and delays (caused by accumulated stock) (Kunc, 2016).

SD models are a collection of integral equations where time is continuous and the size of ds, as depicted in Figure 2.1, is determined by the time step in the modelling software (Kunc, 2016). SD can therefore be summarised as a continuous deterministic modelling technique which attempts to understand the overall performance of a system. The outbound process in this report consists of the four major components needed for a SD simulation; HUs being staged is an example of inflow, HUs being loaded onto a vehicle is an example of outflow, and the monitoring of vehicles required to dock for loading at a certain point in time is an example of a feedback loop. The flows in the outbound process are however not defined by mathematical relationships. The inflow of HUs into the system, for example, is dependent on the picking waves and the number of pickers. As a result of the deterministic nature of the SD, the stochastic nature of the outbound process, for example the time it takes a picker to pick and stage an HU, cannot be accounted for.

DES could be implemented if the system being investigated consists of agents, activities, events and resources. An agent consists of certain attributes and is defined as the reason for a state changing in a system. An agent could also be defined as the flow of information. The outbound process consists of agents; an HU is an agent in the outbound process as the number of HUs being loaded onto a vehicle changes the total number of HUs loaded in a 12-hour shift, and a vehicle is an agent as the number of HUs being loaded onto a vehicle is an attribute of the vehicle. Agents interact with activities and this interaction causes events. Events are defined as a change in a system's state. Resources such as a person, a machine, a process or a waiting area govern the execution of an activity and has a set capacity. Activities are grouped into three types namely delays, queues and logic. The outbound process consists of agents; the process of a picker (resource) picking DUs into an HU and placing the HU in a staging lane is a delay activity stochastic in nature, the staging lanes where HUs queue before being loaded is an example of a queue, and DUs that have to be picked into an HU before the HU could be loaded onto a vehicle is an example of logic (Ingalls, 2013).

After evaluating these three simulation methods it was determined that ABS should not be implemented in this project as the outbound process is not defined by agents, a requisite for ABS. DES and SD could however both be implemented. These methods were investigated to determine which method should be implemented in this project.

2.2 Application

DES and SD are used to develop decision support in logistics and supply chain management. Tako and Robinson (2012) explored the application of DES and SD to determine the instances in which each method was applied, and whether similarities existed in terms of the nature (the type of logistic and supply chain management issues being addressed) and level of their use. Tako and Robinson (2012) analysed 127 papers relevant to this topic. It was determined that 68% of the papers made use of DES, 30% made use of SD and 2% used a combination of the two methods. It was also determined that SD was mainly used in papers containing issues of a strategic nature, while DES was generally used in papers containing issues of an operational or tactical nature.

A scale ranking supply chain issues from strategic to operational/tactical is depicted in Figure 2.2.

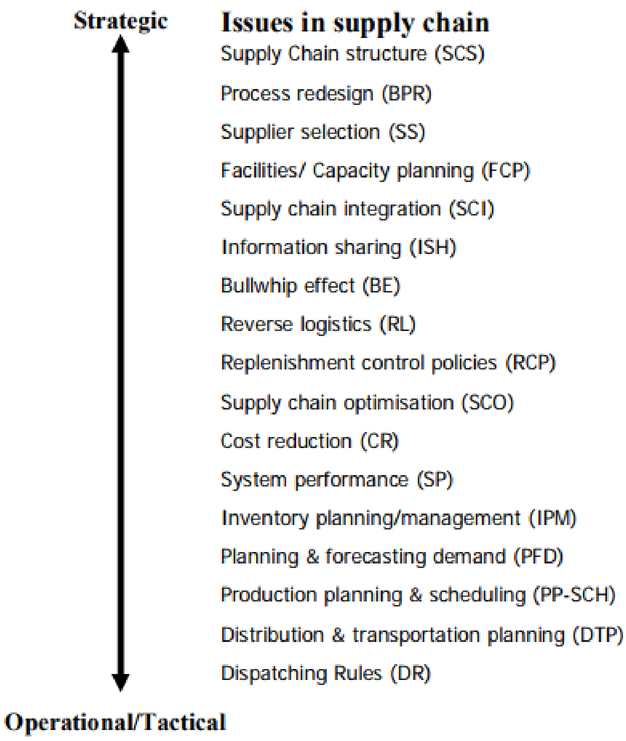

Figure 2.2: Supply chain issue ranking (Tako and Robinson, 2012).

Tako and Robinson (2012) determined that SD is capable of simplifying a complex system and analysing systems by taking the bigger picture into consideration, a view necessary in strategic decisions-making. DES considers the system's operational logic and the stochastic nature of the process, creating an accurate representation of operational and tactical aspects of a process. The classification of an issue as strategic or operational/tactical could therefore provide an indication of which simulation technique to apply in developing a decision support model. It was concluded that the simulation method should be determined by classifying the outbound process's issues as strategic or operational/tactical. The objective of this report is to develop a decision support model to assist in solving operational and tactical issues of the outbound process (refer to section 1.2 Research Question); DES was therefore determined as the simulation method that should be used and was implemented in this project.

2.3 Development

Simulation software with specific functionality is required to develop a DES model. The functional specifications required include (Ingalls, 2013):

- Global variables to test different strategies or configurations.
- A random number generator to account for variables of a stochastic nature such as the duration required by a loader to load a single HU onto a vehicle.
- Scheduling capabilities to plan for future events such as the release of a picking wave or staff members' lunch hour.
- System state variables to describe the state of the system at any given point in time such as the number of vehicles loaded or the outstanding number of picking tasks.
- Statistic collection to validate and analyse the model's result(s).

AnyLogic has a built-in process modelling library that consists of process modelling blocks with predefined functionality including blocks to represent delays, queues and resources. The functionality is however not limited to the built-in libraries as the programming language Java could be used to adjust existing process blocks to execute customised actions defined by the user. The random number generator could create custom distributions determined by observed data or existing distributions such as a Normal or Weibull distribution, allowing accurate representations of the stochastic variables and therefore portraying the real-life system more accurately. The randomness of AnyLogic could be controlled by setting the random seed, allowing reproducible simulation runs of the process crucial during the development and validation phases of the model. AnyLogic University Edition was used in this project due to the software's availability and the capability of providing the functionality that was required to develop a DES model (Grigoryev, 2014).

Sargent (2013) evaluated two methods that could be used to validate a simulation model's output: graphical displays and confidence intervals. By making use of graphical displays such as histograms or density plots the real-life system's results could be compared to the simulation results under the same conditions. The plots represent the distribution of the desired measure allowing comparison of distribution types, variance, mean and range of measure to the simulation model. The simulation model could also be validated by calculating the confidence intervals and comparing the intervals to the measured statistical attributes of the simulation model. An advantage of simulation is that the comparison could be done multiple times by using different random seeds to determine whether the simulation model's results consistently fall within the calculated confidence intervals. Multiple methods could be used to determine confidence intervals. For normally distributed data the interval will be spread evenly around the mean with a range dependant on the confidence level specified. For skewed data bootstrapping, the process of randomly sampling with replacements and therefore assigning a measure of accuracy to a sample estimate such as a mean, is the most reliable method (Orloff and Bloom, 2014).

It was concluded that a DES model should be used due to the operational and tactical issues of the outbound process. AnyLogic was selected as the simulation software to develop the decision support model as this software is capable of providing the required functionality for DES. Graphical displays and confidence intervals should be used to validate the model to ensure that the developed model is an acceptable representation of the outbound process.

Chapter 3

DU volume master data

The outbound process's bin packing algorithm is used to consolidate delivery units (DUs) into handling units (HUs). The bin packing algorithm's objective function is to minimise the total number of HUs required. This is achieved by efficiently packing each HU to ensure maximum use of the HU's capacity. The availability and accuracy of DU volume master data is important as this data is used as an input when the bin packing algorithm allocates DUs to HUs.

Inaccurate DU volume master data could either be overstated or understated which could lead to the bin packing algorithm under utilising or over utilising an HU's capacity. Unavailable DU volume master data could result in the bin packing algorithm allocating the single DU with unavailable volume master data to a single HU, under utilising the HU's capacity. Impacts of under utilised HUs on the outbound process could include:

- Reduced picking productivity which could lead to unachieved picking targets.
- Increased number of HUs being staged which could result in unnecessary congestion in the staging lanes as well as excessive material handling.
- Reduced mean number of DUs per HU and reduced mean number of DUs per transport unit (TU) which could result in less stock being delivered per trip.

Impacts of over utilised HUs on the outbound process could include product damage due to over packing, and incomplete picking tasks. Product damage could result in financial loss as damaged stock cannot be delivered or reused. Incomplete picking tasks could result in DUs being reallocated to different HUs causing unnecessary work for warehouse staff.

The DUs' volume master data could impact the performance and the resource utilisation of the outbound process. The accuracy and availability of DU volume master is therefore valuable and was reviewed.

3.1 Volume availability

The 10790 stock keeping units currently stored in the warehouse are located in 24 different storage sections. The DUs' nature determines in which section the units are stored; a body deodorant is stored in the fire suppression area for example due to the flammable nature of this DU.

To determine the availability of volume master data, DU volume master data was compared to DUs currently being stored in the warehouse. It was determined that 472 of the 10790 DUs currently stored in the warehouse do not contain master data volumes on record.

Figure 3.1 depicts the amount of DUs without volume master data in each warehouse section.

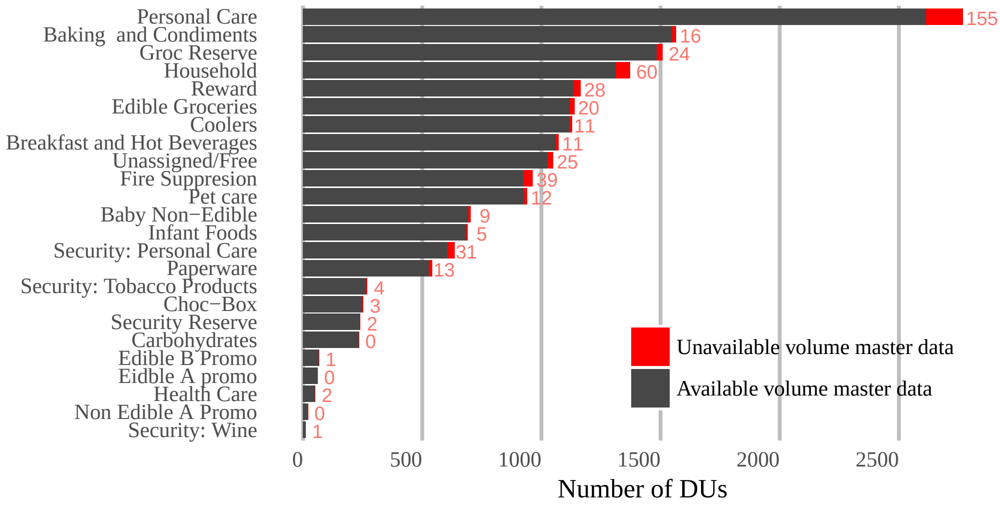

Figure 3.1: The number of DUs with unavailable volume master data by warehouse storage section.

Pick 'n Pay has been in the process of centralising over the past 12 months, adding multiple DUs to the warehouse. The additional DUs could have been added without specified dimensions, which could have resulted in the missing DU volume master data.

Although only 4.37% of the total DUs' volume master data is absent, the unavailable data could impact operations as aforementioned.

3.2 Volume accuracy

To determine the accuracy of volume master data, 100 DUs' volumes were sampled by randomly selecting 25 DUs from each volume quantile to ensure an evenly spread sample. The DUs' volumes were measured and compared to the volume master data on hand. It was determined that all of the samples' actual volumes measured was less than the samples' volume master data on record. Figure 3.2 depicts the percentage difference between the volume master data and the actual volume measured for the 100 DUs that were sampled.

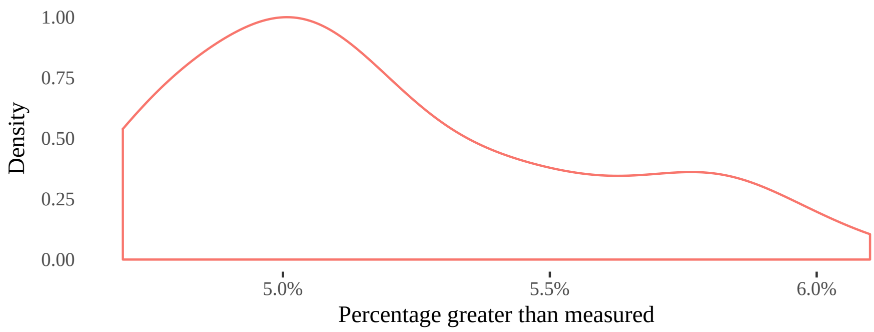

Figure 3.2: The percentage difference between the measured and master volume data for a 100 unique DUs.

Possible causes of the inaccurate volume measurements could be vendors changing products' packaging without notifying Pick 'n Pay of the changes, or inaccurate measurements captured by the three-dimensional scanner used by Pick 'n Pay to establish each DUs's volume.

3.3 Recommendations

Considering that the DUs' volume master data could impact the performance and the resource utilisation of the outbound process it is recommended that Pick 'n Pay should invest time and resources in updating the DU volume master data.

Considering the large amount of DUs in the warehouse, reviewing and updating existing DUs' volume master data could be a time and resource consuming process. It is recommended that vacation work students should be responsible for this process as it does not require specialised skills.

Resources could be allocated to supervise data capturing of DUs being centralised into the warehouse to ensure that new DUs' master volumes are accurate and available.

Chapter 4

The simulation model

The model developed simulates the three discrete events of the outbound process, namely picking/staging, combining and loading. The model was developed by making use of data captured between the 1st of May 2017 and the 30th of June 2017. Data was captured from SAP (transactional information) and shift data (the picking target per shift, the number of delivery units (DUs) picked, the number of handling units (HUs) staged, combined, dropped and loaded, the number of transport units (TUs) loaded and the staffing requirements for the three events).

A single shift consists of 12 hours. A day shift is between 06:00 and 18:00 and a night shift is between 18:00 and 06:00. The model simulated the outbound process from 06:00 on the 1st of May 2017 to 06:00 on the 1st of July 2017 and takes the allowed lunch hour (between 12:00 and 13:00, and 00:00 and 01:00) into consideration.

4.1 Picking/Staging

The initial number of HUs in the staging lanes were defined as 2000 in the simulation model, the actual number of HUs present in the staging lanes at 06:00 on the 1st of May 2017. Figure 4.1 `src_InitialHU` depicts the process block responsible for injecting the initial number of HUs into the model once the simulation model is started.

