Optimization and Comparison of Manual and Semi-Automated Material Handling in a Cross-Dock Using Discrete-Event Simulation

by

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This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Statement of Contribution

The research work in this thesis was initiated as an industrial project between WATMIMS and Canadian Robotics PVT Ltd., self-driving vehicles manufacturer. Experts from the University of Waterloo and Canadian Robotics were involved in deriving the cross-dock working conditions, and simulation model verification and validation process. I was the simulation analyst of that project who modelled and analyzed those cross-dock models, and main author of all reports generated for that project.

I declare, the solution methodology proposed in this thesis using response surface methodology and optimization techniques is my own work, and not part of any other work.

Abstract

A Cross-Dock (CD) is a synchronized unit of a supply chain network, used to sort the goods received from inbound trucks (from a warehouse or factory), and load those products to outbound trucks (for delivery of the goods to retail stores in the supply chain network). Most cross-docks use forklifts, and other manual material handling equipment (MHE) to process the goods on pallets received from inbound trucks. Those pallets are sorted and loaded onto outbound trucks. With the advancements in robotics, it could be beneficial to employ semi-automated material handling techniques in a CD, rather than solely relying on manual material handling. In this thesis, the scope of self-driving vehicles (SDVs) in one such semi-automated cross-dock facility is studied. We compare the cases of purely manual and semi-automated material handling in a cross-dock.

Using simulation, we modelled two cross-dock facilities, one with forklifts only and with a mixture of forklifts and SDVs. Simulation was thus employed to mimic the CD's material handling process, to compare the two MHE configurations. Then the built cross-dock simulation models were optimized using the response surface methodology and mixed integer non-linear programming (MINLP), to achieve the optimal MHE configuration for those facilities operating with the desired levels of performance metrics.

Thereby the manual and semi-automated cross-dock with similar performance (and optimal MHE configurations) are compared and the scope of SDVs in a cross-dock is evaluated. Conclusions are given, and opportunities for further research are presented.

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Chapter 1

Introduction

With the increasing varieties of items demanded by customers, there are increased challenges in shipping the right quantities of those goods from suppliers to each customer. Often the customer requirement for a particular good doesn't meet full truck load (FTL) capacity, resulting in excessive transportation cost because of less-than truck load (LTL) operations. In those cases, suppliers tend to use Distribution Center (DC) or Cross-Dock (CD) facilities to reduce or avoid the LTL shipments.

A DC is operated by receiving inventory as FTL and delivering it to the nearby retail centers or customers in LTL or milk-runs whenever demand arises. This reduces reliance on LTL operations and transportation cost. However, holding additional inventories in DC facilities increases the total inventory cost, reducing the supply chain surplus. On other hand, CD facilities are operated by coordinating with various suppliers and customers. The total demand of various retail centers or customers is received from various suppliers at a central hub. At that cross-dock facility, goods received from various suppliers are sorted and consolidated using labour and material handling equipment (MHE). Requirements of individual retail centers or customers are shipped as FTL or LTL in a Just-In-Time (JIT) manner without holding any inventories at the CD. Cross-Docks have been widely preferred by companies over Distribution Centers because of their low cost operating policy (no on-hand inventory, hence no holding cost).

Various previous research has been carried out with the objective of optimizing cross-docking operations. However, only a few publications were identified focusing on the CD's internal material handling activities, sorting and consolidation. With the increase in CD size, CD modelling difficulty also increases. To reduce the modelling complexities, scholars end up modelling CD material handling activities as a deterministic or stochastic model with various assumptions. Only a few of which were focused on modelling the randomness involved in floor-level material handling activities, they are discussed briefly in subsection 2.1.2 of Chapter 2.

1.1 Material Handling in a Cross-Dock Facility

Performance of a cross-dock is measured through various metrics such as throughput rate (pallets processed per unit time), trucks processed per unit time, average truck turnaround time, MHE utilization rate, doorway or dock utilization rate and shipping accuracy. Those are all directly influenced by the efficiency of material handling activities. MHE such as hand pallet trucks and manual forklifts are widely used in cross-dock facilities to handle the goods received. However recent advances in robotics for material handling, such as Automated Vehicle Storage / Retrieval Systems (AVS/RS), Automated

Storage and Retrieval Systems (AS/RS), Automated Guided Vehicles (AGV) and Self-Driving Vehicles (SDVs) have made the present research possible; to investigate the scope of Self-Driving Vehicles for material handling operations in a cross-dock.

1.1.1 Self-Driving Vehicles

Unlike AGVs, which are programmed to move only on the designated path marked by paint or wire, SDVs can move on the designated aisle width or route by sensing and maneuvering any objects and obstacles in its way. SDV's central control system, the ability to choose optimal routes and their obstacle-maneuvering capabilities, enables SDVs to be a potential alternative for manual forklifts. SDVs can thus be used in a Cross-Dock to transfer pallets or goods received as unit loads.

Material handling systems such as AGVs, AVS/RS and AS/RS may not fit the CD material handling requirements, due to their limited movement and passive decision-making abilities. However, those (non-SDV type) material handling systems (MHS) are ideal for *continuous* material transfer activities between a limited number of stations in manufacturing environments, or for the inventory storage and retrieval process, such as in a distribution center or warehouse.

A generic Cross-Dock facility processing pallets as a unit load, would require manual forklifts to sort and transfer pallets between inbound and outbound trucks. A Cross-Dock facility with SDVs would require a mixture of manual forklifts and SDVs to process pallets. Use of SDVs for Cross-Docking could perhaps reduce the variable cost of operating a CD facility, when compared to a generic manually operated CD facility. The amount of labour required for a facility with SDVs and manual forklifts would likely be less than an all-manual forklift CD.

Hence, this brings forth the hypothesis that it may be financially beneficial to use SDVs and manual forklifts in CD facilities, instead of using manual forklifts only. To validate this hypothesis for the scope of SDVs in a cross-dock facility, it is necessary to compare a cross-dock facility operated only by manual forklifts, to one operated by a mixture of manual forklifts and SDVs.

1.2 Solution Methodology

We thus require a problem-solving framework which can accommodate the randomness involved in a CD material-handling operation and can simultaneously provide flexibility for experimentation by changing the input variables. Discrete event simulation serves this purpose, and meets our requirements well. Simulation software by Rockwell Automation ARENA 15.0, was used for simulation modelling and analysis of the CD facilities which are operated by manual forklifts only and by a mixture of manual forklifts and SDVs. The respective cases are given below;

Model 1) Forklift only cross-dock facility ($FL\text{-}only\ CD$)

Model 2) Forklift-and-SDV cross-dock facility ($FL\text{-}and\text{-}SDV\ CD$)

Both simulation models ($FL\text{-}only\ CD$ and $FL\text{-}and\text{-}SDV\ CD$) were built to be flexible and scalable (to increase the number of Inbound Docks $\times$ Outbound Docks) using

VBA. Simulation modelling assumptions and other operating conditions are discussed later in Chapter 3. Both CD simulation models were experimented independently, by varying the number of MHE used for each operation. Response Surface Methodology (RSM) was used to estimate the prediction equation for output performance metrics of the FL-$only$ CD and of the FL-and-SDV CD in terms of the number of MHE used for each operation.

The quadratic prediction equations computed from RSM were later used to formulate an optimization problem. Its objective function is to minimize the total variable cost of operating the CD facility, subject to constraints on CD performance metrics (throughput rate, throughput rate per MHE, category-wise MHE utilization rate, and Overall MHE utilization rate). Standard or expected levels of the CD performance metrics were set as right-hand sides of the respective constraints.

The formulated optimization problem, which is a Mixed Integer Non-Linear programming (MINLP) model, was solved using the Lingo 17.0 solver. The optimal MHE configurations for Forklift-only and Forklift-and-SDV Dross-Dock facility were found. Financial benefits of choosing Forklift-and-SDV CD over the Forklift-only CD were thereby justified. The overall proposed solution framework is given in Figure 1.1.

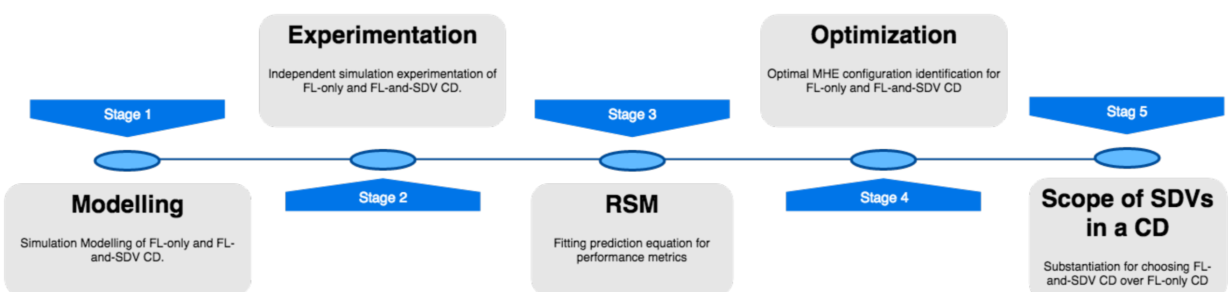

Figure 1.1: Solution Methodology.

1.3 Organization of the Thesis

Rest of this thesis is organized into five chapters. Chapter 2: a brief literature review of relevant works from the past. Chapter 3: an overview of simulation modelling and output analysis. Chapter 4: experiment design for response surface methodology and regression model fitting. Chapter 5: modelling of cross-dock optimization problem and justification of scope of SDVs in a cross-dock facility. Chapter 6: conclusion with pros and cons of the proposed solution methodology.

Chapter 2

Literature Review

The objective is to compare the benefits of a cross-dock operated only by forklifts, versus the forklifts-and-self driving vehicles. We wish to compare the two facilities for cases that yield similar performance measures, but are operated by different types and mixtures of MHE. See Section 3.1 for a brief overview on cross-dock design, and Figures 3.1 & 3.2 for generic layout of a CD facility.

Various papers focus on simulation, optimization and simulation optimization of the cross-docking operation. But only a few were identified that focuses on the modelling and analysis of floor-level material-handling operations. Fewer still optimized the material-handling operations, directly or indirectly.

Research progress in modelling and optimization of cross-dock material handling operations is given in Section 2.1. That is followed by Section 2.2 by a brief survey on applications of AMHE for material-handling activities in warehouses or CD-like facilities.

2.1 Cross-Dock Material Handling Operation

As the size of a CD facility increases, the randomness involved in sorting and consolidation activities increases the modelling and computational difficulties of analyzing the CD operation. Researchers have modelled the cross-docking operations employing both deterministic and stochastic models. Research papers that analyzes the CD operations using deterministic modelling techniques are discussed in subsection 2.1.1. Subsection 2.1.2 considers cross-docking operations using stochastic modelling techniques.

2.1.1 Deterministic Modelling of CD Material Handling Events

Bartholdi and Gue [2000] proposed an optimization model to minimize the labour cost of an LTL cross-docking operation, subject to floor space congestion, i.e, the ratio between average pallet flow to an outbound door and the total area available in front of that door. The formulated objective function [Bartholdi and Gue, 2000] comprises three cost components:

1. Expected labour cost in moving the pallets in rectilinear or manhattan distance between inbound and outbound trucks in the CD.

2. Expected labour spent in waiting to move the pallets, due to interference between the forklifts or traffic congestion within the CD.

3. Expected labour cost of waiting due to dragline (type of MHE) congestion.

The resulting nonlinear minimization problem was solved using simulated annealing by interchanging the pair of trucks docked at the inbound or outbound doors, in a classic truck-scheduling, problem-solving approach [Bartholdi and Gue, 2000]. The solution methodology proposed by Bartholdi and Gue [2000] was implemented at several cross-dock facilities. It has not only proven to reduce the labour cost, but also to reportedly increase the productivity by more than 11% because of reduction in material transfer distance.

Later Bozer and Carlo [2008] followed an approach similar to that of Bartholdi and Gue [2000] to optimize the material-handling movement. They formulated a Mixed Integer Programming (MIP) model for a truck assignment problem in a cross-dock, to minimize the total pallet transfer distance (rectilinear distance between inbound and outbound doors), subject to dock availability. The resulting MIP model was solved using simulated annealing. The major difference between Bozer and Carlo [2008] and Bartholdi and Gue [2000] is the congestion issue in a CD was solved by not assigning more than three outbound trucks adjacent to each other implemented through simulated annealing heuristic. This approach was said to significantly reduce the computer run time to solve the problem, also limited the crowding of forklifts at the outbound, since congestion in general was due to forklifts being assigned to a series of outbound doors next to each other [Bozer and Carlo, 2008].

Boysen [2010] proposed a truck scheduling approach to handle frozen foods in a cross-dock facility operating on a JIT basis with a maximum of 10 to 20 doorways. The objective was to aid the JIT material-handling operation and reduce material transfer and wait times within the facility. A multi-objective truck scheduling problem was modelled and solved using a dynamic programming approach to minimize the flow time, processing time and tardiness of the outbound trucks. Boysen [2010] also proposed a heuristic approach based on simulated annealing to solve the multi-objective truck scheduling problem for a cross-dock with a greater number of doors. The proposed methodology would provide an optimal truck schedule for a small cross-dock with fewer doors, and a near-optimal schedule when there is a greater number of doors. Since the time delays involved in material handling activities are modelled as constant, a simultaneous increase in randomness as the size of a CD facility would make the proposed truck scheduling approach unreliable [Boysen, 2010].

The deterministic modelling techniques suggested by researchers in this subsection clearly fail to address the *randomness* involved in cross-docking material-handling operation. This mandates the need for study by the stochastic or simulation models. Though the deterministic optimization models of a cross-dock material handling operation yield optimal or near-optimal solutions, they do not guarantee optimal solutions in *real* CD facilities. That is because of very high randomness involved in material handling operations [Boysen, 2010]. Research which involves simulation modelling of a CD facility, with randomness in the material handling activities, are discussed in the next subsection.

2.1.2 Stochastic Modelling of CD Material Handling Events

Stochastic or simulation modelling helps researchers to model and analyze the randomness involved in a complex system. These model types enable the analyst to experiment and assess the working conditions of a complex system, which is difficult or infeasible to study in real-world scenarios due to financial or time constraints [Banks et al., 2010]. Better than deterministic models, simulation modelling techniques enable the study of randomness involved in material handling operations in a real-world cross-dock facility. Publications which are focused on simulation modelling of cross-dock material-handling operations are discussed in this subsection. This is followed by a brief overview of simulation optimization techniques for cross-dock simulation models.

Magableh et al. [2005] modelled a generic cross-dock facility using ARENA. They represented the material handling activities involved in a real-world cross-dock facility, to analyze CD performance. In their model, the LTL inbound trucks arrive at the CD facility with a specified interarrival rate. Trucks are docked at the available doors based on FIFO, and the goods are unloaded. Unloaded goods are sorted and loaded to the outbound vehicles by labour, using MHE such as hand pallet trucks, carts or forklifts. Finally, outbound trucks are dispatched from the facility, once the loading is complete. This simulation model was run for 120 hours with 20 replications, and the respective statistics were collected. Statistics included transporter utilization, staging space utilization, cross-dock facility utilization, trucks waiting time, average loading time and average unloading time [Magableh et al., 2005].

Though the model represents the material handling activities with randomness as in a real-world cross-dock facility, the CD performance at varied working conditions was not studied. Also the input parameters or working conditions of the facility (such as facility size, the number of workers, composition of the transporters, etc.,) were not specified explicitly, leaving the reader with an impression that the model built was for a relatively smaller cross-dock (20 to 30 doorways maximum).

Liu and Takakuwa [2009] modelled a CD operating 24x7 under a retail distribution environment to minimize the labour cost, subject to constraints on product or merchandise mix and operator skills (categorized into 3 skill levels). This cross-dock model thus requires three different categories of operators to handle the varied product mix received, based on the skill level needed for each product type. Not to ignore the fact that the demand for those three operators also varies over time, and the cost to employ them depends on their respective skill levels.

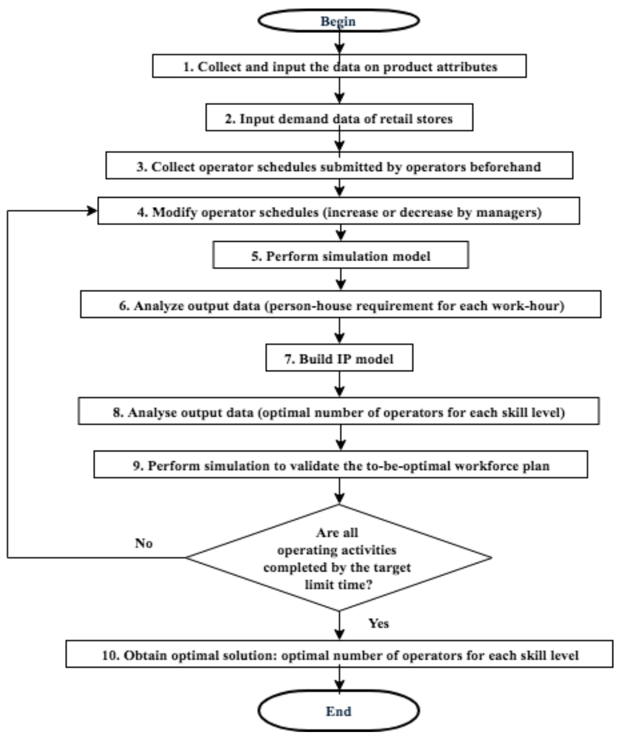

Figure 2.1: Simulation Optimization Framework for Cross-Dock Personnel Planning. Source: Adapted from Liu and Takakuwa [2009].

Liu and Takakuwa [2009] built an ARENA simulation model of a CD, with the demanded product mix and varied level of the workforce from three different operator categories. That simulation model output was used to formulate the constraints of an Integer Programming (IP) model, minimizing the cost of employing three categorizes of skilled operators. The workforce plan obtained from solving the IP model is called the "to-be-optimal" workforce plan, which is fed back to ARENA, remodelling the simulation model by updating the existing workforce plan to "to-be-optimal" workforce plan. Results of the simulation model with the revised workforce plan were later used to assess the ability of the "to-be-optimal" workforce plan to meet the target time limits. It would be concluded as the *optimal* workforce plan if the results of the simulation model with "to-be-optimal" workforce plan satisfies the set target limits, or else the workforce plan in simulation model will be revised manually (based on simulation analyst understanding of the gap between the current and desired state) to recompute the constraints of IP model. This procedure is iterated continuously until the workforce plan achieves the target time limits [Liu and Takakuwa, 2009].

The cross-dock personnel planning methodology proposed by those authors, given in Figure 2.1, is very intuitive. The to-be-optimal workforce plan is revised based on the simulation-analyst's ability to understand the gaps between expected and actual states. The search procedure could be time consuming for a large cross-dock (due to simulation run time and iterative procedure). That procedure would also require a better workforce plan to initiate the iterative process to reach optimality in fewer iterations. And not to ignore that the randomness involved in material handling activities was modelled based on operator movements [Liu and Takakuwa, 2009]; randomness involved in actual MHE movements and their requirements were ignored.

Adewunmi and Aickelin [2010] proposed a simulation optimization framework for cross-docking operations in a distribution center environment, involving order picking and order consolidation activities. All CD operations were performed by 5 to 7 operators using 3 to 5 pieces of MHE. The modelling and computational complexity of such small simulation models are trivial, encouraging the researcher to implement the Common Random Number (CRN), a variation reduction technique for model comparisons. The total cost of operators and MHE usage was minimized, subject to the availability of operators and MHE. Those authors evaluated the objective function by simulation of each feasible set within the solution space because of a relatively very small search space [Adewunmi and Aickelin, 2010]. However, the readers should not ignore the fact that approach to simulation optimization through evaluation of each feasible set within the solution space, and implementation of CRN for a large-scale CD model, would drastically increase the computational and modelling complexities.

Due to computational complexities in simulating all feasible sets within the solution space and modelling complexities in implementing CRN for a large-scale simulation models, other simulation optimization techniques were widely used by the researchers. Those techniques significantly reduces the computational and modeling complexities, which are discussed in next subsection.

Performance of a cross-dock could be influenced by various factors. Studying the effect of those factors in actual real-world scenarios is impractical. Khiong et al. [2011] came up with a simulation experiment to analyze the effect of those factors which could potentially impact the performance of a CD, that processes pallets in the two-step staging process as shown in Figure 2.2. Factors such as material handling methods, freight or product mix, number of forklifts, number of receiving doors, door layouts and size of the cross-dock facility were listed as the potential factors for the simulation experiment.

Two smaller, full-factorial experiments were conducted [Khiong et al., 2011], since analyzing a full-factorial experiment with all those six potential factors would be cumbersome and time consuming, even with only two levels. Performance of the facility was analyzed using two output measures, mean hourly throughput rate per forklift and mean handling time per pallet.

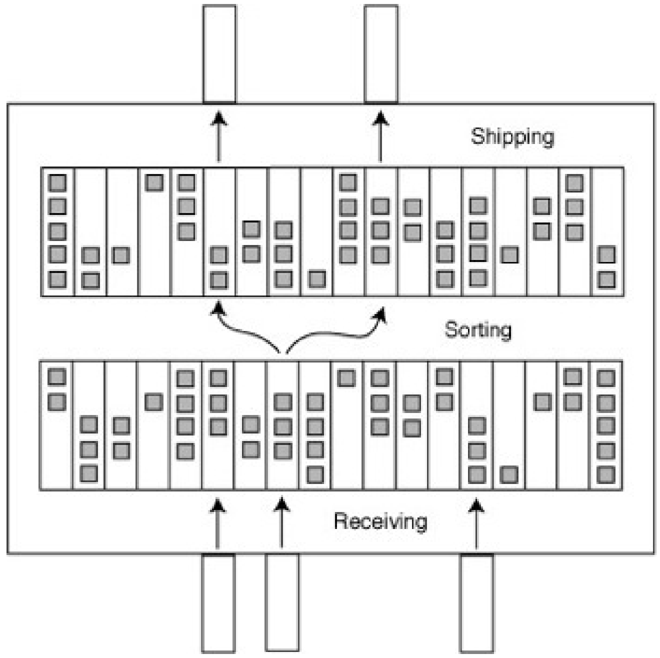

Figure 2.2: Two-step Staging Process in a Cross-Dock Facility.

Source: Adapted from Gue and Kang [2001].

(Exp 1) Impact of door layouts vs number of forklifts.

(Exp 2) Impact of number of receiving doors vs size of CD.

The results of (Exp 1) and (Exp 2) led to the conclusion that the factors which cause congestion are the ones that significantly impact the CD performance. The number of forklifts or MHE used in the facility is one among those significant factors. Though the material handling movements were modelled as they would occur in a real-world cross-dock, and experimented identifying the factors which significantly impacts the CD performance [Khiong et al., 2011], their optimal levels were not identified. This suggests the need for a simulation optimization approach to obtain the best number of MHE required in a cross-dock facility.

Briesemeister and Novaes [2017] proposed a probabilistic modelling technique to analyze the performance of a CD by adapting queueing theory to model the material handling activities of the cross-dock facility. The proposed theoretical queueing model was used to compute the CD performance for a varying level of input parameters, and results were compared to the output of a simulation model built using ARENA. Though a stochastic modelling approach was adapted to model the cross-dock facility, it was modelled in a very high level with queues to process the trucks; and material-handling activities as time delays following log-normal distribution. The only objective of this simulation model was to validate the performance of the proposed theoretical queueing model, not to study the facility itself [Briesemeister and Novaes, 2017].

Simulation Optimization of Cross-Docking Operation

Solving a simulation optimization problem is genrally more complicated than solving a deterministic optimization problem, due to the difficulty in evaluating the objective function. Evaluation of simulation objective function involves independent simulations of each feasible set within the search space. Rather than simulating all of those feasible sets, a few researchers have managed to solve the simulation optimization problem by building and analyzing *meta-models**, to predict the optimal solution of the simulation-optimization problem. Techniques such as Regression Analysis, Response Surface Methods and Neural Networks have been widely used for such purposes [Fu, 2014]. A brief review of research

* A meta-model is a model of an already existing model, and meta-modelling is the process of generating such meta-models. Meta-model is also called as surrogate model.

works which are directly focused on simulation optimization of a cross-docking operation, with or without using meta-modelling techniques is presented in this subsection.

Aickelin and Adewunmi [2008] presented a simulation-optimization methodology for a cross-dock door assignment problem to reduce the MHE pallet-travel distance. This standouts from the deterministic modelling techniques discussed in the previous subsection 2.1.1 by modelling the randomness involved in real-world CD facility, and by providing door assignment decisions dynamically, whenever a truck arrives. Discrete Event Simulation (DES) techniques were used to model a cross-dock with movements involved in transferring the pallets from inbound to outbound trucks, with continuous arrival of vehicles to the facility. Upon a truck arrival, the decision to dock in an assigned doorway was made, using the decision support system programmed within the DES model. A MHE travel distance minimization problem was formulated and solved using a Memetic algorithm to provide the door assignment [Aickelin and Adewunmi, 2008]. However, the number of MHE required, the MHE performance and that of the cross-dock facility were not studied by those authors.

Guignard et al. [2014] proposed a stochastic door assignment approach for the trucks arriving at a CD facility, similar to work of Aickelin and Adewunmi [2008], and compared the results to those of a deterministic assignment model. That substantiated the benefits of using a stochastic modelling approach. A deterministic Cross-Dock Door Assignment Problem (CDAP) was formulated initially, with an objective to minimize the total MHE travel distance. That resulting optimization problem was solved using a convex hull heuristic. On the other hand a simulation model of a cross-dock was built and simulated in MATLAB. Dynamic truck assignments were implemented in that simulation model, a routine that was called in whenever a truck arrived (i.e., this recommended a solution of the resulting

CDAP model for the given situation). Performance comparison of the deterministic and stochastic assignment modelling techniques shows that the dynamic approach yields better results [Guignard et al., 2014].

Shi et al. [2013] proposed a simulation modelling framework to design a robust JIT-based auto-parts CD distribution centre, such that the system is insensitive to the supply chain uncertainties. A DES model of a CD facility was built with the randomness involved in truck arrival, auto-parts processing rate, demand uncertainty at assembly plants, failure and repair of barcode scanners. The cross-dock facility optimization problem was modelled with multi-objectives involving three performance measures which are influenced by five factors [Shi et al., 2013]:

Obj 1) Minimize the waiting time of parts in the staging area.

