MASTER

Optimal fleet assignment in inland container logistics

Karunakaran, J.

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Optimal Fleet Assignment in Inland Container Logistics

Janarthanan Karunakaran
Master Thesis
1286706

First Supervisor	dr.ir. M. Firat, TU/e - Information Systems
Second Supervisor	dr.ir. R.M. Dijkman, TU/e - Information Systems
Company Supervisor	M. Van Dijk, Van Berkel Logistics
Third Assessor	dr.ir. L.P. Veelenturf, TU/e - OPAC

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Date

24 March 2020

Name

Janarthanan Karunakaran

ID-number

1286706

Signature

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Abstract

Inland container logistics has many challenges to solve in their daily operations. This study considers one such challenge: agglomeration and distribution of containers to production and consumption centres from *Inland Terminal Veghel (ITV)*, owned and operated by *Van Berkel Logistics (VBL)*. VBL is a container logistics service provider operating in the Netherlands, Belgium and Germany. Inland container distribution at ITV involves container transportation through trucks. The challenge is to fulfil container transport requests from customers with the available fleet. The motivation of the study is to increase operational visibility, to optimise fleet use and to minimise cost of daily operations at ITV.

The study aims to solve the daily fleet assignment problem with time windows (FAPTW) involving assignment of container transport requests or orders to trucks in the fleet. Initially, the research devises two fleet assignment policies: an *economic assignment* approach and a *greedy assignment* approach. Then, the study formulates mixed-integer linear programming (MILP) models based on the policy. From the results of the models, the research compares two policies with actual routing with respect to four attributes: cost, number of trucks used, on-time service and computation times. Analysis reveals both basic MILP model and *one-to-many* matching model based on greedy policy are performing better than the actual routing plans at *Van Berkel Logistics*.

Keywords: Fleet Assignment, inland container logistics, Scheduling, Linear programming, MILP

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Executive Summary

Introduction

This master thesis aims to develop a decision support system for daily fleet assignment process in inland container terminal at Veghel owned and operated by *Van Berkel Logistics (VBL)*. The current fleet planning practise for trucking containers is time-consuming and error-prone. The research proposes a system to replace the cumbersome manual-planning process for trucking containers to production and consumption centres from the inland container terminal Veghel.

Research Methodology

The research methodology involves finding relevant operational aspects of fleet assignment and legal driving regulations that affects the daily fleet assignment plans. After determining the solution objectives for fleet assignment problem with time windows, the research explores relevant literature from multiple fields to devise fleet assignment policy and to mathematically model the case. Then, the research performs computational experiments with the developed models and evaluates their performance with actual (manual) routing plans.

Results and Conclusion

From the literature survey, the research devises two fleet assignment policies: first, *economic assignment* that aims to minimise service deadline violations, utility and assignment costs, and second, *greedy assignment* policy that intends to maximise the utilisation of trucks with on-time rewards by assigning as many orders as possible (starting from the cheapest truck in the fleet). Based on the policy for fleet assignment, the research develops three models: *basic* model, *optimal trip* model and *matching truck* model. Among the three models, *optimal trip* model performs worse than the other two models, in terms of utility and assignment cost, and number of trucks used. On comparing the results of the computation experiments, basic model and matching truck model performs better than actual routing on four solution attributes: on-time service plans, number of trucks used, and utility and assignment costs. With relaxation, basic model is comparable to matching truck model in terms of computation time. In terms of solution objectives, basic model (with relaxation) outperforms the matching truck model. However, for particular cases where there is a very high demand for trucking containers owing to congestion at the port and *VBL* is unable to fulfil demands with its fleet and known charters, basic model provides no solution to such infeasible cases. In such cases, matching truck model assigns as many orders a possible to the given fleet of trucks and leaves few orders unassigned. *VBL* can sell those unassigned orders to other *logistics service providers*.

The study recommends following future works in the fleet assignment problem with time windows: *Real-time assignment* of trucks to orders will be challenging as it involves real-time tracking of trucks and takes on-road traffic into account. Consider *flexible time windows* for order service. Introducing customer-specific deadline *violation tolerances* can provide further insight into the analysis. In the greedy approach, changing *order of optimising trucks* may lead to different results. Testing the models with more data instances may also provide better insights on the performance of models.

Contents

List of abbreviations

TEU	Twenty foot Equivalent
VBL	Van Berkel Logistics
ITV	Inland Terminal Veghel
KAT	Inland Terminal Cuijk
RTM	Port of Rotterdam
ERP	Enterprise Resource Planning
ICT	Inland Container Terminal
UNCTAD	United Nations Conference on Trade and Development
JIT	Just in Time
CDP	Container Distribution Problem
VRP	Vehicle Routing Problem
FAPTW	Fleet Assignment Problem with Time windows
MMSP	Multi-machine scheduling problem
CoDeP	Concrete Delivery Problem
MILP	Mixed Integer Linear Programming
m-TSPTW	multiple travelling salesman problem with time windows Delivery Problem
RMCDSP	Ready-mix Concrete Distribution scheduling Problem
mICT	multi-size inland container transportation problem
MIP	mixed-integer programming
VNS	Variable Neighbourhood search
FTPDPTW	Full-Truckload Pickup and Delivery Problem with Time Windows
PMSP	Parallel Machine Scheduling Problem
AFAP	Airline Fleet Assignment Problem

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Chapter 1

Introduction

In the first section, Chapter 1 introduces the container logistics industry and briefs the role of port and inland terminals in hinterland transportation. Second section explains the operations of inland container terminal at Veghel and the current planning practise followed for fleet assignment for transporting containers. Third elucidates the motivation for the study, fourth lists the research questions and the last mentions the report structure.

1.1 Introduction to Container Logistics Industry

Logistics has gained prominence across the globe as the economy grew increasingly specialised and globalised. The ever-changing economic environment, such as production patterns, globalisation, urbanisation, environmental concerns have further fuelled this trend[7]. Ever since the introduction of containers in the 1960s, global trade and shipping have grown in multitudes. The innovation of *containerization* in transport, attributed to Malcolm Mclean: an American trucker who conceived the idea of separating the tractor from the trailer part of his trucks, standardizing the trailer and enabling it to be transported with its contents intact. With containerization, the labour productivity in ports has risen in multi-folds as transport of goods are reduced to a single box. This lead to containers playing a significant role in the world trade, enabling transportation through air, sea and road[12].

United Nations Conference on trade and development (UNCTAD) attributes the global merchandise over 80 percent by volume and over 70 percent by value to sea-freight. More than half of the total value of seaborne trade is through containerized cargo transport by *liner shipping carriers*. For global trade and development, maritime transport is highly significant [1]. The global containerized trade volumes are growing every year, and in 2018, it increased by 2.6 percent amounting to 152 million TEUs [3] as depicted in figure 1.1. To meet the growing containerised trade demands, the port being a gateway to the cargo (containers), have to be competitive and efficient in its operations. Also, over the years, the role of ocean ports have evolved from the 'interface between land and sea transport' to 'dynamic nodes in the complex international production/distribution network'[6].