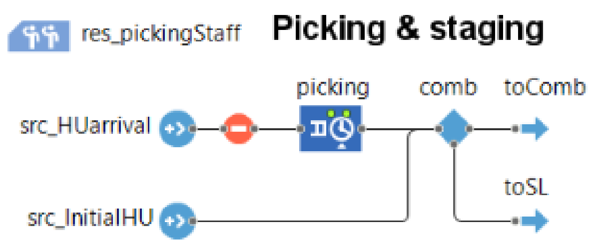

Figure 4.1: The picking/staging event of the simulation model.

The picking target and the manning requirements for each shift are used as an input from an excel sheet; these inputs update when a new shift starts. Multiple picking waves are released at predetermined times in each shift, representing a fraction of the picking target for that shift. On release, HUs enter the model. Figure 4.1 `src_HUarrival` depicts the process block responsible for injecting HUs into the model. When the HU has entered the model, DUs get allocated to the HU. The number of DUs allocated to an HU is sampled out of a custom distribution based on observed DUs per HU.

As an HU enters the `picking` process block as depicted in Figure 4.1, a picker is seized from the `res_pickingStaff` resource pool that defines the number of pickers available. The HU is delayed while the picker allocated to the HU stages the HU. The duration of the delay is based on a Log normal distribution fitted to the data by using the maximum likelihood method with a mean log parameter of 2.64 and a standard deviation log parameter of 1.29 as depicted in Figure 4.2.

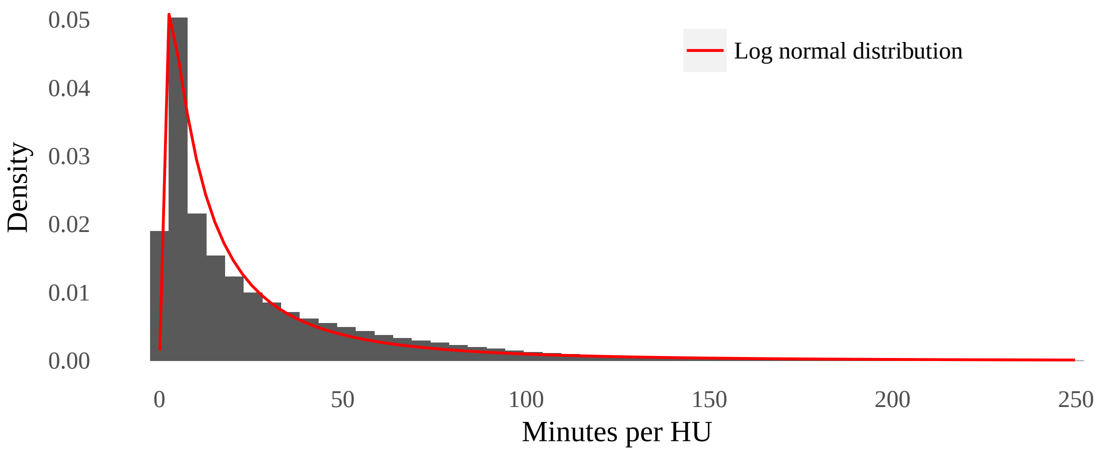

Figure 4.2: Staging time per HU fitted with the Log normal distribution.

Once an HU has been staged the model decides whether the HU should be combined by making use of a probability distribution. The probability was calculated by determining the total HUs combined as a fraction of the total number of HUs staged during a shift. The probability is represented by a Normal curve with a mean of 0.28 and a standard deviation of 0.05 as depicted in Figure 4.3.

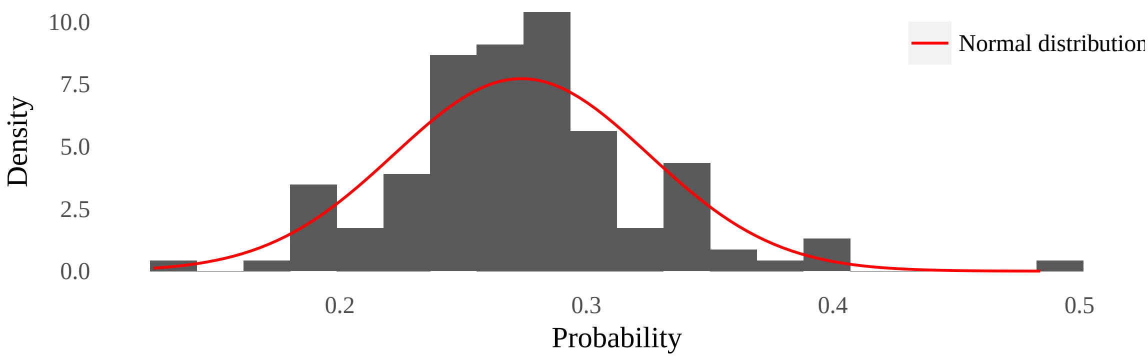

Figure 4.3: Probability of an HU being combined fitted with a Normal distribution.

If the model determined that an HU could be combined, the `toComb` process block as depicted in Figure 4.1 sends the HU to the combining process in the staging lanes. If the HU could not be combined, the HU is sent to the staging lanes and awaits being loaded.

The key measures determined in the picking/staging events are the number of DUs picked per shift and the number of HUs staged per shift.

4.2 Combining

HUs that could be combined enter the combining event and await to be combined by a staff member as depicted in Figure 4.4. During this event the DUs of one HU are combined with another HU. The model assumes that only two HUs could be combined as this is the norm in the real-life outbound process.

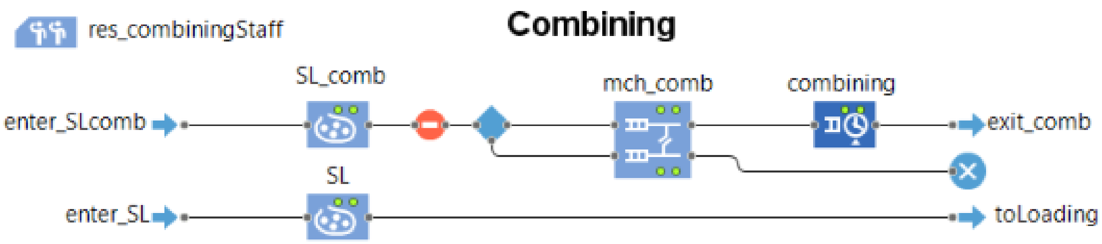

Figure 4.4: The combining event of the simulation model.

The duration of the HU delay is based on the time it takes the staff member to execute the combine event. This time is based on a Log normal distribution fitted to the data by using the maximum likelihood method with a mean log parameter of 0.37 and a standard deviation parameter of 1.28 as depicted in Figure 4.5.

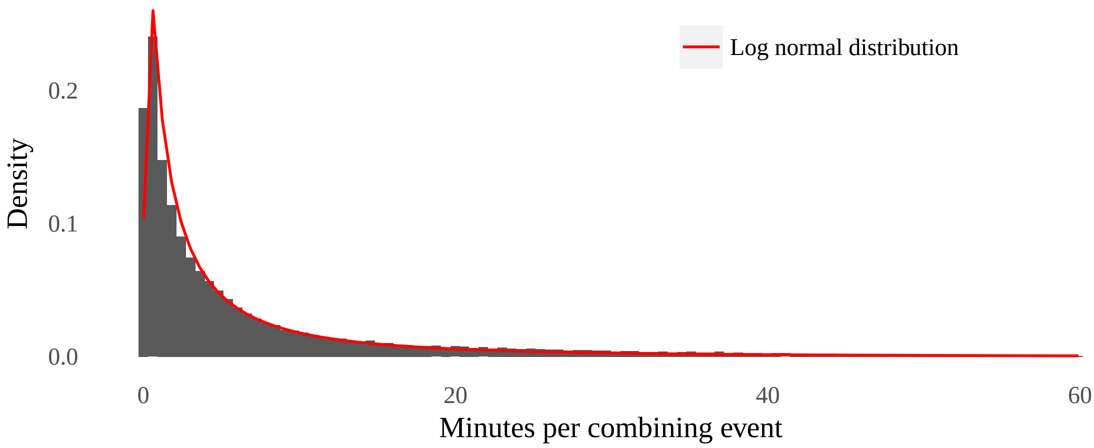

Figure 4.5: Time it takes to combine two HUs fitted with the Log normal distribution.

Once an HU has been completed in the combining event the HU could be loaded. The key measure for the combining event is the number of HUs combined per shift.

4.3 Loading

The loading event is dependant on the TUs and HUs that are awaiting loading. The loading event therefore consists of two sub-events namely the docking of a TU and the loading of a TU.

4.3.1 TU arrival

The simulation model inserts TUs to be loaded (as depicted as `src_vehiclesAvail` in Figure 4.6) as an input every hour. The model takes into account the number of HUs awaiting loading, the mean number of HUs per TU, and the time of day. The time of day is taken into consideration as Pick 'n Pay stores' receiving times largely dictate the number of TUs required for loading during a shift as the majority of stores only receive during the day. Roughly 65% of all TUs loaded in a day are loaded during the night shift to ensure that HUs are delivered during the day.

Each TU receives a unique trip number and the number of HUs that should be loaded. The number of HUs allocated to a TU is sampled from a custom distribution based on the number of HUs per TU observed. Once a TU exits the `del_arrival` process block as depicted in Figure 4.6, the TU seizes an available dock door from the `res_dockDoors` resource pool (the total number of dock doors) as depicted in Figure 4.6. The delay between TU docking and TU loading is as a result of the warehouse operations, such as the printing of a load sheet, required before TUs could be loaded. The delay duration is sampled from a custom distribution based on historic observations.

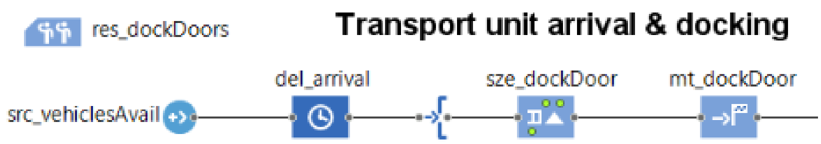

Figure 4.6: TUs arriving for loading in the simulation model.

Once a TU exists the `del_LoadStart` process block as depicted in Figure 4.7, the TU enters the `wait_loader` process block as depicted in Figure 4.7 and the model allocates a loader to the TU. When a loader has been allocated to load, the TU enters the `wait_Loading` process block as depicted in Figure 4.7. The TU is issued for loading and the number of HUs that need to be loaded from the `SL` process block (as depicted in Figure 4.4) is released.

Figure 4.7: TU issued for loading in the simulation model.

4.3.2 TU loading

HUs are each allocated a trip number as well as the loader allocated for loading the associated TU. HUs awaiting loading enter the loading process as depicted by the `enter_Loading` process block in Figure 4.8.

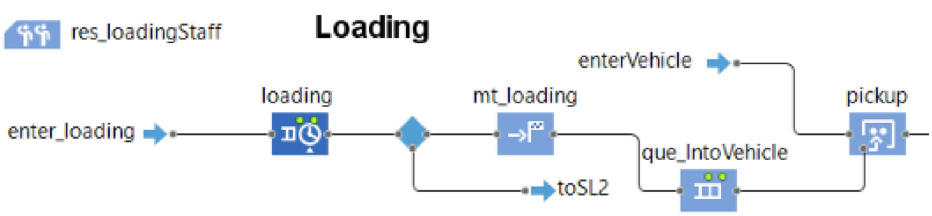

Figure 4.8: HUs being loaded in the simulation model.

The model makes use of a decision block to determine whether the HU will be dropped. This decision is based on a probability associated with the number of HUs in the staging lanes.

Figure 4.9 illustrates how the probability to drop an HU increases as the number of HUs in the staging lanes increase. If the HU is dropped, the HU returns to the staging lanes.

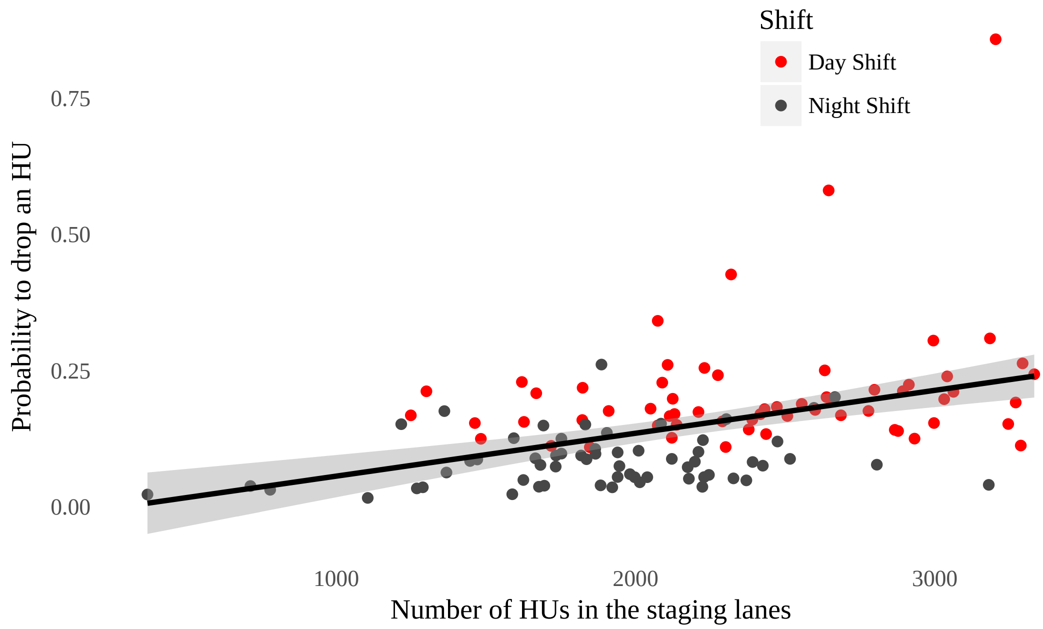

Figure 4.9: Probability of an HU being dropped and the number of HUs in the staging lanes.

The allocated loader loads a single TU at a time. The duration of the HUs' delay is determined by the time it takes a loader to load an HU into a TU. This time is represented by a Log normal distribution fitted to the data by using the maximum likelihood method with a mean log parameter of 1.12 and a standard deviation parameter of 0.59 as depicted in Figure 4.10.