Obj 2) Minimize the number of parts exceeding the threshold time limit.

Obj 3) Maximize the throughput rate.

Fac 1) Number of inbound doors.

Fac 2) Number of outbound doors.

Fac 3) Number of forklifts.

Fac 4) Number of Converyors.

Fac 5) Threshold time limit allowed to wait in staging area.

Shi et al. [2013] experimented with the built simulation model, using a full factorial design and a central composite design, to identify the relationship between the performance measures and the factors. The proposed relationship was established using three prediction equations. The factor levels are optimized using a response surface approach to achieve the desired performance level.

A hybrid simulation modelling technique for a cross-dock facility was introduced by Suh [2015]. The model represented the overall inventory flow from the suppliers to distributors via the CD. Agent-Based modelling techniques were used to model the suppliers and distributors in the logistics network, and a DES approach was used to model the cross-dock facility. Hybridization of agent-based and DES modelling techniques enabled the overall simulation model (built in Anylogic) to address the uncertainties involved in information and inventory flow, from supply to demand nodes of the logistics network. While the simulation model did not focus on material handling activities of the facility, the objective was to assess the feasibility and performance of a cross-docking operation for the given product suppliers and distributors [Suh, 2015].

The proposed CD model was operated with the given input parameters such as distributor order wait time, percentage of trailers departing with full load, SKU wait time, and trailer wait time [Suh, 2015]. Performance of the CD facility was assessed via output measures such as a total number of trailers used, SKU througput time, LTL fill rate and percentage of LTL trucks leaving the dock. A full factorial simulation run (resulting in 100,000 total replications) was performed to build a regression model for each of the performance measures. Input parameter levels were optimized to minimize SKU throughput time, to minimize the total number of trailers used, to maximize LTL fill rate and to minimize the percentage of LTL trailers leaving the dock [Suh, 2015].

From the exhaustive search for previous research work on simulation modelling of cross-dock material handling activities and simulation optimization of cross-dock performance metrics, very little published research was found whose emphasis was on optimizing the total number of MHE required. This is discussed in the previous subsection 2.1.2. Most research works were focused on optimizing the total number of material handling movements through deterministic modelling techniques, as discussed in subsection 2.1.1. But no publications to date emphasize the applications of AMHE or Self-Driving Vehicle in a cross-docking facility.

2.2 Autonomous Material Handling

A brief review of research on the scope of AGV and SDV for material handling activities in distribution centre or CD-like facilities are discussed in this subsection. No previous publications, focusing on applications of SDVs for material-handling purposes have been found. However, various research works on AGVs for automated material handling activities in factory, warehouse or distribution centre like facilities were identifed. Some of those papers which are close to the objective of this thesis are discussed in this section.

Autonomous material handling equipment (AMHE) move on a dedicated path, making them ideal for warehouse material storage and retrieval processes. Ito and Abadi [2002] developed an agent-based simulation model to assess the inventory planning strategies and the performance of information exchange for an AMHS in a warehouse. The proposed simulation model consists of three subsystems:

1. Agent-based Communication System (ACS).
2. Agent-based MATerial Handling system (AMATH).
3. Agent-based Inventory Planning and CONtrol system (AIPCON).

Those subsystems interact with each other to mimic the forward and backward inventory flow between the suppliers and customers via the warehouse facility. AMATH assigns an AGV to perform the transshipment request based on FIFO rule, whenever a material storage (inbound truck to warehouse), material transfer (inbound truck to outbound truck) or material retrieval (warehouse storage to outbound truck) request is raised by the ACS. Material handling delays were modelled as time delays to wait for an AGV and AGV travel times [Ito and Abadi, 2002]. Although, the proposed framework did not account for the performance or optimal number of AGVs, it was used to assess the warehouse inventory requirements to avoid back-orders.

Kesen and Bayko [2007] modelled a Job shop environment using ARENA, where the jobs are processed on their own sequence through various processing stations transferred by AGVs. The built simulation model was assessed using four mean-performance metrics (1) job throughput time, (2) queue length, (3) number of jobs per unit time and (4) inter-job departure times. Four factors were chosen to be varied over two levels $F1$ - number of vehicles, $F2$ - vehicle dispatching rule, $F3$ - number of Kanban and $F4$ - job arrival rate . The main effects and interaction effects of the factors were analyzed for their significance, but their optimal levels was not identified [Kesen and Bayko, 2007].

Peixoto et al. [2016] used DES modelling techniques to assess the impact of new AMHS for order-picking in a warehouse and the results were compared to the performance of a manually operated facility. The proposed framework involves two DES models, one representing an actual warehouse (with no autonomous MHE) and the second representing a facility with the proposed changes (with autonomous MHE and other sequencing rules). The randomness involved because of demand uncertainty, labour availability, traffic congestion, etc., was modelled. That enabled the researcher to use the model to validate and assess the real-world decisions (to implement AMHE and the performance of the warehouse at varied operating conditions) by use of the model. However, the optimal AMHE requirements were not studied, although the differences in performance between two facilities were justified through confidence intervals [Peixoto et al., 2016].

To conclude this chapter, we emphasize that the differences in operating characteristics of AGVs and SDVs should not be ignored. Those are distinct such as manoeuvring between obstacles and smart decision making abilities to choose optimal path, which make the SDVs movement equivalent to the movement of manual forklifts in a free path. Therefore simulation of SDVs for material handling applications in a cross-dock requires modelling techniques which are similar to the simulation of manual forklifts, not AGVs. Further, cross-dock material-handling operation requires a greater number of MHE and additional transshipment assignments compared to warehouse or distribution centre. This mandates the need for further research to validate the scope of SDVs in a CD.

Chapter 3

Simulation Modelling

It is very expensive and time consuming to establish a new facility or to make changes and improvements to the existing facility (system). This makes it difficult to study their implications in real life and causes uncertainties in the decision-making process. Simulation modelling is a way to create a virtual or digital model of an already existing real-world facility or a proposed new facility, in a computer environment to study their performance, subject to various working conditions. Simulation modelling techniques can drastically save cost and time; it can also act as a decision support system (DSS) to support various decisions and business strategies delivering robust decisions [Law, 2015].

Simulation techniques have been widely used in various fields. Advancements in computational capabilities made it possible to use simulation for various applications such as modelling and analysis of bank teller operations, transportation systems (airports, flights, ports, subways and buses), space shuttles, mining operations, construction engineering and project management, healthcare, logistics networks and inventory modelling

[Banks et al., 2010]. Discrete-event Simulation is a type of simulation modelling technique: Activities in the system are modelled in a discrete sequence of events in time. That is, events occur at a particular instant in time and change the state of the system. For more information on DES modelling techniques and analysis, refer to the textbooks on simulation modelling and analysis by Banks et al. [2010] or Law [2015].

We employ DES techniques to model and analyze the forklift-only and forklift-and-SDV cross-dock facilities. The ability to model the randomness and time delays involved in CD material-handling activities as a discrete sequence of events in time makes DES techniques apt and adequate to model a cross-dock facility.

Two simulation models, are required respectively for a FL-only and FL-and-SDV CD, to validate the scope of SDVs in a cross-dock. Simulation modelling and analysis of those two facilities are discussed in this chapter. The rest of this chapter is organized into four sections. Section 3.1 defines the shape, size and dimensions of a cross-dock facility. A brief overview of material handling assumptions and the pallet flow process are contained in Section 3.2. Section 3.3 defines the output measures which are used to assess the performance of each CD, while Section 3.4 contains an overview of our simulation modelling of cross-docks using ARENA and the resulting output analysis.

3.1 Cross-Dock Design

Design of a cross-dock determines the potential volume of goods which can be processed there. Design includes, but is not limited to, CD shape, number of inbound and outbound doors, CD size, size of the staging area, aisle width, MHE parking area, MHE charging stations and the measuring stations. These all together, account for the design of a CD; detailed representation of all those factors is beyond the scope of this study. The part of a CD required to validate the stated hypothesis is the dedicated material-handling region. That is the number of doors and door size, facility shape, staging area and aisle width for MHE.

3.1.1 Number of Doorways and Dock Size

There are two types of doorways in a cross-dock, one for inbound trucks and another for outbound. The ***inbound doors*** are dedicated to offload the material received from the inbound trucks. The ***outbound doors*** are analogously dedicated to load the consolidated materials to the outbound vehicles received from the inbound trucks. The required number of outbound doors is decided based on the number of destinations served by the CD. The necessary number of inbound doors is based on the dispatch sequence or the constraints in loading the outbound trucks.

For this research, a cross-dock is assumed to have a total of 100 doors, each $15ft$ wide. The numbers of doors for inbound and outbound trucks are assigned based on the material handling-assumptions discussed later in Section 3.2 of this chapter.

3.1.2 Facility Shape

A cross-dock facility may come in various shapes such as **I** (long narrow rectangular), **L**, **H**, **U**, **T**, **H**, **X** and **E**. Bartholdi and Gue [2004] performed a computational experiment to study the labour efficiency of a CD with different shapes and an increasing number of doors. Based on their work, **I**-shaped cross-docks were found to be labour efficient for facilities with fewer than 150 doors, **T**-shaped cross-docks are appropriate for the facilities ranging from 150 to 200 doors, and **X**-shaped cross-docks are best for CDs with more than 200 doors. The results of Bartholdi and Gue [2004] have been widely accepted by various researchers, supply chain and cross-docking experts.

Hence, an **I**-shaped narrow rectangular cross-dock facility with 100 doors is assumed. That is, 50 doors on opposite sides of a facility, resulting in a total length of $750ft$ on each side.

3.1.3 Staging Area and Aisle Width

In an ideal cross-dock, the materials are received as a unit load and marked with destination identification (printed, colour coded or barcoded). They can then be directly loaded to the outbound trucks from the inbound truck using MHE such as forklifts or hand pallet trucks, but only if the outbound trucks are available and docked at the outbound doors. In cases where the destination trucks are not available or the material received requires sorting and consolidation, those goods will be placed in a temporary storage area called a **Staging Area** for further action. A cross-dock facility with an inadequate staging area would experience serious congestion and time delays; an excessive staging area would result in un-utilized floor space.

Forklift-Only Cross-Dock Facility

The following are our chosen geometries for this CD.

Staging Area: Floor space of $58 \times 15 ft^2$ is dedicated for one pair of doors from opposite sides to stage the pallets.

Aisle Width for Forklifts: Floor space of $30 \times 15 ft^2$ is dedicated in front of each door, for the forklifts to manoeuvre, move between the doors, sort, unload and load the trucks.

Facility layout of the assumed forklift-only cross-dock is given in Figure 3.1.

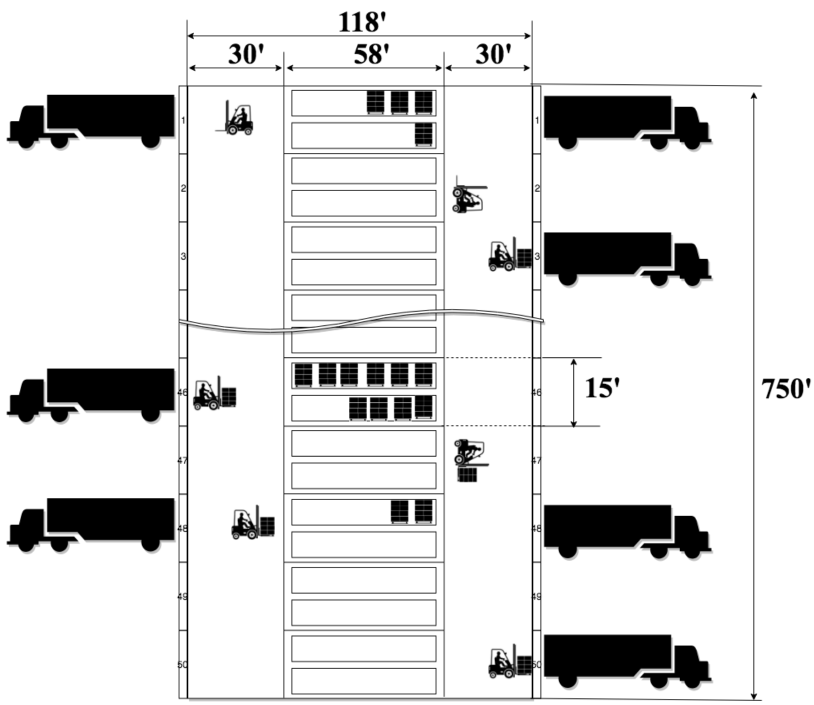

Figure 3.1: Facility Layout: Forklift-Only Cross-Dock Facility.

Forklift-and-Self-Driving Vehicle Cross-Dock Facility

Staging Area: Floor space of $13 \times 15 ft^2$ is dedicated for one pair of doors from opposite sides to stage the pallets.

Aisle Width for Forklifts: Floor space of $30 \times 15ft^2$ is dedicated in front of each door for the forklifts to manoeuvre, unload and load the trucks.

Aisle Width for Self-Driving Vehicles: Floor space of $12 \times 150ft^2$ called an SDV path, is dedicated for the SDVs to move back and forth across all 50 doors. A floor space of $6 \times 15ft^2$ is dedicated on either side of the $12ft$ wide SDV path, across 50 doors, for the SDVs to park.

The facility layout of the assumed forklift-and-SDV cross-dock is given in Figure 3.2.

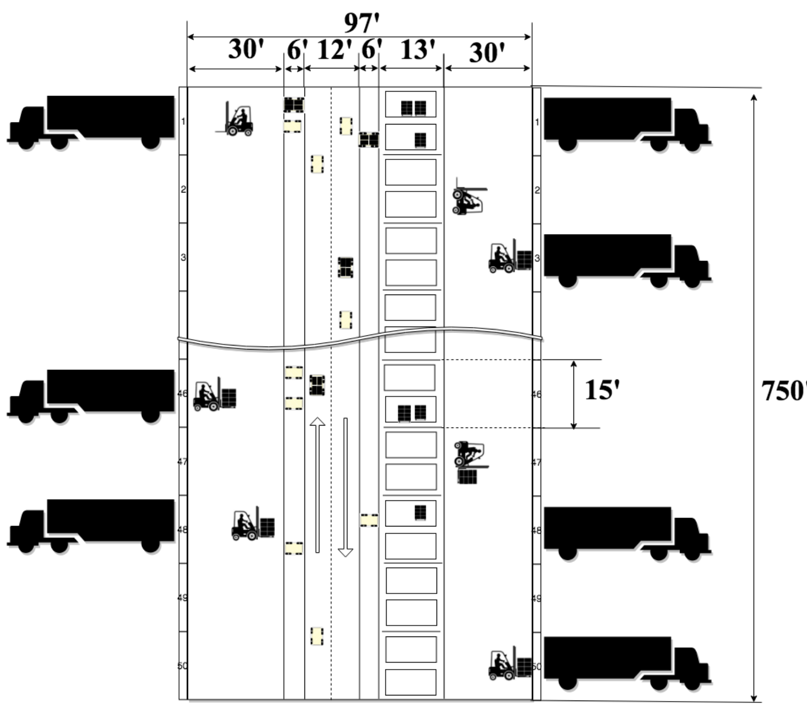

Figure 3.2: Facility Layout: Forklift-and-Self-Driving Vehicle Cross-Dock Facility.

3.2 Material Handling Assumptions

Various material-handling activities are performed in a cross-dock, creating multiple discrete sequences of events in time. Precise modelling of all those events would make a simulation model an accurate representation of a real-world facility. That can only be achieved by closely studying the cross-dock, and collecting and analyzing the data of the facility. That data collection and analysis must particular attention to operating conditions, material flow process, working behaviour of MHE, sequencing or priority rules for MHE and trucks. Studying the detail characteristics of a real cross-dock is a time consuming process.

Due to the difficulties in getting access to such a cross-dock, those real-world characteristics and facility working behaviour were not studied. After a series of brainstorming sessions with CD subject matter expert and the SDV manufacturer, various assumptions were made to build a generic cross-dock model with two MHE configurations. One configuration had forklifts only, and the other both forklifts-and-Self-Driving Vehicles. Assumptions which are common to both models are discussed in subsection 3.2.1, followed by subsection 3.2.2 and 3.2.3 on assumptions which are unique to the particular cross-dock MHE configuration (forklifts only; forklifts plus SDVs) of the particular CD.

3.2.1 General Assumptions

(GA 1) Inbound (IB) and outbound (OB) trucks are always available throughout the simulation run time. Those trucks are ready to offload or load at any point in time, without any dock scheduling conflicts.

(GA 2) There are 50 inbound doors on the left-hand side of the **I**-shaped cross-dock facility and 50 outbound doors on the right-hand side.

(GA 3) IB trucks arrive at a CD with inter-arrival time 0 (more precisely, the facility does not need to wait for an inbound vehicle). This is assumed to maintain our focus on the internal material handling activities of a facility.

(GA 4) The number of pallets carried on each IB truck has a uniform distribution over (20, 26), i.e., full capacity of a $53ft$ trailer. Those pallets are ready to offload.

(GA 5) Pallets received from the IB trucks are sorted and then loaded to the respective OB trucks as a *unit load*, without any change in their properties.

(GA 6) Pallets can be moved only by MHE such as forklifts or SDVs.

(GA 7) The destination dock of each pallet received is assigned based on an equal probability. That is, pallets received from the inbound trucks can be designated to any destination dock with a probability of $(\frac{1}{number\ of\ outbound\ doors})$.

(GA 8) Each and every outbound truck require $UNIF(20, 26)$ pallets to be loaded onto it, before departing from the cross-dock facility.

(GA 9) MHE are available throughout the simulation runtime, without any downtime.

(GA 10) There is no traffic congestion within the cross-dock.

(GA 11) Forklifts and SDVs are allocated based on their proximity to the "job call". By this we mean the nearness of free MHE to the pallet in question.

(GA 12) Inbound or outbound truck has a changeover time of $TRIA\ (2,\ 3,\ 5) mins$*. That is the time taken for a processed truck (offload inbound truck or loaded outbound truck) to depart and a unprocessed truck to dock at a doorway.

3.2.2 Forklift-only Cross-Dock Facility

The two assumed generic types of cross-docks differ in their MHE configuration. The forklift-only cross-dock facility is with three zones or stations: inbound docks, a staging area and outbound docks (see Figure 3.3).

Inbound Docks (IB-D): This zone includes the inbound doors on the left-hand side, where the inbound trucks are parked or docked to offload the pallets, and the $30ft$ space in between the inbound doors and staging area.

Staging Area (SA): A floor space of $58 \times 15ft^2$ is dedicated for the process of pallet sorting and consolidation, after the pallets have been offloaded from inbound trucks through IB-D.

Outbound Docks (OB-D): Included in this zone are the outbound doors on the right-hand side, where the outbound trucks are parked or docked to load the pallets, and the $30ft$ space in between the staging area and outbound doors.

In the forklift-only CD (Figure 3.3) manual forklifts are used to offload pallets from the trucks parked at IB-D, and stage those pallets in SA. Post sorting and consolidation

* Acquired from cross-dock SME.

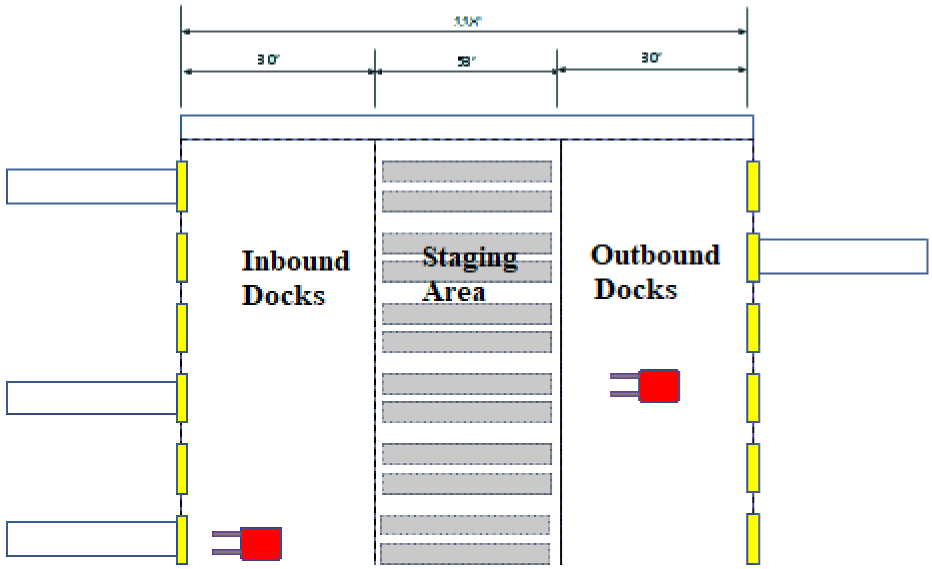

Figure 3.3: Forklift-only Cross-Dock Facility: Zone Classification.

from SA, manual forklifts load pallets to respective outbound trucks parked at OB-D.

Categories of MHE in Forklift-only CD facility

Manual forklifts are the only MHE used in a forklift-only cross-dock. Based on offloading or loading activity in which they engage, they are categorized as inbound forklifts and outbound forklifts respectively.

Inbound Forklift (IB-FL): Forklifts which are dedicated to offload and stage the pallets from an inbound truck to the respective staging area. They can move across the inbound doors or between an inbound door and the staging area.

Outbound Forklift (OB-FL): Forklifts which are dedicated to sort and load the pallets from the staging area to the destination trucks that are at the outbound doors. They can move between the staging area and outbound doors to load the pallets from that SA to the outbound (destination) trucks.

The flow process of pallets from inbound trucks to outbound trucks in a Forklift-only cross-dock is given in Figure 3.4 as a swimlane.

Modelling Assumptions: Forklift-only cross-dock facility

1. An inbound forklift assigned to a particular truck offloads pallets individually, one by one, from that inbound vehicle to the staging area, based on a time delay due to the distance travelled and speed.

2. The staging area ($58 \times 15 ft^2$) in front of an inbound door is dedicated for the pallets received only from that respective door.

3. An inbound forklift assigned to offload an inbound truck is relieved only after the offloading is complete.

4. If the staging area is full, the assigned IB-FL will wait for the pallets to be moved by an OB-FL, to complete the offloading process.

5. Each pallet can be assigned to any destination dock with equal probability, before being picked up by an OB-FL.

The assumed forklift-only cross-dock facility is modelled with the given general and modelling assumptions. The other design parameters and various time delays involved in the

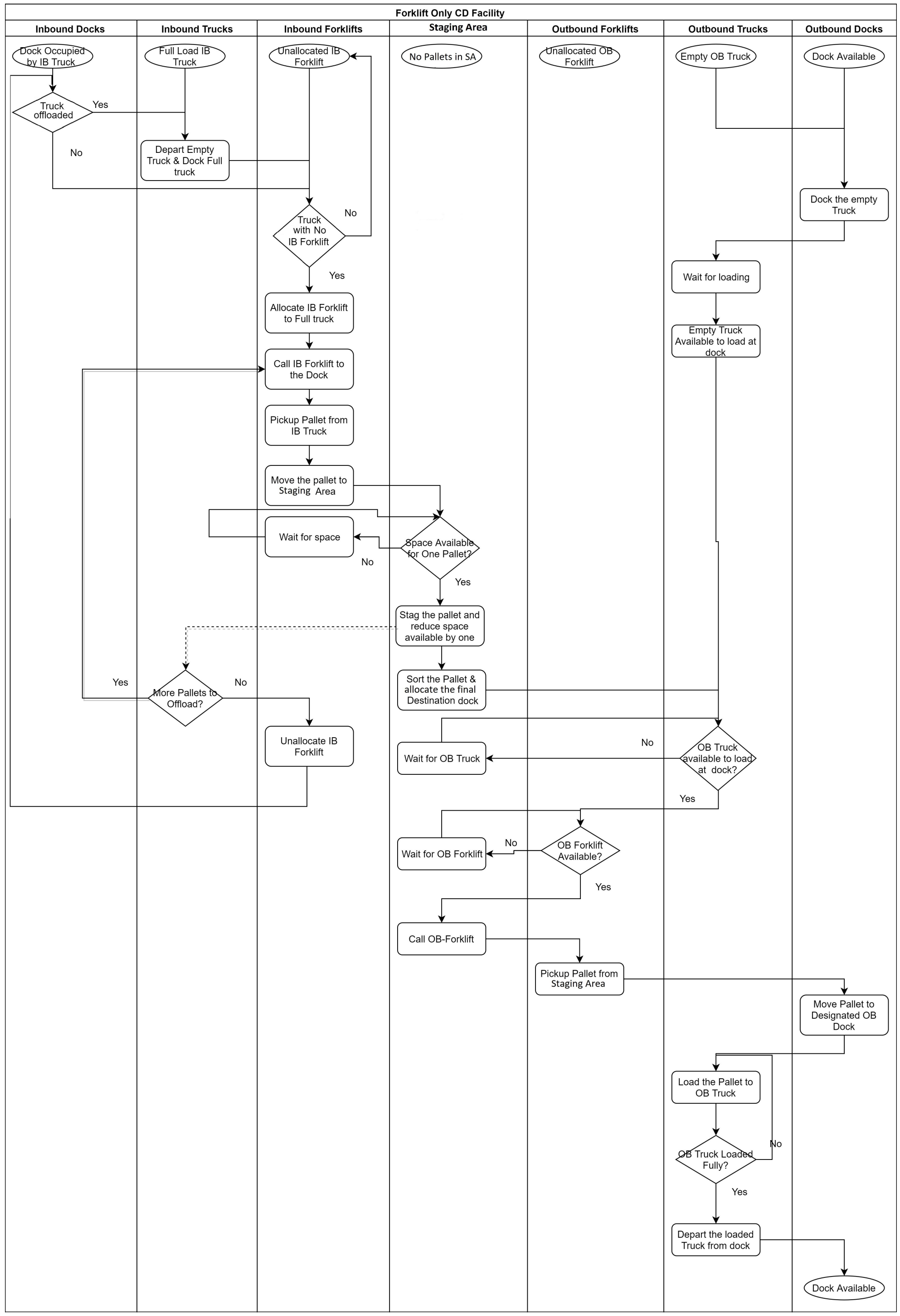

Figure 3.4: Swimlane Diagram: Forklift-only Cross-Dock Facility.

material-handling activities of a cross-dock facility are given in Table 3.1. The choices of decision variables (number of inbound and outbound forklifts), for the FL-only CD to operate under the *optimal* conditions are discussed later in Chapter 5.