Inland container logistics or the hinterland transport of containers influences the competitiveness of port. The UNCTAD clearly states that land transport access to and fro port is as important as access to maritime transport networks for the port to be competitive. It negatively impacts on the activities of the port terminal operator, if there is lack of or ineffective connection between port terminal and centres of production, distribution and consumption in the transport networks (like inland container terminals), even if the port is highly efficient[3]. Thus, this shifts the onus of the inland container terminals (ICT) to be efficient in their operations to cater to the changing roles of the port, to have effective inland distribution systems between centres of production, consumption and to meet the increasing demands of container-handling at the ports. This thesis is a study in the direction of making ICT more efficient in their operations. The aim of the study is to plan and schedule the trucking operations of the ICT better to evolve effective distribution systems.

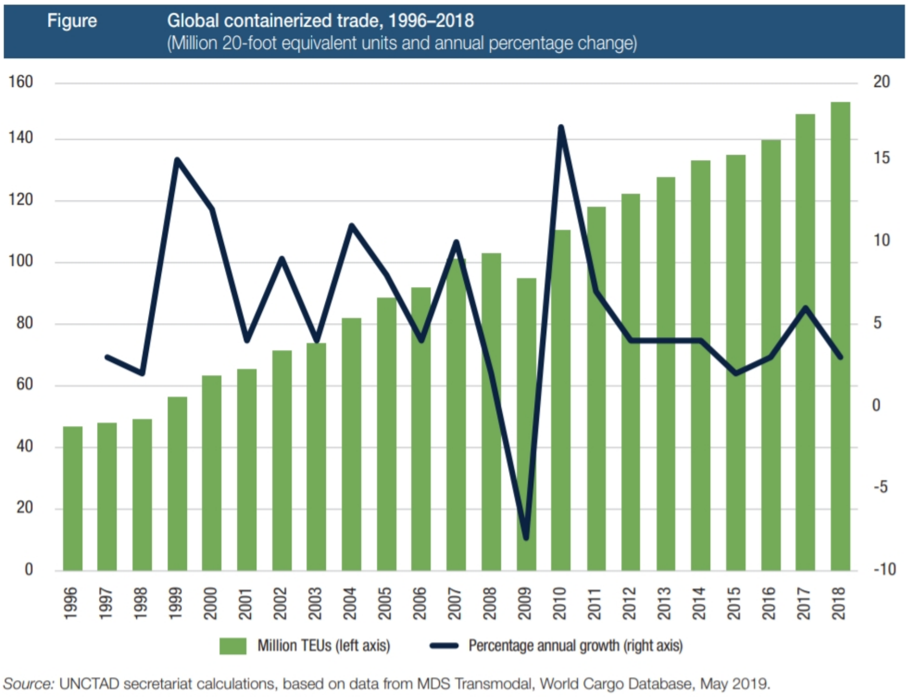


Figure 1.1: Volume of global containerized trade between 1996-2018

The study is conducted at Inland Terminal Veghel (ITV) owned by Van Berkel Logistics (VBL), which is a crucial player in the container distribution chain in the region of North-brabant. In 2005, VBL was started as a transport company, and it is a *logistics service provider* that operates predominantly in the region of North Brabant. However, the clients of VBL are spread across the Netherlands (esp. North Brabant), Belgium and Germany.

1.2 Operations of Inland container Terminal Veghel

This section explains the container movement patterns in inland container logistics, the current planning practise at inland terminal Veghel and highlights the drawbacks of the manual planning.

1.2.1 Container Flow Patterns

VBL transports containers from and to the port of Rotterdam and Antwerp to its inland terminal Veghel (ITV) through its barges. From ITV, the containers are transported between locations as specified in the client order demands. Figure 1.2 represents container flow between Port, ICT and client locations. At times, due to shorter delivery time windows or other unforeseen situations like the bad weather stalling barging operations, the containers are transported between Rotterdam port and ITV through trucks. The focus of the logistics scheduling in the study involves the last-mile distribution of containers to client locations and container movements between ports of Rotterdam / Antwerp and ITV through trucks.

1.2.2 Current Planning Practise

Inland terminal Veghel (ITV) has a fleet of trucks at its disposal to cater last-mile distribution of containers. Also, it hires charters to meet demand overflows of trucking containers. At present, in ITV, the fleet assignment involves a central planning approach illustrated in figure 1.3: knowing the availability of trucks in the fleet for the day and assigning them to serve orders for the day. Here, order refers to the container

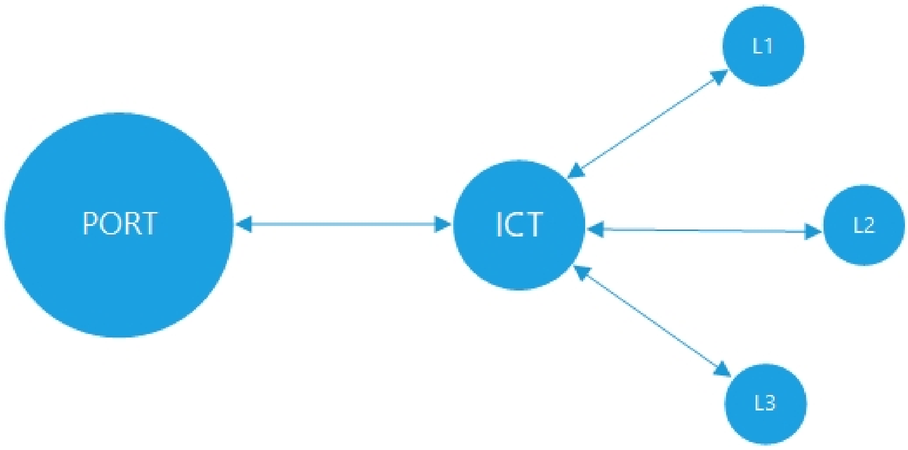


Figure 1.2: Container Flows in Inland Container Terminal at Veghel (ITV)

movement between ITV and a specific location by truck. Typically, planners make the order assignments to truck the previous day of order service and monitor the assignments during the service day. These are the steps for planning the day:

- Knowing the list of the orders to serve for the day
- Recording driver and truck availability for the day
- Assign feasible trucks to orders considering driver preferences, ability and delivery time windows
- Keep assigning until all orders are assigned

The study, too, adopts a central planning approach.
Generally, the planner fetches the list of orders from the database in *Modality* and plans assignment in spreadsheet i.e. *MS-Excel*. *Modality* is the order entry database from which the planner exports order list to *MS-Excel*. It takes on an average 8 hours of manual labour to plan for a day. There are two planners who work on truck assignment. One, plans for the following day assigning orders to trucks and the other supervises the plan that the first planner makes for the day. The outcome of the study emulates the role of the first planner.

1.2.3 Drawbacks of Current Practise

The steps that the planner follows in manual planning are cumbersome and time consuming, leads to error prone even at times infeasible assignments. Errors in manual planning include

- *Infeasible plans:* assigning trucks incapable of serving the order.
- *Conflicting assignment:* allotting multiple orders to a truck to serve at a time.
- *Resource Occlusion:* using a critical truck (like the port ones) for near-by delivery and lacking it for crucial orders later in the day.
- *Order Omissions:* At times, orders are left unassigned to any truck. Though this is rare, it is detrimental to trucking operations.