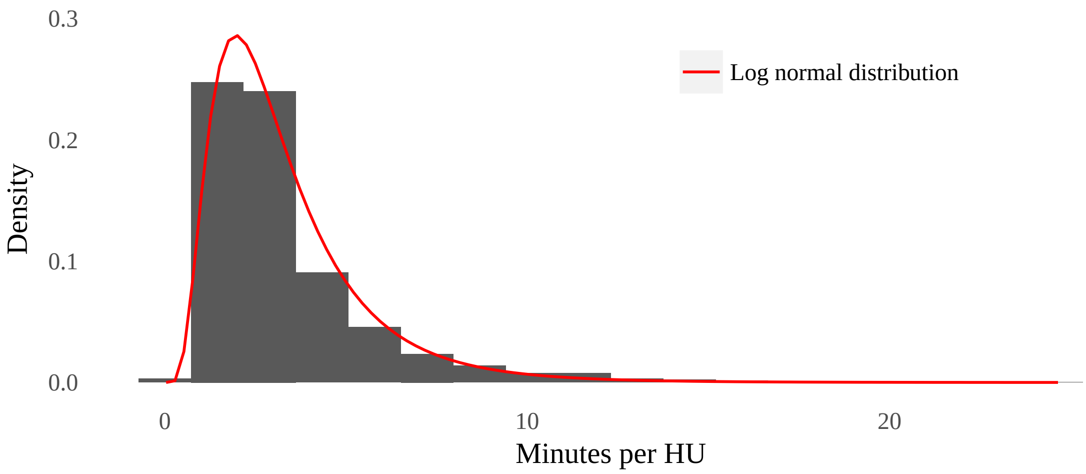

Figure 4.10: Loading time per HU fitted with the Log normal distribution.

There is a delay between the last HU loaded onto a TU and the TU despatch as depicted in Figure 4.11. The delay duration is sampled from a custom distribution based on historic observations. Once a TU exits the delay the seized dock door is released and the TU exits the model.

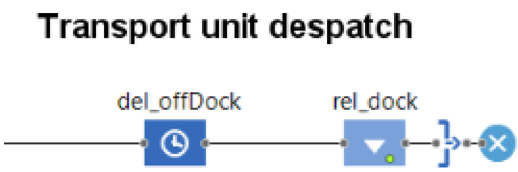

Figure 4.11: TUs despatching in the simulation model.

The key measure identified for the loading event is the number of HUs loaded per shift, the number of HUs dropped per shift, the number of TUs loaded per shift, the number of DUs per HU when loaded onto a TU, and the TU loading times.

4.4 Simulation model summary

The simulation model as depicted in Figure 4.12 was developed to evaluate the impact of tactical and operational decisions on the outbound process. The tactical and operational decisions that could be evaluated by the model include:

- Manning quantities.
- The size of the picking wave.
- The release time of the picking wave.
- Task completion rates.
- Arrival times of TUs.

Structural decisions could however not be addressed with the developed model. It is concluded that the developed model has the functional capabilities to be able to address the concerns mentioned in Section 1.2, Research question.

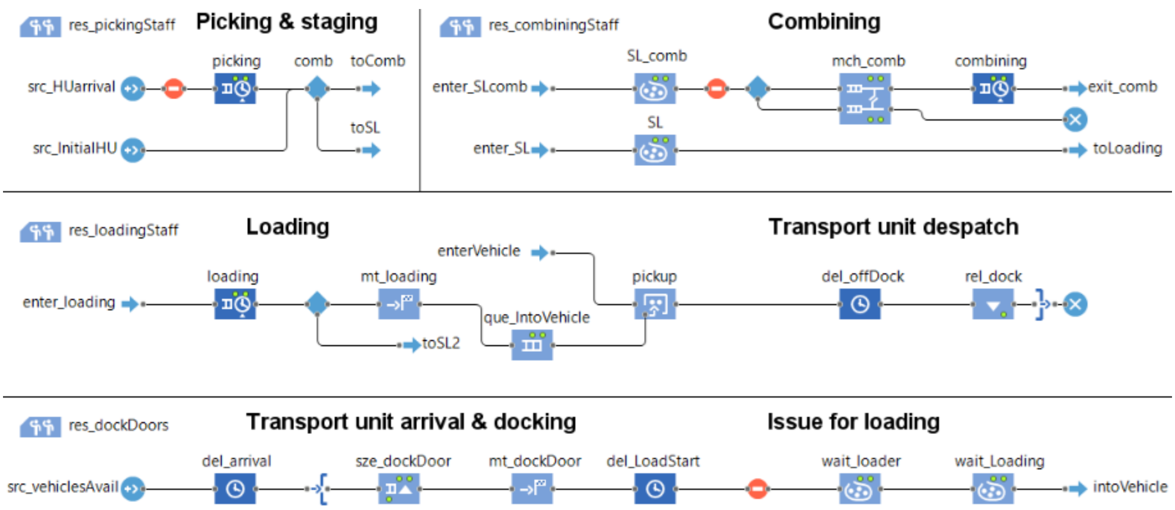

Figure 4.12: The developed simulation model.

Chapter 5

Model validation

Key measures that the model could be validated against were identified. The measures include:

- Number of delivery units (DUs) per handling unit (HU) after loading.
- Loading time per transport unit (TU).
- HUs staged, combined, dropped and loaded per shift.
- Number of TUs loaded per shift.

Two methods of model validation were used; a distribution plot to compare the actual measured values and the values generated by the simulation model, and confidence intervals for each measure's mean by using observed data gathered between the 1st of May 2017 and the 30th of June 2017.

5.1 Distribution plots

The importance of comparing the density plots of the observed data and the simulated data is that it provides an indication of the range and statistical nature of each measure. This indicates whether the simulation model accurately accounts for the variability of the real life process. Density plots comparing each measure's observed data and simulated results were generated and are depicted in Figure 5.1 to Figure 5.8.

Figure 5.1 illustrates the density plot of the observed and simulated data for the number of DUs picked per shift.

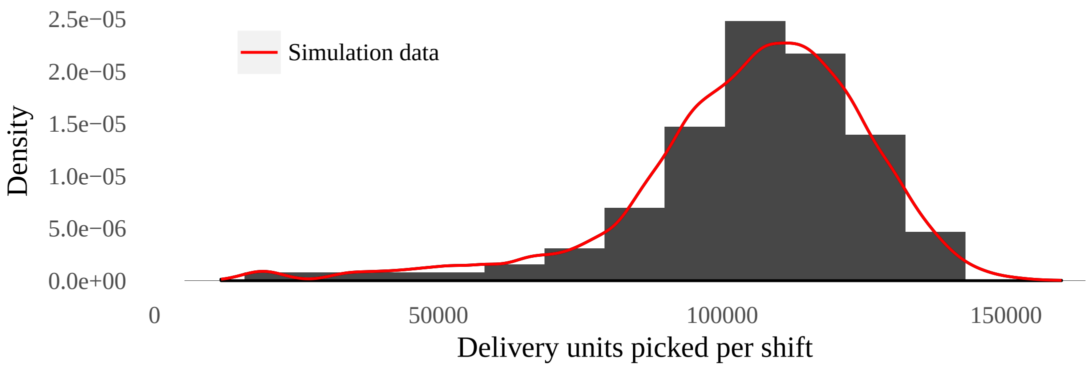

Figure 5.1: Density plot of observed data and simulated results for the number of DUs picked per shift.

Figure 5.1 indicated that the simulation model generates the same distribution as the observed data for the number of DUs picked per shift. This finding was expected as the picking target was provided as an input in the simulation model.

Figure 5.2 illustrates the density plot of the observed and simulated data for the number of HUs staged per shift.

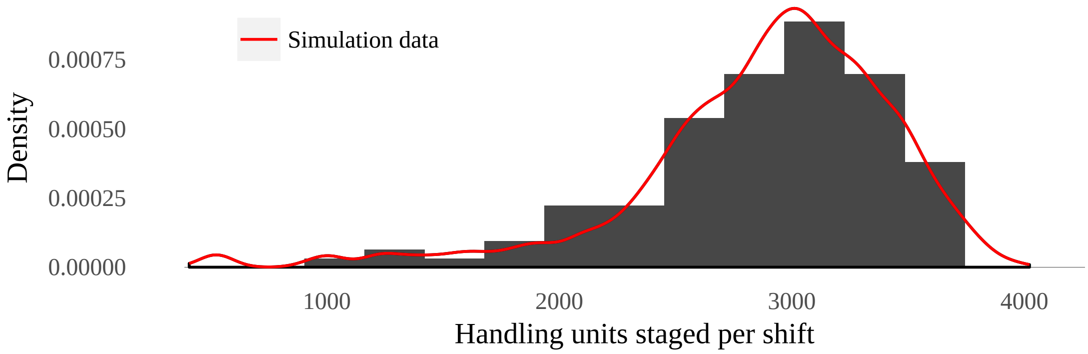

Figure 5.2: Density plot of observed data and simulated results for the number of HUs staged per shift.

The number of HUs staged is dependant on the number of DUs allocated to each HU by the simulation model, a number sampled out of a custom distribution as previously mentioned. Figure 5.2 illustrates that the number of HUs staged per shift follows the same distribution for the observed data and the simulated data. The number of DUs picked per shift and the number of HUs staged per shift is an important function of the simulation model as it represents the start of the outbound process. It was concluded that the values generated by the simulation model for these two measures are accurate in comparison to the observed data.

Figure 5.3 illustrates the density plot of observed data and simulated data for the number of HUs combined per shift.

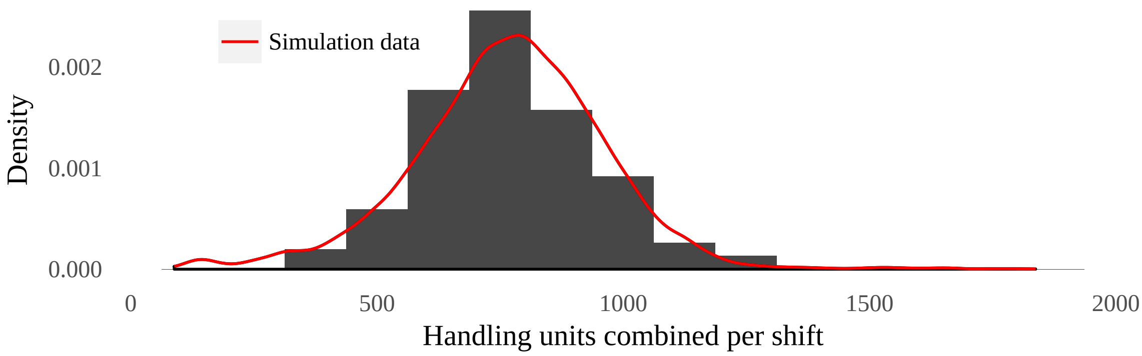

Figure 5.3: Density plot of observed data and simulated results for the number of HUs combined per shift.

An increase in HUs combined per shift decreases the total number of HUs in the staging lanes, relieving staging lane congestion. The simulation model should accurately depict the number of HUs being combined per shift to ensure a realistic flow of HUs into and out of the staging lanes. Figure 5.3 illustrates that the simulation model follows the same distribution for the number of HUs combined per shift as the observed data.

Figure 5.4 illustrates the density plot of the observed data and simulated data for the number of HUs dropped per shift.

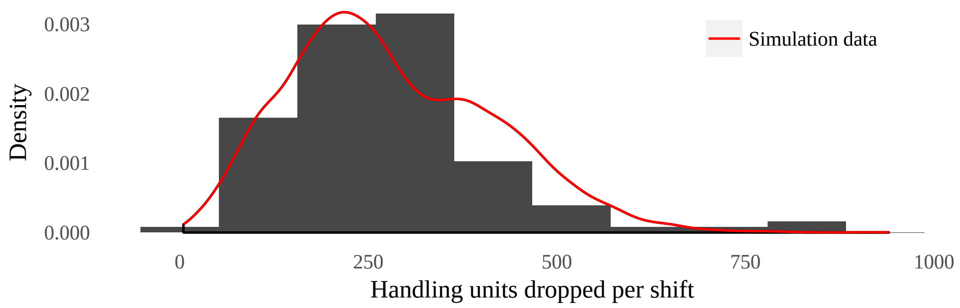

Figure 5.4: Density plot of observed data and simulated results for the number of HUs dropped per shift.

Considering that the significant amount of dropped HUs per shift is one of the concerns being addressed in this report, the simulation model should be able to produce results consistent with the observed data so that the right conclusions could be made. Figure 5.4 illustrates that the simulation model follows the same distribution for the number of HUs dropped per shift as the observed data.

Figure 5.5 and Figure 5.6 illustrate the density plots of the number of HUs loaded per shift and the number of TUs loaded per shift for the observed data and the simulated data.

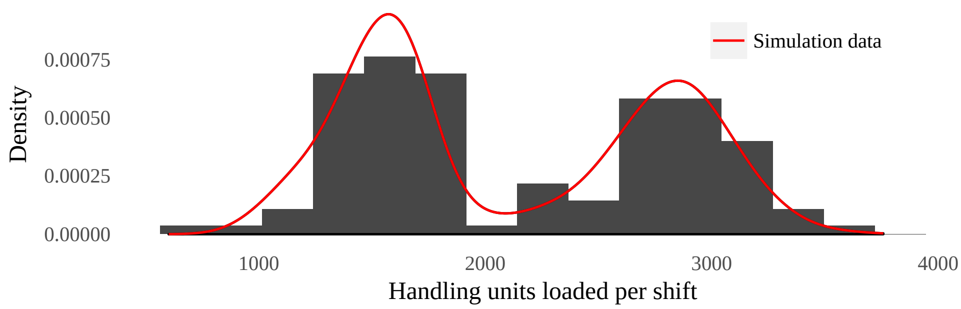

Figure 5.5: Density plot of observed data and simulated results for the number of HUs loaded per shift.

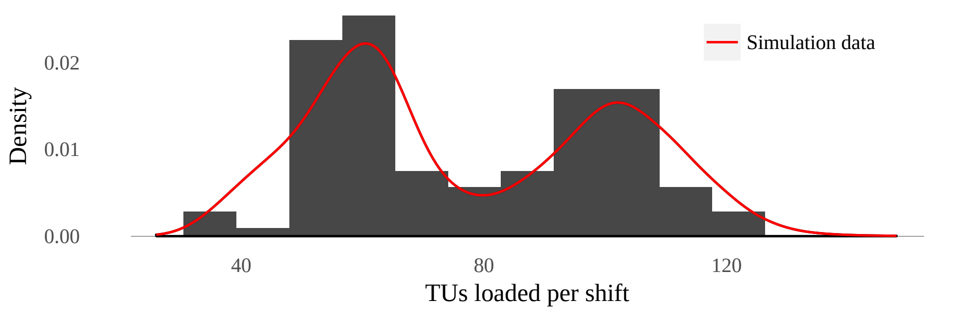

Figure 5.6: Density plot of observed data and simulated results for the number of TUs loaded per shift.

Figure 5.5 and Figure 5.6 are bimodal; this is as a result of the number of TUs loaded during day shifts and night shifts. As mentioned in Subsection 4.3.1 TU arrival, 65% of the daily TUs loaded are loaded during the night shift due to most stores having day-time receiving. The lower mode thus indicates the number of HUs and TUs loaded during the day shift and the upper mode the number of HUs and TUs loaded during the night shift. Figure 5.5 and Figure 5.6 illustrate that the number of HUs and TUs loaded generated by the simulation model follows the same distribution as the observed data.