Parameter	**Value**
Model Naming	(IB-FL).(OB-FL)
CD working or simulation run time	$7.5hr/day$.
Facility Dimension	
Length of the facility	$750ft$.
Width of the facility	$118ft$.
Trucks	
Inbound or Outbound Truck Inter-arrival time	0.
Pallets per Inbound or Outbound Truck	$UNIF(20, 26)$.
Docks	
Number of Inbound Doors or Docks	50.
Number of Outbound Doors or Docks	50.
Staging area space capacity	30 Pallets in $15 \times 26ft^2$
Forklift average speed	
IB-FL or OB-FL with pallet*	$316ft/min$ or $1.61m/s$.
IB-FL or OB-FL without pallet*	$548ft/min$ or $2.78m/s$.
Time delays	
IB or OB truck changeover time†	$TRIA(2, 3, 5)$ $mins$.
IB or OB Forklift travel time	$\frac{Manhattan \quad Distance}{Speed}$
Forklift time to maneuver and pickup pallets†	$UNIF(8, 12)$ $secs$.
Forklift time to maneuver and drop pallets†	$UNIF(8, 12)$ $secs$.

Table 3.1: Design Parameters: Forklift-only Cross-Dock Facility.

*Source: [The MHEDA Journal] www.themhedajournal.org/2013/03/06/facts-about-forklifts

†Acquired from cross-dock SME.

3.2.3 Forklift-and-Self-Driving Vehicle Cross-Dock Facility

As mentioned earlier, the assumed generic type of forklift-and-SDV cross-dock facility is operated using manual forklifts and SDVs. The CD is thus designed and modelled to support those material handling activities. The facility layout of such a system given in Figure 3.2.

The sortation and consolidation activities of a cross-dock are the most cumbersome, result in huge floor and traffic congestion. Immense labour and supervision are required to sort and validate the accuracy of the sorting activities. SDVs thus come in handy when it comes to the consolidation of unit load items. Once a pallet is loaded to it, an SDV can auto-detect the destination of that inbound pallet (using identification techniques such as RFIDs or with instructions given by the master computers used for job allocation). The SDV will thereby transfer pallets to those respective outbound doors, significantly reducing the labour requirement.

The proposed facility for a generic type of forklift-and-SDV cross-dock is comprised of five stations (see Figure 3.5) to support those material-handling activities, which are listed as follows:

Inbound Docks (IB-D): These include inbound doors, where inbound trucks are parked or docked to offload the pallets, and the $30ft$ space between inbound doors and the inbound drop-off point. This space is dedicated for the offloading forklifts to move between doors, to manoeuvre or to load the pallets offloaded from trucks to pallet holder or SDVs waiting at the inbound drop-off point.

Inbound Drop-off Point (IB-DP): Each IB-D has a dedicated spot for SDVs to park and pick up the pallets (with an area of $6 \times 15 = 90ft^2$), separated from the inbound doorways by a distance of $30ft$. Each IB-DP also has a pallet holder to which an offloading forklift can drop off a pallet if an SDV is not immediately available for pickup.

Outbound Pickup Point (OB-PP): Each outbound dock or doorway has a dedicated spot for SDVs to park near the outbound docks or doors (again, with an area of $90sq.ft$), for an outbound forklift to pick up pallet from the SDV.

Staging Area (SA): Dedicated $13 \times 15ft^2$ floor space for sorted pallets, the latter ready to be loaded to outbound trucks from the respective doorway.

Outbound docks (OB-D): Located at the right hand side of the facility, where the outbound trucks dock. These are separated from the SA by a distance of $30ft$ for the outbound-loading forklifts (outbound forklifts) to manoeuvre and move between docks.

Facility layout representing the preceding five stations in the forklift-and-SDV cross-dock facility is given in 3.5. Pallets from inbound trucks docked at IB-D are offloaded using the manual forklifts and loaded to the SDVs waiting at IB-DP. SDVs sort the pallets and transfer them to the designated doorways OB-DP. A manual forklift is allocated to pick up each pallet from an SDV at OB-DP. That pallet will be staged in SA, or loaded to an outbound truck at OB-D based on truck availability.

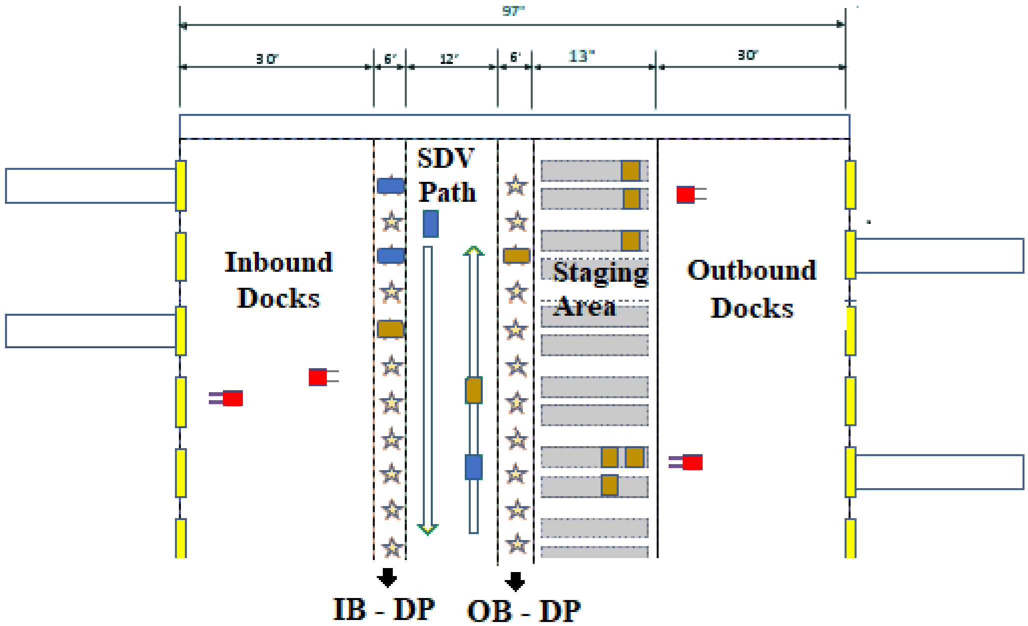

Figure 3.5: Forklift-and-Self-Driving Vehicle Cross-Dock Facility: Zone Classification.

Categories of MHE in Forklift-and-SDV CD Facility

MHE used in a forklift-and-SDV CD are grouped into three categories based on the offloading, sorting or loading activities they engage in as inbound forklifts, SDVs and outbound forklifts respectively.

Inbound Forklift (IB-FL): Inbound forklifts are dedicated to offload the pallets from inbound trucks, and load each pallet to an SDV if available, or else to the pallet holder. Inbound forklifts move across the inbound docks (when empty), or between the inbound dock and the inbound drop-off point, to offload the trucks.

Self-Driving Vehicle (SDV): SDVs are dedicated to sort and deliver pallets from IB-DP to OB-PP. They move between IB-DP and OB-PP, following a rectilinear or Manhattan distance through the dedicated $12ft$ SDV path. An SDV can pick up a pallet directly from an inbound forklift or a pallet holder at IB-DP (but not from the floor), and requires an outbound forklift to offload the pallet.

Outbound Forklift (OB-FL): Outbound forklifts are used to load the pallets to outbound trucks from SDVs or SA. Pallets are sorted and delivered by an SDV at OB-PP; outbound forklifts load pallets directly to an outbound truck if available, or else stage pallets in the SA. Pallets staged will later be loaded to trucks by an OB-FL once the trucks are available.

The flow of pallets from inbound to outbound trucks in a generic type of forklift-and-SDV CD is given in Figure 3.6 as swimlane diagram.

Modelling Assumptions: Forklift-and-Self-Driving Vehicle Cross-Dock Facility

1. An IB-FL assigned to a particular truck offloads all pallets one by one, based on the time required to travel the distance between IB-D and IB-DP.

2. Pallets picked up by IB-FLs from inbound trucks are loaded to an SDV, if available at IB-DP, or else to the free pallet holder. If neither one is available, IB-FL will wait for an SDV at IB-DP.

3. An IB-FL assigned to offload an inbound truck is relieved only after the offloading is complete.

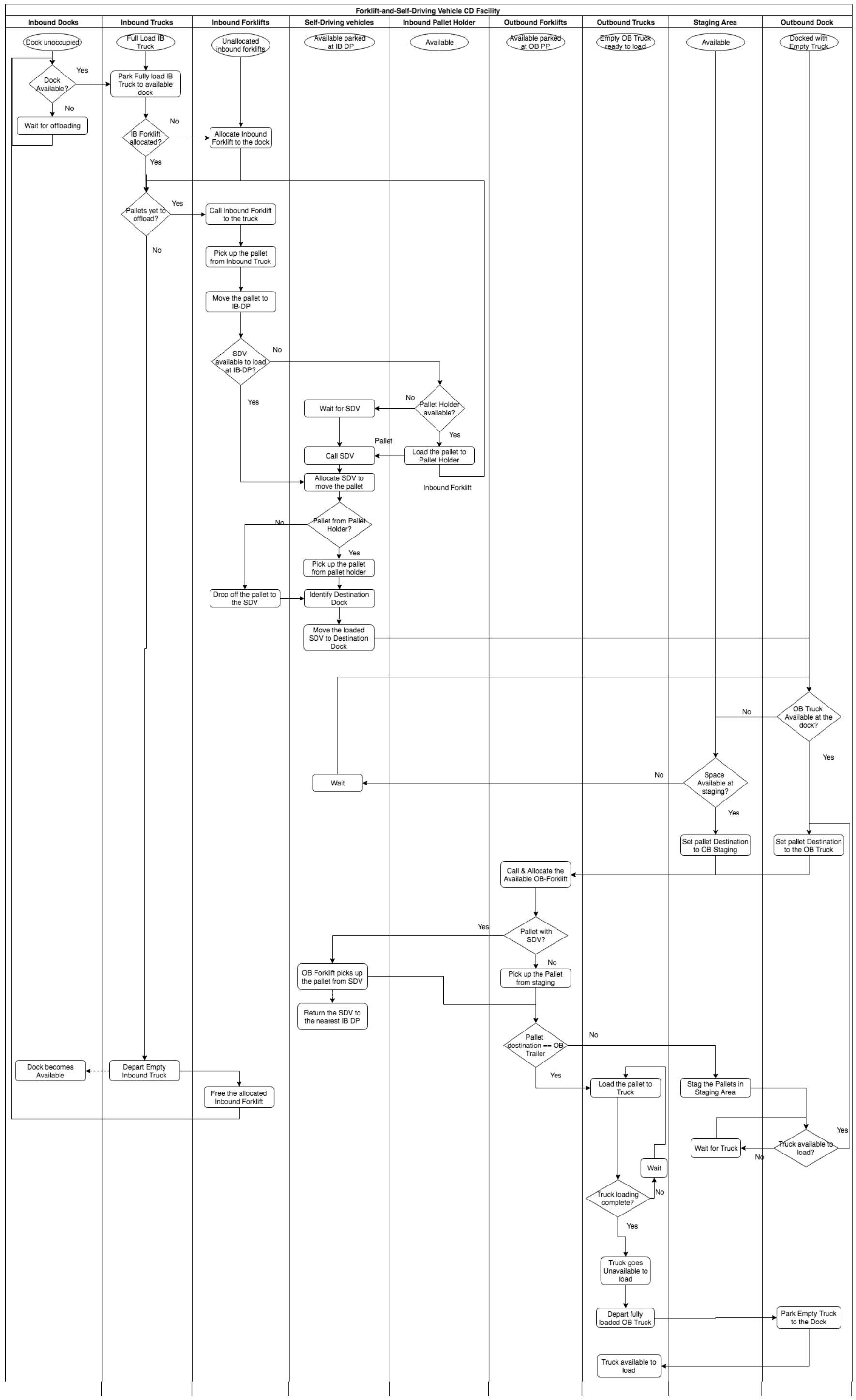

Figure 3.6: Swimlane Diagram: Forklift-and-Self-Driving Vehicle Cross-Dock Facility.

4. SDVs transfer the pallets collected from IB-DP to OB-PP in a rectilinear path (or Manhattan distance), manoeuvring between obstacles in its path.

5. After offloading pallets at OB-PP, a free SDV will return to the shortest active IB-DP (having the least number of SDVs) within a 10-dock distance.

6. After an SDV is allocated to transfer a pallet, that pallet is assigned to any destination dock with equal probability.

7. If an outbound truck is not available at the destination dock, the respective pallets will be staged at the staging area to free the SDV. If neither the outbound truck nor the staging area is available, then the SDV will wait for an outbound truck to offload.

8. Pallets staged in SA will be loaded to an outbound truck by OB-FLs, once a truck is available at OB-D.

The assumed forklift-and-SDV cross-dock facility is modelled with the stated general and modelling assumptions. The other design parameters and various time delays involved in the material handling activities of a CD are given in Table 3.2. Choices of decision variables (number of inbound forklifts, SDVs and outbound forklifts), for the forklift-and-SDV cross-dock facility to operate optimally are discussed later in Chapater 5.

*Acquired from SDV manufacturer.

†Acquired from cross-dock SME.

Parameter	Value
Model Naming	(IB-FL).(SDV).(OB-FL)
CD working/simulation run time	$7.5hr/day$.
Facility Dimension	
Length	$750ft$.
Width	$97ft$.
Trucks	
IB or OB Truck Inter-arrival time	0
Pallets per IB or OB Truck	$UNIF(20, 26)$.
Docks	
Number of Inbound Doorways or Docks	50.
Number of Outbound Doorways or Docks	50.
OB Staging capacity	13 Pallets in $15 \times 13ft^2$.
Number of pallet holders	1 .
MHE Speed	
Forklifts with pallet	$316ft/min$ or $1.61m/s$.
Forklifts without pallet	$548ft/min$ or $2.78m/s$.
SDV with or without pallets*	$316ft/min$ or $1.61m/s$.
Time delays	
IB or OB Truck changeover time	$TRIA(2, 3, 5)mins$.
MHE travel time delays	$\frac{Manhattan\ \ Distance}{Speed}$
MHE time to maneuver and pick up pallets†	$UNIF(8, 12)secs$.
MHE time to maneuver and drop off pallets†	$UNIF(8, 12)secs$.

Table 3.2: Design Parameters: Forklift-and-SDV Cross-Dock Facility.

3.3 Output Performance Measures

As discussed in Section 2.1 of the literature review, various output measures are used by researchers to assess the performance of a cross-dock facility. Some of these measures are “Average Throughput rate”, “Average Throughput rate / MHE”, “Average Number of Trucks Processed / Day”, “Average Pallet Flow Time”, “Outbound Truck Tardiness”, “Transporter or MHE Utilization rate”, “Staging Space Utilization rate”, “Cross-Dock

Facility Utilization rate", "Dock or Doorway Utilization rate", "Average Truck Waiting Time", "Average Loading and Unloading time", and "Pallet Waiting Time at SA". While a few of those provide insight on overall CD performance, most of the others emphasizes particular operations at a cross-dock: MHE, doors or trucks.

For example, measures such as Average Throughput rate, Average Pallet Flow Time or CD Utilization rate provide insight on overall effectiveness and capability of cross-docking operation on different scales of measure. On the other hand, measures such as Outbound Truck Tardiness, MHE Utilization rate, Average Loading or Unloading time are performance indicators of only certain aspects of CD operation (truck scheduling procedure) or the entities (MHE) in a cross-dock. Hence the identification of appropriate output measure(s) is critical to assess the scope of SDVs in a cross-dock. Studying inappropriate performance metrics may result in analyzing a components which are not relevant.

After a series of brainstorming sessions, *Average Throughput rate, Average Throughput rate/ MHE* and *Average MHE Utilization rate* were chosen to study the performance of cross-dock material handling operations, and to validate the capability of SDVs. Together, these measures provide better insight on the overall effectiveness of material handling activities in a CD facility.

3.3.1 Average Throughput Rate - δ

δ is an average of the total number of pallets processed per day in a cross-dock. This provides an insight on the facility's overall material handling capability for a given MHE configuration. However, the efficient utilization of MHE cannot be known by from considering δ only. The cross-dock objective is to maximize δ.

$$
\begin{aligned}
\text{Let} \qquad P_i &= \text{ Number of pallets processed on day i.} \\
N &= \text{ Total number of replications or days.} \\
\text{Then} \qquad \delta &= \frac{\sum_{i=1}^{N} P_i}{N}
\end{aligned}
\tag{3.1}
$$

Unit of δ is *pallets/day* or *ppd*.

3.3.2 Average MHE Utilization Rate - U

The ratio between the total MHE uptime and the total MHE time in a facility is *Overall MHE Utilization rate* - U_O. U_O provides insight on *aggregate* utilization of the MHE in a CD, rather than attempting to analyze individually. Any MHE idle time incurs cost in terms of improper utilization of labour and MHE.

$$
\begin{aligned}
\text{Let} \qquad UT_{ij} &= \text{Uptime of } i^{th} \text{ MHE in the } j^{th} \text{ replication.} \\
T &= \text{Simulation runtime / replication.} \\
c &= \text{Total number of MHE in a cross-dock.} \\
c &= X_I + X_O + X_S \\
X_S &= 0 \qquad (for\ FL\text{-}only\ CD). \\
\text{Then} \qquad U_O &= \frac{\sum_{i=1}^{c} \sum_{j=1}^{N} UT_{ij}}{T \times c \times N} \times 100\ \%
\end{aligned}
\tag{3.2}
$$

The category-wise MHE Utilization rates are also computed for IB-FLs (U_I), SDVs (U_S) and OB-FLs (U_{OB}). The cross-dock objectives are to maximize the overall and category-wise MHE utilization rate.

$$
\begin{aligned}
\text{Let} \qquad UTI_{ij} &= \text{ Uptime of } i^{th} \text{ IB-FL in the } j^{th} \text{ replication.} \\
UTS_{ij} &= \text{ Uptime of } i^{th} \text{ SDV in the } j^{th} \text{ replication.} \\
UTO_{ij} &= \text{ Uptime of } i^{th} \text{ OB-FL in the } j^{th} \text{ replication.} \\
X_I &= \text{ Total number of inbound forklifts in a CD.} \\
X_S &= \text{ Total number of self-driving vehicles a CD.} \\
X_O &= \text{ Total number of outbound forklifts in a CD.}
\end{aligned}
$$

$$
\text{Then} \qquad U_I = \frac{\sum_{i=1}^{X_I} \sum_{j=1}^{N} UTI_{ij}}{T \times X_I \times N} \times 100 \ \% \tag{3.3}
$$

$$
U_S = \frac{\sum_{i=1}^{X_S} \sum_{j=1}^{N} UTS_{ij}}{T \times X_S \times N} \times 100 \ \% \tag{3.4}
$$

$$
U_{OB} = \frac{\sum_{i=1}^{X_O} \sum_{j=1}^{N} UTO_{ij}}{T \times X_O \times N} \times 100 \ \% \tag{3.5}
$$

Even though the MHE Utilization rate provides an insight on its usage and idleness, it does not account for MHE efficient usage in a facility. That is, can fewer MHE be used to process a greater number of pallets? Poor MHE allocation in an FL-only CD (between IB-FLs and OB-FLs) or FL-and-SDV CD (between IB-FLs, SDVs and OB-FLs) may result in achieving maximum MHE Utilization rate. However, that allocation would not account for their efficient usage.

3.3.3 Average Throughput Rate / MHE - δ_M

δ_M provides a balance between the above two performance metrics. It is a ratio between Average Throughput rate (δ) and a total number of MHE in a cross-dock. δ_M

yields insight on how efficiently pallets are processed using the MHE in a facility. The cross-dock objective is to maximize δ_M.

$$\delta_m = \frac{\sum_{i=1}^{N} P_i}{N \times c} \tag{3.6}$$

δ_m is measured in $pallets/day/MHE$ or ppd/MHE.

3.4 ARENA Simulation Model Overview

ARENA 15.0, the simulation software by Rockwell Automation, was used for simulation modelling of cross-dock facilities. Two independent simulation models were built, representing the forklift-only and forklift-and-SDV cross-docks, following the material handling assumptions and working parameters established in Section 3.2.

3.4.1 Cross-Dock Modelling in ARENA

The major simulation components of the FL-only and FL-and-SDV cross-dock facilities are given in Table 3.3. Visual Basic API (Application Programming Interface) in ARENA was used to model a scalable cross-dock facility with increasing numbers of inbound and outbound doors. When there is need to study a facility with greater number of doors, this scalability technique comes in handy, reducing the modelling time from days to nearly a minute. However, as stated in material handling assumptions of subsection 3.1.1, the number of doors is fixed as 50×50 (IB doors × OB doors).

The built simulation model was set to terminate when the simulation clock time reaches $7.5hrs$, assuming one shift or $8hrs$ of operation with $30mins$ break and no simulation warm-up period.

Components	**Forklift-Only CD**	**Forklift-and-SDV CD**
Entity	Pallets Inbound Trucks Outbound Trucks	Pallets Inbound Trucks Outbound Trucks
Transporter	Inbound Forklifts $-X_I$ Outbound Forklifts $-X_O$	Inbound Forklifts $-X_I$ Self-Driving Vehicles $-X_S$ Outbound Forklifts $-X_O$
Resources	Pallet Holder -0	Pallet Holder -1
Stations	Inbound Docks -50 Staging Area -50 Outbound Docks -50	Inbound Docks -50 Inbound-DP -50 Outbound-PP -50 Staging Area -50 Outbound Docks -50
State Variables	Staging Area capacity -30 IB-D availability - Yes or No OB-D availability - Yes or No	Staging Area capacity -26 IB-D availability - Yes or No OB-D availability - Yes or No

Table 3.3: Components of Simulation Model.

Verification and validation of a simulation model is critical to ensure that the model represents the actual system [Rossetti, 2010]. The built simulation models for the FL-only and FL-and-SDV cross-docks were verified and validated by the group of members involving a cross-dock SME, a simulation analyst from the SDV manufacturer, and other representatives of that SDV manufacturer.

3.4.2 Simulation Results

The built cross-dock simulation model requires one other major input parameter, besides those given in Tables 3.1 and 3.2 to execute. That is the cross-dock MHE configuration. The MHE configuration of an FL-only CD is a combination of X_I and X_O; and of X_I, X_S and X_O for an FL-and-SDV CD.

These parameters determine the cross-dock's material handling performance, and (a major portion of) variable operating cost of the facility. Both forklift-only and forklift-and-SDV CD models were simulated with various MHE configurations* identified from brainstorming sessions, 5 replications each (to graphically visualize the relationship between MHE configuration and cross-dock performance metrics.). Each replication allowed independent realizations of the particular random variables. The respective performance metrics were computed and analyzed at varying levels of MHE configuration in terms of δ, U_O, and δ_M.

Forklift-only Cross-Dock Facility

The performance of a forklift-only CD is determined by the combination of inbound and outbound forklifts present in that facility. To understand the relationship between the MHE configuration and CD performance metrics, the FL-only CD was simulated (5 replication each) with 96 varied MHE configurations given in Table 3.4, and their respective statistics were recorded†. The simulation results of those 96 models are presented in this subsection. Poor MHE configuration, which would be inadequate for CD material handling

*Each MHE configuration of a cross-dock facility is an independent simulation model.

† See subsection 3.4.3 for all feasible MHE configurations available within the search space.

process as advised by cross-dock SME, and the MHE configurations with no change in trend (of CD performance) are excluded from the study.

Average Throughput rate - δ

δ of a CD operating at varying levels of X_I and X_O is given in Figure 3.7. δ is represented on the graph's left-hand side (primary vertical axis) for fixed levels of X_I, for a varying level of X_O on the horizontal axis. The average throughput rate increases gradually when there are simultaneous increases in the numbers of inbound and outbound forklifts, but that increase begins to plateau. Either X_I or X_O can act as a bottleneck if allocated suboptimally.

Average Throughput rate per MHE - δ_M

δ_M of a CD facility operating at varying levels of X_I and X_O is given in Figure 3.7, with δ_M on the right-hand side (secondary vertical axis) of the graph. As shown in that figure for a fixed level of X_I, δ_M increases to a maximum and then decreases with an increase in X_O. An *inverted-V* shaped pattern is consistently followed for all fixed levels of X_I. Optimal allocation of forklifts between inbound offloading and outbound loading is a critical factor to maximize δ_M. Since the pallet-inflow capacity of a CD does not exceed a certain limit for a given X_I, the maximization of $delta_M$ requires use of adequate or optimal levels of X_O to process pallets.

MHE Utilization rate - $U_O, U_I,$ ***and*** U_{OB}

Similar to δ_M, U_O follows an *inverted-V* shaped pattern. As shown in Figure 3.8 for a fixed level of X_I, U_O increases to a maximum and then decreases, following that *inverted-V* shaped pattern consistently for fixed levels of X_I. The inversely proportional trend observed between the category-wise MHE utilization rate of IB-FLs (U_I) and OB-FLs (U_{OB}) shown in Figure 3.9 provides better insight for that pattern observed in Figure 3.8 for a fixed level of X_I and increasing X_O.

Some of the other performance metrics (Average Pallet Processing Time, Average Truck Processing Time and Average Number of Trucks Processed/Day) are given in Appendix A.1.

MHE		Inbound Forklifts					
		20	25	30	35	40	45
Outbound Forklifts	40	x	x				
	45	x	x				
	50	x	x	x	x	x	x
	55	x	x	x	x	x	x
	60	x	x	x	x	x	x
	65	x	x	x	x	x	x
	70	x	x	x	x	x	x
	75	x	x	x	x	x	x
	80	x	x	x	x	x	x
	85	x	x	x	x	x	x
	90		x	x	x	x	x
	95		x	x	x	x	x
	100		x	x	x	x	x
	105			x	x	x	x
	110			x	x	x	x
	115			x	x	x	x
	120			x	x	x	x
	125			x	x	x	x
	130				x	x	x
	135				x	x	x
	140				x	x	x

Table 3.4: MHE Configuration: Forklift-Only Cross-Dock Facility.