To avoid these, the study aims to propose a process automation for fleet assignment.

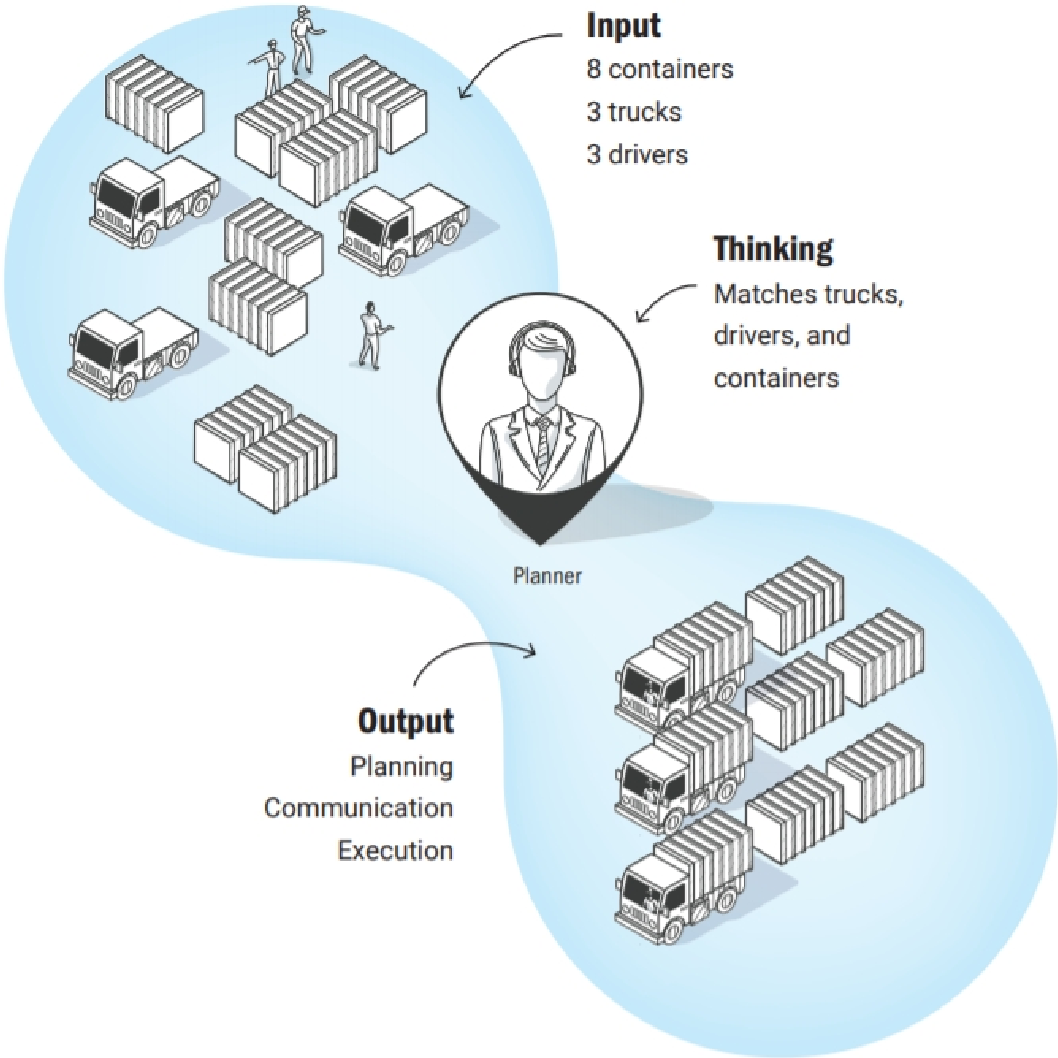


Figure 1.3: Central Planning of a Container Distribution Problem - CDP [4]

1.3 Motivation of the study

The motivation for the study st ems from the UNCTAD's annual reports on maritime transport wherein it cites digitalization in ports, as a factor that is evolving at an accelerated pace has profound implications on port operations. Also, container terminals are increasingly adopting higher levels of automation to improve their efficiency and productivity [2]. Furthermore, in the annual *review of maritime transport* report of 2019 [6], UNCTAD states as follows:

"Players in the shipping industry are increasingly taking advantage of digitalization and joint collaborative platforms and solutions enabled by new technologies and innovations. The report also notes that the introduction of automation in global transport will be 'evolutionary, rather than revolutionary'"

It mentions the benefits of such solutions includes greater supply chain visibility, better use of underutilized resources, and adds flexibility for service providers.

1.4 Research Questions

This section briefly explains the main research question and lists its sub-questions. The main research question is as follows:

RQ *How to automate daily fleet assignment process to truck containers between production / consumption centers and inland container terminal?*
The process automation has to make feasible plans to fulfil container transport requests that the inland terminal receives. These are the sub-questions of the research:

SQ1 *What are the operational aspects that needs to be considered for the daily fleet assignment?*

SQ2 *What are the legal driving regulations that affects the daily fleet assignment plans?*

SQ3 *What is the truck allocation policy for the daily fleet assignment to fulfil container transport requests?*

SQ4 *How to mathematically model the case based on the proposed policy, including the operational aspects and driving regulations for the daily fleet assignment?*

SQ5 *Based on testing of the models, determine which is the suitable policy for daily fleet assignment at the inland container terminal?*

1.5 Structure of the Report

Following introduction in chapter 1, Chapter 2 elaborates the problem, and Chapter 3 explores relevant research works involving similar problems and briefs their approach. Chapter 4 proposes policy for fleet assignment and formulates the mathematical model based on the policy. Chapter 5 discusses the results of computational experiment of the models formulated in Chapter 4. Chapter 6 concludes the study, offers further recommendations to the company and discusses possible future work.

Chapter 2

Problem Description

This chapter unfolds the problem, and its characteristics, explains the solution characteristics and objectives. Also, it establishes the research goals and the approach towards achieving it. Lastly, the chapter concludes with defining the scope of the study.

2.1 Problem Introduction

The study involves logistics planning challenge arising out of container distribution problem (CDP) in hinterland transportation. There is a network of nodes for distribution, with the inland container terminal at Veghel (ITV), being the central node (depot of containers). The ITV aggregates and distributes containers from/to consumption and production centres referred to as *clients or customers* in the report. Predominantly, barges forward (collects) containers to (from) the port terminals. Since VBL employs trucks to transport containers to the port as well, port terminals in Rotterdam and Antwerp are considered as nodes in the network, too. Generally, customers place orders with VBL specifying the address and the time to transport containers to (or from) known as the *service location* and *service deadline* of the order. VBL references orders with a unique booking number, container details (like container number, dimensions, type: reefer/regular), customer, service location and deadline. The following sections describes the fleet characteristics, truck routing plans and terminal-operations characteristics description to understand daily trucking plans.