Figure 5.7 illustrates the density plot of observed data and simulated data for the number of DUs per HU when loaded onto a TU.

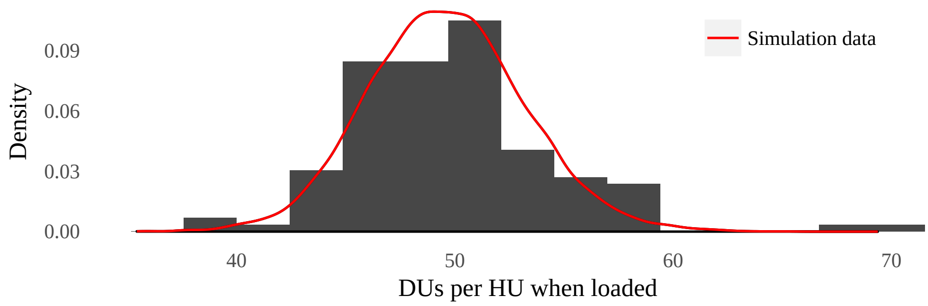

Figure 5.7: Density plot of observed data and simulated results for the number of DUs per HU.

The mean number of DUs per HU indicates the combining event's effectiveness. Figure 5.7 illustrates that the mean DUs per HU when loaded onto a TU, as generated by the simulation model, follows the same distribution as the observed data. The Figure 5.7 also illustrates that the combining event in the simulation model achieves the same effectiveness as the real-life process.

Figure 5.8 illustrates the density plot of observed data and simulated data for the TU loading times.

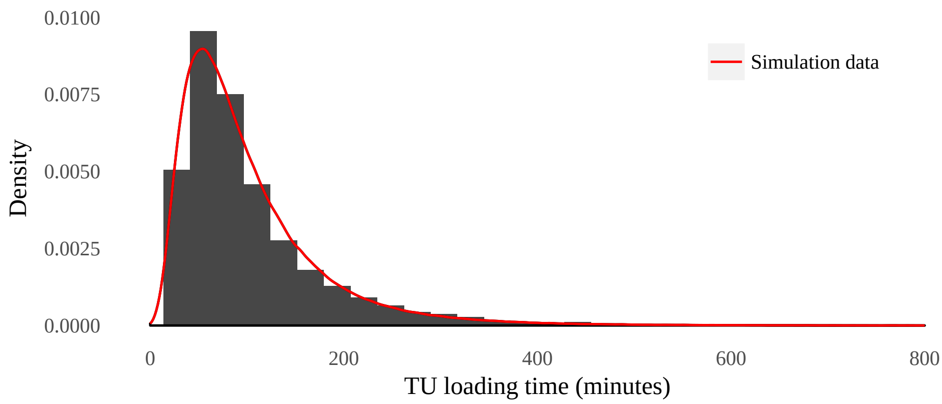

Figure 5.8: Density plot of observed data and simulated results for TU loading times.

Considering that excessive TU loading times is one of the concerns being addressed in this report, the simulation model should be able to produce results consistent with the observed data so that the right conclusions could be made. Figure 5.8 illustrates that the TU loading times generated by the simulation model follows the same distribution as the observed data.

5.2 Confidence intervals

The mean confidence intervals of each measure, based on the observed data, provides a method to test whether the data generated by the simulation model conforms to approximately the same mean as the observed data's population. The mean confidence intervals of the identified measures were calculated based on the nature of the measures' distributions. A confidence level of 99% was used in the calculation of the confidence intervals.

It was determined that the number of HUs combined per shift, the mean DUs per HU, and the number of HUs and TUs loaded per shift are represented by Normal distributions; the t-test was used to determine confidence intervals. The number of DUs picked per shift, the number of HUs staged per shift and the number of HUs dropped per shift are represented by skewed distributions; the bootstrap method was used to determine confidence intervals. 100 independent simulation runs were conducted and the mean of each measure for each simulation-run was compared to the calculated confidence intervals. The results are depicted in Figure 5.9 to Figure 5.18.

Figure 5.9 illustrates the frequency histogram of the mean DUs picked per shift generated by the simulation model in relation to the mean confidence interval of the number of DUs picked per shift of the observed data.

Figure 5.9: Frequency histogram of the simulated mean DUs picked per shift in relation to the calculated confidence interval.

Figure 5.10 illustrates the frequency histogram of the mean HUs staged per shift generated by the simulation model in relation to the mean confidence interval of the number of HUs staged per shift of the observed data.

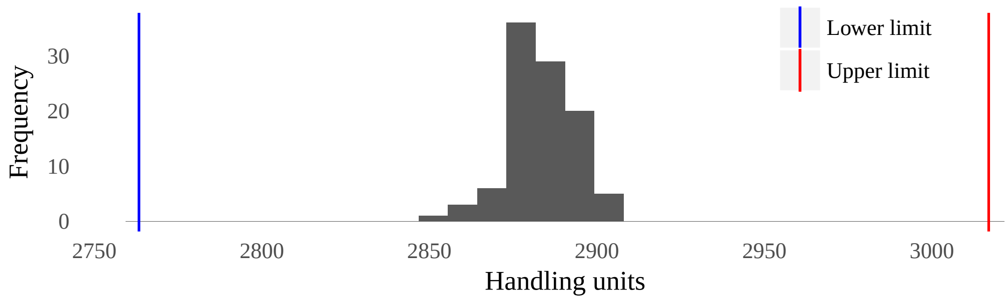

Figure 5.10: Frequency histogram of the simulated mean HUs staged per shift in relation to the calculated confidence interval.

Figure 5.9 and Figure 5.10 illustrate that the mean number of DUs picked per shift and the mean number of HUs staged per shift generated by the simulation model fall within the confidence intervals.

Figure 5.11 and Figure 5.12 illustrate the frequency histograms of the mean HUs combined and dropped per shift generated by the simulation model in relation to the mean confidence interval of the number of HUs combined (Figure 5.11) and dropped (Figure 5.12) per shift of the observed data.

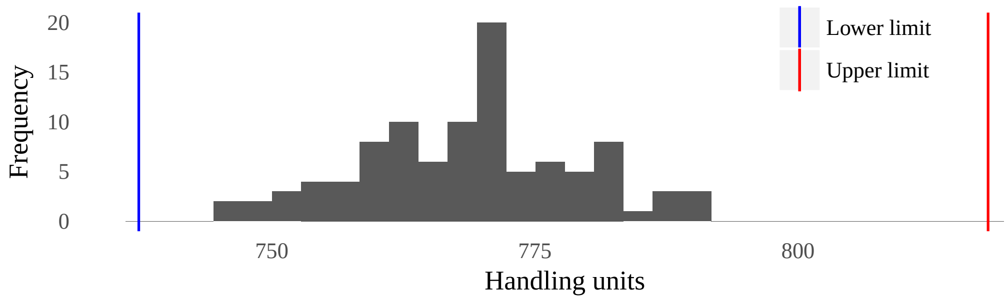

Figure 5.11: Frequency histogram of the simulated mean HUs combined per shift in relation to the calculated confidence interval.

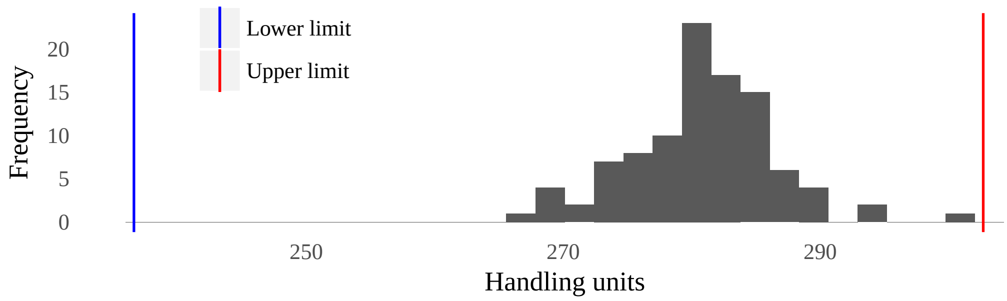

Figure 5.12: Frequency histogram of the simulated mean HUs dropped per shift in relation to the calculated confidence interval.

Figure 5.11 and Figure 5.12 illustrate that the mean number of HUs combined and dropped per shift generated by the simulation model fall within the confidence intervals.

The mean confidence intervals for the number of HUs and TUs loaded per shift was calculated for the day shift and night shift to take the bimodal nature of these measures into consideration. Figure 5.13 and Figure 5.14 illustrate the number of HUs and TUs loaded as generated by the simulation model in relation to the mean confidence interval of the number of HUs and TUs loaded per day shift of the observed data.

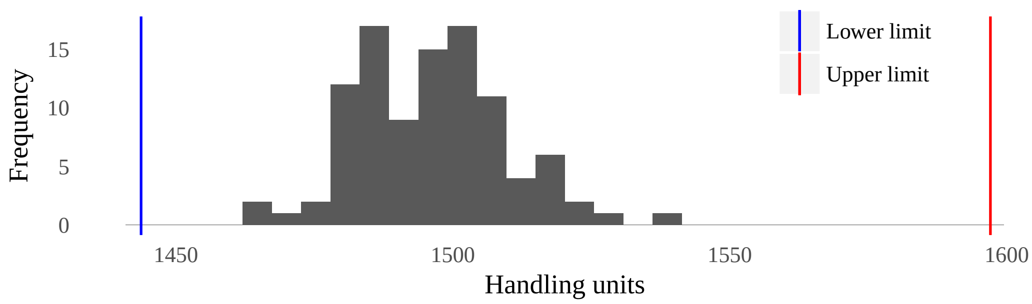

Figure 5.13: Frequency histogram of the simulated mean HUs loaded per day shift in relation to the calculated confidence interval.

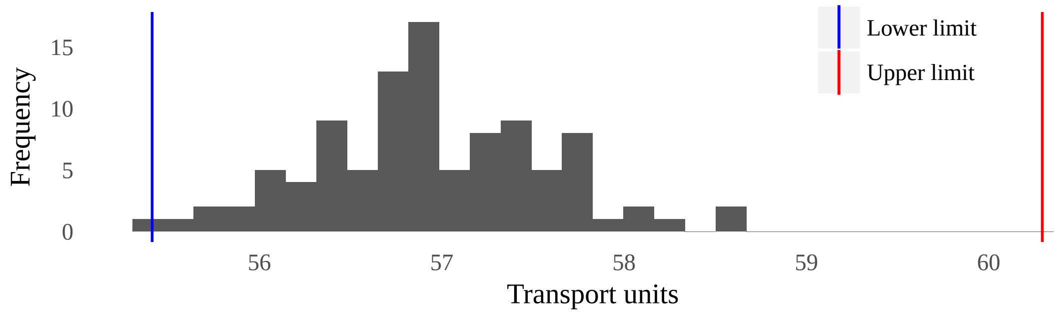

Figure 5.14: Frequency histogram of the simulated mean TUs loaded per day shift in relation to the calculated confidence interval.

Figure 5.15 and Figure 5.16 illustrate the mean number of HUs and TUs loaded as generated by the simulation model in relation to the mean confidence interval of the number of HUs and TUs loaded per night shift of the observed data.

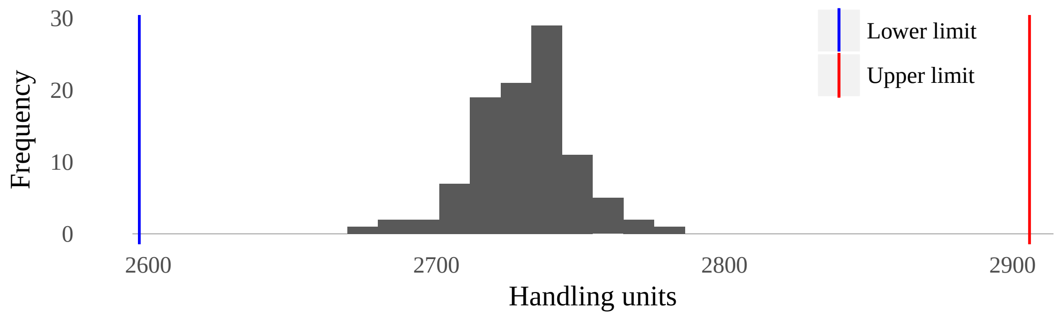

Figure 5.15: Frequency histogram of the simulated mean HUs loaded per night shift in relation to the calculated confidence interval.

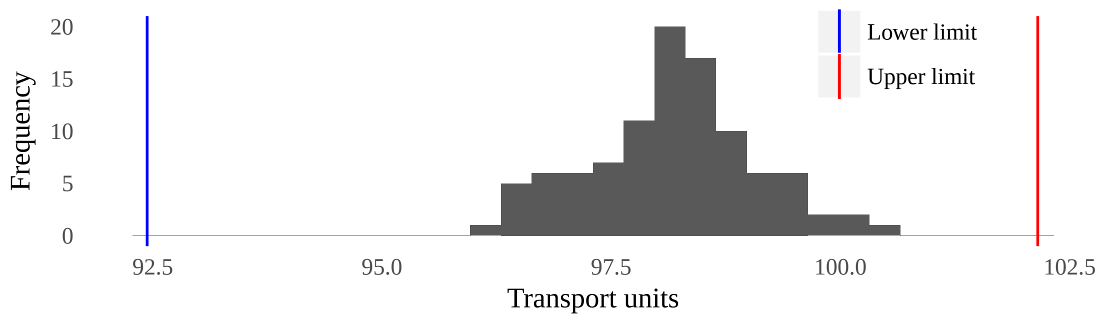

Figure 5.16: Frequency histogram of the simulated mean TUs loaded per night shift in relation to the calculated confidence interval.

Figure 5.13 to Figure 5.16 illustrate that the mean number of HUs and TUs loaded per day shift and night shift as generated by the simulation model fall within the confidence intervals.

Figure 5.17 illustrates the frequency histogram of the mean DUs per HU when loaded onto a TU as generated by the simulation model in relation to the confidence interval of the observed data.

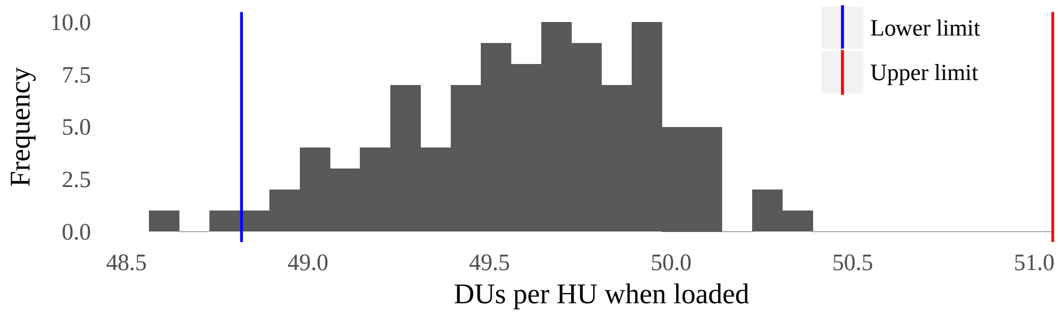

Figure 5.17: Frequency histogram of the simulated mean DUs per HU when loaded onto a TU in relation to the calculated confidence interval.