[*Note: Blank cells are omitted from our analysis.*]

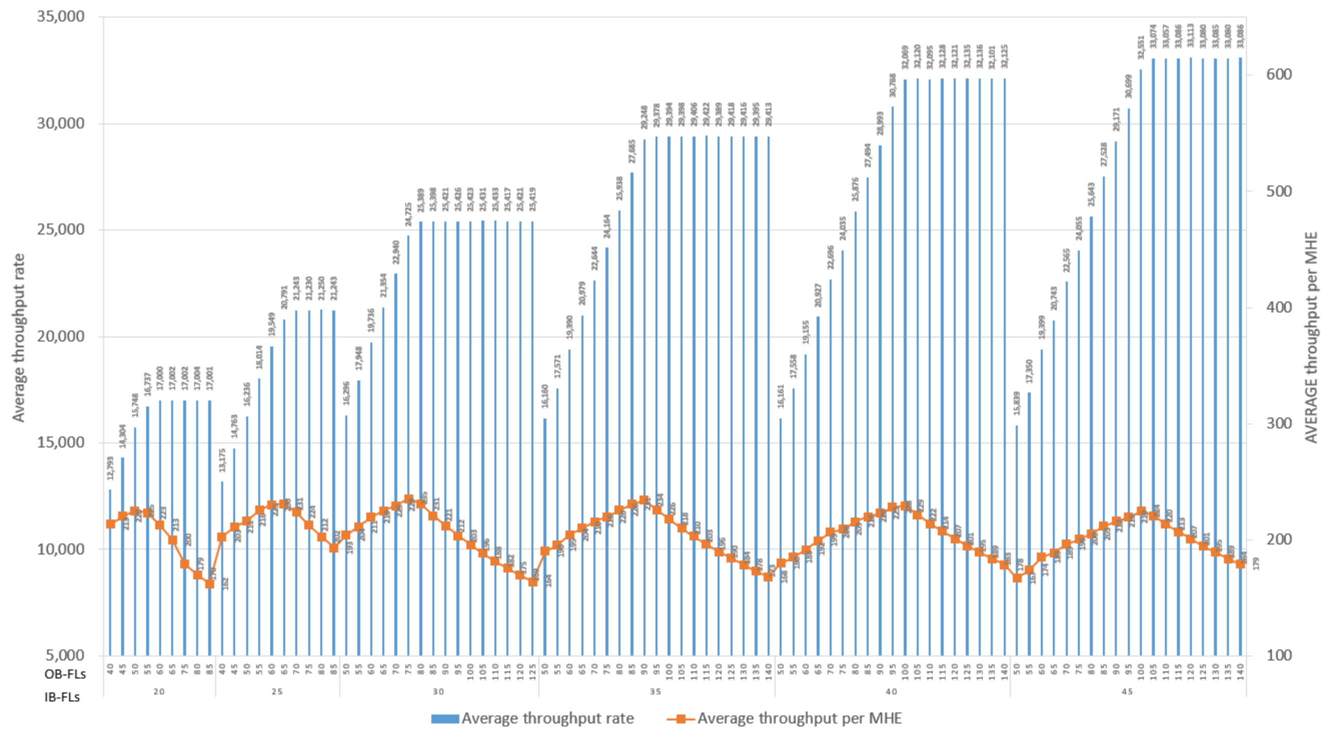

Figure 3.7: Forklift-only Cross-Dock Facility: Average Throughput Rate.

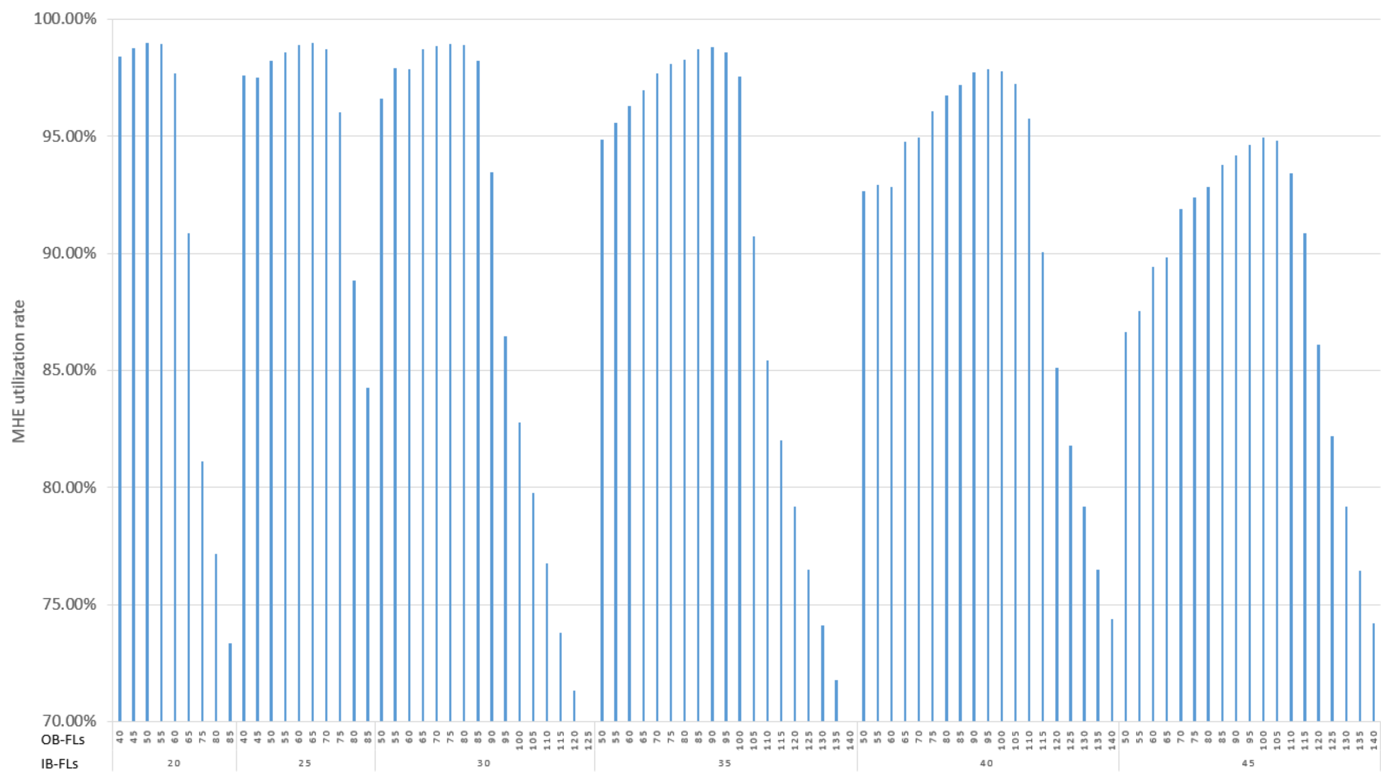

Figure 3.8: Forklift-only Cross-Dock Facility: Overall MHE Utilization Rate.

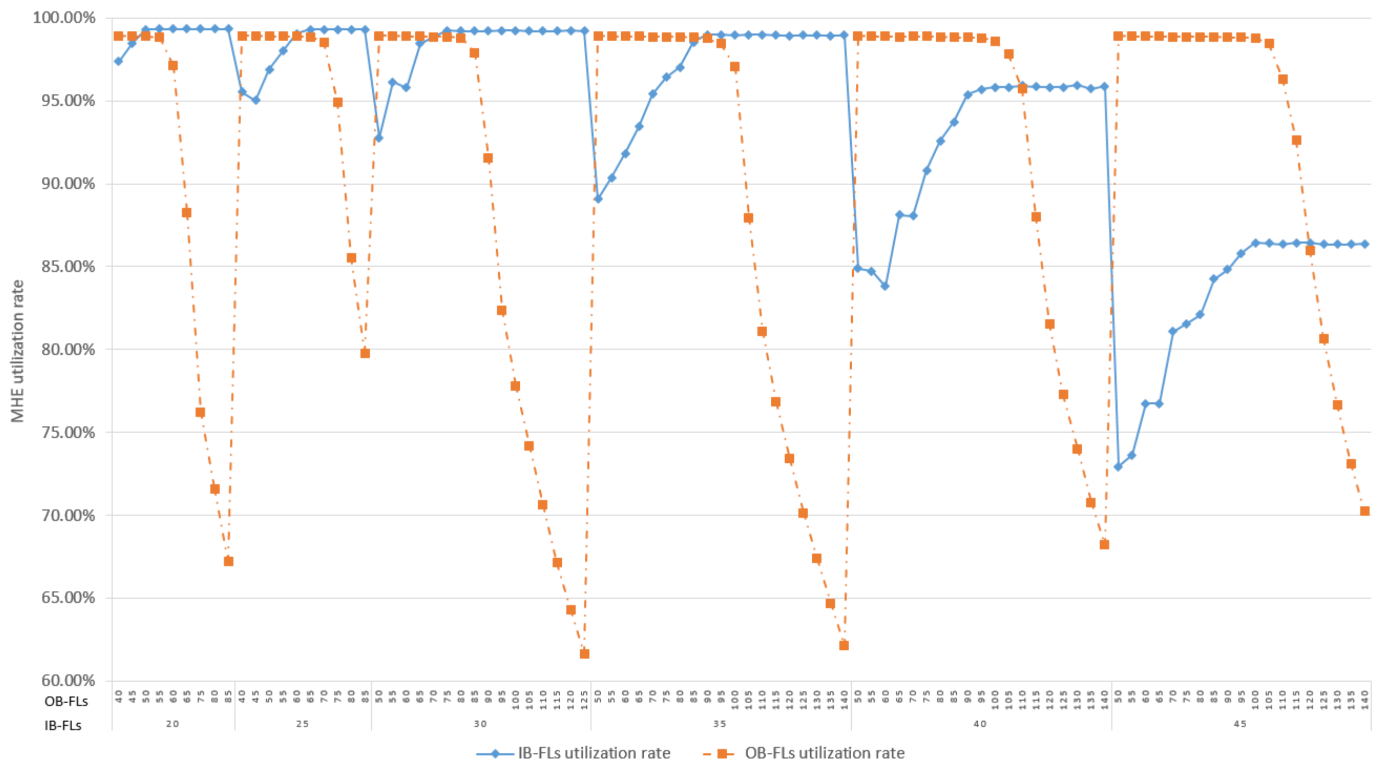

Figure 3.9: Forklift-only Cross-Dock Facility: Category-wise MHE Utilization Rate.

[*Note: category-wise MHE Utilization rate is MHE Utilization rate of IB-FLs -* U_I *and OB-FLs -* U_{OB}]

Forklift-and-Self-Driving Vehicle Cross-Dock Facility

The forklift-and-SDV cross-dock model was simulated for all 277 MHE configurations given in Table 3.5 (poor MHE configuration which would be inadequate for CD material handling process as advised by cross-dock SME and configurations for which no change in trend are excluded from the study), independently for 5 replications each, to study the relationship between MHE configuration and CD performance metrics. The number of dimensions required to graphically visualize the impact of MHE configuration on those metrics increases to four (X_I, X_S, X_O and performance metric itself) for the FL-and-SDV CD. Therefore to better interpret the relationship, the performance metrics are graphically represented on the vertical axis, for a fixed level of X_I, followed by fixed levels of X_O, and varying levels of X_S on the horizontal axis of the 2D graph. This enables the reader to graphically visualize the impact of MHE configuration on the cross-dock performance metrics.

Average Throughput rate - δ

δ of a forklift-and-SDV cross-dock facility is given in Figure 3.10. For fixed levels of X_I and X_O, δ increases gradually and plateaus as there is an increase in X_S. δ increases for a simultaneous increase in X_I and X_O, when the SDVs are sufficiently available to sort the pallets between offloading and loading. Allocation of appropriate numbers of MHE for offloading (X_I), sorting (X_S) and loading (X_O) results in a higher throughput rate for forklift-and-SDV CD. Sub-optimal allocation of any of these, individually, can act as a bottleneck.

Average Throughput per MHE - δ_M

δ_M of a forklift-and-SDV cross-dock facility is given in Figure 3.10. The *inverted-V* shaped pattern is observed for some MHE combinations of fixed levels of X_I-and-X_O : 30-and-25, 35-and-25, 35-and-30 and 45-and-30. The inconsistent appearance of *inverted-V* pattern could be because of insufficient data points to visualize the hidden pattern, or else due to a drastic increase in the total number of MHE ($\boldsymbol{c}$) in the facility, causing a different pattern.

For the same average throughput rate - δ, δ_M of the FL-and-SDV CD turns out to be significantly lower than δ_M of the FL-only CD. This is due to the fact that the former requires a greater number of MHE in terms of SDVs, to achieve a similar average throughput rate as the FL-only CD. This is obviously due to the nature of CD design and material handling assumptions: FL-only CD requires only two categories of MHE, for offloading (IB-FLs) and sorting-and-loading (OB-FLs); while the FL-and-SDV CD requires three, for offloading (IB-FLs), sorting (SDVs) and loading (OB-FLs).

MHE Utilization ate - $U_O,\ U_I,\ U_S$ ***and*** U_{OB}

U_O of a forklift-and-SDV CD is given in Figure 3.11. Similar inconsistent appearance of the *inverted-V* shaped pattern is observed for U_O as was found in δ_M. However, analysis of category-wise MHE utilization rate ($U_I,\ U_S,\ U_{OB}$) given in Figure 3.12 yields comparatively better insights for those inconsistent *inverted-V* patterns.

Figure 3.12 shows that within the fixed levels of X_I and X_O, U_{OB} increases and begins to plateau, while U_S decreases; This is because of the limited pallet-inflow capacity for a given X_I. U_I stays constant at a maximum level when X_I is low, and reduces steeply (in intervals of X_O and X_S) with simultaneous increases in $X_I,\ X_S$ and X_O. This causes an inconsistent inverted-V shaped pattern observed in Figure 3.11.

3.4.3 Finding Optimal MHE Configuration for a Cross-Dock

Statistical comparison or optimization of a simulation model requires a minimum of 30 replications each. Assuming an FL-only CD, the number of IB-FLs can range between 25 to 45 and the number of OB-FLs can range between 50 to 140, yielding 1,800 independent MHE configurations. The runtime of each replication of a CD simulation model programmed in ARENA takes a minute on average, in a computer system with a configuration of Intel(R) Core(TM)i7-3537U CPU @ 2.0 GHz processor, 6GB RAM manufactured by ASUS.

Just the independent simulation of a forklift-only cross-dock for 1,800 feasible MHE configurations 30 replications each, would take *25 days* for the ARENA run time alone. On the other hand, *1,250 days* of computer run time would be required to simulate 30 replications of each of the 60,000 feasible MHE configurations, for the forklift-and-SDV cross-dock (assuming the CD can operate with an MHE configuration of between 25 and 45 IB-FLs, 50-150 SDVs and 25-55 OB-FLs). Therefore, it requires enormous computer run time ***nearly 3.5 years*** to simulate all that feasible MHE configurations, 30 replications each. Which is not a desirable time limit to wait for a decision.

Hence, first and foremost, to understand the impact of MHE configuration on the CD performance metrics, we chose to simulate 5 replications of selected MHE configurations and analyze those outputs for both cross-dock facilities. Which considerably helped to establish the relationship between performance metrics and the MHE configuration of a cross-dock facility (see subsection 3.4.2). But the optimal MHE configuration stays unknown due to the difficulties in validating the greater number of feasible MHE configurations available within the solution space.

Secondly, we propose a simulation optimization technique in Chapter 4 and 5 to overcome the issues related to computational difficulties in finding the optimal MHE configuration from the greater search space.

IB-FLs	OB-FLs	SDVs																		
		50	55	60	65	70	75	80	85	90	95	100	105	120	125	130	135	140	145	150
30	25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	
	30			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	35						x	x	x	x	x	x	x	x	x	x	x			
	40										x	x	x	x	x	x	x			
35	25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		
	30			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	35					x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	40							x	x	x	x	x	x	x	x	x	x	x	x	x
	45													x	x	x	x	x	x	x
	50													x	x	x	x			
40	25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			
	30			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	35					x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	40							x	x	x	x	x	x	x	x	x	x	x	x	x
	45										x	x	x	x	x	x	x	x	x	x
	50													x	x	x	x	x	x	
	55																x	x	x	x
45	25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				
	30			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		
	35					x	x	x	x	x	x	x	x	x	x	x	x			
	40							x	x	x	x	x	x	x	x	x	x	x	x	
	45										x	x	x	x	x	x	x	x		
	50													x	x	x	x			
	55																		x	
55	50														x					x
	55																		x	

Table 3.5: MHE Configuration: Forklift-and-SDV Cross-Dock Facility.

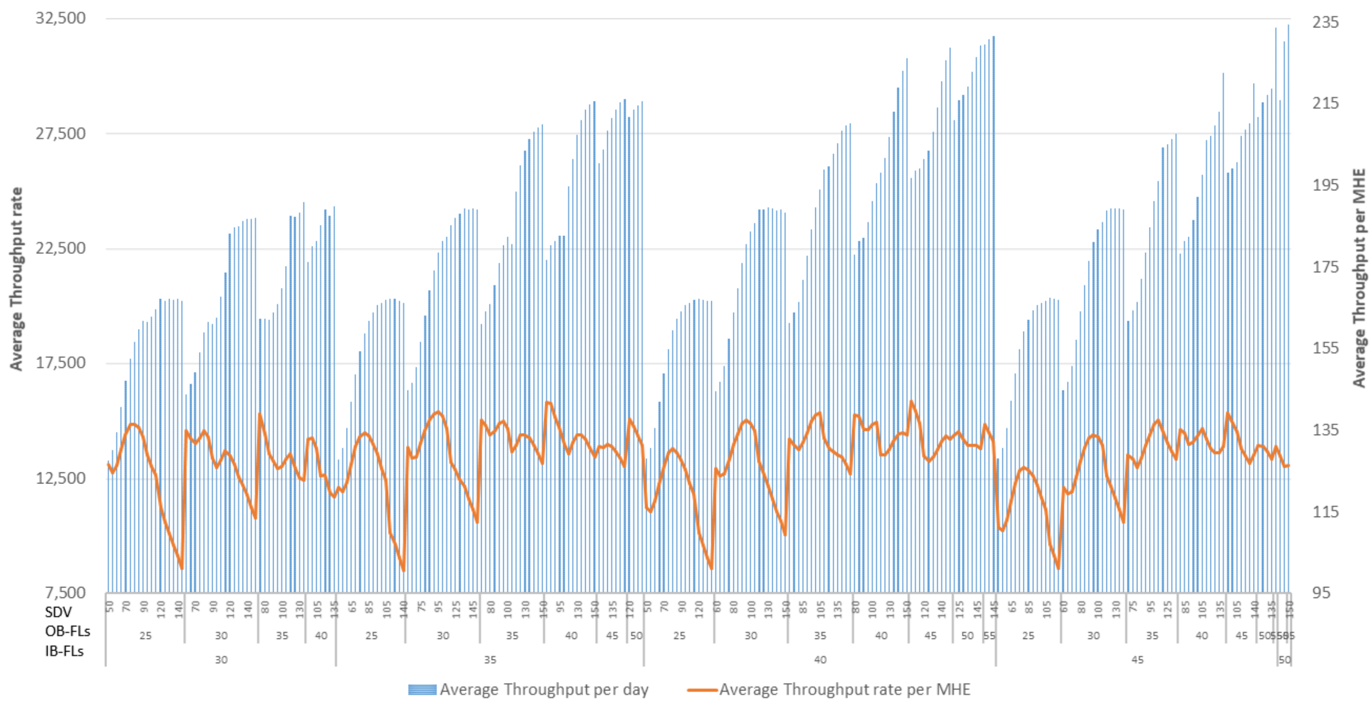

Figure 3.10: Forklift-and-SDV Cross-Dock Facility: Average Throughput Rate.

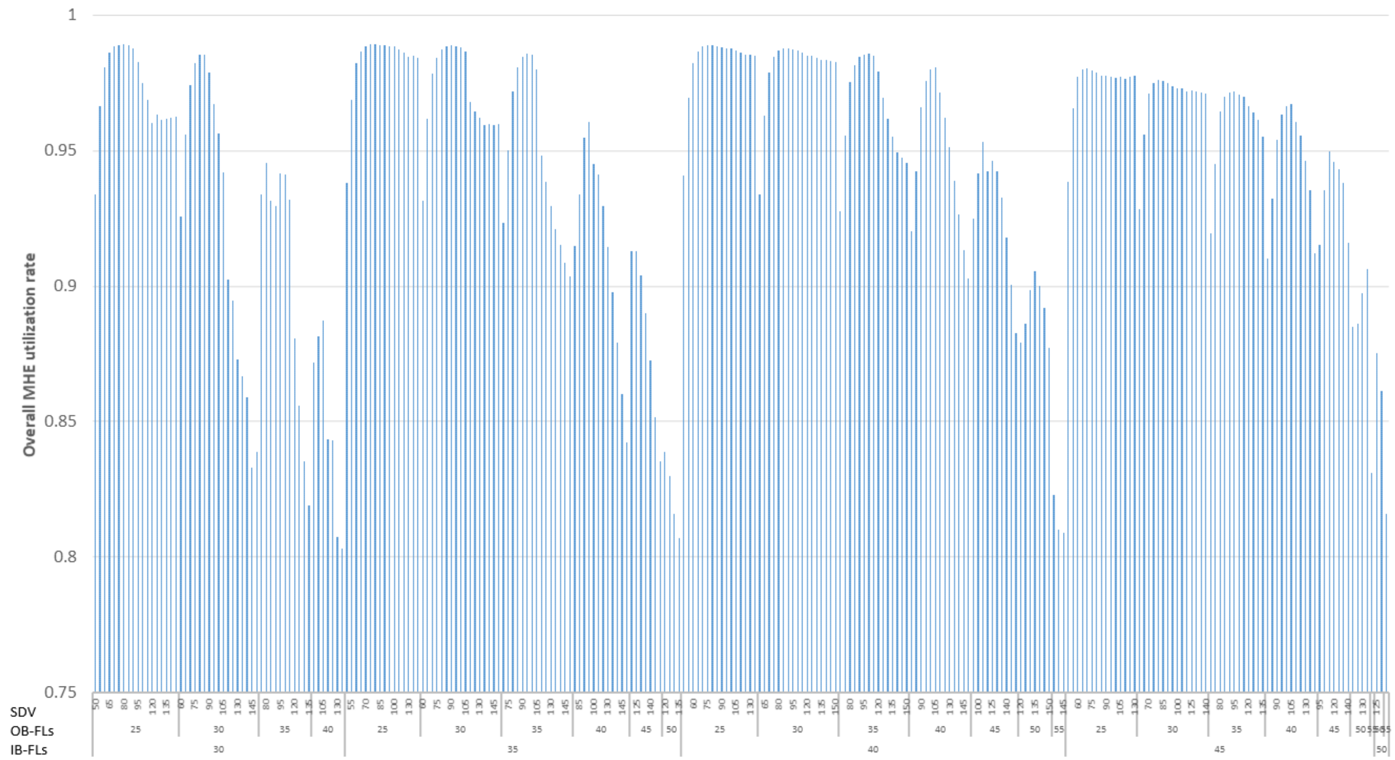

Figure 3.11: Forklift-and-SDV Cross-Dock Facility: Overall MHE Utilization Rate.

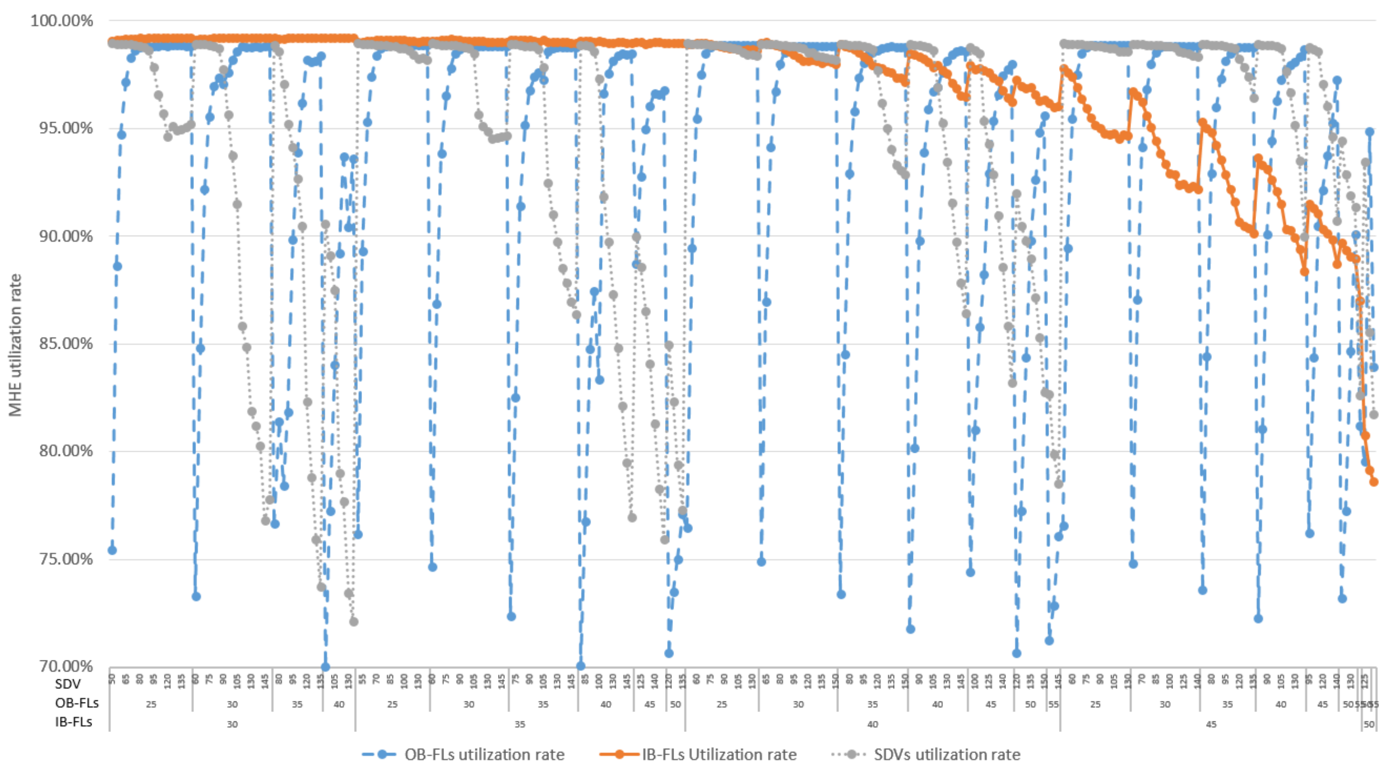

Figure 3.12: Forklift-and-SDV Cross-Dock Facility: Category-wise MHE Utilization Rate.