2.1.1 Fleet Characteristics

Every truck in the fleet and the charters are capable of transporting all containers regardless of its type (reefers, regular) and dimensions (20 TEU, 40 TEU). However, the drivers with their ability, license permits and preferences alter the capability of the trucks. The capability of trucks to cover distances is called the *radius of operation*. Accordingly, fleet classification is as follows:

- *Terminal trucks:* Drivers with less driving experiences and just graduated from driving college can drive to service locations situated within 5 km radius from ITV. The trucks they drive constitute terminal trucks in the fleet.
- *Regional trucks:* Experienced drivers either without a permit or prefer to avoid going to ports drive the regional trucks. They serve all service locations except the port terminals.
- *Port trucks:* Well-experienced drivers with permit and preference to drive to port terminals drive port trucks. Port trucks serve all nodes in the network.

The fleet of trucks (considered as resource in the problem) is homogeneous in capacity and heterogeneous in capability. The charter hires are either of regional or port type. Consequently, orders are classified into the terminal, regional and port orders, depending on where the service location is in the network. Figure

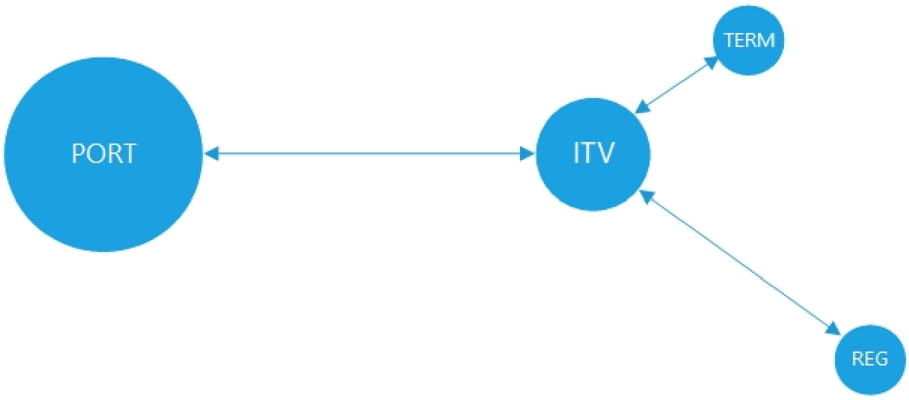


Figure 2.1: Fleet classification in terms of radius of operation

2.1 depicts the three types of trucks: port, regional (as REG) and terminal (as TERM). The size of nodes in figure 2.1 has nothing to do with the container volumes trucked to them from ITV but a mere indication of the node's geographical size.

2.1.2 Routing Plans

Inland container distribution logistics is a particular case of the Vehicle Routing Problem (VRP). Unlike the classical VRP, where the truck loads cargo and serves multiple locations in a trip, where a trip is defined as the movement of truck originating from a logistic hub (ITV in this case) and may visit multiple customer locations and returns to the hub. Here, the routes (or trips) of a truck are dedicated to serve a single customer and returns to the terminal. So, there is no selection of location is involved in determining the route plans in the container distribution problem (CDP). As distances between the ITV and the serving

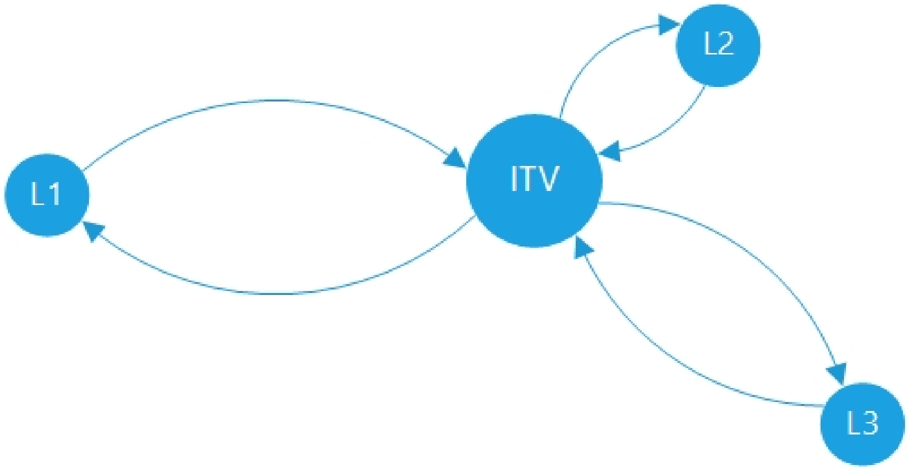


Figure 2.2: Routing plans of Trucks at ITV

node is considered as constant, *driving duration* (of an order) between the nodes and ITV is deterministic. The time a truck spends at the serving node, known as *process duration* (of an order), is deterministic as well. Process duration includes loading / unloading the container with contents, waiting time, time for document clearances and gate entry at the serving node. Service duration of the node, i.e. the sum of process duration at the node and twice the driving duration (including the return to ITV) to the node, is a property for a node and is deterministic. Figure 2.2 illustrates the routing plans of trucks, with ITV as the central node and L1, L2, L3 represents the nodes that the trucks serve (port terminals and customer locations). To explain how one trip is performed, consider a day with terminal operation windows (of 4.00

hrs in the morning to 18.00 hrs in the evening) having order *o* from customer at L3 (regional order) to deliver a container with deadline of 12.00 noon, driving duration to L3 from ITV is 45 minutes and the order process duration is 30 minutes. Then the latest departure time from terminal for the truck *t* serving order *o* is 11.15hr. Total service or trip duration for serving the order lasts for 120 minutes. Since this is a regional order, the serving truck can be of either regional or port type. The truck *t* has to depart at least by latest departure time to deliver the container on-time. Even if the truck *t* serves the order violating the deadline it has to be within 18.00hrs the terminal operational window

2.1.3 Terminal-Operations Characteristics

Typically, an operational day consists of a mix of orders with multiple nodes with service duration ranging from 25 minutes to 4 hours. At times, on a day, a customer may request multiple containers, so trucks drive multiple times to the same node as well. Usually, in 2019, ITV has catered to 105 to 115 number of orders on an average day. However, on exceptional days orders could be as high as 150. Terminal has 32 trucks in its fleet for fulfilling container transport requests to customers. To meet demand overflow in trucking containers, terminal hires charters. Generally, in the weeks when the weather conditions are unfavourable for barging, or if there is congestion at the port of Rotterdam, then the terminal hires a higher number of chartered trucks as the demand for trucking container increases. Terminal operations starts at 4.00 hr in the morning and closes by 18.00 hr in the evening. Occasionally, it may start early or extend little more than an hour. So operational window is in the range 14 to 16 hours. The planning aims to serve all orders within the terminal operational window, .

2.2 Problem Characteristics

As orders have latest time to serve the node, or the *service (delivery) deadline*, and the CDP involves order to truck assignment problem, it decomposes as fleet assignment problem with time windows (FAPTW) at an ICT. The challenge of the study is to solve the FAPTW at inland terminal Veghel.
The case has a network of nodes (service locations and port) each connected to the terminal as part of inland container logistics. Inland terminal receives transportation requests or orders to transport containers with deadlines. Terminal has a fleet of trucks at the start of the day. The challenge is to serve orders in this network with a given fleet of trucks and meet order deadlines. To transport any container in the case, the truck departs from the inland terminal, performs service at the node and returns to the inland terminal. Though trucks exchange containers at the serving node (deliver a full and pick up empty container or vice versa), generally, they all do a round trip.
Following passages elucidates the terminology, properties of network, order and truck. Table 2.1 specifies the set and parameters of fleet assignment problem with time windows. The following subsections explains the real-life concepts and components of the problem including the terminology involved, properties of order, truck and the problem constraints.