Figure 5.17 illustrates that the mean number of DUs per HU when loaded onto a TU generated by the simulation model mostly falls within the calculated confidence intervals. The values outside the calculated confidence intervals are not a concern as the values missed the interval by less that 0.5.

Figure 5.18 illustrates the frequency histogram of the loading time per TU as generated by the simulation model in relation to the mean confidence interval of the loading time per TU from the observed data.

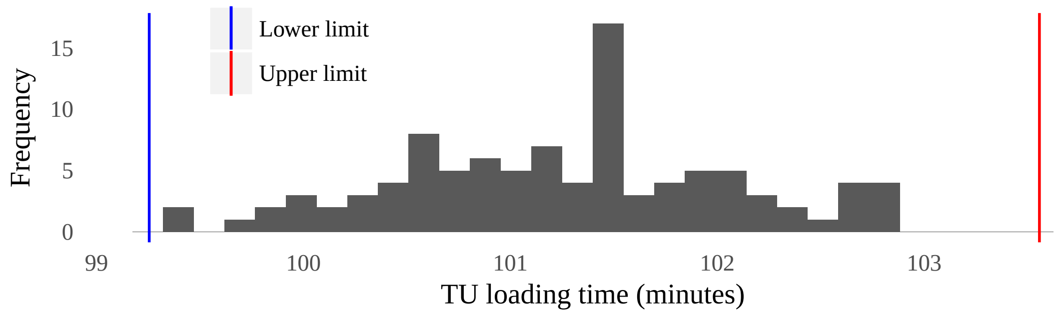

Figure 5.18: Frequency histogram of the simulated mean TU loading time in relation to the calculated confidence interval.

Figure 5.18 illustrates that the loading times per TU generated by the simulation model falls within the calculated confidence intervals.

5.3 Model validation conclusion

After comparing the distribution plots and confidence intervals of the identified measures to the simulated results it was concluded that the developed simulation model is a credible representation of the outbound process. It could therefore be assumed that performing scenario modelling by making use of the developed model could generate credible representations of the outbound process that could provide insights in the decision-making process.

Chapter 6

Scenario modelling

Observed data and data generated by the validated simulation model were used to determine the root causes of the excessive number of dropped handling units (HUs) per shift and the excessive transport unit (TU) loading times. It was determined that the two concerns are as a result of staging lane congestion. High quantities of HUs in the staging lanes increase the probability of dropped HUs as it becomes more likely that the HUs will not be found by loaders. Loaders waste time searching for HUs which contributes to excessive TU loading times.

6.1 Identifying solutions

By investigating the flow of HUs into and out of the staging lanes per shift, the cause of staging lane congestion could be comprehended. Due to the fact that the majority of TUs loaded per day is loaded during the night shift, the flow of HUs out of the staging lanes exceeds the flow of HUs into the staging lanes, relieving staging lane congestion during the night shift. During the day shift however the flow of HUs into the staging lanes exceeds the flow of HUs out of the staging lanes causing an accumulation of HUs in the staging lanes. Figure 6.1 illustrates the density plots of the flow of HUs into and out of the staging lanes per minute per shift.

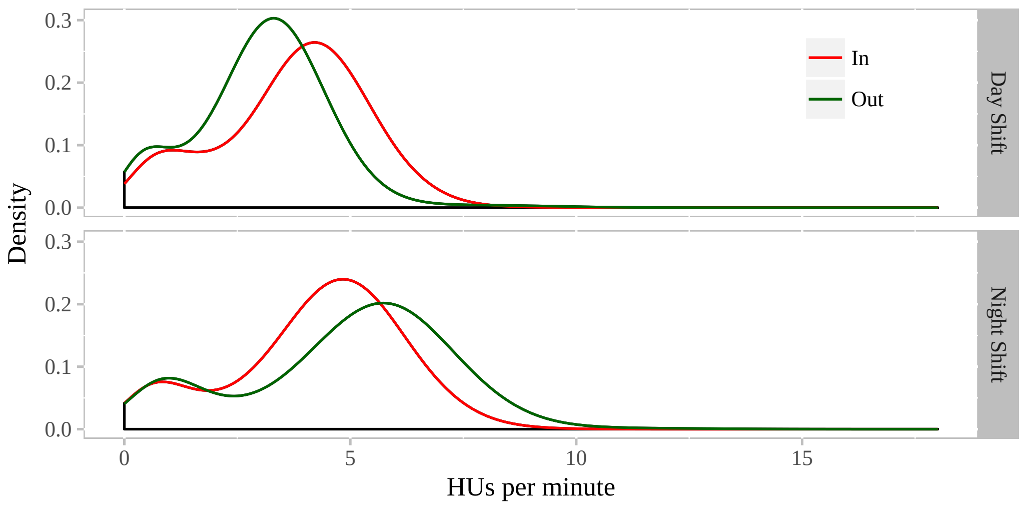

Figure 6.1: Density plots of the flow of HUs into and out of the staging lanes during day shifts and night shifts.

It was determined that the probability of dropping an HU during the day shift is higher than during the night shift due to higher staging lane congestion; as the number of HUs in the staging lanes increases, the probability of dropping HUs increases.

Figure 6.2 illustrates the increase in the probability of dropped HUs as the number of HUs in the staging lanes increases.

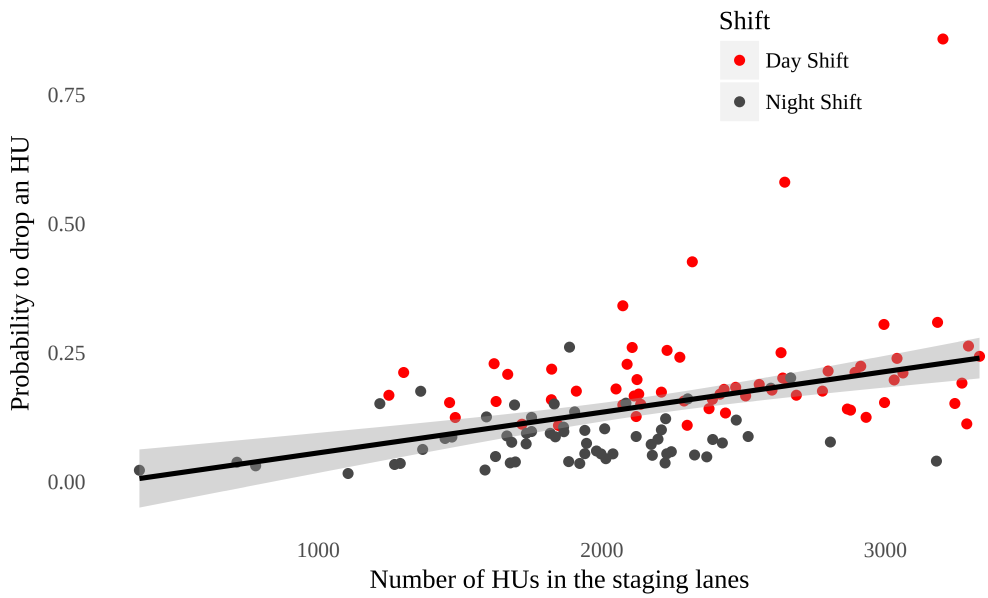

Figure 6.2: Probability of an HU being dropped compared to the number of HUs in the staging lanes.

Figure 6.3 illustrates the probability of an HU being dropped during the day shift and night shift.

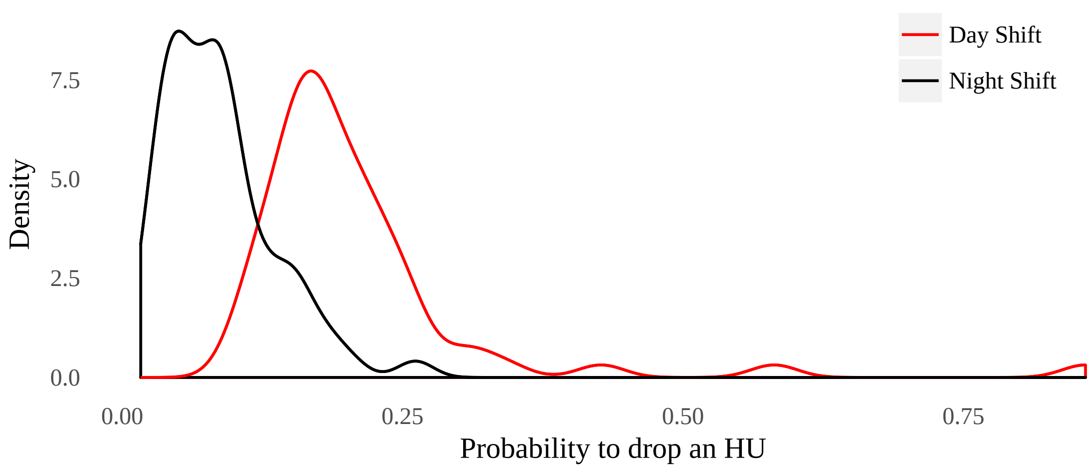

Figure 6.3: Density plots of the probability of an HU being dropped during the day shift and the night shift.

Figure 6.3 illustrates that the probability of dropping an HU is higher during the day shift than the night shift due to staging lane congestion. The selected scenarios' objective is to reduce the mean and range of the number of HUs in the staging lanes to reduce the total number of dropped HUs in the staging lanes and therefore the loading time per TU.

Figure 6.4 illustrates the frequency histogram of the number of HUs present in the staging lanes as captured by the simulation model every 5 minutes.

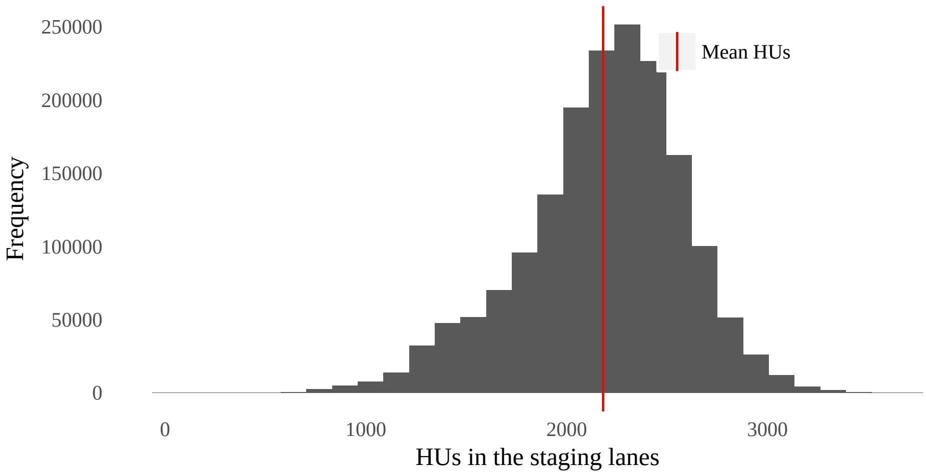

Figure 6.4: Frequency histogram of the number of HUs in the staging lanes sampled every 5 minutes.

6.2 Increase in night-time receiving stores

This scenario's proposed solution attempts to reduce congestion in the staging lanes by increasing the number of stores that receive orders during night time (18:00-06:00). The TUs loaded during the night shift primarily deliver to stores with day-time receiving (06:00-18:00) and the TUs loaded during the day shift primarily deliver to stores with night-time receiving. Increasing the number of stores with night-time receiving will increase the number of TUs loaded during the day shift and decrease the number of TUs loaded during the night shift; this will increase the flow of HUs out of the staging lanes during the day preventing staging lane congestion.

The proposed solution does not state which stores should change from day-time to night-time receiving but evaluates the impact that an equal amount of day-time receiving stores and night-time receiving stores could have on the outbound process.

In order to simulate this scenario, the simulation model's TU arrival was adapted to account for the increased number of stores with night-time receiving. No additional changes were made to the simulation model, ensuring that the proposed solution's effects could be evaluated in isolation.

6.3 Distribution of weekly volume

This scenario's proposed solution attempts to reduce staging lane congestion by adjusting stores' nominated delivery days to evenly distribute the total weekly volume throughout the week. This results in a constant picking target for each shift throughout the week. The constant picking target results in a constant flow of HUs into the staging lanes which reduces spikes of HUs flowing into the staging lanes.

This proposed solution does not state the required nominated delivery days for each store to achieve the evenly distributed weekly volume but evaluates the impact that this change could have on the outbound process.

In order to simulate this scenario, the simulation model's input was adapted to ensure that the size of the picking target was constant for each shift throughout a week; this was done to evaluate the effect of the evenly distributed weekly volume. No additional changes were made to the simulation model, ensuring that the proposed solution's effects could be evaluated in isolation.

6.4 Scenario results

Measures that could provide insight into the outbound process's performance were used to validate each scenario's proposed solution. The measures include:

- HUs dropped per shift.
- Loading time per TU.
- Number of HUs per TU.
- Number of HUs in the staging lanes.
- The flow of HUs into and out of the staging lanes.

The measures' results were obtained for each scenario by simulating each scenario 100 times. The input data used to simulate each scenario was captured between the 1st of August 2017 and the 31st of August 2017; this data set was not used in the development of the simulation model to ensure unbiased results.

6.4.1 Scenario 1 - Increase in night-time receiving stores

The solution proposed in this scenario attempts to relieve staging lane congestion by creating a steady flow of HUs out of the staging lanes by increasing the number of TUs loaded during the day shift. The solution could result in a pull-system, where the loading of TUs pulls HUs from the staging lanes. The results are depicted in Figure 6.5 to Figure 6.9. Statistical summaries are provided for each figure in Table 6.1 to Table 6.6.

Figure 6.5 illustrates the density plot of the flow of HUs into and out of the staging lanes per minute, for both day and night shifts.