[*Note: MHE Utilization rate of IB-FLs* - U_I, *SDVs* - U_S *and OB-FLs* - U_{OB}]

Chapter 4

Response Surface Methodology

Optimization of the MHE configuration for the forklift-only or the forklift-and-SDV cross-dock simulation model becomes a complex process, due to the enormous computer runtime required to validate the objective function for all feasible MHE configurations within a large solution space. Therefore, we propose to use a *meta-modelling* approach to find the optimal MHE configuration in a fast time-efficient manner.

The goal of the proposed simulation meta-modelling approach is to develop prediction models (using Response Surface Methodology (RSM)) for the CD performance metrics. The exploratory variables, MHE configurations, will be used to formulate the constraints of an optimization problem. The corresponding objective is to minimize the total variable cost incurred by operating MHE in a cross-dock facility. Solving that optimization model will result in the optimal MHE configuration, i.e., the MHE configuration with minimum variable operating cost, and whose levels of cross-dock performance metrics are expected values. Fu [2014] presented various simulation-optimization techniques, of which Response

Surface Methodology (RSM) meets our requirement to built prediction models.

Variance reduction techniques such as correlated sampling or common random numbers (CRN) are widely used for simulation comparison purposes. CRN technique reduces the variance between two simulation models by using same or correlated stream of random numbers. It results in dependency or correlation between response variables of two systems. That is, if CRN is applied the response variable$-Y_i$ obtained from simulation of MHE configuration $(X_I.X_O)$ will be correlated to Y_i' obtained from $(X_I'.X_O')$ [Banks et al., 2010]. However RSM technique requires the response variables to be independent to each other, i.e., $COV(Y_i, Y_i') = 0$. Using CRN along with RSM would violate that requirement; and require further analysis through blocking of experiments if CRN is used [Fu, 2014].

Therefore, we experimented both the forklift-only and the forklift-and-SDV cross-dock simulation models, independently without CRN at various levels of MHE configuration (exploratory variables). The response surface (or regression) models were estimated for the CD performance metrics (δ, δ_M, U_O, U_I, U_{OB}, and U_S). Those regression models were later used to formulate separate optimization models, individually for forklift-only and forklift-and-SDV CD facilities, to optimize their MHE configurations.

A brief overview of the experiments designed for the FL-only and FL-and-SDV cross-docks, and factor definitions for both CD models, are given in Section 4.1, followed by Section 4.2 on regression model fitting.

4.1 Response Surface Design

A full-factorial experiment is designed for a forklift-only and forklift-and-SDV cross-dock simulation model with varying levels of MHE configuration.

4.1.1 Factors

Forklift-only Cross-Dock Facility

Performance of the FL-only CD facility is studied by varying two factors, the number of inbound and outbound forklifts in a CD. The number of levels for those two factors, and their factor levels are given in Table 4.1.

Factors	**Notation**	**Number of Levels**	**Factor Levels**
Number of IB-FLs	X_I	5	25, 30, 35, 40, 45
Number of OB-FLs	X_O	10	50, 60, 70, . . . , 130, 140

Table 4.1: RSM Factor Definition: Forklift-only Cross-Dock Facility.

Forklift-and-SDV Cross-Dock Facility

We experimented with the performance of the forklift-and-SDV cross-dock by varying three factors, numbers of IB-FLs, SDVs and OB-FLs in the CD facility. The number of levels for those three factors, and their factor levels are given in Table 4.2.

Factors	**Notation**	**Number of Levels**	**Factor Levels**
Number of IB-FLs	X_I	5	25, 30, 35, 40, 45
Number of SDVs	X_S	11	50, 60, 70, . . . , 140, 150
Number of OB-FLs	X_O	7	25, 30, 35, 40, 45, 50, 55

Table 4.2: RSM Factor Definition: Forklift-and-SDV Cross-Dock Facility

4.1.2 Replications

The full-factorial experiment, as designed in subsection 4.1.1, results in a total of 50 (5x10) treatment combinations for the forklift-only CD, and 385 (5x11x7) treatment combinations for the forklift-and-SDV CD. Each treatment combination is replicated 15* times in ARENA; performance metrics (δ, δ_M, U_O, U_I, U_{OB}, and U_S) for those respective combinations are recorded as a point estimate for each replication.

4.2 Model Fitting

The estimated response variables for CD performance metrics are defined as follows;

$$\text{Predicted Average Throughput rate} = \widehat{\delta} \tag{4.1}$$

$$\text{Predicted Average Throughput rate / MHE} = \widehat{\delta_M} \tag{4.2}$$

$$\text{Predicted Average Overall MHE Utilization rate} = \widehat{U_O} \tag{4.3}$$

$$\text{Predicted Average IB-FLs Utilization rate} = \widehat{U_I} \tag{4.4}$$

* Chosen following the number of replications = 10 used by Shi et al. [2013] to fit cross-dock response surface model, under similar situation.

$$\text{Predicted Average OB -FLs Utilization rate} = \widehat{U_{OB}} \tag{4.5}$$

$$\text{Predicted Average SDVs Utilization rate} = \widehat{U_S} \tag{4.6}$$

The prediction variables for CD performance metrics defined from Eqs (4.1) to (4.5) are applicable for both the forklift-only and forklift-and-SDV cross-dock facilities, Eq (4.6) is applicable only for the forklift-and-SDV cross-dock.

To establish the relationship between CD performance metrics (response variable) and MHE configuration (expoloratory variables) in a form $\widehat{R} = f(X_I,\ X_O)$ or $\widehat{R} = f(X_I,\ X_O,\ X_S)$, four types of response surface models are considered.

Here $R =$ Response variable or CD performance metric.

$\widehat{R} =$ Predicted CD performance metric.

Model 1) **Linear**: First order polynomial model.

$$FL\text{-}only\ CD :: \quad \widehat{R} = \beta + \beta_I X_I + \beta_O X_O$$

$$FL\text{-}and\text{-}SDV\ CD :: \quad \widehat{R} = \beta + \beta_I X_I + \beta_S X_S + \beta_O X_O$$

Model 2) **Linear+Interaction**: First order polynomial + two-way interaction model.

$$FL\text{-}only\ CD :: \quad \widehat{R} = \beta + \beta_I X_I + \beta_O X_O + \beta_{IO} X_I X_O$$

$$\begin{aligned} FL\text{-}and\text{-}SDV\ CD :: \quad \widehat{R} &= \beta + \beta_I X_I + \beta_S X_S + \beta_O X_O \\ &\quad + \beta_{IS} X_I X_S + \beta_{IO} X_I X_O + \beta_{SO} X_S X_O \end{aligned}$$

Model 3) **Linear+Square**: Second order polynomial, without two-way interaction.

$$FL\text{-}only\ CD :: \quad \widehat{R} = \beta + \beta_I X_I + \beta_{II} X_I^2 + \beta_O X_O + \beta_{OO} X_O^2$$

$$FL\text{-}and\text{-}SDV\ CD :: \quad \widehat{R} = \beta + \beta_I X_I + \beta_{II} X_I^2 + \beta_S X_S + \beta_{SS} X_S^2 + \beta_O X_O + \beta_{OO} X_O^2$$

Model 4) **Quadratic**: Second order polynomial, with two-way interaction.

$$FL\text{-}only\ CD :: \quad \widehat{R} = \beta + \beta_I X_I + \beta_{II} X_I^2 + \beta_O X_O + \beta_{OO} X_O^2 + \beta_{IO} X_I X_O$$

$$FL\text{-}and\text{-}SDV\ CD :: \quad \widehat{R} = \beta + \beta_I X_I + \beta_{II} X_I^2 + \beta_S X_S + \beta_{SS} X_S^2 + \beta_O X_O + \beta_{OO} X_O^2 + +\beta_{IS} X_I X_S + \beta_{IO} X_I X_O + \beta_{SO} X_S X_O$$

4.2.1 Model Fitting: Forklift-only Cross-Dock Facility

Using Minitab, 20[†] regression models were estimated for each performance metric and their summary statistics are given in Table 4.3 (See appendix B.1 for a brief overview on regression model fitting). Hypothesis test 1 and Hypothesis test 2 enabled testing the validity of the built regression models.

Hypothesis Test 1: *Ability of the fitted regression model to explain the variation caused by the exploratory variables or significance of the regression model.*

[†] 4 types of response surface models for all five performance metrics

H_0: Regression model does not explain the variation caused by exploratory variables.

H_1: Regression model explains the variation caused by exploratory variables.

Significance level, $\alpha = 0.05$.

Hypothesis Test 2: *Presence of unexplained source of non-random variation or lack-of-fitness test.*

H_0: All sources of non-random variation are explained by the regression model.

H_1: Not all sources of non-random variation are explained by the regression model.

Significance level, $\alpha = 0.05$

Inference

Hypothesis test 1: Regression (Reg) p-value $< \alpha$ statistically validates that the given regression model[‡] significantly explains the variation in cross-dock performance metrics caused by changes in levels of X_I and X_O. That is, the built regression models are significant. However, Hypothesis test 1 does not reveal if there is any *non-random* source of variation left unexplained by the regression model.

Hypothesis test 2: From Lack-of-Fitness (LOF) p-value $< \alpha$, it is statistically evident that a non-random source of variation is left unexplained by the fitted regression model. This can be further explicitly seen from the heteroscedastic (or non-homogeneous) residual distribution of the fitted regression model shown in subsection B.1.3 of Appendix B. In regression modelling, heteroscedasticity could arise because of two reasons; 1) one or more

[‡] Linear, Linear + Interaction, Linear + Square, Quadratic

	Model	Reg P-value	LOF P-value	PRESS	R^2 (%)	R^2_{pred} (%)	R^2_{Adj} (%)	s	RMSE
$\widehat{\delta}$	Linear	0	0	6134471468	71.3	71.1	71.2	2853	2515
	Linear+Interaction	0	0	3791015991	82.3	82.1	82.3	2241	2566
	Linear+Square	0	0	3040699307	85.9	85.7	85.8	2004	2799
	Quadratic	**0**	**0**	**670845369**	**96.9**	**96.8**	**96.9**	**941**	**958**
$\widehat{\delta_M}$	Linear	0	0	350284	31.1	30.5	30.9	21.56	19.64
	Linear+Interaction	0	0	202800	60.2	59.8	60.1	16.39	19.45
	Linear+Square	0	0	211353	58.5	58.1	58.7	16.71	21.70
	Quadratic	**0**	**0**	**62468**	**87.8**	**87.6**	**87.8**	**9.08**	**8.94**
$\widehat{U_O}$	Linear	0	0	3.86	65.8	65.5	65.7	0.072	0.210
	Linear+Interaction	0	0	2.36	79.1	78.9	79.0	0.056	0.214
	Linear+Square	0	0	2.31	79.7	79.4	79.6	0.055	1.791
	Quadratic	**0**	**0**	**0.80**	**93.0**	**92.9**	**93.0**	**0.032**	**0.091**
$\widehat{U_I}$	Linear	0	0	1.05	72.2	72.0	72.1	0.037	0.033
	Linear+Interaction	0	0	0.90	76.3	76.0	76.2	0.037	0.479
	Linear+Square	0	0	0.43	88.7	88.5	88.6	0.024	0.034
	Quadratic	**0**	**0**	**0.28**	**92.8**	**92.6**	**92.7**	**0.019**	**0.019**
$\widehat{U_{OB}}$	Linear	0	0	3.62	81.8	81.6	81.7	0.694	0.210
	Linear+Interaction	0	0	2.49	87.5	87.4	87.5	0.057	0.214
	Linear+Square	0	0	2.31	88.5	88.3	88.4	0.055	1.791
	Quadratic	**0**	**0**	**1.16**	**94.2**	**94.1**	**94.2**	**0.039**	**0.156**

Table 4.3: Model Fitting: Forklift-only Cross-Dock Facility.

significant exploratory variables were left unconsidered while modelling, 2) higher-order polynomial terms or different a regression modelling technique (like piece-wise regression) were required to model the unexplained source of variation.

Due to lack of access to real-world cross-dock facilities, there were difficulties in identifying the other potential exploratory variables. Hence the experiments were conducted by considering only MHE configuration as the only potential factors. Studying a real-world CD facility could possibly reveal other factors. Those could significantly impact the cross-dock performance, but were not considered in here.

The coefficient of determination (R^2), predicted (R^2_{pred}) and adjusted coefficient of determination (R^2_{Adj}) values of quadratic regression models are significantly high, and close to each other for all five performance metrics. Further inclusion of higher-order terms (cubes or higher) may result in over-fitting.

Therefore, from Hypothesis test 1 and Hypothesis test 2, we conclude that all estimated regression models for the performance metrics of the forklift-only cross-dock facility are significant. However, there is a need for further analysis to address the unexplained non-random sources of variation.

Due to various constraints, we assume that each fitted regression model has no unexplained source of non-random variation, to perform further analysis and to identify the optimal MHE configuration.

Model Selection

PRESS (Predicted Residual Sum of Squares)[§], R^2, R^2_{pred} and R^2_{Adj} values of the regression models given in Table 4.3, are considered for model selection process. "**s**" is the standard error of the fitted regression model, and RMSE (Root Mean Squared Error) is the error measure between the simulation output of the cross-dock models[¶] and regression-predicted results for the same MHE configuration.

For each performance metric, a regression model with the least PRESS statistic and highest R^2_{Adj} is selected for further analysis. Quadratic regression models, marked

[§] PRESS=$\sum_{i=1}^{N}(R_i - \widehat{R}_{i,-i})^2$, Lower the better $::$ $\widehat{R}^2_{i,-i}$ is Predicted response of fitted regression model without i^{th} observation.

[¶] These are discussed in simulation results of subsection 3.4.2

bold and highlighted in Table 4.3, turn out to be the best fit for all 5 performance metrics based on PRESS and R^2_{Adj} statistics. The selected regression models for the corresponding performance metrics of the forklift-only cross-dock facility are listed below;

$$\begin{aligned}
\widehat{\delta} = &-13688.7 \ + \ 823.6 \times X_I \ + \ 315.6 \times X_O \\
&- \ 18.4 \times X_I^2 \ - \ 2.6 \times X_O^2 \\
&+ \ 8.7 \times X_I \times X_O
\end{aligned} \tag{4.7}$$

$$\begin{aligned}
\widehat{\delta_M} = &\ 136.33 \ + \ 3.962 \times X_I \ + \ 0.362 \times X_O \\
&- \ 0.138 \times X_I^2 \ - \ 0.017 \times X_O^2 \\
&+ \ 0.069 \times X_I \times X_O
\end{aligned} \tag{4.8}$$

$$\begin{aligned}
\widehat{U_M} = &\ 0.62275 \ + \ 0.023509 \times X_I \ - \ 0.00071 \times X_O \\
&- \ 0.000562 \times X_I^2 \ - \ 0.000054 \times X_O^2 \\
&+ \ 0.000219 \times X_I \times X_O
\end{aligned} \tag{4.9}$$

$$\begin{aligned}
\widehat{U_I} = &\ 0.499352 \ + \ 0.025742 \times X_I \ + \ 0.002618 \times X_O \\
&- \ 0.000572 \times X_I^2 \ - \ 0.000022 \times X_O^2 \\
&+ \ 0.00007 \times X_I \times X_O
\end{aligned} \tag{4.10}$$

$$\begin{aligned}
\widehat{U_{OB}} = &\ 0.684438 \ + \ 0.020197 \times X_I \ - \ 0.001311 \times X_O \\
&- \ 0.000417 \times X_I^2 \ - \ 0.000052 \times X_O^2 \\
&+ \ 0.000191 \times X_I \times X_O
\end{aligned} \tag{4.11}$$

4.2.2 Model Fitting: Forklift-and-SDV Cross-Dock Facility

Four regression models were estimated for all six forklift-and-SDV cross-dock performance metrics. Summary statistics for all those 24 regression models are given in Table 4.4. Hypothesis testing was done to validate the significance of regression models and regression models lack-of-fitness. Both tests yield similar statistical inference, as was seen in subsection 4.2.1 for regression models of the forklift-only cross-dock facility.

Therefore, we conclude that all the linear, linear + interaction, linear + square and quadratic regression models, estimated for all six performance metrics, are statistically significant. We assume there is no unexplained source of non-random variation (see Appendix B.2 for more analysis on regression model fitting.).

Model Selection

For each performance metric, a regression model with the least PRESS statistic and highest R^2_{Adj} is selected for further analysis. The quadratic regression model turns out to be the best fit for all six performance metrics. Those respective models are marked bold and highlighted in Table 4.4 The selected regression models for the corresponding performance metrics of the forklift-and-SDV CD are given in Eq 4.12 to Eq 4.17.

$$\begin{aligned}
\widehat{\delta} = & -13354.1493 + 1021.8703 \times X_I + 89.5301 \times X_S + 107.5189 \times X_O \\
& - 22.6917 \times X_I^2 - 1.0839 \times X_S^2 - 6.2406 \times X_O^2 \\
& + 4.5356 \times X_I \times X_S + 10.0245 \times X_I \times X_O \\
& + 1.7879 \times X_S \times X_O
\end{aligned} \tag{4.12}$$

	Model	Reg P-value	LOF P-value	PRESS	R^2 (%)	R^2_{pred} (%)	R^2_{Adj} (%)	s	RMSE
$\widehat{\delta}$	Linear	0	0	29143358964	76.8	76.8	76.8	2245	2245
	Linear+Interaction	0	0	18465421544	85.3	85.3	85.3	1786	1785
	Linear+Square	0	0	16964451208	86.5	86.5	86.5	1712	1711
	Quadratic	**0**	**0**	**6251135915**	**95.0**	**95.0**	**95.0**	**1039**	**1038**
$\widehat{\delta_M}$	Linear	0	0	824020	22.8	27.2	22.8	11.94	11.94
	Linear+Interaction	0	0	537615	49.7	49.6	49.7	9.64	9.63
	Linear+Square	0	0	456626	57.3	57.2	57.3	8.88	8.88
	Quadratic	**0**	**0**	**169237**	**84.2**	**84.1**	**84.2**	**5.41**	**5.40**
$\widehat{U_O}$	Linear	0	0	26.57	66.8	66.8	66.8	0.068	0.068
	Linear+Interaction	0	0	16.18	79.8	79.8	79.8	0.053	0.053
	Linear+Square	0	0	16.14	79.8	79.8	79.8	0.053	0.052
	Quadratic	**0**	**0**	**5.14**	**93.6**	**93.6**	**93.6**	**0.030**	**0.030**
$\widehat{U_I}$	Linear	0	0	2.132	54.1	54.1	54.1	0.0192	0.0192
	Linear+Interaction	0	0	1.638	64.8	64.7	64.8	0.0168	0.0168
	Linear+Square	0	0	1.638	64.8	64.7	64.8	0.0168	0.0135
	Quadratic	**0**	**0**	**0.558**	**88.0**	**88.0**	**88.0**	**0.0098**	**0.0098**
$\widehat{U_{OB}}$	Linear	0	0	62.29	81.1	81.1	81.1	0.1083	0.1038
	Linear+Interaction	0	0	49.41	85.1	85.0	85.0	0.0924	0.0924
	Linear+Square	0	0	49.41	85.1	85.0	85.0	0.0924	0.0885
	Quadratic	**0**	**0**	**32.44**	**90.2**	**90.2**	**90.2**	**0.0749**	**0.0748**
$\widehat{U_S}$	Linear	0	0	36.82	68.0	67.9	68.0	0.0798	0.0798
	Linear+Interaction	0	0	14.93	87.0	87.0	87.0	0.0508	0.0508
	Linear+Square	0	0	14.93	87.0	87.0	87.0	0.0508	0.0704
	Quadratic	**0**	**0**	**6.80**	**94.1**	**94.1**	**94.1**	**0.0343**	**0.0342**

Table 4.4: Model Fitting: Forklift-and-Self-Driving Vehicles Cross-Dock Facility.

$$
\begin{aligned}
\widehat{\delta_M} = {} & 41.3728 + 5.3649 \times X_I - 0.1321 \times X_S - 0.0761 \times X_O \\
& + -0.1259 \times X_I^2 - 0.0059 \times X_S^2 - 0.0338 \times X_O^2 \\
& + 0.0227 \times X_I \times X_S + 0.0500 \times X_I \times X_O \\
& + 0.0106 \times X_S \times X_O
\end{aligned} \tag{4.13}
$$

$$
\begin{aligned}
\widehat{U_O} = {} & 0.4888 + 0.0410 \times X_I - 0.0006 \times X_S - 0.0130 \times X_O \\
& - 0.0008 \times X_I^2 - 3.14 \times 10^{-5} \times X_S^2 \\
& + 0.0001 \times X_I \times X_S + 0.0001 \times X_I \times X_O \\
& + 4.07 \times 10^{-6} \times X_S \times X_O
\end{aligned} \tag{4.14}
$$

$$
\begin{aligned}
\widehat{U_I} = {} & 0.5147 + 0.0259 \times X_I + 0.0011 \times X_S + 0.0015 \times X_O \\
& - 0.0003 \times X_I^2 + 8.64 \times 10^{-7} \times X_S^2 + 1.10 \times 10^{-5} \times X_O^2 \\
& - 3.58 \times 10^{-5} \times X_I \times X_S - 4.9 \times 10^{-5} \times X_I \times X_O \\
& - 6.50 \times 10^{-6} \times X_S \times X_O
\end{aligned} \tag{4.15}
$$

$$
\begin{aligned}
\widehat{U_S} = {} & 0.5563 + 0.0390 \times X_I - 0.0045 \times X_S - 0.0035 \times X_O \\
& - 0.0008 \times X_I^2 - 1.63 \times 10^{-5} \times X_S^2 + 5.9466 \times 10^{-5} \times X_O^2 \\
& + 0.0002 \times X_I \times X_S + 0.0001 \times X_I \times X_O \\
& - 8.32 \times 10^{-5} \times X_S \times X_O
\end{aligned} \tag{4.16}
$$

$$
\begin{aligned}
\widehat{U_{OB}} = {} & 0.5549 + 0.0355 \times X_I + 0.0056 \times X_S - 0.0335 \times X_O \\
& - 0.0007 \times X_I^2 - 4.828 \times 10^{-5} \times X_S^2 - 3.4910^{-5} \times X_O^2 \\
& + 0.0001 \times X_I \times X_S + 0.0003 \times X_I \times X_O \\
& + 6.19 \times 10^{-5} \times X_S \times X_O
\end{aligned} \tag{4.17}
$$

The fitted regression models for the performance metrics of the forklift-only and forklift-and-SDV cross-dock facilities were used to formulate respective models to optimize the MHE configuration. The formulation and optimization of those models is given in Chapter 5.

Chapter 5

Optimization of Cross-Dock MHE Configuration

Two independent optimization models were formulated in terms of MHE configuration, respectively for the FL-only CD and for the FL-and-SDV CD. The objective is to minimize the total variable operating cost of a CD, subject to constraints on CD performance metrics that will yield desired level of performance. Each formulated optimization model will yield the optimal or near-optimal* MHE configuration and the total variable cost of operating that CD. Thus, the scope of SDVs in a CD could be validated by comparing the total variable operating cost of the two respective cross-docks.

Optimization model formulations for the FL-only and the FL-and-SDV CD are given in Section 5.1. Those models are solved in Section 5.2. The overall feasibility of using SDVs in a CD is substantiated in Section 5.3. Section 5.4: concludes with the

* Based on prediction accuracy of the regression models.

statistical validation of the proposed optimal MHE configuration.

5.1 Cross-Dock MHE Optimization Model

A generic optimization model to minimize the total variable cost incurred by the MHE in a cross-dock facility is formulated as follows;

$$\textbf{Min} \quad \text{Total Variable cost of operating a CD}$$

$$\textbf{Subject to:}$$

$$\text{Predicted performance level.} \geq \text{Desired performance level.}$$

$$\text{That is,} \qquad \widehat{R} \geq \overline{R}$$

Where, $\overline{R}$ is the desired level of CD performance metric.

5.1.1 MHE Optimization Model: Forklift-only CD

The variable cost of operating a CD includes labour and MHE operating cost.

$$\begin{aligned}
\text{Let} \quad L &= \text{Labour cost per day.} \\
M &= \text{Unit forklift operating cost per day.} \\
\text{Then} \quad L &= 31.43 \times 8 = \$251.43/day^{*} \\
M &= \text{Cost of electricity consumed by MHE per day}^{\dagger} \\
&\quad + \quad \text{Cost of MHE repair and maintenance per day}^{\ddagger} \\
&= \$\ 260.88/day + \$\ 10.31/day
\end{aligned}$$

$$M \;= \$\ 271.20/day.$$

Assuming forklift operators constitute the only labour required for the forklifts, and no other workforce is required for material handling in a CD, the total variable cost (TVC) of operating an FL-only CD is expressed as Eq (5.1).

Decision Variables

- X_I - Number of IB-FLs.
- X_O - Number of OB-FLs.

$$\text{TVC of FL-only CD} = \; L \times (X_I + X_O) + M \times (X_I + X_O) \tag{5.1}$$

Then, the resulting optimization model for an FL-only CD is formulated as follows;

$$\textbf{Min } \text{TVC} \;=\; 522.63 \times (X_I + X_O) \tag{5.2}$$

Subject To

Constraint 1: Average Throughput rate

$$\begin{aligned} -13688.7 \;+\; 823.6 \times X_I \;+\; 315.6 \times X_O \\ -\; 18.4 \times X_I^2 \;-\; 2.6 \times X_O^2 \end{aligned}$$

*Forklift operator, average hourly wages = \$ 31.43/hr [Source: Payscale, Canada]

†Electric forklift power consumption rate = 3.5kW/hr [Source: http://raymondhandling.com]

†Cost of electricity = \$ 9.32/kWh [Source: Waterloo North Hydro Inc.]