2.2.1 Terminology

- *Network:* The inland container logistics network (referred as the network) comprises of following nodes: inland terminal, service locations and port. Each node is connected to the inland terminal and the time to drive between nodes is deterministic (so as the distances between them).
- *Terminal:* An inland terminal (referred as the terminal in this document) serves as central depot for collection and distribution of containers. So, typically it is the origin of all truck movements for serving any order.
- *Port:* Port is the sea-land interface where the vessels discharge (or load) containers after a voyage across the sea. In terms of the problem, port is the node where trucks deliver or pick up containers on any day.
- *Customers:* Customers (also referred to as Client) are an external party who places container transport requests or orders with the inland terminal Veghel.

- *Orders:* Orders involve container movement through truck between the terminal and service node (customer service location or port) in the network. Orders are distinguished by their type, service location. O is the set of orders and the following section describes its properties (indexed by o).
- *Trucks:* In terms of the problem, trucks transport containers between nodes. So their availability is key to serve an order. T is the set of trucks and its properties are indexed by t.
- *Service location:* Service location is a node in the network where truck transports container, It could be delivery or pickup of a container or both. It is part of the order description and specific to each order.
- *Trip:* Trip of a truck contributes to serve an order. In a trip, truck originates from the terminal serves a node (container transaction happens) and returns to terminal. All trips are dedicated to one node (customer) alone.
- *Nodes:* Terminal serves as the central node to which all other nodes are connected. Other nodes being the port and customer service locations of orders.
- *Distances between Nodes:* These are deterministic and orders have an origin (terminal) and a destination (client location or port). Hence, the driving duration between the nodes is considered to be deterministic.

2.2.2 Properties of Order

Orders have a set of properties which helps in formulating the fleet assignment problem with time window and are listed as follows:

- *Driving duration and Return duration for an order*: Driving duration c_o is the time required to drive to the service location from the terminal. Return duration is the time taken to drive back to the terminal after delivering or picking up the container. Both the return and driving duration are deterministic and depends upon the delivery or pickup location and its distance from the inland terminal.
- *Process duration for an order*: Process duration p_o is the time that a truck spends at the serving node for loading (or unloading) the contents of the container. It includes the waiting time for loading (or unloading) at the node. It is deterministic and is a constant for a specific customer.
- *Service duration for an order s_o*: Also known as the *trip duration of an order*, it is the total time duration needed for a truck to serve order o, where $s_o = 2c_o + p_o$.
- *Latest departure time from terminal for a truck to serve an order d_o*: It is the latest time that the truck has to start from the terminal to the service location to meet the *service (delivery) deadline l_o* from terminal for a truck to serve order o, where $d_o = l_o - c_o$.
- *Order type*: Orders are of three types depending upon the distance of delivery or pickup of containers and the service location namely:
  - *Terminal Orders*: Nodes of orders that are located in and around the inland terminal: say within a distance of 5km.
  - *Regional orders*: Orders that are above 5 km but not to the seaport.
  - *Port Orders*: Orders that have container movements to or from the seaport of Rotterdam or Antwerp.
- *Order hierarchy h_o*: is a derived measure and has a discrete value. It increases as its node is farther from the inland terminal.

Set	*Description*
O	*Set of orders indexed by o,*
T	*Set of trucks indexed by t,*
Parameters	
type (o)	*type of order o,* type(o) ∈ {*port, terminal, regional*},
type (t)	*type of truck t,* type(t) ∈ {*port, terminal, regional, chartered*},
c_o	*driving duration between terminal and service node of order o,* $c_o \in N$,
p_o	*process duration of the order o at the service node,* $p_o \in N$,
l_o	*service (delivery) deadline of an order o,* $l_o \in N$,
h_o	*hierarchy of order o,* $h_o \in \{0,1,2\}$,
h_t	*hierarchy of truck t,* $h_t \in \{1,2,3\}$,
w_t	*utility cost of truck t*$\in T$, $w_t \in N$
w_{max}	*maximum value of the utility cost of trucks*$\in T$, $w_{max} \in N$

Table 2.1: Sets and Parameters of Fleet Assignment Problem with Time Windows

2.2.3 Properties of Truck

The study classifies the trucks in the fleet based on its radius of operation. The classification influences the utility costs and hierarchy.

- *Operational Radius*: Certain trucks in the fleet have limitation of serving orders depending upon the distance from the inland terminal due to its driver ability, license permit and preference. The distance up to which the trucks can serve orders is the operational radius.
- *Truck type*: There are typically three types of trucks depending upon operational radius namely
  - *Terminal trucks*: Trucks that can serve terminal orders only.
  - *Regional trucks*: Trucks that can serve both regional and terminal orders but no port orders.
  - *Port trucks*: Trucks that can serve all three types of orders: port, regional and terminal orders.
  - *Chartered Trucks*: If there is a demand overflow of orders, then terminal hires chartered trucks to fulfill the unassigned orders. Charters are of either port or regional type.
- *Hierarchy of truck t* represented as h_t: It is a derived parameter based on the above classification. The logic behind the value: larger the radius of operation for the truck larger the hierarchy value.
- *Utility Cost or cost of use*: Utility cost of a truck t depends upon the criticality of truck which indeed, depends on its operational radius. The values follow the same logic as hierarchy: larger the operational radius higher the costs. The study considers the cost of use and cost of truck assignment to be of same value.

Type	Truck hierarchy h_t	Order hierarchy h_o	Utility cost w_t
Terminal	1	0	1
Regional	2	1	5
Port	3	2	10
Charter-regional	2	-	15
Charter-port	3	-	20

Table 2.2: Order and Truck Hierarchy, Utility Cost- Type wise

Table 2.2 represents the type-wise hierarchy of orders and trucks, utility cost of trucks. The hierarchy values start from 0 for terminal orders and 1 for terminal trucks. Order hierarchy is taken 1 lower than the trucks of the same type to indicate orders can be served by trucks of higher hierarchical values. It increases by 1 for both of them (as the distance of node for the order increases and as service capability of the truck increases). The utility cost of the truck starts from 1 for terminal trucks and increases in multiples of 5 as its service capability for the trucks in the fleet. However, for charter-regional trucks, the study takes a higher value than the ones in the fleet because, it is economical for ITV to use the ones in its fleet fully, then hire charters. That is why charter-regional has a higher utility cost than the port trucks in the fleet despite charter-regional trucks' lower service capability. However, the service capability of charter-port and port truck in the fleet, charter-regional and regional truck is the same. So are their corresponding hierarchical values.