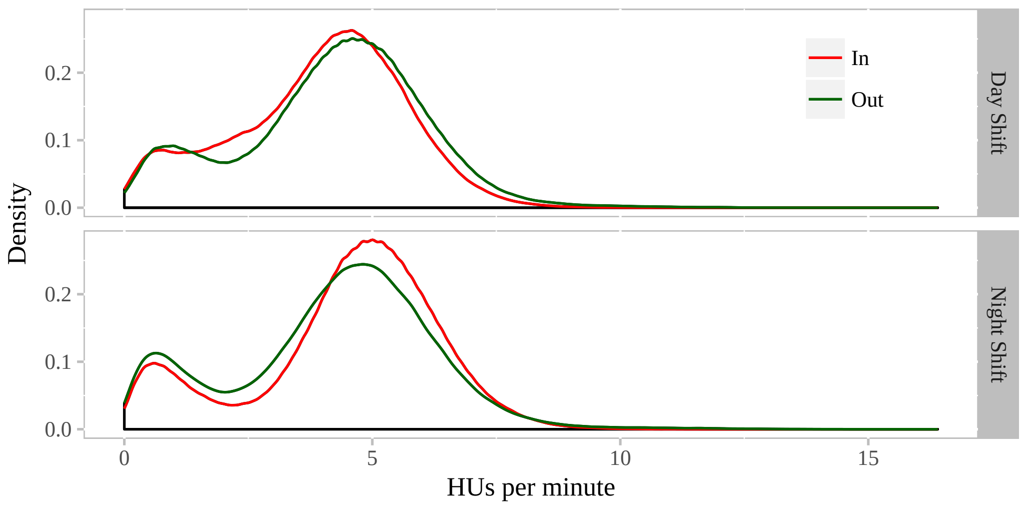

Figure 6.5: Density plots of the flow of HUs into and out of the staging lanes during day shifts and night shifts.

This solution's impact could be evaluated be comparing the flow of HUs into and out of the staging lanes for day shifts and night shifts. Figure 6.5 depicts that the flow of HUs out of the staging lanes for the day shift is similar to the flow of HUs out of the staging lanes for the night shift as a result of an increase in TUs loaded during the day shift.

Table 6.1 and Table 6.2 provide statistical summaries of the flow of HUs into and out of the staging lanes for the observed data and the simulated data of this scenario for day shifts and night shifts.

Table 6.1: Statistical summary of the flow of HUs into and out of the staging lanes during day shifts of the observed data and day shifts of this scenario's simulated data.

	In		**Out**	
Element	**Observed data**	**Scenario 1**	**Observed data**	**Scenario 1**
Mean	3.73	3.83	3.04	4.21
Median	4	4.1	3.2	4.4
Standard deviation	1.64	1.66	1.49	1.87
Min	0.0	0.0	0.0	0.0
Max	11.8	12.0	14.2	14.8

Table 6.1 indicates that the difference between the outflow's median and inflow's median during the day shift for the observed data is 0.8 HUs per minute which indicates that the population of HUs increased with 0.8 HUs per minute during the day shift. The simulated data indicates that the difference between the outflow's median and inflow's median during the day shift is -0.3 HUs per minute which indicates that the population of HUs decreased with 0.3 HUs per minute during the day shift; this indicates that staging lane congestion could be relieved during a day shift.

Table 6.2: Statistical summary of the flow of HUs into and out of the staging lanes during night shifts for the observed data and the scenario's data.

	In		**Out**	
Element	**Observed data**	**Scenario 1**	**Observed data**	**Scenario 1**
Mean	4.28	4.29	4.92	4.25
Median	4.6	4.7	5.4	4.4
Standard deviation	1.86	1.87	2.29	2.01
Min	0.0	0.0	0.0	0.0
Max	13.6	13.2	18.0	16.4

Table 6.2 indicates that the difference between the outflow's median and inflow's median during the night shift for the observed data is -0.8 HUs per minute which indicates that the population of HUs decreased with 0.8 HUs per minute during the night shift.

The simulated data indicates that the difference between the outflow's median and inflow's median during the night shift is 0.3 HUs per minute which indicates that the population of HUs increased with 0.3 HUs per minute during the night shift.

The reduced rate at which the number of HUs increase and decrease during night shifts and day shifts indicates that this scenario's solution reduces the volatility of HUs' flow into and out of the staging lanes which could reduce the mean number of HUs in the staging lanes.

Figure 6.6 illustrates the effect of reduced HU flow volatility on the number of HUs in the staging lanes.

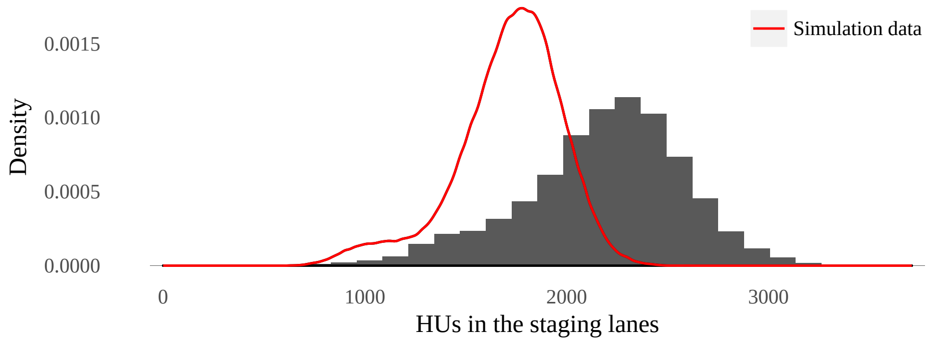

Figure 6.6: Density plot of observed data and simulated results for the number of HUs in the staging lanes sampled every 5 minutes.

Table 6.3: Statistical summary of HUs in the staging lanes for the observed data and simulated data.

HUs in the staging lanes		
Element	**Observed data**	**Scenario 1**
Mean	2181	1712
Median	2225	1743
Standard deviation	402.3	267.1
Min	780	620
Max	3710	2609

Table 6.3 depicts that the scenario's mean and median for HUs in the staging lanes are smaller than that of the observed data, illustrating the effect of the reduced HU flow volatility. After analysing Figure 6.6 and Table 6.3 it was concluded that the solution proposed in Scenario 1 reduces congestion in the staging lanes; it was therefore assumed that the dropped HUs per shift would be reduced too.

Figure 6.7 illustrates the density plot of the observed data and simulated data for the number of HUs dropped per shift.

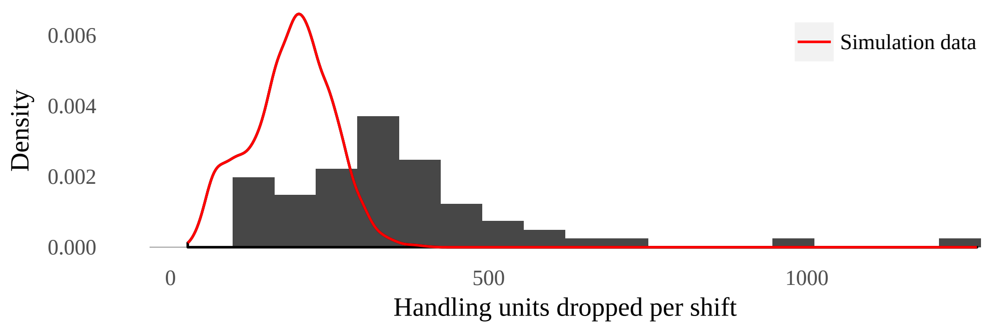

Figure 6.7: Density plot of observed data and simulated results for the number of HUs dropped per shift.

Figure 6.7 illustrates that the reduced staging lane congestion results in a decrease in dropped HUs per shift. Table 6.4 provides a statistical summary of the number of dropped HUs for the observed data and the simulated data.

Table 6.4: Statistical summary of the number of dropped HUs per shift of the observed data and the simulated data.

Dropped HUs per shift		
Element	**Observed data**	**Scenario 1**
Mean	353.6	188.5
Median	312.5	194
Standard deviation	196.3	64.5
Min	108	27
Max	1267	404

Table 6.4 illustrates that this scenario's solution reduces the mean and median of the dropped HUs per shift. The standard deviation and the maximum number of dropped HUs per shift indicates that the proposed solution also reduces the range of dropped HUs which leads to more predictable and therefore a more manageable number of dropped HUs.

Figure 6.8 illustrates the density plot of observed data and simulated data for the TU loading times.

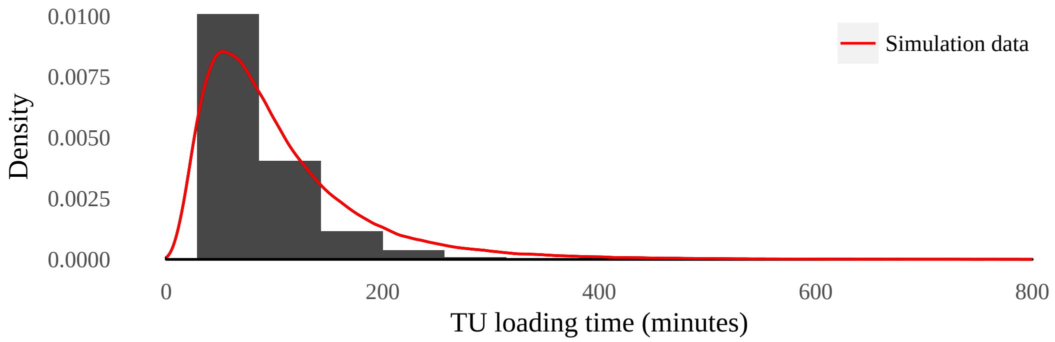

Figure 6.8: Density plot of observed data and simulated results for TU loading times.

Figure 6.8 illustrates that there is not a significant difference between the observed data and the simulated data for TU loading times. Table 6.5 provides a statistical summary of the TUs loading times for the observed data and the simulation data.

Table 6.5: Statistical summary of TU loading times of the observed data and simulated data.

TUs loading time		
Element	**Observed data**	**Scenario 1**
Mean	101.9	102.3
Median	78.75	77.9
Standard deviation	78.3	78.1
Min	15.3	16.9
Max	824.5	839.2

The information in Table 6.5 confirms that there is not a significant difference between the TU loading times for the observed data and the simulated data. The benefit of the proposed solution with regards to TU loading is visible in the number of HUs per TU.

Figure 6.9 illustrates the density plot of observed data and simulated data for the HUs per TU.

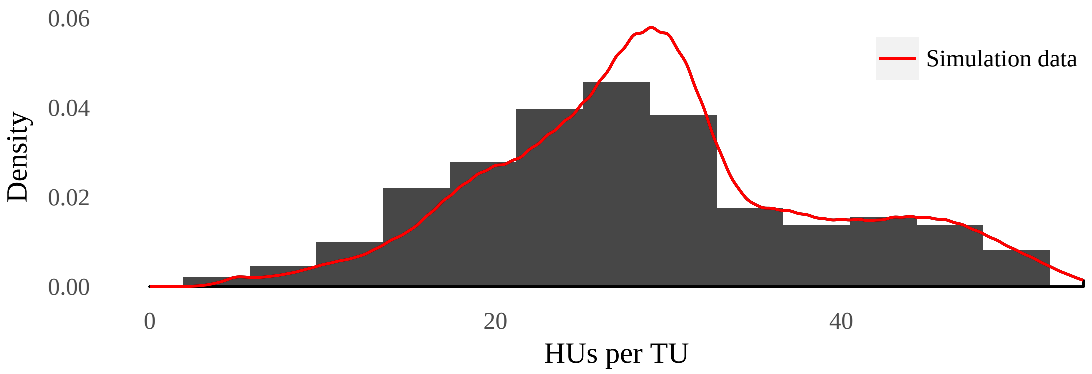

Figure 6.9: Density plot of observed data and simulated results for the number of HUs per TU.

Figure 6.9 indicates an increase in the mean number of HUs per TU in the proposed solution. Table 6.6 provides a statistical summary of the HUs per TU for the observed data and the simulated data.

Table 6.6: Statistical summary of HUs per TU of the observed data and simulated data.

HUs per TU		
Element	**Observed data**	**Scenario 1**
Mean	27.9	29.4
Median	27	29
Standard deviation	10.2	9.6
Min	2	2
Max	53	53

Table 6.6 depicts an increase in the mean and median HUs per TU in the proposed solution. It can therefore be concluded that the reduced staging lane congestion increases the loading rate per HU. The mean loading rate observed per HU is 3.65 minutes per HU. The proposed solution produces an HU loading rate of 3.47 minutes per HU. The increased HU loading rate is not visible in the total TU loading time as the reduced number of dropped HUs causes more HUs to be loaded, resulting in higher HUs per TU. The proposed solution does therefore not improve the total TU loading time but the loader efficiency which results in higher TU space utilisation.

It can be concluded that the solution proposed in this scenario could potentially reduce the number of dropped HUs per shift and increase TU loading efficiency.

6.4.2 Scenario 2 - Distribution of weekly volume

The solution proposed in this scenario attempts to relieve staging lane congestion by enforcing a steady flow of HUs into the staging lanes by evenly distributing weekly volumes. The weekly volumes being distributed evenly ensures constant picking targets for day shifts and night shifts throughout the week. The solution could result in a push-system, where the constant picking target pushes HUs through the outbound process. The results of this scenario are depicted in Figure 6.10 to Figure 6.14. Statistical summaries for each figure are provided in Table 6.7 to Table 6.12.

Figure 6.10 illustrates the density plot of the flow of HUs into and out of the staging lanes for both day and night shifts.

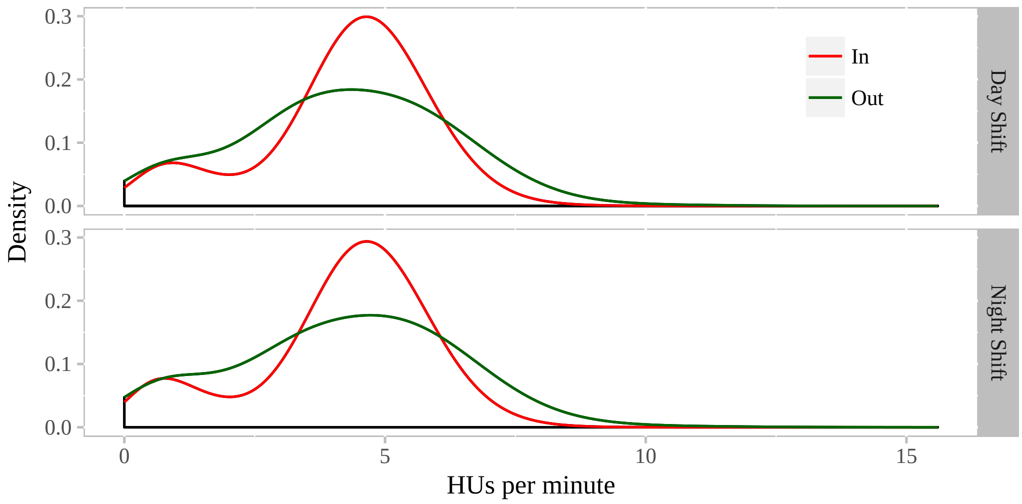

Figure 6.10: Density plots of the flow of HUs into and out of the staging lanes during day shifts and night shifts.