‡Cost of forklift repair and maintenance = \$ 1.289/hr [Source: http://raymondhandling.com]

$$+\ 8.7 \times X_I \times X_O \ \geq \overline{\delta} \tag{5.3}$$

Constraint 2: Average Throughput rate per MHE

$$\begin{aligned} 136.33 \ +\ 3.962 \times X_I \ +\ 0.362 \times X_O \\ -\ 0.138 \times X_I^2 \ -\ 0.017 \times X_O^2 \\ +\ 0.069 \times X_I \times X_O \ \geq \overline{\delta_M} \end{aligned} \tag{5.4}$$

Constraint 3: Overall MHE Utilization rate

$$\begin{aligned} 0.62275 \ +\ 0.023509 \times X_I \ -\ 0.00071 \times X_O \\ -\ 0.000562 \times X_I^2 \ -\ 0.000054 \times X_O^2 \\ +\ 0.000219 \times X_I \times X_O \ \geq \overline{U_O} \end{aligned} \tag{5.5}$$

Constraint 4: Inbound Forklifts Utilization rate

$$\begin{aligned} 0.499352 \ +\ 0.025742 \times X_I \ +\ 0.002618 \times X_O \\ -\ 0.000572 \times X_I^2 \ -\ 0.000022 \times X_O^2 \\ +\ 0.00007 \times X_I \times X_O \ \geq \overline{U_I} \end{aligned} \tag{5.6}$$

Constraint 5: Outbound Forklifts Utilization rate

$$\begin{aligned} 0.684438 \ +\ 0.020197 \times X_I \ -\ 0.001311 \times X_O \\ -\ 0.000417 \times X_I^2 \ -\ 0.000052 \times X_O^2 \\ +\ 0.000191 \times X_I \times X_O \ \geq \overline{U_{OB}} \end{aligned} \tag{5.7}$$

$$25 \ \leq \ X_I \ \leq \ 45 \tag{5.8}$$

$$50 \ \leq \ X_O \ \leq \ 140 \tag{5.9}$$

$$X_I,\ X_O \in \mathbb{Z} \tag{5.10}$$

5.1.2 MHE Optimization Model: Forklift-and-SDV CD

Manual forklifts in a CD incur labour and forklift operating cost. SDVs incur operating cost only. In the long-term, assuming the operating costs of SDVs and manual forklifts are equal, the optimization model to minimize the total variable cost of a forklift-and-SDV cross-dock can be formulated as follows;

Decision Variables	X_I	- Number of IB-FLs.
	X_S	- Number of SDVs.
	X_O	- Number of OB-FLs.

$$\begin{aligned} \text{TVC} \;=\; & (L+M) \times X_I + M \times X_S + (L+M) \times X_O \\ \textbf{Min}\ \text{TVC} =\; & 522.63 \times (X_I + X_O) + 271.20 \times X_S \end{aligned} \tag{5.11}$$

Subject To:

Constraint 1: Average Throughput rate

$$\begin{aligned} &-13354.1493 + 1021.8703 \times X_I + 89.5301 \times X_S + 107.5189 \times X_O \\ &\quad -22.6917 \times X_I^2 - 1.0839 \times X_S^2 - 6.2406 \times X_O^2 \\ &\quad +4.5356 \times X_I \times X_S + 10.0245 \times X_I \times X_O \\ &\quad +1.7879 \times X_S \times X_O \geq \overline{\delta} \end{aligned} \tag{5.12}$$

Constraint 2: Average Throughput rate per MHE

$$41.3728 + 5.3649 \times X_I - 0.1321 \times X_S - 0.0761 \times X_O$$

$$+ - 0.1259 \times X_I^2 - 0.0059 \times X_S^2 - 0.0338 \times X_O^2$$
$$+0.0227 \times X_I \times X_S + 0.0500 \times X_I \times X_O$$
$$+0.0106 \times X_S \times X_O \geq \overline{\delta_M} \tag{5.13}$$

Constraint 3: Overall MHE Utilization rate

$$0.4888 + 0.0410 \times X_I - 0.0006 \times X_S - 0.0130 \times X_O$$
$$-0.0008 \times X_I^2 - 3.1400 \times 10^{-5} \times X_S^2$$
$$+0.0001 \times X_I \times X_S + 0.0001 \times X_I \times X_O$$
$$+4.07 \times 10^{-6} \times X_S \times X_O \geq \overline{U_O} \tag{5.14}$$

Constraint 4: Inbound Forklifts Utilization rate

$$0.5147 + 0.0259 \times X_I + 0.0011 \times X_S + 0.0015 \times X_O$$
$$-0.0003 \times X_I^2 + 8.64 \times 10^{-7} \times X_S^2 + 1.10 \times 10^{-5} \times X_O^2$$
$$-3.58 \times 10^{-5} \times X_I \times X_S - 4.9 \times 10^{-5} \times X_I \times X_O$$
$$-6.50 \times 10^{-6} \times X_S \times X_O \geq \overline{U_I} \tag{5.15}$$

Constraint 5: Self-Driving Vehicles Utilization rate

$$0.5563 + 0.0390 \times X_I - 0.0045 \times X_S - 0.0035 \times X_O$$
$$-0.0008 \times X_I^2 - 1.63 \times 10^{-5} \times X_S^2 + 5.9466 \times 10^{-5} \times X_O^2$$
$$+0.0002 \times X_I \times X_S + 0.0001 \times X_I \times X_O$$
$$-8.32 \times 10^{-5} \times X_S \times X_O \geq \overline{U_S} \tag{5.16}$$

Constraint 6: Outbound Forklifts Utilization rate

$$0.5549 + 0.0355 \times X_I + 0.0056 \times X_S - 0.0335 \times X_O$$

$$-0.0007 \times X_I^2 - 4.828 \times 10^{-5} \times X_S^2 - 3.4910^{-5} \times X_O^2$$

$$+0.0001 \times X_I \times X_S + 0.0003 \times X_I \times X_O$$

$$+6.19 \times 10^{-5} \times X_S \times X_O \;\geq \overline{U_{OB}} \qquad (5.17)$$

$$25 \;\leq\; X_I \;\leq\; 45 \qquad (5.18)$$

$$50 \;\leq\; X_S \;\leq\; 155 \qquad (5.19)$$

$$25 \;\leq\; X_O \;\leq\; 55 \qquad (5.20)$$

$$X_I,\; X_S,\; X_O \in \;\mathbb{Z} \qquad (5.21)$$

5.2 Optimal MHE Configuration

The formulated optimization model for FL-only (Eq (5.2) to Eq (5.10)) and FL-and-SDV cross-dock (Eq (5.11) to Eq (5.21)) is a mixed-integer nonlinear programming (MINLP) model. The objective function is linear and the constraints are nonlinear. Both MINLP models are solved using Lingo 17.0 solver for an increasing level of expected throughput rate ($\bar{\delta}$), expected Overall MHE Utilization rate ($\overline{U_O}$) of 80%, and expected category-wise MHE utilization rate ($\overline{U_I}$, $\overline{U_{OB}}$, and $\overline{U_S}$) of 65% . $\overline{\delta_M}$ for forklift-only CD is set as $200 ppd/MHE$, and $120 ppd/MHE$ for forklift-and-SDV CD†.

The optimal MHE configurations obtained by solving the MINLP models are given in Table 5.1. Validity of the optimality is assessed statistically later in Section 5.4.

† Since the FL-and-SDV CD requires a greater number of MHE than the FL-only CD to achieve smiliar δ.

$\overline{\delta}$	**FL-only**		**FL-and-SDV**			**TVC (\$/day)**		**Optimal Model**
	$\mathbf{X_I}$	$\mathbf{X_O}$	$\mathbf{X_I}$	$\mathbf{X_S}$	$\mathbf{X_O}$	**FL-only**	**FL-and-SDV**	
20,000	32	60	33	81	31	48,082	55,416	FL-only
21,000	33	63	35	87	31	50,172	58,088	FL-only
22,000	33	67	35	90	34	52,263	60,469	FL-only
23,000	32	72	36	94	36	54,354	63,122	FL-only
24,000	34	74	36	98	39	56,444	65,775	FL-only
25,000	36	77	37	104	40	59,057	68,447	FL-only
26,000	36	81	38	110	41	61,148	71,120	FL-only
27,000	37	85	40	113	43	63,761	74,024	FL-only
28,000	38	89	39	115	52	66,374	78,747	FL-only
29,000	39	94	42	122	48	69,510	80,123	FL-only
30,000	42	97	41	127	55	72,646	84,615	FL-only

Table 5.1: Optimal MHE Configuration, if $M =$ \$ 271.20/day.

5.3 Scope of SDVs in a Cross-Dock

The assumed cost of electricity, \$ $9.32/kWh$, is based on extreme conditions. It may vary, depending on location and commodity discounts. The objective function cost coefficient changes, if we happen to assume lower electricity charges, say \$ $4.66/kWh$ or \$ $3.11/kWh$, which are realistic (later two values corresponds to $M =$ \$ $140.76/day$ or \$ $97.28/day$). This leads to a change in optimality. Therefore the optimal MHE configuration for all those three cases are examined (without commodity discounts and peak consumption, with discounts and peak consumption, with discounts and off-peak consumption).

The revised objective functions for the FL-only and FL-and-SDV cross-docks, if

M = \$ 140.76/shift, are given in Eq (5.22) and Eq (5.23). Their optimal MHE configurations and total variable operating cost are given in Table 5.2. The optimal MHE configuration for the FL-only CD, presented earlier in Table 5.1, still holds, but changes for the FL-and-SDV CD.

$$\text{For FL-only CD:} \quad \textbf{Min} \;\; 392.19 \times (X_I + X_O) \tag{5.22}$$

$$\text{For FL-and-SDV CD:} \quad \textbf{Min} \;\; 392.19 \times (X_I + X_O) + 140.76 \times X_S \tag{5.23}$$

$\overline{\delta}$	**FL-only CD**			**FL-and-SDV CD**				**Optimal Model**	**Savings / year (\$)**
	X_I	X_O	**TVC (\$)**	X_I	X_S	X_O	**TVC (\$)**		
20,000	32	60	36,081	32	87	29	36,170	FL-only	NA
21,000	33	63	37,650	33	93	30	37,799	FL-only	NA
22,000	33	67	39,219	34	96	32	39,398	FL-only	NA
23,000	32	72	40,788	35	102	33	41,026	FL-only	NA
24,000	34	74	42,357	36	106	35	42,766	FL-only	NA
25,000	36	77	44,317	37	110	37	44,506	FL-only	NA
26,000	36	81	45,886	38	117	38	46,275	FL-only	NA
27,000	37	85	47,847	39	119	41	48,126	FL-only	NA
28,000	38	89	49,808	40	124	43	50,006	FL-only	NA
29,000	39	94	52,161	41	128	46	52,138	FL-and-SDV	5631
30,000	42	97	54,514	41	127	55	55,527	FL-only	NA

Table 5.2: Optimal MHE Configuration, if M = \$ 140.76/day.

Similarly the revised objective functions for both cross-docks if M = \$ 97.28/day are given in Eq (5.24) and Eq (5.25). The corresponding optimal MHE configurations and total variable costs are given in Table 5.3.

$$\text{For FL-only CD:} \quad \textbf{Min} \;\; 348.70 \times (X_I + X_O) \tag{5.24}$$

$$\text{For FL-and-SDV CD:} \quad \textbf{Min} \;\; 348.70 \times (X_I + X_O) + 97.28 \times X_S \tag{5.25}$$

$\bar{\delta}$	**FL-only CD**			**FL-and-SDV CD**				**Optimal**	**Savings/**	**Fixed**†	**PP**
	X_I	X_O	**TVC ($)**	X_I	X_S	X_O	**TVC ($)**	**Model**	**Year** * ($)	**Cost (in $M)**	**(in years)**
20,000	32	60	32,080	32	96	26	29,563	FL-and-SDV	604,061	17.1	14.15
21,000	33	63	33,475	32	99	29	30,901	FL-and-SDV	617,707	17.48	14.15
22,000	33	67	34,870	33	102	31	32,239	FL-and-SDV	631,354	17.93	14.2
23,000	32	72	36,265	35	105	32	33,577	FL-and-SDV	645,000	18.45	14.3
24,000	34	74	37,660	36	112	33	34,956	FL-and-SDV	648,946	19.8	15.26
25,000	36	77	39,403	36	116	36	36,391	FL-and-SDV	722,933	20.33	14.06
26,000	36	81	40,798	38	117	38	37,883	FL-and-SDV	699,586	20.4	14.58
27,000	37	85	42,541	39	125	39	39,359	FL-and-SDV	763,872	21.9	14.33
28,000	38	89	44,285	40	130	41	40,891	FL-and-SDV	814,512	22.73	13.95
29,000	39	94	46,377	40	131	46	42,732	FL-and-SDV	874,853	22.5	12.86
30,000	42	97	48,469	41	127	55	45,830	FL-and-SDV	633,490	21.23	16.75

Table 5.3: Optimal MHE Configuration, if $M = \$\ 97.28$/day.

When the MHE operating costs are lower, it is financially beneficial to employ both forklifts and SDVs in a cross-dock, rather than using manual forklifts only. The savings/year and payback period (PP) for the additional fixed cost, from choosing the FL-and-SDV CD instead of the FL-only CD, are given in Table 5.3. *Note:* The payback period will be reduced by half if there are two 8hr shifts per day.

*No of days in a year = 5days x 4weeks x 12months; one 8hr shift per day

†Cost of an Forklift = $ 75,000 [Source: http://www.costowl.com/b2b/forklift-electric-cost.html]

†Cost of an SDV = $ 150,000

5.4 Validation of Optimal MHE Configuration

If the regression model predictions are accurate[‡], then the MHE configurations suggested from solving the MINLP model for FL-only and FL-and-SDV CD would be the *optimal*, and yield similar performance measures equivalent to predicted performance (that is, δ of FL-only CD = δ of FL-and-SDV CD = $\widehat{\delta}$). Or else, the result be prediction errors and near-optimal MHE configurations. As mentioned earlier in Section 4.2, there exhibit a non-random source of variation, left unexplained by the regression models (Eq (4.7) to Eq (4.17)). As a result, the regression models fail to predict the CD performance metrics accurately, having huge $\boldsymbol{s}$ and RMSE.

The forklift-only and forklift-and-SDV cross-docks models are simulated with 'the optimal MHE configurations found by solving the MINLP models'. Later the validity of the 'proposed optimal MHE configurations' was assessed to verify if the FL-only and FL-and-SDV CDs yield similar average throughput rates. The statistical comparisons of average throughput rates for all pairs of 'proposed optimal MHE configurations' are given in Table 5.4. It shows that those forklift-only and forklift-and-SDV cross-docks performance metrics are not equal (that is, the difference between the average throughput rate of the forklift-only and forklift-and-SDV CDs is statistically significant).

We conclude, therefore, that the MHE configurations obtained from solving the MINLP models are ***efficiently allocated***, not necessarily optimal. Modelling the unexplained source of non-random variations in the residuals (see Sections B.1 and B.2 of Appendix B) to the regression models by adapting other advanced regression models, or else incorporating other potential exploratory variables to the existing regression model,

[‡] That is, $\widehat{\delta}$ *is not statistically different* from δ.

$\overline{\delta}$	**FL-only**				**FL-and-SDV**				**t-Test p-value**	
	Model	$\widehat{\delta}$	δ	**TVC ($)**	**Model**	$\widehat{\delta}$	δ	**TVC ($)**	**n=8**	**n=30**
M = $ 217.20 / day.										
20,000	32.60	20,105	19,512	48,082	33.81.31	20,001	19,629	55,416	0.03	0.00
21,000	33.63	21,103	20,401	50,172	35.87.31	21,045	21,070	58,088	0.00	0.00
22,000	33.67	22,162	21,681	52,263	35.90.34	22,021	21,793	60,469	0.02	0.01
23,000	32.72	23,115	23,412	54,354	36.94.36	23,037	22,751	63,122	0.00	0.00
24,000	34.74	24,049	23,988	56,444	36.98.39	24,000	19,056	65,775	0.00	0.00
25,000	36.77	25,117	24,926	59,057	37.104.40	25,021	24,363	68,447	0.00	0.00
26,000	36.81	25,989	26,244	61,148	38.110.41	26,002	24,928	71,120	0.00	0.00
27,000	37.85	26,997	27,496	63,761	40.113.43	27,006	26,048	74,024	0.00	0.00
28,000	38.89	27,956	28,820	66,374	39.115.52	28,027	27,268	78,747	0.00	0.00
29,000	39.94	29,032	30,441	69,510	42.122.48	29,029	27,790	80,123	0.00	0.00
30,000	42.97	30,039	31,486	72,646	41.127.55	30,033	30,431	84,615	0.00	0.00
M = $ 140.76 / day.										
20,000	32.60	20,105	19,512	36,081	32.87.29	20,005	20,402	36,170	0.00	0.00
21,000	33.63	21,103	20,401	37,650	33.93.30	21,050	21,488	37,799	0.02	0.01
22,000	33.67	22,162	21,681	39,219	34.96.32	22,018	22,296	39,398	0.00	0.00
23,000	32.72	23,115	23,412	40,788	35.102.33	23,010	22,955	41,026	0.00	0.00
24,000	34.74	24,049	23,988	42,357	36.106.35	24,027	23,538	42,766	0.00	0.00
25,000	36.77	25,117	24,926	44,317	37.110.37	25,019	23,996	44,506	0.00	0.00
26,000	36.81	25,989	26,244	45,886	38.117.38	26,012	24,808	46,275	0.00	0.00
27,000	37.85	26,997	27,496	47,847	39.119.41	27,010	25,415	48,126	0.00	0.00
28,000	38.89	27,956	28,820	49,808	40.124.43	28,007	26,376	50,006	0.00	0.00
29,000	39.94	29,032	30,441	52,161	41.128.46	29,077	27,440	52,138	0.00	0.00
30,000	42.97	30,039	31,486	54,514	41.127.55	30,033	30,431	55,527	0.00	0.00
M = $ 97.28 / day.										
20,000	32.60	20,105	19,512	32,080	32.96.26	20,029	20,524	29,563	0.00	0.00
21,000	33.63	21,103	20,401	33,475	32.99.29	21,024	20,702	30,901	0.00	0.00
22,000	33.67	22,162	21,681	34,870	33.102.31	22,023	21,376	32,239	0.00	0.00
23,000	32.72	23,115	23,412	36,265	35.105.32	23,019	22,834	33,577	0.00	0.00
24,000	34.74	24,049	23,988	37,660	36.112.33	24,013	23,485	34,956	0.00	0.00
25,000	36.77	25,117	24,926	39,403	36.116.36	25,008	24,241	36,391	0.00	0.00
26,000	36.81	25,989	26,244	40,798	38.117.38	26,012	24,808	37,883	0.00	0.00
27,000	37.85	26,997	27,496	42,541	39.125.39	27,017	26,260	39,359	0.00	0.00
28,000	38.89	27,956	28,820	44,285	40.130.41	28,009	27,397	40,891	0.00	0.00
29,000	39.94	29,032	30,441	46,377	40.131.46	29,069	27,944	42,732	0.00	0.00
30,000	42.97	30,039	31,486	48,469	41.127.55	30,033	30,431	45,830	0.00	0.00

Table 5.4: Statistical Validation of Optimal MHE Configuration.

would improve the prediction accuracy. Thereby, the optimal MHE configuration may be predicted using the proposed solution methodology.

5.5 Results

Solving the formulated MINLP model resulted in many interesting insights. They are presented as follows;

- ❖ The total number of MHE required in a cross-dock increases drastically for an increase in the desired level of average throughput rate. The total number of MHE in each category increases simultaneously to achieve that desired mean average throughput.

- ❖ When the MHE operating cost reduces, using a mixture of forklifts and SDVs in a cross-dock results in lower total variable operating cost than a manually operated facility with similar levels of performance metrics. See Tables 5.1, 5.2 and 5.3 for the impact of changes in MHE operating cost on the total variable operating cost and optimal MHE configuration. This leads us to conclude that using forklift-and-SDVs in a CD could be financially beneficial, relative to using forklifts only, at lower operating cost (or electricity charges).

- ❖ Statistical comparison of the manual and semi-automated cross-dock actual throughput rates shows that the difference between their actual performance is significantly different. This is due to lack of fitness of regression models used to formulate the optimization model constraints. However, the predictive accuracy can be improved by studying other potential factors which could significantly impact the cross-dock performance metrics.

Chapter 6

Conclusion

The solution methodology proposed in this thesis, to find the optimal MHE configuration for forklift-only and forklift-and-SDV cross-docks operating at similar performance levels, only yields *efficient* MHE configuration. This is due to regression models lack-of-fitness (that is, $\widehat{\delta}$ is statistically different from δ).

FL-only CD			FL-and-SDV CD			CI for difference in mean			Savings/	PP
Model	$\boldsymbol{\delta}$	**TVC($)**	**Model**	$\boldsymbol{\delta}$	**TVC ($)**	**Lower Bound**	**Mean**	**Upper Bound**	**year ($)** *	**(in years)** †
32.72	23,412	36,265	36.112.33	23,485	34,956	-147	-73	1	628,387	22.56
36.81	26,244	40,798	39.125.39	26,260	39,359	-71	-17	38	690,864	19.65
39.94	30,441	46,377	41.127.55	30,431	45,830	-48	9	67	262,723	61.95

Table 6.1: MHE Configurations of Cross-Docks with Similar δ.

Even though the MINLP model fails to provide the optimal MHE configuration, manual identification and comparison the of FL-only and FL-and-SDV CDs given in Table

*No of working hours = 8 x 2 x 5 x 4 x 12 (two shifts per day); Operating cost, M = $ 97.28 / day.

†Cost of Forklift = $ 75,000; Cost of SDV = $ 150,000

6.1 for the facilities yielding similar δ. Their similarity in performance is justified through a confidence interval for the difference in average throughput rate for those facilities at a $significance\ level\ of$ 0.05. Savings/year and payback period(PP), given in that table, show that "using SDVs in a cross-dock facility could be financially beneficial, for lower MHE operating cost". We should not ignore the fact that the MHE configurations given in Table 6.1 are not the optimal, and are obtained from Table 5.4. The optimal MHE configuration may have much higher savings per year and faster payback.

6.1 Summary of Research

In this thesis, we have proposed a simulation-optimization technique to optimize the MHE configuration of two cross-dock facilities with similar performance measures. The goal was to validate the scope of self-driving vehicles in a cross-dock. The overall summary of our research is given as the following steps as follows:

Step 1: Floor-level pallet movements in a cross-docking centre were modelled using ARENA. Two simulation models, for forklift-only and forklift-and-self-driving vehicle cross-docks, were constructed. The two different MHE configurations (forklift-only and forklift-and-SDV) would thus support material-handling activities in the respective CDs.

Step 2: Due to computational complexities and time limitations in finding the optimal MHE configuration, RSM was used to fit a regression model, in a form *CD performance metric* = $\boldsymbol{f}$*(MHE configuration).*

Step 3: Then we built two independent MINLP models, for FL-only and FL-and-SDV cross-docks, to minimize the variable operating cost, subject to constraints on CD performance metrics. Those constraints were modelled using the fitted regression models of CD performance metrics on the left-hand side and desired level of respective CD performance metrics on the right-hand side.

Step 4: Each MINLP model was solved using the Lingo 17.0 solver. The respective models would yield the optimal MHE configuration for the FL-only and FL-and-SDV CDs operating at similar performance levels, if the desired levels of performance were set to be the same, and the fitted regression models could predict accurately.

6.1.1 Pros of Proposed Solution Methodology

- ❖ It could be used to solve the complex simulation optimization problems (of any system, not limited to cross-dock centres) with a greater search space in a shorter time span.

- ❖ It could be used for simulation optimization and comparison of multiple systems, subject to constraints on various performance metrics, eliminating family-wise error rate due to multiple-comparison.

6.1.2 Cons of Proposed Solution Methodology

- ❖ Requires an in-depth knowledge of the system to precisely model the existing system, and to identify the factors and factor levels for RSM.
- ❖ The regression models should significantly explain *all* sources of variation caused by the exploratory variables, with no unexplained sources of non-random variation. Otherwise, the result will be only a near-optimal, or even suboptimal, solution.

6.2 Suggestions for Future Study

We wish to propose a few potential research ideas for future studies, which could be explored from this thesis.

- ❖ Improve the prediction accuracy of the regression models incorporating other exploratory variables (like product mix or labour required for sorting other than forklift operators), and thus compute the MHE configurations for the FL-only and FL-and-SDV CDs that is closer to optimal. s
- ❖ Remodel and analyze the proposed cross-docks with uncertainties in the supply and demand, MHE breakdowns, traffic congestion and less-than-truckload shipment operations.
- ❖ Reformulate and analyze the proposed MINLP model with an objective to optimize one or more cross-dock performance metrics, now subject to additional constraints on costs, space or other measures.

- Study the scope of self-driving vehicles for *order picking* in a CD. This would be for the case in which some outbound pallets require a mix of items from other inbound pallets.

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APPENDICES

Appendix A

Cross-Dock Performance Metrics

A.1 Performance Metrics: Forklift-only Cross-Dock

A.1.1 Average Pallet Processing Time

From Figure A.1, it is clear that the average pallet processing or flow time (bar from primary axis) reduces gradually as there is an increase in the number of outbound forklifts, for a given number of inbound forklifts. Hence, outbound forklifts clearly act as a bottleneck to processing pallets in a shorter interval. This has an inverse effect on the average throughput rate (line from secondary axis). As expected, the higher the throughput rate, the lower the average pallet processing time.