2.2.4 Constraints of the Problem

The problem has a set of operational constraints and legal driving regulations that the model has to comply. The operational constraints are on the basis of inputs from the truck planning and the EU regulation [8] is the source of legal ones. All model formulations described include these constraints, however their mathematical model shall vary in each of them. Operational constraints can be classified as assignment and temporal constraints. The assignment constraints are as follows:

- *C1 – Exactly one trip for each order*: Each order has to be served in a single trip of a truck only. None of the orders needs to be carried out by multiple trips or trucks i.e. all orders are served by one truck in a trip only.
- *C2 – At most one order for each trip*: Each truck should be assigned only one order at a time as multiple orders can't be served simultaneously by any truck in a trip. This has to do with the capacity of trucks: transporting one container at a time. It involves a temporal as well as assignment aspect.
- *C3 – Truck-Order Compatibility*: Only a feasible truck depending upon their operational radius can be assigned to a order. In the sense:
  - Port orders can be assigned only to port or charter-port trucks.
  - Regional orders can be assigned to either regional, charter-regional, port, or charter-port trucks but not terminal trucks.
  - Terminal orders can be assigned to any of the truck type.

  Temporal Constraints involved in the problem includes:
- *C4 – Time window of the terminal*: Departure time for trucks from the terminal for serving an order has to be after the start of the inland terminal. Also, all orders must be served within the operational window of the terminal.
- *C5 – Consistent arrivals and departure times of trips*: Trucks can depart for a trip (serving an order) only after arriving at the terminal completing the previous trip (order service).

The model considers legal compliance for drivers outlined by EU regulation as drivers influences the fleet and truck characteristics. They are as follows:

- *C6 - Scheduling break*: In the EU regulation article 7 [8], a driver has to take two breaks in a 6-hour work period: one, 15 minutes-break and one 30 minutes-break. Drivers take 15 minutes-break at the serving nodes as the process duration of any node is usually 15 minutes or more. So after 6 hours of work, the truck and its driver have a break of 30 minutes and do not take up any order. This can be done by postponing the departure time of the order that the driver (and the truck) serves immediately after operating for 6 hours.
  To explain the break scheduling, consider a truck (with a driver) that starts at 6.00hr in the morning, serves its first order in the day with 3 hours of trip duration (between 6.00 hr and 9.00 hr), the second order with 2 hours of trip duration (between 9.00 hr and 11.00 hr), and the third order with 1 hour of trip duration (between 11.00 hr and 12.00 hr). All three trips has 20 minutes of process duration which is included in the trip duration. Then, the fourth order

that the driver (and the truck) takes can be only from 12.30 hr. This can be also viewed as an elongation of the third trip's duration by 30 minutes.

– *C7 - Caps on driving time and working time*: EU regulation Article 6 clause 1 [8], specifies that for a driver the driving duration should be within 9 hours in a day. Article 8 clause 2 [8] mentions rest time for drivers as 11 hours in day, so working time can be 13 hours. However, the ITV restricts it to 12 hours a day. Due to the caps on driving time and working time of drivers, the number of 30 minute-breaks need to be scheduled reduces to 1 in the case.

2.3 Solution Characteristics and Quality

This section explains the solution description and elucidates the solution objectives.

2.3.1 Solution Description

The study formulates a mathematical model to the fleet assignment problem with time windows (FAPTW) based on the above-listed objectives and intends to achieve the optimal fleet assignment. As the parameters of the FAPTW, is considered as deterministic, mixed-integer linear programming (MILP) model is formulated. The study explains the model by introducing the decision variables, then defines the objective function and finally models the constraints. To summarise the constraints in the Subsection 2.2.4, the main constraints in the model are:

- Assign all orders to feasible truck considering operational capability.
- Assign exactly one trip of a truck to an order.
- Assign orders adhering to temporal feasibility: one, departure time of a trip for a truck has to be after completion of previous trip and second, all trips of a truck has to be within the terminal operational window.
- Schedule break to truck once its trip or service duration exceeds 6 hours.
- Assign orders to trucks complying to the legal driving and working hours of drivers.

2.3.2 Objectives

Since, orders have latest time to serve the node, or the *service (delivery) deadline*, and the CDP involves order to truck assignment problem, it decomposes as fleet assignment problem with time windows (FAPTW) at an ICT. The challenge of the study is to solve the FAPTW at inland terminal Veghel.
Generally, one of the primary motives of logistic services is to keep customers delighted and the most common one being on-time order delivery performance, which forms the first objective of the problem. Though hiring chartered trucks to cater to overflowing demands is necessary, it costs a lot to the inland container terminal Veghel (ITV). So, the second motive is to hire charters as few as possible on a service day. The third motive is to reduce the number of trucks used in the fleet for the service day as it helps to reduce the fleet operations cost in a day for ITV. The study considers following objectives for the daily fleet assignment problem with time windows:

- *Achieve high on-time performance:* Minimise Order Deadline Violations.
- *Minimise Assignment Costs:* Assignment of trucks to serve order has a cost. Minimising assignment costs ensures - orders of a type is assigned to trucks of the same type, prevents resource occlusion 1.2.3, ultimately minimising the hiring of charters (and the additional costs it incurs to the company).
- *Minimise utility costs:* For trucks, there is a fixed cost of use. So minimising the number of trucks used on the day will reduce the overhead expenses like that of driver remuneration on the day.

These are hierarchical objective with the same order listed above as customer do not encourage violating order deadlines. As with other logistics scheduling problems like VRP, it is tempting to reduce the number of trips that a truck makes in a day to reduce the cost of a day's operations. However, it is infeasible in the case. It is because of the fact, in the container distribution problem (CDP) described here, a truck serves one node (customer or port) in a single trip. Technically, the cost of driving to a node is constant (as distances between are taken as invariable) and process duration at a specific service node is also considered to be invariable. So, the operation costs are fixed for serving a customer, leading to deterministic operation costs for the logistics service provider (VBL) in a day. That is why the study aims to reduce the operation cost by minimising the number of resources (trucks in this case) utilised in the day.

2.4 Research Goals

The main goal of the study is to develop a decision support system of assigning orders to fleet of trucks in inland container logistics. The sub-goals of the study is to determine a suitable fleet assignment policy by mathematically modelling:

- *operational aspects* of fleet assignment.
- *legal driving regulations* of European Union for truck drivers that affect fleet assignment.

The study adopts the following steps to achieve the research goal.

- Literature survey on resource allocation policy to learn how similar problems are approached.
- Based on the literature survey, devise fleet assignment policy for ITV considering the objectives defined in subsection 2.3.2.
- From the policy proposed, formulate mathematical models.
- Testing the models with instances and evaluating the results with actual routing. This is to understand the performance of the models considering the actual routing plans.

2.5 Scope of the study

Though the drivers are an integral part of the container distribution problem, the study does not take drivers into account for fleet assignments. Nevertheless, it considers the driver preferences, ability and license permits and includes them in the fleet characteristics. FAPTW considers orders with deadline for which containers are available to serve customers on a specific day. The impact of barging operations affecting container availability and container detention charges on fleet assignment are outside the bounds of this study. Also, the primary focus is to solve the FAPTW by MILP models, evaluate the results of the models, and compare it with actual routing plans on the following solution attributes: cost, number of trucks used and on-time performance.