Figure 6.10 depicts that the flow of HUs into the staging lanes is similar for the day shift and night shift as a result of the volume being evenly distributed throughout a week. The proposed solution's impact can be seen by evaluating the difference between the flow of HUs into and out of the staging lanes for day shifts and night shifts. Table 6.7 and Table 6.8 provide a statistical summary of the flow of HUs into and out of the staging lanes for the observed data and the simulated data for day shifts and night shifts.

Table 6.7: Statistical summary of the flow of HUs into and out of the staging lanes during the day shift for the observed data and the simulated data.

	In		Out	
Element	**Observed data**	**Scenario 2**	**Observed data**	**Scenario 2**
Mean	3.73	4.428	3.04	4.212
Median	4	4.4	3.2	4.2
Standard deviation	1.64	1.62	1.49	2.03
Min	0.0	0.0	0.0	0.0
Max	11.8	11.8	14.2	15.4

‘ Table 6.7 indicates that the difference between the outflow's median and inflow's median during the day shift for the simulated data is 0.2 HUs per minute which indicates that the population of HUs increased with 0.2 HUs per minute during the day shift. This flow rate is significantly less than the 0.8 HUs per minute from the observed data.

Table 6.8: Statistical summary of the flow of HUs into and out of the staging lanes during the night shift of the observed data and simulated data.

	In		Out	
Element	**Observed data**	**Scenario 2**	**Observed data**	**Scenario 2**
Mean	4.28	4.17	4.92	4.21
Median	4.6	4.4	5.4	4.5
Standard deviation	1.86	1.68	2.29	2.12
Min	0.0	0.0	0.0	0.0
Max	13.6	11.0	18.0	15.6

Table 6.8 indicates that the difference between the outflow's median and inflow's median during the night shift is -0.1 HUs per minute which indicates that the population of HUs decreased with 0.1 HUs per minute during the night shift. It was concluded that this solution reduces the volatility of the flow of HUs into and out of the staging lanes.

Figure 6.11 illustrates the effect of the reduced HU flow volatility on the number of HUs in the staging lanes.

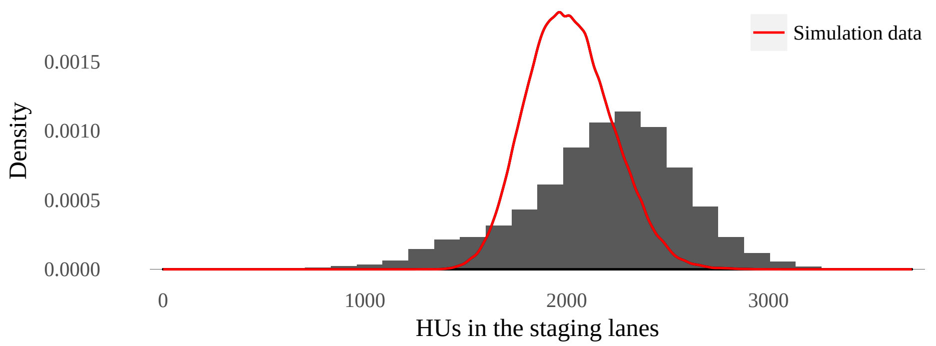

Figure 6.11: Density plot of observed data and simulated results for the number of TUs loaded per shift.

Table 6.9: Statistical summary of HUs in the staging lanes of the observed data and the simulated data.

	HUs in the staging lanes	
Element	**Observed data**	**Scenario 2**
Mean	2181	2015
Median	2225	2005
Standard deviation	402.3	209.1
Min	780	1267
Max	3710	3045

Table 6.9 illustrates a smaller mean and median for HUs in the staging lanes for the simulated data than the observed data. The smaller standard deviation indicates the impact of the reduced HU flow volatility. From Figure 6.11 and Table 6.9 it was concluded

that the solution proposed in this scenario reduces congestion in the staging lanes; it was therefore assumed that the dropped HUs per shift would be reduced too.

Figure 6.12 illustrates the density plot of the observed data and simulated data for the number of HUs dropped per shift.

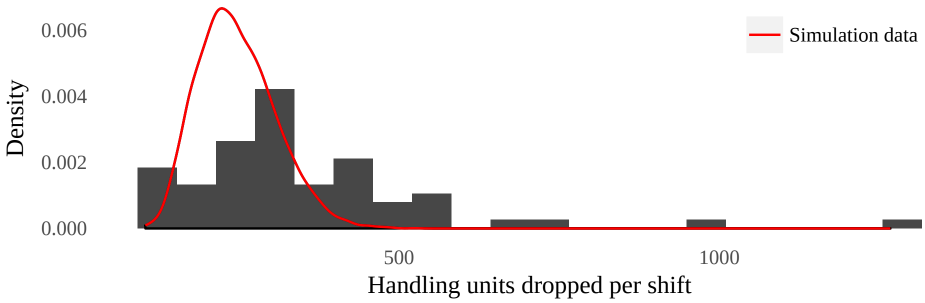

Figure 6.12: Density plot of observed data and simulated results for the number of HUs dropped per shift.

Figure 6.12 depicts that reduced staging lane congestion results in a decrease in the number of dropped HUs per shift. Table 6.10 provides a statistical summary of the number of dropped HUs for the observed data and the simulated data.

Table 6.10: Statistical summary of the number of dropped HUs per shift of the observed data and the simulated data.

Dropped HUs per shift		
Element	**Observed data**	**Scenario 2**
Mean	353.6	246.6
Median	312.5	241
Standard deviation	196.3	61
Min	108	104
Max	1267	524

Table 6.10 depicts that this scenario's solution reduces the mean and median of the dropped HUs per shift. The standard deviation and the maximum number of dropped HUs per shift indicates that the proposed solution also reduces the range of dropped HUs.

Figure 6.13 illustrates the density plot of observed data and simulated data for the TU loading times.

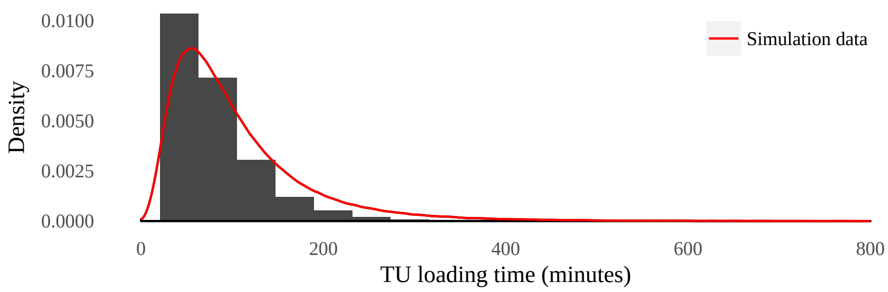

Figure 6.13: Density plot of observed data and simulated results for the number of TUs loaded per shift.

Figure 6.13 illustrates that there is not a significant difference between the observed data and the simulated data for TU loading times. Table 6.5 provides a statistical summary of the TUs loading times for the observed data and the simulation data.

Table 6.11: Statistical summary of TU loading times of the observed data and the simulated data.

TUs loading time		
Element	**Observed data**	**Scenario 1**
Mean	101.9	101.6
Median	78.75	79.9
Standard deviation	78.3	78.8
Min	15.3	17.9
Max	824.5	844.6

The information in Table 6.11 confirms that there is not a significant difference between the TU loading times for the observed data and the simulated data. The benefit of the proposed solution with regards to TU loading is visible in the number of HUs per TU.

Figure 6.14 illustrates the density plot of observed data and the simulated data for the HUs per TU.

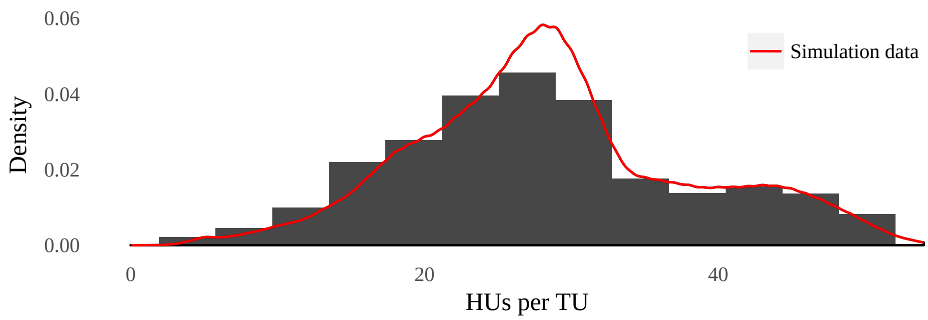

Figure 6.14: Density plot of observed data and simulated results for the number of HUs per TU.

Figure 6.14 indicates an increase in the mean number of HUs per TU in the proposed solution. Table 6.12 provides a statistical summary of the HUs per TU for the observed data and the simulated data.

Table 6.12: Statistical summary of HUs per TU of the observed data and the simulated data.

HUs per TU		
Element	**Observed data**	**Scenario 1**
Mean	27.9	28.67
Median	27	28
Standard deviation	10.2	9.4
Min	2	2
Max	53	53

Table 6.12 depicts an increase in the mean and median HUs per TU in the proposed solution. It can therefore be concluded that the reduced staging lane congestion increases

the loading rate per HU. The mean loading rate per HU is 3.65 minutes per HU. The proposed solution produces an HU loading rate of 3.55 minutes per HU. The increased HU loading rate is not visible in the total TU loading time as the reduced number of dropped HUs causes more HUs to be loaded, resulting in higher HUs per TU. The proposed solution does therefore not improve the total TU loading time but the loader efficiency which results in higher TU space utilisation.

It can be concluded that the solution proposed in this scenario could potentially reduce the number of dropped HUs per shift and increase TU loading efficiency and capacity utilisation.

Chapter 7

Conclusion and Recommendations

7.1 Conclusion

It was concluded that staging lane congestion causes excessive numbers of dropped handling units (HUs). Congestion in the staging lanes increases the probability of HUs not being located which results in HUs being dropped. This contributes to excessive transport unit (TU) loading times as loading staff spend time locating HUs which reduces the loading efficiency.

The availability and accuracy of the delivery unit (DU) volume master data directly contributes to staging lane congestion. It was determined that several DUs do not have master volume data on record. The bin packing algorithm will thus allocate these single DUs to an HU which results in an under utilised HU and more HUs being used than required. It was determined that out of the 100 DUs measured 100 DUs' actual volume is less than the volume recorded in the DU volume master file. This causes the bin packing algorithm to insufficiently fill each HU which results in an excessive amount of HUs being used.

Two scenarios, namely an increase in night-time receiving and the distribution of weekly volumes, were investigated to determine the impact of each on the number of dropped HUs and TU loading times. It was concluded that either solution proposed could potentially reduce the number of dropped HUs per shift. The scenarios' TU loading times do not indicate a significant reduction, but the loading rate per HU and the HUs per TU increased.

The measures with the largest potential financial impact were identified and used to evaluate each scenario's cost implications. The measures included the mean:

- HUs dropped per shift.
- Minutes to load an HU.
- HUs per TU.

A reduction in the number of dropped HUs per shift could result in less additional trips required to deliver the dropped HUs which could result in a reduced number of kilometres travelled. An increase in loading efficiency could result in less loading staff required per shift, which could result in reduced labour expenses. An increase in HUs per TU could result in an increase in HUs delivered per kilometre travelled which could reduce the total cost to deliver stock to Pick 'n Pay stores.

Table 7.1 depicts the mean number of dropped HUs per shift, minutes per HU loaded and HUs per TU for both scenarios' results and the observed data.

Table 7.1: Summary of the mean value for each finacial measure for both scenarios and the observed data.

Measure	Observed data	Scenario 1	Scenario 2
HUs dropped per shift	353.6	188.5	246.6
HU loading rate per minute	27.9	29.4	28.67
HUs per TU	3.65	3.47	3.55

Table 7.1 indicates that Scenario 1 could result in higher cost savings for Pick 'n Pay's distribution centre (DC).

The potential cost impact of implementing each scenario's proposed solution was considered. It was determined that both scenarios have low implementation costs for the Pick 'n Pay DC as both scenarios propose tactical solutions. Pick 'n Pay stores will however have to incur costs to implement the proposed solutions.

For Pick 'n Pay stores to change from day-time to night-time receiving the stores would have to reschedule receiving staff. As some non-centralised vendors(stock is not distributed by the Pick 'n Pay DC) deliver directly to the Pick 'n Pay store, it cannot be assumed that the stores could simply move their day-time receiving staff to the night-time as they may have to receive stock from non-centralised vendors during the day-time. Security implications could also impact night-time receiving.

The moving or reduction of Pick 'n Pay stores' nominated delivery days could result in an increase in receiving staff required over weekends which could result in additional over-time costs.

It was concluded that by making use of the decision support model developed, the scenarios could be evaluated to make informed decisions regarding the outbound process. It was determined that both scenarios could address the outbound process's concerns. The first scenario, the increase of stores with night-time receiving, addresses the concerns more efficiently. It is therefore recommended that the first scenario's solution should be implemented.

7.2 Recommendations

After the completion of this project recommendations could be made regarding the development of the simulation model, root causes for dropped HUs, and the implementation of the proposed solution.

It is recommended that functionality should be added to the simulation model so that the trip time of a TU could be considered. This functionality should allow users to specify a fixed number of available TUs which could assist users in evaluating the impact that the proposed solution could have on the fixed number of TUs required.

This project confirmed that staging lane congestion is one of the main causes of the excessive number of dropped HUs per shift. Reduced congestion does however not completely eliminate the occurrence of dropped HUs. It is therefore recommended that Pick 'n Pay should investigate the root cause(s) of dropped HUs. Additional cause(s) for dropped HUs could include HUs being staged in the incorrect staging lanes and HUs unintentionally being moved to the incorrect lane during the combining process.

The simulation model indicated that reduced staging lane congestion does not significantly reduce TU loading times but could improve the HU loading rate. It is recommended that Pick 'n Pay should investigate alternative methods for staging. Currently each staging lane represents a single Pick 'n Pay store per picking wave. It is recommended that

Pick 'n Pay should investigate the possibility of each staging lane representing a TU per picking wave. This could ensure that TUs' HUs are staged in a single lane which could reduce loaders' travelling time which could reduce TU loading times.

Pick 'n Pay should investigate the feasibility of implementing the proposed solution by evaluating stores' co-operation and willingness to change from day-time to night-time receiving. If it is determined that a suitable amount of stores are prepared to adjust, multiple variations of The Assignment Problem exist which could provide a method of selecting which Pick 'n Pay stores should be moved from day-time receiving to night-time receiving.

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Appendix A

Industry sponsorship form.