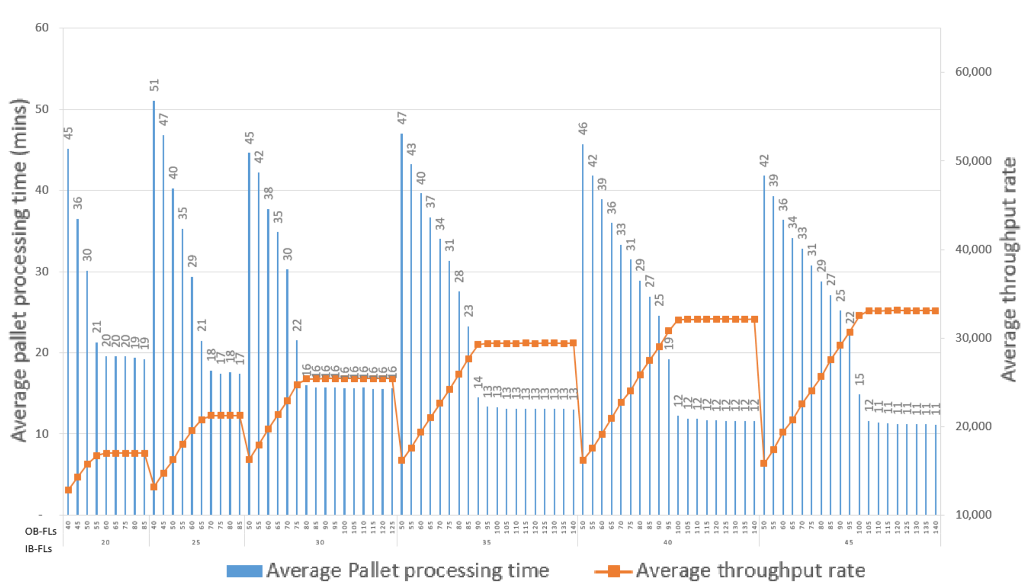

Figure A.1: Forklift-only Cross-Dock Facility: Average Pallet Processing Time.

A.1.2 Average Truck Processing Time

From Figure A.2, for a given number of inbound forklifts in the Forklift-only CD, the number of outbound forklifts in a facility can act as a bottleneck to process trucks quickly. An increase in outbound forklifts directly reduces the average truck processing time.

Hence, with a given number of IB-FLs in an FL-only CD, the number of OB-FLs should be increased sufficiently to process trucks as quickly as possible.

A.1.3 Average Number of Trucks Processed per Day

From Figure A.3, for a given number of inbound forklifts in an FL-only CD, outbound forklifts act as a bottleneck to process additional trucks. An increase in OB-FLs

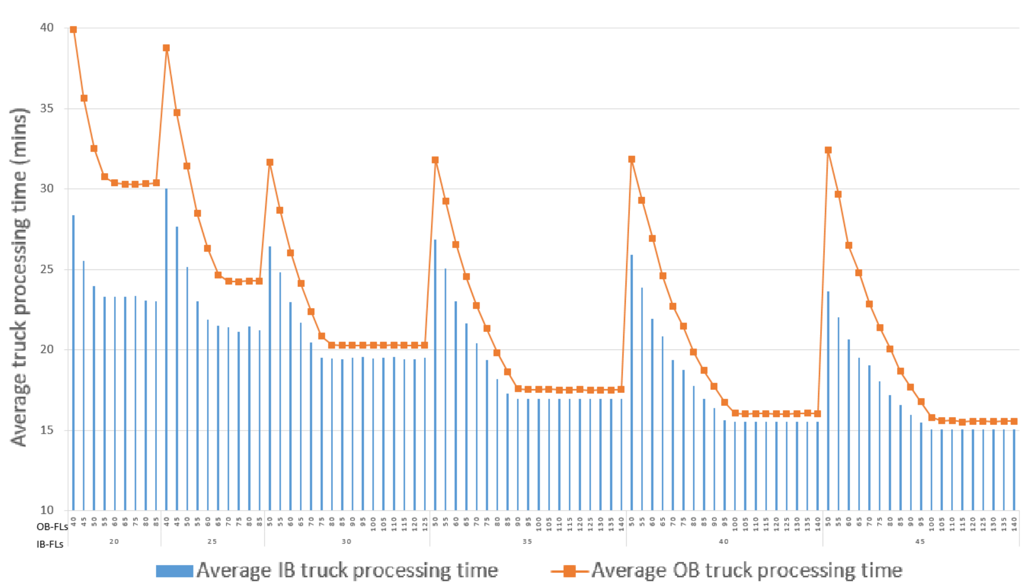

Figure A.2: Forklift-only Cross-Dock Facility: Average Truck Processing Time.

directly increases the average number of Trucks/Day that can be processed. That is, when there are fewer OB-FLs, the buffer area gets filled and acts as a bottleneck for offloading trucks. This results in the processing of a low number of inbound trucks/day. Since it takes more time to sort and load the pallets from the buffer area, when there are fewer OB-FLs, an increase in the number of OB-FLs directly increases the truck-processing capacity of the CD.

Hence, for any FL-only facility, and a given number of IB-FLs, the number of OB-FLs should be increased sufficiently, to be able to process a greater number of inbound or outbound trucks/day.

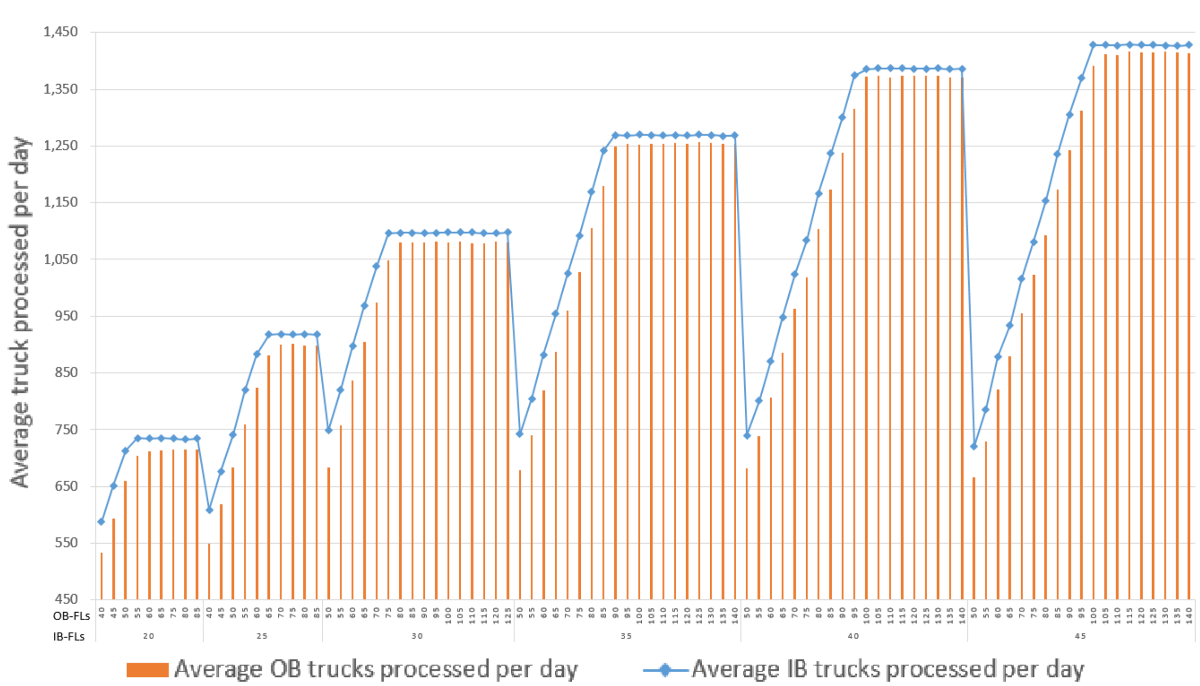

Figure A.3: Forklift-only Cross-Dock Facility: Average Number of Trucks per Day.

A.2 Performance Metrics: Forklift-and-SDV Cross-Dock

A.2.1 Average Pallet Processing Time

Figure A.4 indicates that, given the number of inbound forklifts for the FL-and-SDV CD facility, SDVs and outbound forklifts can each act as a bottleneck to process pallets. That is, an increase in either SDVs or OB-FLs results in processing pallets in a shorter time. When SDVs are fewer, they act as a bottleneck for pallets waiting for SDVs. When SDVs are sufficiently high for the given number of IB-FLs and a lower number of OB-FLs,

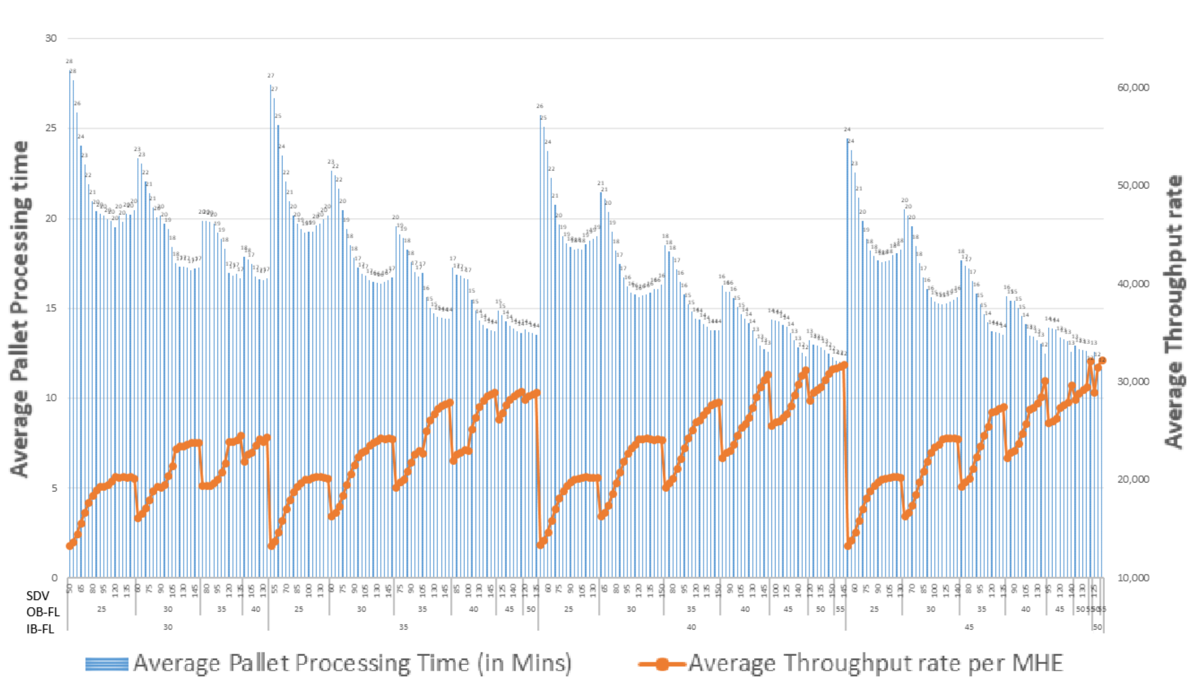

Figure A.4: Forklift-and-SDV Cross-Dock Facility: Average Pallet Processing Time.

pallets spend their time waiting for OB-FLs.

Hence, in an FL-and-SDV CD, with a given number of IB-FLs, the number of SDVs and OB-FLs should both be sufficiently increased to process the pallets as quickly as possible.

A.2.2 Average Truck Processing Time

From Figure A.5, for a given number of inbound forklifts in the FL-and-SDV CD facility, SDVs and outbound forklifts can each act as a bottleneck to process trucks. Thus, an increased number of SDVs and OB-FLs results in processing trucks as quickly as pos-

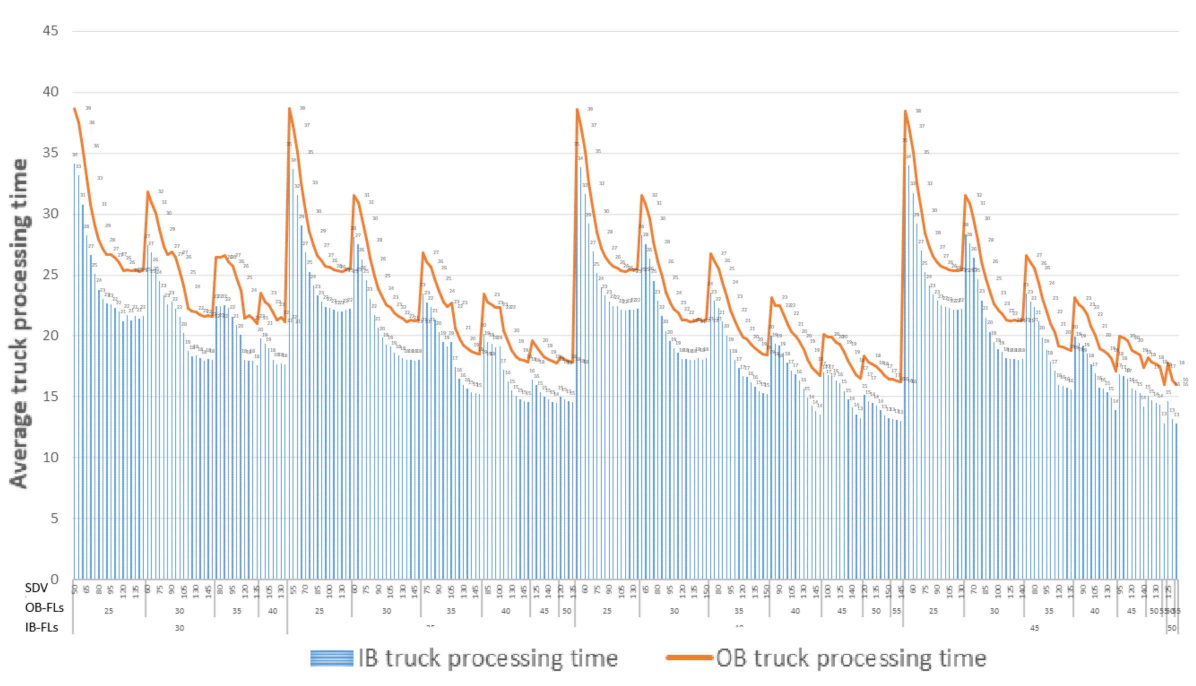

Figure A.5: Forklift-and-SDV Cross-Dock Facility: Average Truck Processing Time

sible. When there are insufficient SDVs, they act as a bottleneck for IB-FLs to offload pallets from inbound trucks, resulting in those IB-FLs having to wait for SDVs. When SDVs are sufficiently numerous for the given number of IB-FLs with fewer OB-FLs, most SDVs spend their time waiting for OB-FLs, resulting in a bottleneck for offloading and loading as well.

Hence, in an FL-and-SDV facility, for a given number of IB-FLs, both SDVs and OB-FLs should be increased sufficiently to reduce the average truck processing time.

A.2.3 Average Number of Trucks Processed per Day

For a given number of inbound forklifts in the FL-and-SDV CD, Figure A.6 indicates that either SDVs or outbound forklifts can act as a bottleneck to process more trucks. Therefore, we need to provide sufficient numbers of SDVs and OB-FLs to process more trucks/day. That is, when there are fewer SDVs, they act as a bottleneck for IB-FLs to offload pallets from the inbound trucks, resulting in the IB-FLs waiting for SDVs. But when SDVs are sufficiently numerous for the given number of IB-FLs, fewer OB-FLs result in the SDVs waiting for OB-FLs. Hence, both the number of SDVs and OB-FLs should be sufficiently increased for the FL-and-SDV CD facility to process more inbound or outbound trucks/day.

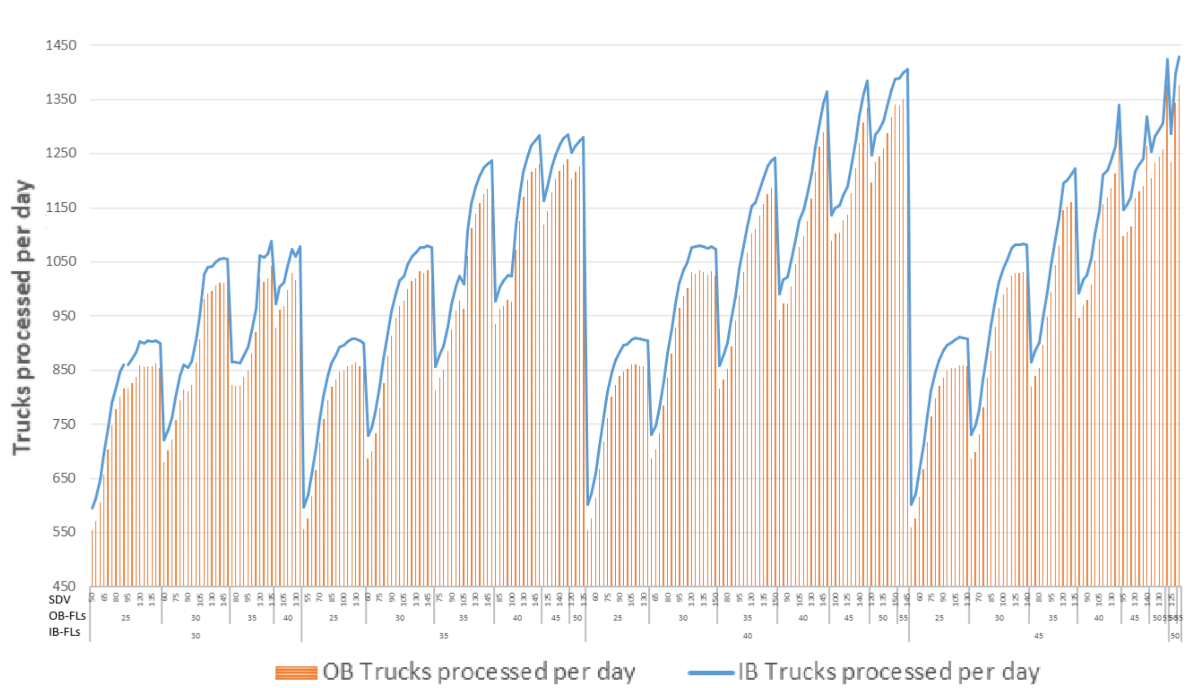

Figure A.6: Forklift-and-SDV Cross-Dock Facility: Average Number of Trucks per Day.

Appendix B

Response Surface Models

As mentioned in Section 4.2 of Chapter 4, four regression models (linear, linear + interactions, linear + square, and quadratic) were considered for model fitting. Statistical inference of those models which were selected for further analysis are given in this chapter.

B.1 RSM: Forklift-only Cross-Dock

B.1.1 Analysis of Variance: FL-only CD

We experimented with two potential factors (X_I and X_O), to assess their contribution towards variation in CD performance metrics. The resulting sources of variance and their significance are given in Table B.1.

Analysis of variance (ANOVA) shows that all sources of variation are significant, based on F-statistic p-value at a significance level of $\alpha = 0.05$, and significantly contribute

ANOVA	Source	DF	Seq SS	Adj SS	Adj MS	F	P
$\boldsymbol{\delta}$	**Regression**	5	20531750098	20531750098	4106350020	4636.04	0
	Linear	2	15111890183	833279096	416639548	470.38	0
	$\boldsymbol{X_I}$	1	4860514814	167417528	167417528	189.01	0
	$\boldsymbol{X_O}$	1	10251375369	752061935	752061935	849.07	0
	Square	2	3086661897	3086661897	1543330949	1742.41	0
	$\boldsymbol{X_I \times X_I}$	1	444769494	444769494	444769494	502.14	0
	$\boldsymbol{X_O \times X_O}$	1	2641892403	2641892403	2641892403	2982.68	0
	Interaction	1	2333198017	2333198017	2333198017	2634.16	0
	$\boldsymbol{X_I \times X_O}$	1	2333198017	2333198017	2333198017	2634.16	0
	Residual Error	744	658994916	658994916	885746		
	Lack-of-Fit	44	644962550	644962550	14658240	731.22	0
	Pure Error	700	14032366	14032366	20046		
	Total	749	21190745014				
$\boldsymbol{\delta_M}$	**Regression**	5	442613	442613	88523	1073.78	0
	Linear	2	156874	4383	2191	26.58	0
	$\boldsymbol{X_I}$	1	28133	3874	3874	46.99	0
	$\boldsymbol{X_O}$	1	128740	989	989	11.99	0.001
	Square	2	139125	139125	69562	843.79	0
	$\boldsymbol{X_I \times X_I}$	1	24870	24870	24870	301.67	0
	$\boldsymbol{X_O \times X_O}$	1	114255	114255	114255	1385.91	0
	Interaction	1	146615	146615	146615	1778.43	0
	$\boldsymbol{X_I \times X_O}$	1	146615	146615	146615	1778.43	0
	Residual Error	744	61336	61336	82		
	Lack-of-Fit	44	59984	59984	1363	705.85	0
	Pure Error	700	1352	1352	2		
	Total	749	503949				

Table B.1: Analysis of Variance: Forklift-only Cross-Dock.

ANOVA	Source	DF	Seq SS	Adj SS	Adj MS	F	P
U_I	**Regression**	5	3.4753	3.47531	0.695062	1908.92	0
	Linear	2	2.7049	0.19246	0.096229	264.29	0
	X_I	1	2.1758	0.16355	0.163552	449.18	0
	X_O	1	0.5291	0.05177	0.05177	142.18	0
	Square	2	0.618	0.618	0.309001	848.64	0
	$X_I \times X_I$	1	0.4291	0.42914	0.429139	1178.59	0
	$X_O \times X_O$	1	0.1889	0.18886	0.188862	518.69	0
	Interaction	1	0.1524	0.15237	0.152371	418.47	0
	$X_I \times X_O$	1	0.1524	0.15237	0.152371	418.47	0
	Residual Error	744	0.2709	0.2709	0.000364		
	Lack-of-Fit	44	0.1122	0.11218	0.002549	11.24	0
	Pure Error	700	0.1587	0.15872	0.000227		
	Total	749	3.7462				
U_{OB}	**Regression**	5	18.5518	18.5518	3.71037	2411.84	0
	Linear	2	16.1037	0.127	0.06351	41.28	0
	X_I	1	3.1314	0.1007	0.10068	65.44	0
	X_O	1	12.9724	0.013	0.01299	8.44	0.004
	Square	2	1.3169	1.3169	0.65847	428.03	0
	$X_I \times X_I$	1	0.2288	0.2288	0.22877	148.7	0
	$X_O \times X_O$	1	1.0882	1.0882	1.08818	707.35	0
	Interaction	1	1.1312	1.1312	1.13116	735.28	0
	$X_I \times X_O$	1	1.1312	1.1312	1.13116	735.28	0
	Residual Error	744	1.1446	1.1446	0.00154		
	Lack-of-Fit	44	1.1368	1.1368	0.02584	2332.07	0
	Pure Error	700	0.0078	0.0078	0.00001		
	Total	749	19.6964				

Table B.1 (continued): Analysis of Variance: Forklift-only Cross-Dock.

ANOVA	Source	DF	Seq SS	Adj SS	Adj MS	F	P
U_O	**Regression**	5	10.4	10.4	2.07999	1977.91	0
	Linear	2	7.3596	0.1501	0.07507	71.39	0
	$\boldsymbol{X_I}$	1	0.9464	0.1364	0.13641	129.71	0
	$\boldsymbol{X_O}$	1	6.4132	0.0038	0.00381	3.62	0.057
	Square	2	1.5522	1.5522	0.77611	738.02	0
	$\boldsymbol{X_I \times X_I}$	1	0.4142	0.4142	0.41415	393.83	0
	$\boldsymbol{X_O \times X_O}$	1	1.1381	1.1381	1.13807	1082.22	0
	Interaction	1	1.4882	1.4882	1.48819	1415.15	0
	$\boldsymbol{X_I \times X_O}$	1	1.4882	1.4882	1.48819	1415.15	0
	Residual Error	744	0.7824	0.7824	0.00105		
	Lack-of-Fit	44	0.7534	0.7534	0.01712	413.61	0
	Pure Error	700	0.029	0.029	0.00004		
	Total	749	11.1824				

Table B.1 (continued): Analysis of Variance: Forklift-only Cross-Dock.

towards their respective performance metrics (R). The exception is the performance metric - U_O, whose main effect - X_O is insignificant. Even though the main effect (X_O) of U_O turns out to be insignificant, the square (X_O^2) and interaction ($X_I \times X_O$) effects derived from the main effects have strong significance. Exclusion of the main effect would result in exclusion of its higher-order and interaction effects as well. Hence we decide to retain the insignificant main effect - X_O.

The residual-error component is split into two, as lack-of-fit (LOF) and pure error. In general, a source of variation is categorized into two, as assignable (or non-random) and random*. LOF statistically validates the presence of non-random source of variance in the

* The variations caused by the known factors (controllable or uncontrollable) are non-random or assignable sources of variation. The variation due to natural randomness is random variation or (pure) error.

error or residuals. LOF p-value < α [†] shows that there is a non-random source of variance in the error component. This may lead to inferior prediction accuracy.

B.1.2 Regression Coefficient Estimation: FL-only CD

The regression coefficients are estimated for each performance metric following the least square method; their estimates and significance are given in Table B.2. It shows that all regression coefficients (β, β_I, β_O, β_{II}, β_{OO} and β_{IO}) are strongly significant, at a significance level of $\alpha = 0.05$[‡], and they significantly contribute towards estimating their respective performance metrics ($\widehat{R}$). The exception is the regression model $\widehat{U_O}$, whose t-test p-value for $\beta_O = 0.057 > \alpha$.

Even though the main effect of the term X_O is (nearly) insignificant, resulting in an insignificant regression coefficient - β_O, the square (X_O^2) and interaction ($X_I \times X_O$) effects resulting from the main effect (X_O) possess strong significance. Hence the regression coefficient β_O is retained in spite of its insignificance, due to its higher-order significant effects.