Chapter 3

Literature Discussion

To frame resource allocation policy for fleet assignment and to model it mathematically, chapter 3 elaborates literature involving similar problems. First, the study searches literature in container distribution logistics to model the fleet assignment problem with time windows (FAPTW), then it looks into other sectors like concrete delivery logistics, manufacturing and airline fleet assignment. Also, the study summarises research involving driver assignment to fleet. In manufacturing, the literature revolves around multi-machine scheduling problem (MMSP) with minimizing tardiness as it is equivalent to FAPTW. The study compares FAPTW with airline fleet assignment as well. The following passages discuss literature related to these cases.

3.1 Related work in Distribution Logistics

The literature survey in distribution logistics revolves around three problems namely container distribution logistics, driver assignment cases to a fleet of vehicles and concrete delivery problem.

3.1.1 Container Distribution Logistics

Zhang et al [20] mathematically model an inland container logistics challenge based on a preparatory graph formulation to solve a multiple-travelling salesman problem with time windows (m-TSPTW). The paper accounts for four container movements: inbound full and inbound empty to the depot, outbound full and outbound empty from the depot. The paper considers multiple depots and homogeneous fleet as part of the problem. However, FAPTW considers one central terminal and a heterogeneously capable fleet. Though FAPTW includes all container movements, it does not classify the container movement like Zhang et al[20]. Funke and Kopfer [9] provide an extension of Zhang et al [20]. The paper describes a multi-size inland container transportation problem (mICT) with a heterogeneous fleet and formulates mixed-integer linear programming model with two different objective functions: minimisation of total travel distance and minimisation of total operation time of the trucks and compares the results. The model solves the combined problem of assigning containers to requests and building routes for trucks. Further, in their paper, Nossack and Pesch [16] model a truck scheduling problem as full-truckload pickup and delivery problem with time windows (FTPDPTW) to minimise the total truck operating time of all trucks in use. The authors classify transportation requests into two: pickup and delivery and solve it by a two-stage heuristics: a route construction heuristic and a route improvement heuristics. They consider containers as full truck-load and formulate the FTPDPTW analogous to m-TPSTW [20] involving multiple depots and a homogeneous fleet of trucks to transport containers.

3.1.2 Concrete Delivery Problem

One of the logistics cases where distribution from a central node occurs is in the concrete delivery problem (CoDeP). The demands for concrete arise from constructors situated around the concrete factories and the

delivery has to before the ready-mix concrete starts to set (as it is perishable). Also, constructors do not like late deliveries at it affects their project schedules. So delivery within the requested time window is an essential aspect of concrete logistics. Trucks start trips from the concrete factory and deliver ready-mix to a constructor and return to the factory. However, trucks in CoDeP are usually of heterogeneous capacity unlike the homogeneous fleet capacity of the fleet assignment problem with time windows (FAPTW).
Schmid et al [18], consider a Ready-mix-concrete delivery scheduling problem (RMCDSP), propose a hybrid solution using MILP formulation and a variable neighbourhood search (VNS) approach. Using VNS the paper generates feasible solutions for medium-sized real-world test instances and uses MILP to improve solution quality. Like the FAPTW, RMCDSP has the following characteristics: one truck serves an order at a time, no multiple orders are loaded in the truck at the same time. As constructors require constant inflow, single deliveries should take place on-time but delivery is not supposed to be postponable. Unlike FAPTW, in RMCDSP a single order typically is executed by multiple trucks due to capacity constraints of the truck. Even, if the trucks are partially full, only one order is filled in a truck at a time. Generally, an order is completed with multiple deliveries which is contrary to FAPTW where one order is completed (served) in one trip. Constructors place orders with time windows within which the first delivery should happen and it cannot be early. The following deliveries can happen thereafter, and even beyond the time window. However, if the first delivery is after the end of the time window, then it will be penalised accordingly.
Kinable et al [13] develop two MIP models for solving CoDeP by approaching it as capacitated vehicle routing problem with time windows and split deliveries, and Parallel Machine scheduling problem (PMSP). The paper aims to find efficient routes for a fleet of heterogeneous vehicles, operating between concrete production centres and construction sites with strict scheduling and routing constraints. The authors propose two heuristics: first, a best-fit scheduling procedure and second, utilising MIP model to improve delivery schedules locally. The comparison of CoDeP to PMSP lead the study to find equivalent problems in manufacturing for FAPTW.

3.1.3 Driver Assignment Problem

To include driver capability and preference in the model, the following driver assignment literature is helpful. Knust and Schumacher [14] formulate a MILP model to assign drivers who possess the different ability to every tank truck in a shift. The objective is to provide a feasible schedule for the driver assignment to tank trucks taking driver characteristics into account. Monnerat et al [15] consider a problem to assign both vehicles and driver to a set of planned trips in an institution for employee commutation. The objective of the studied problem is to minimise the total cost of assignment of two distinct and dependent resources (trucks and drivers) using a matheuristic based on genetic algorithm. Canadian minimum truck duration driver scheduling problem described by Goel [10] takes into account of the legal service regulations like the maximum amount of driving and the minimum off-duty time for truck drivers. The paper presents a MILP model to determine a schedule complying the driving regulations.

3.2 Related work in Manufacturing

The multi-machine scheduling problem (MMSP) involves jobs or processes being assigned to machines. In FAPTW, trucks can be seen as transportation resource just like the machines in MMSP and serving order (trip) is similar to processing a job. Jobs in MMSP have processing times so as the orders have trip or service duration. Machines have setup time to start processing orders. Likewise, the trucks in FAPTW have loading time during which the truck picks a container at the inland terminal. As it is considered to be constant (of 5 minutes) for all trucks, it is included in the driving duration of the order.
Sadykov and Wosley [17] describe a multi-machine assignment scheduling problem (MMASP), with any job that can be processed at any machine and each machine can process only one job at a time. Processing of a job can begin only after its release date and must be completed latest by its deadline. Similarly, in FAPTW terminal starting time is the release time, one truck can serve one order in a trip and orders have a service (delivery) deadline. But MMASP has homogeneous machines that can process any job, different from FAPTW. Objective of the paper is to minimise the total processing cost of all the jobs. It formulates a mixed-integer linear programming (MIP) model, and then proposes multiple algorithms to analyse the

best solution for the case. The paper considers cost for processing a job whereas in FAPTW has resource (truck) utility cost. In their paper [21], Zhu and Heady develop a mixed-integer programming formulation to minimise job earliness and tardiness in a multi-machine scheduling problem. The formulation involves setup times based job-sequencing and processing times based on job-machine sequencing and due-dates. The interesting aspect of the paper is the varying cost-penalties for jobs that the FAPTW proposes as one of the extensions of its basic model.