Department of Industrial & Systems Engineering
Final Year Projects
Identification and Responsibility of Project Sponsors

All Final Year Projects are published by the University of Pretoria on *UPSpace* and thus freely available on the Internet. These publications portray the quality of education at the University and have the potential of exposing sensitive company information. It is important that both students and company representatives or sponsors are aware of such implications.

Key responsibilities of Project Sponsors:

A project sponsor is the key contact person within the company. This person should thus be able to provide the best guidance to the student on the project. The sponsor is also very likely to gain from the success of the project. The project sponsor has the following important responsibilities:

1. Confirm his/her role as project sponsor, duly authorised by the company. Multiple sponsors can be appointed, but this is not advised. The duly completed form will considered as acceptance of sponsor role.
2. Review and approve the Project Proposal, ensuring that it clearly defines the problem to be investigated by the student and that the project aim, scope, deliverables and approach is acceptable from the company's perspective.
3. Review the Final Project Report (delivered during the second semester), ensuring that information is accurate and that the solution addresses the problems and/or design requirements of the defined project.
4. Acknowledges the intended publication of the Project Report on UP Space.
5. Ensures that any sensitive, confidential information or intellectual property of the company is not disclosed in the Final Project Report.

Project Sponsor Details:

Company:	**Resolve solution partners**
Project Description:	**Staging lane simulation for a large retailer**
Student Name:	**Werner Willem van Niekerk**
Student number:	**12079619**
Student Signature:	
Sponsor Name:	**Stephan Mare**
Designation:	**Continuous improvement manager**
E-mail:	**smare@resolvesp.com**
Tel No:	**+27 11 574 3392**
Cell No:	**+27 71 850 2137**
Fax No:	
Sponsor Signature:	

Appendix B

Sampled DUs with measured dimensions.

	Product.Short.Description	cm3	Quantile	L	W	H
1	ALL GOLD TOMATO COCKTAIL ORIGINAL 200ML	2240.896	1stQuantile	16.4	12.2	11.2
2	CLORETS ORIGINAL GUM 14.5GR	729.925	1stQuantile	9.7	17.5	4.3
3	COLGATE A/CAVITY T/PAST BUBBLEFRUIT 50ML	2662.400	1stQuantile	10.4	16.0	16.0
4	DERMO EXPERTISE R/VITALFT L/R SPF25 50ML	2513.104	1stQuantile	13.1	10.9	17.6
5	ELVIVE MOUSSE FREE STYLE EXT FIRM 200ML	3053.120	1stQuantile	14.0	9.4	23.2
6	GOLDCREST ORANGE MARMALADE 340GR	2646.000	1stQuantile	12.0	24.5	9.0
7	INECTO H/COL SUPER BLACK NATURALS 50ML	2213.400	1stQuantile	10.2	15.5	14.0
8	JOHNSON'S BABY EASY COMB SPRAY 150ML	1965.600	1stQuantile	21.0	5.2	18.0
9	JOHNSON'S BABY SOAP ALOE VERA 100GR	1466.640	1stQuantile	19.4	9.0	8.4
10	LENTHERIC K/SCOPE TOO HOT TO HNDLE 100ML	1411.550	1stQuantile	10.9	7.4	17.5
11	LENTHERIC MASCULIN DEO B/S EXTREME 150ML	2510.080	1stQuantile	16.0	10.6	14.8
12	NIVEA FOR MEN F/CREAM MOIST F/GEL 50ML	1557.504	1stQuantile	31.2	5.2	9.6
13	NO NAME SOUP MIX 500GR	1311.000	1stQuantile	23.0	19.0	3.0
14	NUTRILIDA V/GUARD FIZZY CHEWS 60EA	2734.875	1stQuantile	18.7	12.5	11.7
15	OLD SPICE STICK CHAMPION 50ML	1515.822	1stQuantile	19.3	6.6	11.9
16	PANTENE 2IN1 SHMP/CON SMOOTH&SLEEK 200ML	2221.128	1stQuantile	11.7	11.3	16.8
17	PETER STUYVESANT RED EVOLVE PMP 20EA	791.544	1stQuantile	3.9	23.6	8.6
18	PLAYGIRL DEODORANT TEMPTATION 90ML	1713.120	1stQuantile	12.0	8.6	16.6
19	PNP 11W BC CW SPIRAL 1P BX	2873.000	1stQuantile	13.0	17.0	13.0
20	PONDS AGE MIRACLE REG FACIAL FOAM 100ML	1288.560	1stQuantile	11.8	7.0	15.6
21	SHIELD DEODORANT SACHET REFILL ACTV 50ML	989.184	1stQuantile	19.2	5.6	9.2
22	STIMOROL AIR RUSH CHEWING GUM MENTHOL	936.000	1stQuantile	15.0	10.4	6.0
23	TWISP CHERRY PURE REFILL 20ML	292.404	1stQuantile	5.9	5.9	8.4
24	VINOLIA SOAP LAVENDER 125GR	2640.000	1stQuantile	26.4	10.0	10.0
25	VITA−THION EFFERVESCENT TABS 20EA	1494.255	1stQuantile	13.3	10.7	10.5

	Product.Short.Description	cm3	Quantile	L	W	H
1	BEACON ALLSRT NON/LIQ MINI FRT 75GR	6244.560	2ndQuantile	25.2	21.0	11.8
2	BEENO FLATTIES HEALTHY TREATS 120GR	7956.000	2ndQuantile	12.0	39.0	17.0
3	BOB MARTIN S/MOIST D/TREAT J/CARE 45GR	4933.500	2ndQuantile	22.0	11.5	19.5
4	CANDEREL VANILLA SWEETENER 40GR	5554.176	2ndQuantile	22.6	19.2	12.8
5	COLMAN'S ENGLISH MUSTARD POWDER 100GR	4689.924	2ndQuantile	25.8	14.9	12.2
6	DEWFRESH UHT MANG/ORNGE NECT JUICE 200ML	6144.000	2ndQuantile	32.0	16.0	12.0
7	DOVE CONDITIONER PURE CARE 250ML	4534.920	2ndQuantile	17.0	11.7	22.8
8	FIESTA HAIRSPRAY SUPER HOLD 300ML	4082.272	2ndQuantile	10.6	16.6	23.2
9	GARNIER CONDIT COCONUT OIL&COCOA 200ML	5383.104	2ndQuantile	18.4	15.9	18.4
10	GARNIER SHAMP AVO OIL&SHEA BUTTER 250ML	5796.700	2ndQuantile	18.2	17.5	18.2
11	LEA&PERRINS HP SAUCE ORIGINAL 255GR	5759.424	2ndQuantile	19.8	14.4	20.2
12	NANDO'S P PERILEMON&HERB 250ML	4243.715	2ndQuantile	18.5	11.3	20.3
13	NANDO'S PERI−PERI GARLIC 250ML	4222.400	2ndQuantile	11.6	18.2	20.0
14	PNP CHUNKY BEEF DOG FOOD 400GR	7560.000	2ndQuantile	30.0	22.5	11.2
15	PNP S SURE SPF30 CONTINUOUS SPRAY 125ML	4522.000	2ndQuantile	14.0	19.0	17.0
16	PURITY AQUEOUS CREAM FRAG FREE 350ML	3843.840	2ndQuantile	26.0	17.6	8.4
17	PURITY BABY POWDER ESSENTIALS 200GR	4052.700	2ndQuantile	15.8	15.0	17.1
18	RHODES TOMATO&ONION MIX 410GR	7305.984	2ndQuantile	22.4	30.2	10.8
19	SATISKIN HANDWASH CINNAMON&HONEY 400ML	4804.800	2ndQuantile	22.0	15.6	14.0
20	SENSODYNE REPAIR&PROTECT WHITE 75ML	4186.875	2ndQuantile	14.5	16.5	17.5
21	STUDIO PRO LOCK IT EXTRA STRENGTH 400ML	5684.224	2ndQuantile	18.2	12.2	25.6
22	TRESEMME SHAMPOO MOISTURE RICH 900ML	6448.440	2ndQuantile	17.4	17.0	21.8
23	VICKS INHALER BLISTER 1ML	6222.816	2ndQuantile	24.6	18.6	13.6
24	WEIGH−LESS MOUSSE CHOCOLATE 50GR	5137.844	2ndQuantile	14.2	22.9	15.8
25	WELLINGTON'S CHILLI SCE SWEET HOT 375ML	8000.000	2ndQuantile	25.0	16.0	20.0

	Product.Short.Description	cm3	Quantile	L	W	H
1	ALL JOY SOYA SAUCE 250ML	8116.80	3rdQuantile	24.0	17.8	19.0
2	BIOCRYSTAL POWDER RUBY GRAPEFRUIT 1KG	9161.04	3rdQuantile	29.4	19.0	16.4
3	BISCOTTI CANDY DELIGHTS 140GR	14700.00	3rdQuantile	24.5	30.0	20.0
4	CAPE COOKIES MINI DBL DELIGHT BISC 200GR	12651.41	3rdQuantile	39.6	19.6	16.3
5	CARTWRIGHTS CURRY POWDER EXT SPICY 100GR	13897.52	3rdQuantile	36.4	16.6	23.0
6	FLAMING TIGER SRIRACHA H/CHILL SCE 450ML	11970.00	3rdQuantile	20.0	28.5	21.0
7	GLADE AIR FRESHENER FRESH LEMON 300ML	8994.15	3rdQuantile	23.0	16.5	23.7
8	GOLDEN CLOUD READY MIX BRAN MUFFIN 500GR	12494.59	3rdQuantile	35.2	30.6	11.6
9	HUG IN A MUG HAZELNUT CAPPUCINO 10X24GR	16186.46	3rdQuantile	33.3	24.8	19.6
10	LIL−LETS MAXI REGULAR UNSCENTED 10EA	13050.72	3rdQuantile	31.8	15.2	27.0
11	LIQUI−FRUIT CRANBERRY COOLER 1.5L	14241.45	3rdQuantile	28.5	19.0	26.3
12	NOLA MAYONNAISE CREAMY STYLE 730GR	13728.00	3rdQuantile	30.0	26.0	17.6
13	ONG'S PLUM SAUCE 255GR	8671.50	3rdQuantile	18.0	20.5	23.5
14	OROS READY TO DRINK ORANGE 300ML	14581.44	3rdQuantile	36.0	24.4	16.6
15	PECK'S ANCHOVETTE 85GR	8977.92	3rdQuantile	33.4	22.4	12.0
16	PEDIGREE D/FOOD CHIC&RICE IN JELLY 100GR	10657.10	3rdQuantile	39.5	19.0	14.2
17	PNP L/F INSTN NOODLE M/ROOM 75GR	12579.46	3rdQuantile	32.8	13.6	28.2
18	PNP 4 BEAN MIX 400GR	16006.14	3rdQuantile	44.8	30.8	11.6
19	PNP CHOC CREAM CEREAL BARS 30GR 6EA	13781.90	3rdQuantile	29.8	28.2	16.4
20	PNP MUTTON SOUP 60GR	10596.68	3rdQuantile	38.2	19.0	14.6
21	RAID SUPER FAST CIK INSECTID 180ML	12501.22	3rdQuantile	31.8	21.6	18.2
22	ROBERTSONS M/B REF SPC SHISANYAMA 151GR	12803.70	3rdQuantile	26.8	19.5	24.5
23	SAFARI PEANUTS ROASTED & SALTED 450GR	16308.86	3rdQuantile	31.2	39.6	13.2
24	STEERS SAUCE HOT PERI PERI 375ML	14018.20	3rdQuantile	31.0	23.8	19.0
25	STYLING DRED 2 SPRAY SHAMPOO 350ML	9604.80	3rdQuantile	23.2	18.0	23.0

	Product.Short.Description	cm3	Quantile	L	W	H
1	ALWAYS PLATINUM NIGHT 7EA	17952.72	4thQuantile	31.0	22.8	25.4
2	BEIGEL&BEIGEL TRADITIONAL PRETZELS 200GR	45356.25	4thQuantile	41.0	37.5	29.5
3	BOB MARTIN C/CON CAT RICH CHICKEN 1.8KG	24360.00	4thQuantile	40.0	29.0	21.0
4	BOKOMO PRONUTRO CHOCOLATE 750GR	31692.67	4thQuantile	32.8	39.6	24.4
5	CANINE CUISINE D/F A SM BRD CH&RI 1.75KG	43520.00	4thQuantile	68.0	32.0	20.0
6	CROSSE&BLACKWELL TRIM REG DRESSING 790GR	19297.92	4thQuantile	38.0	27.6	18.4
7	GALLO PORTUGESE OLIVE OIL 750ML	20942.64	4thQuantile	30.6	23.6	29.0
8	KELLOGG'S COCO POPS ORIGINAL 350GR	60357.12	4thQuantile	38.4	29.0	54.2
9	KNORR SOUP BEEF & ONION 200GR	29143.05	4thQuantile	37.0	26.7	29.5
10	MAYNARDS WINE GUMS ROUND 400GR	19491.84	4thQuantile	36.0	28.8	18.8
11	MR MUSCLE TILE CLEAN CNTRY FIELDS 750ML	23611.13	4thQuantile	33.4	25.8	27.4
12	NESTLE CERELAC INF CEREALRICE 250GR	36424.00	4thQuantile	29.0	31.4	40.0
13	PALMOLIVE SHAMPOO ANTI DANDRUFF 350ML	18869.76	4thQuantile	41.6	21.0	21.6
14	PNP ALL PUR CLN CR SP/FRESH 750ML	29400.00	4thQuantile	35.0	30.0	28.0
15	PNP DISHWASHING MACHINE POWDER 1KG	28908.43	4thQuantile	40.8	29.4	24.1
16	PURINA H M ADULT GOURMET MEDLEY 1.8KG	27682.11	4thQuantile	40.7	30.5	22.3
17	RAID INSECTICIDE DP L/ODOUR 300ML	22030.12	4thQuantile	40.4	26.6	20.5
18	RIGOR THICK BLEACH CORAL REEF 750ML	39081.28	4thQuantile	23.9	51.1	32.0
19	ROBERTSONS JIKELELE CAYENNE PEPPER 100GR	20499.52	4thQuantile	37.6	18.8	29.0
20	ROYCO SOUP CHILLI BEEF&GREEN PEPPER 45GR	20995.20	4thQuantile	24.0	32.4	27.0
21	ROYCO SOUP HEARTY BEEF 50GR	20712.67	4thQuantile	32.4	24.4	26.2
22	SAFARI CAKE MIX CHOICE 250GR	21260.80	4thQuantile	40.0	30.2	17.6
23	SKIP INTELL FLEX W POWDER 2KG	35907.30	4thQuantile	32.5	39.6	27.9
24	SUNLIGHT DISHWASHING LIQUID 1.5L	28195.39	4thQuantile	35.4	26.2	30.4
25	SUNLIGHT SOAP ALOE FRESH 175GR	21947.81	4thQuantile	29.6	22.2	33.4