B.1.3 Residual Analysis: FL-only CD

The residual[§] plots for all cross-dock performance metrics are given in Figure B.1. The probability plots and histograms in that figure show that the residuals of the fitted regression models are not normally distributed. In addition, the scatter plot (*Versus Fits*)

[†] From subsection 4.2.1, Hypothesis test 2

[‡] From subsection 4.2.1, Hypothesis test 1

[§] Residual = $R - \widehat{R}$

$\widehat{R}$	Term	Coef	SE Coef	T stat	P-value
$\widehat{\delta}$	**Constant**	-13688.7	1200.7	-11.401	0
	$\boldsymbol{X_I}$	823.6	59.91	13.748	0
	$\boldsymbol{X_O}$	315.5	10.83	29.139	0
	$\boldsymbol{X_I^2}$	-18.4	0.82	-22.409	0
	$\boldsymbol{X_O^2}$	-2.6	0.05	-54.614	0
	$\boldsymbol{X_I \times X_O}$	8.7	0.17	51.324	0
$\widehat{\delta_M}$	**Constant**	136.33	11.5838	11.769	0
	$\boldsymbol{X_I}$	3.962	0.5779	6.855	0
	$\boldsymbol{X_O}$	0.362	0.1045	3.463	0.001
	$\boldsymbol{X_I^2}$	-0.138	0.0079	-17.369	0
	$\boldsymbol{X_O^2}$	-0.017	0.0005	-37.228	0
	$\boldsymbol{X_I \times X_O}$	0.069	0.0016	42.171	0
$\widehat{U_I}$	**Constant**	0.499352	0.024344	20.512	0
	$\boldsymbol{X_I}$	0.025742	0.001215	21.194	0
	$\boldsymbol{X_O}$	0.002618	0.00022	11.924	0
	$\boldsymbol{X_I^2}$	-0.00057	0.000017	-34.331	0
	$\boldsymbol{X_O^2}$	-2.2E-05	0.000001	-22.775	0
	$\boldsymbol{X_I \times X_O}$	0.00007	0.000003	20.457	0
$\widehat{U_{OB}}$	**Constant**	0.684438	0.05004	13.678	0
	$\boldsymbol{X_I}$	0.020197	0.002497	8.09	0
	$\boldsymbol{X_O}$	-0.00131	0.000451	-2.906	0.004
	$\boldsymbol{X_I^2}$	-0.00042	0.000034	-12.194	0
	$\boldsymbol{X_O^2}$	-5.2E-05	0.000002	-26.596	0
	$\boldsymbol{X_I \times X_O}$	0.000191	0.000007	27.116	0
$\widehat{U_O}$	**Constant**	0.62275	0.041372	15.052	0
	$\boldsymbol{X_I}$	0.023509	0.002064	11.389	0
	$\boldsymbol{X_O}$	-0.00071	0.000373	-1.903	0.057
	$\boldsymbol{X_I^2}$	-0.00056	0.000028	-19.845	0
	$\boldsymbol{X_O^2}$	-5.4E-05	0.000002	-32.897	0
	$\boldsymbol{X_I \times X_O}$	0.000219	0.000006	37.619	0

Table B.2: Regression Coefficients: Forklift-only Cross-Dock.

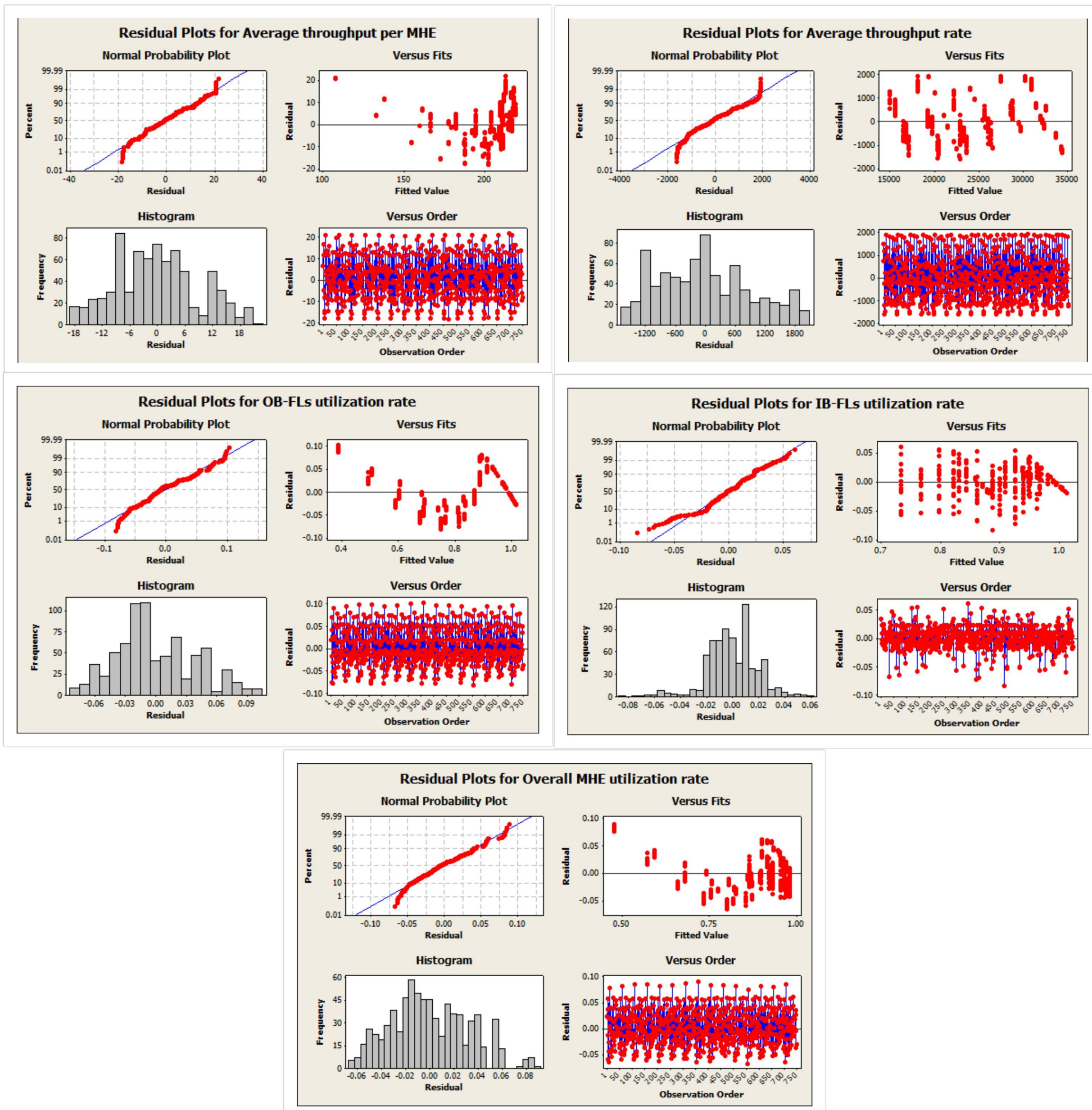

Figure B.1: Residual Analysis: Forklift-only Cross-Dock.

between the residuals $(R - \widehat{R})$ and fitted values $(\widehat{R})$ shows a clear existing pattern. This is not favourable.

All these showcase heteroscedasticity or non-homogeneous residual distribution. That is, the fitted regression model fails to explain some sources of non-random variation existing in the system.

B.2 RSM: Forklift-and-SDV Cross-Dock

B.2.1 Analysis of Variance: FL-and-SDV CD

We experimented with three potential factors $X_I,\ X_S$ and X_O to assess their contribution towards the variations in CD performance metrics. The resulting sources of variance and their significance are given in Table B.3. Analysis of variance shows that for a CD performance metric - δ_M, the main effect (X_O) is insignificant at a significance level of $\alpha\ =\ 0.05$, but has to be retained because of its higher orders significance $(X_O^2,\ X_I \times X_O$ and $X_S \times X_O)$. However, the square effect (X_O^2) of the performance metric - U_O is excluded because of its insignificance.

Apart from those two, all other sources of variation were found significant, based on F-statistic p-value, and contribute towards their respective performance metrics. LOF p-value $<\ \alpha$ shows that there is a non-random source of variation left unexplained by the regression models.

ANOVA	Source	DF	Seq SS	Adj SS	Adj MS	F	P
$\boldsymbol{\delta}$	**Regression**	9	1.19E+11	1.19E+11	1.32E+10	12256.35	0
	Linear	3	9.62E+10	2.1E+09	7E+08	648.01	0
	$\boldsymbol{X_I}$	1	2.39E+10	1.81E+09	1.81E+09	1672.22	0
	$\boldsymbol{X_S}$	1	6.13E+10	4.99E+08	4.99E+08	462.09	0
	$\boldsymbol{X_O}$	1	1.1E+10	55250328	55250328	51.17	0
	Square	3	1.22E+10	1.22E+10	4.06E+09	3761.01	0
	$\boldsymbol{X_I * X_I}$	1	5.2E+09	5.2E+09	5.2E+09	4819.71	0
	$\boldsymbol{X_S * X_S}$	1	5.29E+09	5.29E+09	5.29E+09	4901.04	0
	$\boldsymbol{X_O * X_O}$	1	1.69E+09	1.69E+09	1.69E+09	1562.28	0
	Interaction	3	1.07E+10	1.07E+10	3.56E+09	3299.64	0
	$\boldsymbol{X_I * X_S}$	1	5.94E+09	5.94E+09	5.94E+09	5501.67	0
	$\boldsymbol{X_I * X_O}$	1	2.9E+09	2.9E+09	2.9E+09	2687.46	0
	$\boldsymbol{X_S * X_O}$	1	1.85E+09	1.85E+09	1.85E+09	1709.81	0
	Residual Error	5765	6.22E+09	6.22E+09	1079699		
	Lack-of-Fit	375	6.05E+09	6.05E+09	16133819	498.97	0
	Pure Error	5390	1.74E+08	1.74E+08	32335		
	Total	5774	1.25E+11				
$\boldsymbol{\delta_M}$	**Regression**	9	897655	897655	99739	3410.74	0
	Linear	3	243563	54482	18161	621.03	0
	$\boldsymbol{X_I}$	1	192576	49767	49767	1701.85	0
	$\boldsymbol{X_S}$	1	50411	1088	1088	37.2	0
	$\boldsymbol{X_O}$	1	575	28	28	0.95	0.33
	Square	3	367434	367434	122478	4188.32	0
	$\boldsymbol{X_I * X_I}$	1	160434	160434	160434	5486.28	0
	$\boldsymbol{X_S * X_S}$	1	157350	157350	157350	5380.83	0
	$\boldsymbol{X_O * X_O}$	1	49650	49650	49650	1697.85	0
	Interaction	3	286658	286658	95553	3267.56	0
	$\boldsymbol{X_I * X_S}$	1	148841	148841	148841	5089.85	0
	$\boldsymbol{X_I * X_O}$	1	72256	72256	72256	2470.91	0
	$\boldsymbol{X_S * X_O}$	1	65560	65560	65560	2241.94	0
	Residual Error	5765	168585	168585	29		
	Lack-of-Fit	375	163308	163308	435	444.82	0
	Pure Error	5390	5277	5277	1		
	Total	5774	1066240				

Table B.3: Analysis of Variance: Forklift-and-SDV Cross-Dock.

ANOVA	Source	DF	Seq SS	Adj SS	Adj MS	F	P
U_I	**Regression**	9	4.08411	4.08411	0.45379	4708.08	0
	Linear	3	2.51098	1.19001	0.39667	4115.44	0
	X_I	1	2.22306	1.16344	1.16344	12070.66	0
	X_S	1	0.22403	0.08127	0.08127	843.17	0
	X_O	1	0.06389	0.01092	0.01092	113.26	0
	Square	3	1.07772	1.07772	0.35924	3727.11	0
	$X_I * X_I$	1	1.06914	1.06914	1.06914	11092.33	0
	$X_S * X_S$	1	0.00337	0.00337	0.00337	34.91	0
	$X_O * X_O$	1	0.00521	0.00521	0.00521	54.09	0
	Interaction	3	0.49541	0.49541	0.16514	1713.31	0
	$X_I * X_S$	1	0.36984	0.36984	0.36984	3837.13	0
	$X_I * X_O$	1	0.10119	0.10119	0.10119	1049.88	0
	$X_S * X_O$	1	0.02438	0.02438	0.02438	252.91	0
	Residual Error	5765	0.55566	0.55566	0.0001		
	Lack-of-Fit	375	0.55139	0.55139	0.00147	1856.74	0
	Pure Error	5390	0.00427	0.00427	0		
	Total	5774	4.63977				
U_S	**Regression**	9	107.988	107.988	11.9987	10221.22	0
	Linear	3	78	4.603	1.5345	1307.15	0
	X_I	1	35.346	2.64	2.6397	2248.67	0
	X_S	1	37.643	1.311	1.3108	1116.65	0
	X_O	1	5.011	0.06	0.0605	51.5	0
	Square	3	8.125	8.125	2.7085	2307.24	0
	$X_I * X_I$	1	6.787	6.787	6.7869	5781.5	0
	$X_S * X_S$	1	1.185	1.185	1.1853	1009.74	0
	$X_O * X_O$	1	0.153	0.153	0.1532	130.47	0
	Interaction	3	21.863	21.863	7.2877	6208.05	0
	$X_I * X_S$	1	17.46	17.46	17.46	14873.49	0
	$X_I * X_O$	1	0.41	0.41	0.4097	349.03	0
	$X_S * X_O$	1	3.993	3.993	3.9932	3401.64	0
	Residual Error	5765	6.768	6.768	0.0012		
	Lack-of-Fit	375	6.657	6.657	0.0178	866.52	0
	Pure Error	5390	0.11	0.11	0		
	Total	5774	114.756				

Table B.3 (continued): Analysis of Variance: Forklift-and-SDV Cross-Dock.

ANOVA	Source	DF	Seq SS	Adj SS	Adj MS	F	P
	Regression	9	297.339	297.339	33.0377	5893.39	0
	Linear	3	267.463	10.934	3.6446	650.14	0
	$\boldsymbol{X_I}$	1	29.687	2.187	2.1873	390.17	0
	$\boldsymbol{X_S}$	1	77.603	1.973	1.9733	352.01	0
	$\boldsymbol{X_O}$	1	160.173	5.369	5.3695	957.83	0
	Square	3	16.965	16.965	5.6551	1008.78	0
	$\boldsymbol{X_I * X_I}$	1	6.409	6.409	6.4088	1143.23	0
	$\boldsymbol{X_S * X_S}$	1	10.504	10.504	10.5038	1873.71	0
$\boldsymbol{U_{OB}}$	$\boldsymbol{X_O * X_O}$	1	0.053	0.053	0.0528	9.42	0.002
	Interaction	3	12.911	12.911	4.3036	767.69	0
	$\boldsymbol{X_I * X_S}$	1	6.424	6.424	6.4236	1145.87	0
	$\boldsymbol{X_I * X_O}$	1	4.28	4.28	4.2804	763.55	0
	$\boldsymbol{X_S * X_O}$	1	2.207	2.207	2.2068	393.65	0
	Residual Error	5765	32.318	32.318	0.0056		
	Lack-of-Fit	375	31.947	31.947	0.0852	1239.44	0
	Pure Error	5390	0.37	0.37	0.0001		
	Total	5774	329.657				
	Regression	8	74.7895	74.7895	9.34868	10532.62	0
	Linear	3	53.3755	7.6592	2.55306	2876.38	0
	$\boldsymbol{X_I}$	1	25.4532	2.9104	2.91038	3278.96	0
	$\boldsymbol{X_S}$	1	0.7856	0.0246	0.0246	27.72	0
	$\boldsymbol{X_O}$	1	27.1366	2.7774	2.77745	3129.19	0
	Square	2	11.0239	11.0239	5.51193	6209.97	0
	$\boldsymbol{X_I * X_I}$	1	6.5824	6.5824	6.58245	7416.06	0
	$\boldsymbol{X_S * X_S}$	1	4.4414	4.4414	4.44141	5003.88	0
$\boldsymbol{U_O}$	**Interaction**	3	10.3901	10.3901	3.46338	3901.99	0
	$\boldsymbol{X_I * X_S}$	1	9.5863	9.5863	9.58631	10800.34	0
	$\boldsymbol{X_I * X_O}$	1	0.7943	0.7943	0.79428	894.86	0
	$\boldsymbol{X_S * X_O}$	1	0.0096	0.0096	0.00956	10.77	0.001
	Residual Error	5766	5.1179	5.1179	0.00089		
	Lack-of-Fit	376	5.0173	5.0173	0.01334	715.41	0
	Pure Error	5390	0.1005	0.1005	0.00002		
	Total	5774	79.9073				

Table B.3 (continued): Analysis of Variance: Forklift-and-SDV Cross-Dock.

$\widehat{\boldsymbol{R}}$	**Term**	**Coef**	**SE Coef**	**T**	**P**
$\widehat{\boldsymbol{\delta}}$	**Constant**	-13354.1	617.769	-21.617	0
	$\boldsymbol{X_I}$	1021.9	24.989	40.893	0
	$\boldsymbol{X_S}$	89.5	4.165	21.496	0
	$\boldsymbol{X_S}$	107.5	15.03	7.153	0
	$\boldsymbol{X_I^2}$	-22.7	0.327	-69.424	0
	$\boldsymbol{X_S^2}$	-1.1	0.015	-70.007	0
	$\boldsymbol{X_O^2}$	-6.2	0.158	-39.526	0
	$\boldsymbol{X_I \times X_S}$	4.5	0.061	74.173	0
	$\boldsymbol{X_I \times X_O}$	10	0.193	51.841	0
	$\boldsymbol{X_S \times X_O}$	1.8	0.043	41.35	0
$\widehat{\boldsymbol{\delta_M}}$	**Constant**	41.3728	3.21502	12.869	0
	$\boldsymbol{X_I}$	5.365	0.13005	41.253	0
	$\boldsymbol{X_S}$	-0.1322	0.02168	-6.099	0
	$\boldsymbol{X_O}$	-0.0762	0.07822	-0.974	0.33
	$\boldsymbol{X_I^2}$	-0.126	0.0017	-74.069	0
	$\boldsymbol{X_S^2}$	-0.0059	0.00008	-73.354	0
	$\boldsymbol{X_O^2}$	-0.0339	0.00082	-41.205	0
	$\boldsymbol{X_I \times X_S}$	0.0227	0.00032	71.343	0
	$\boldsymbol{X_I \times X_O}$	0.05	0.00101	49.708	0
	$\boldsymbol{X_S \times X_O}$	0.0107	0.00023	47.349	0
$\widehat{\boldsymbol{U_I}}$	**Constant**	0.514788	0.005837	88.196	0
	$\boldsymbol{X_I}$	0.02594	0.000236	109.867	0
	$\boldsymbol{X_S}$	0.001143	0.000039	29.037	0
	$\boldsymbol{X_O}$	0.001511	0.000142	10.642	0
	$\boldsymbol{X_I^2}$	-0.00033	0.000003	-105.32	0
	$\boldsymbol{X_S^2}$	0.000001	0	5.909	0
	$\boldsymbol{X_O^2}$	0.000011	0.000001	7.355	0
	$\boldsymbol{X_I \times X_S}$	-3.6E-05	0.000001	-61.945	0
	$\boldsymbol{X_I \times X_O}$	-5.9E-05	0.000002	-32.402	0
	$\boldsymbol{X_S \times X_O}$	-6E-06	0	-15.903	0

Table B.4: Regression Coefficients: Forklift-and-SDV Cross-Dock.

$\widehat{R}$	Term	Coef	SE Coef	T	P
$\widehat{U_S}$	**Constant**	0.556363	0.02037	27.313	0
	$\boldsymbol{X_I}$	0.039073	0.000824	47.42	0
	$\boldsymbol{X_S}$	-0.00459	0.000137	-33.416	0
	$\boldsymbol{X_O}$	-0.00356	0.000496	-7.177	0
	$\boldsymbol{X_I^2}$	-0.00082	0.000011	-76.036	0
	$\boldsymbol{X_S^2}$	-1.6E-05	0.000001	-31.776	0
	$\boldsymbol{X_O^2}$	0.000059	0.000005	11.423	0
	$\boldsymbol{X_I \times X_S}$	0.000246	0.000002	121.957	0
	$\boldsymbol{X_I \times X_O}$	0.000119	0.000006	18.682	0
	$\boldsymbol{X_S \times X_O}$	-8.3E-05	0.000001	-58.324	0
$\widehat{U_{OB}}$	**Constant**	0.554935	0.044514	12.467	0
	$\boldsymbol{X_I}$	0.035567	0.001801	19.753	0
	$\boldsymbol{X_S}$	0.005631	0.0003	18.762	0
	$\boldsymbol{X_O}$	-0.03352	0.001083	-30.949	0
	$\boldsymbol{X_I^2}$	-0.0008	0.000024	-33.812	0
	$\boldsymbol{X_S^2}$	-4.8E-05	0.000001	-43.286	0
	$\boldsymbol{X_O^2}$	-3.5E-05	0.000011	-3.069	0.002
	$\boldsymbol{X_I \times X_S}$	0.000149	0.000004	33.851	0
	$\boldsymbol{X_I \times X_O}$	0.000385	0.000014	27.632	0
	$\boldsymbol{X_S \times X_O}$	0.000062	0.000003	19.841	0
$\widehat{U_O}$	**Constant**	0.488814	0.016359	29.88	0
	$\boldsymbol{X_I}$	0.041027	0.000716	57.262	0
	$\boldsymbol{X_S}$	-0.00063	0.000119	-5.265	0
	$\boldsymbol{X_O}$	-0.01307	0.000234	-55.939	0
	$\boldsymbol{X_I^2}$	-0.00081	0.000009	-86.117	0
	$\boldsymbol{X_S^2}$	-3.1E-05	0	-70.738	0
	$\boldsymbol{X_I \times X_S}$	0.000182	0.000002	103.925	0
	$\boldsymbol{X_I \times X_O}$	0.000166	0.000006	29.914	0
	$\boldsymbol{X_S \times X_O}$	0.000004	0.000001	3.281	0.001

Table B.4 (continued): Regression Coefficients: Forklift-and-SDV Cross-Dock.

B.2.2 Regression Coefficient Estimation: FL-and-SDV CD

The regression coefficients were estimated through the least-square method for all performance metrics; their significance is given in Table B.4. The table shows that, apart from β_O for the performance metric - $\widehat{\delta_M}$, all other regression coefficients are significant and contribute towards their performance metrics at the given level of significance, $\alpha = 0.05$.

B.2.3 Residual Analysis: FL-and-SDV CD

The residual plots for all performance metrics of the forklift-and-SDV cross-dock are given in Figure B.2. The probability plots and histograms given in that figure show that the residuals of fitted regression models are not normally distributed. In addition, the scatter plot (*Versus Fits*) between the residuals and fitted values shows a clear existing pattern, again unfavourable, between the residuals and fitted values.

This demonstrates heteroscedasticity, the failure of a homogeneous residual distribution once more. This further validates the lac of fitness of the regression models discussed in subsection 4.2.2 of Chapter 4.

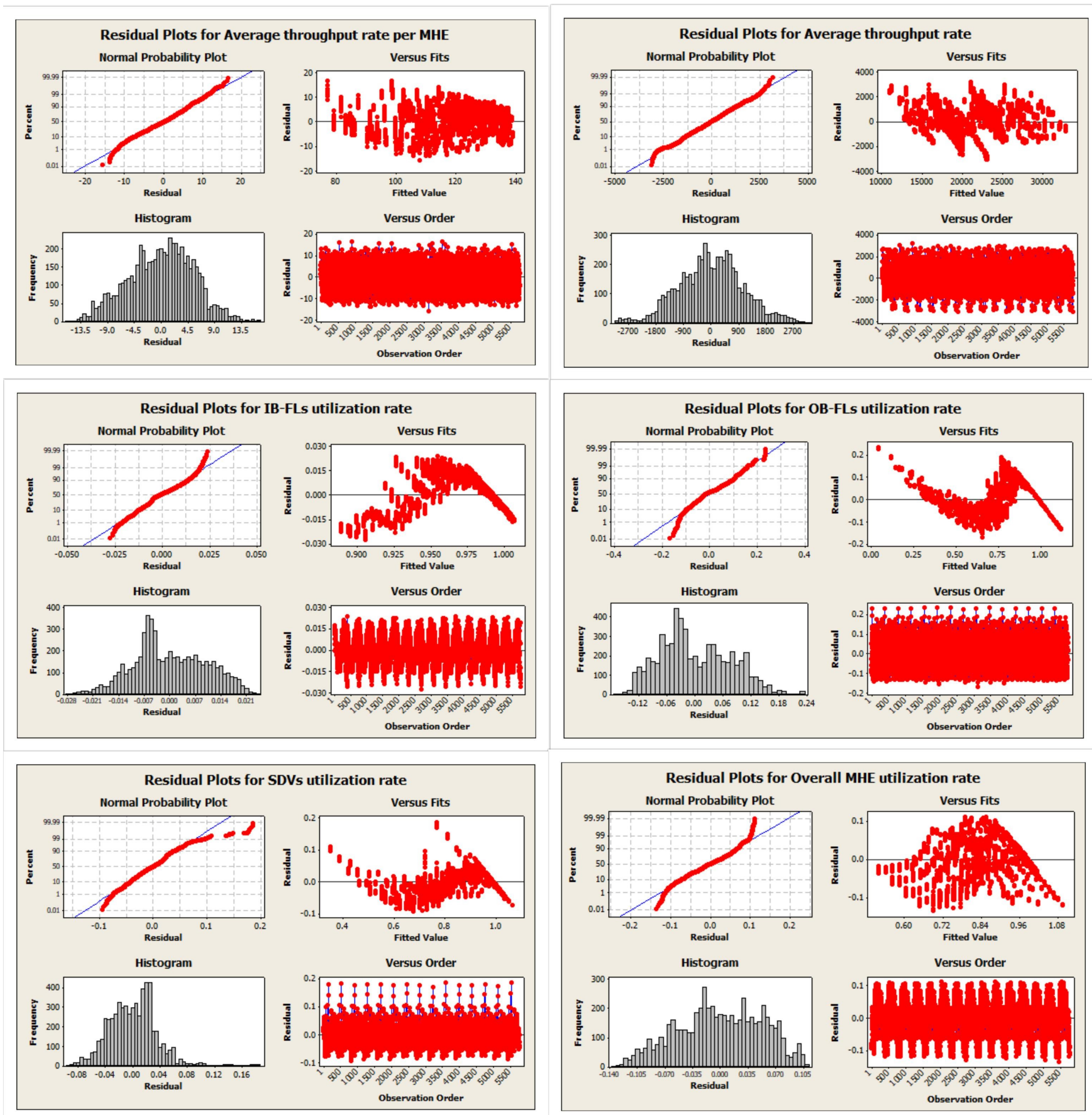

Figure B.2: Residual Analysis: Forklift-and-SDV Cross-Dock.