3.3 Related work in Airline Fleet Assignment

Airline fleet assignment problem (AFAP) has a set of flight schedules between cities and a heterogeneous fleet of aeroplanes to fly between those cities. Similarly, FAPTW has a set of orders (trips) between the terminal and nodes in the network. The flying times (trip duration) are considered deterministic. The significant difference is that the FAPTW has a central node from which the trucks drive whereas the aeroplanes do not have one such central node.
Hane et al [11] describe an AFAP to determine the type of aircraft that has to fly between cities. It proposes a linear programming formulation to minimise the assignment cost. Similarly, Anzoom and Hasin [5] develop a model to estimate profitability from the fleet assignment for airlines using the ant colony algorithm. Their goal is to maximise the profit for aircraft assignment including revenue from ticket prices and flight operations cost.

3.4 Related work in *One-to-Many* Assignment Problem

FAPTW has a set of truck and set of orders to match (assign). However, if the trucks are decoupled and treated as single agent, then the planning is relatively simpler than considering the entire fleet. This is similar to the *one-to-many* assignment (matching) problems in literature. Stable college admissions also follows the same *one-to-many* assignment problem where there are a number of students and a number of colleges. Each student has a strict preference ordering over all colleges, and each college also has a strict preference ordering over all students. Similarly FAPTW, has a set of trucks and a set of orders. Like student preferences, Trucks (and its drivers) have hierarchy and orders have hierarchy derived from its distance from the terminal. Viriyakattiyaporn [19] presents a comparison between college admissions mechanisms and compares between student-optimal admission and college-optimal admission. The author proposes theorems for matching and presents computational results of an applicants to jobs (program) matching. The author concludes though college-optimal admissions may be tempting for the college to apply, it may not be stable outcomes. So student-optimal admissions are stable. Here stable means that the outcome of matching meets the intention of assignment. In FAPTW, stability corresponds to capability of truck to serve the specific order it is assigned with. So, the study formulates a truck-optimal approach in one of the models.

Literature survey explores multiple fields for formulating the fleet assignment problem with time windows. Research papers in container logistics and concrete delivery problem help in modelling the operational constraints of the fleet assignment problem. Research works from driver assignment cases help in modelling the constraints of legal driving regulations. Multi-machine scheduling problem with minimising tardiness, airline fleet assignment problem and *one-to-many* assignment (stable college admissions) influences in shaping the fleet assignment policy.

Chapter 4

Methodology

From the literature, the study proposes two fleet assignment policies: economical assignment and greedy assignment. Economical assignment policy aims to minimise the utility cost and assignment costs of trucks, and achieve high on-time performance. Greedy assignment policy intends to greedily utilise the trucks (i.e. maximise the number of orders served by a truck) with rewards for being on-time. For both the policies, the study formulates a blended objective mixed integer linear programming model.

4.1 Basic Formulation

The basic formulation adopts the economical assignment policy with the primary objective of minimising delivery violations and the secondary objective is to minimise the cost of assignment and utility of trucks. This formulation considers the entire fleet at once and optimises the fleet assignment. The following sections explain the main real-life concepts and components of the problem.

4.1.1 Decision Variables

For the fleet assignment problem with time windows, there is a list of decision variables as in Table 4.1. The assignment variable $Y_{t,m,o}$ denotes which order is assigned to which truck.

$$Y_{t,m,o} = \begin{cases} 1, & \textit{if Order o is assigned to Truck t as its } m^{th} \textit{order} \\ 0, & \textit{Otherwise.} \end{cases}, \tag{4.1}$$

The assignment decision variable $Y_{t,m,o}$ is binary indicating that truck t serves order o in its m^{th} trip. The

Decision Variables	*Description*
$Y_{t,m,o}$	*Binary indicating that truck t serves order o in its* m^{th}*trip*
$Z_{t,m}$	*Continuous, specifies the departure time of truck t serving its* m^{th}*order*
τ_o	*Binary indicating order o is violated*
$C_{t,m}$	*Binary indicating total working time of truck t is greater than 6 hours in the* m^{th}*trip*
$x_{t,m,o}$	*Binary indicating that truck t violates service deadline of order o in its* m^{th}*trip*
$\alpha_{t,m}$	*Binary indicating the trips that truck t drives on exceeding 6 hours of service*
$\beta_{t,m}$	*Binary to identify the trip m when truck t exceeds 6 hours of service for the first time*
$\gamma_{t,m}$	*Binary enforcing a break for truck t in its* m^{th}*trip*
U_t	*Binary to indicate if truck t is used in the day*

Table 4.1: Decision Variables of the basic formulation

maximum trips that any truck can do on a given day is denoted by ub_{trips}. The upper bound for trips

ub_{trips} is calculated as follows: it is the first instance when sum of the total trip or service duration (in ascending order) of the day $(2c_o + p_o)$ exceeds the operational time window $(e_d - b_d)$ in the day. Here, b_d is the earliest operational time and e_d represents the latest operational time of the day for the terminal. So the range of trip number m is from 1 to ub_{trips}. The second decision variable $Z_{t,m}$ is continuous and indicates the truck t departure time for its m^{th} trip. It is between the earliest operational time b_d and the latest operational time of the day e_d for the terminal. Both b_d and e_d are in minutes.

$$Z_{t,m} \in [b_d, e_d], \quad \forall t \in T, \quad m \in [1, ub_{trips}] \tag{4.2}$$

The third decision variable τ_o denotes late serve (or delivery violation). An order is said to be served late if the start of the truck is beyond the latest departure time corresponding to the order.

$$\tau_o = \begin{cases} 1, & if \quad Z_{t,m} > d_o \quad and \quad Y_{t,m,o} = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.3}$$

$$C_{t,m} = \begin{cases} 1, & \text{\textit{if truck t has operated more than 360 minutes from 1 to m-1 trips}} \\ 0, & Otherwise. \end{cases}, \tag{4.4}$$

The truck operated time involves total trip duration of the truck during the day from trip 1 to *trip (m-1)*. $C_{t,m}$ has value of 1 for all trips that the truck drives after 360 minutes of working time.

$$x_{t,m,o} = \begin{cases} 0, & if \quad Y_{t,m,o} = 1 \quad and \quad \tau_o = 1 \\ 1, & Otherwise. \end{cases}, \tag{4.5}$$

$$\alpha_{t,m} = \begin{cases} 1, & if \quad C_{t,m} = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.6}$$

$$\beta_{t,m} = \begin{cases} 1, & if \quad C_{t,m} = 1 \quad and \quad C_{t,n} = 0 \quad \forall \quad n < m \\ 0, & Otherwise. \end{cases}, \tag{4.7}$$

The maximum number of trips possible in a day for any truck is represented by ub_{trips}.

$$\gamma_{t,m} = \begin{cases} 1, & if \quad both \quad \alpha_{t,m} = 1 \quad and \quad \beta_{t,m} = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.8}$$

$$U_t = \begin{cases} 1, & if \quad truck \quad t \quad has \quad served \quad any \quad order \\ 0, & Otherwise. \end{cases}, \tag{4.9}$$

4.1.2 Objective Function

Though its a blended objective formulation, the primary is to minimise deadline and secondary is to minimise the costs of truck assignment in the fleet and the truck utility cost for the day. So it has a hierarchical objective function with high penalty for delivery violation. In all the models, M represents the big M of the big M Method (M has a very large value). The first and the second terms in the below expression constitutes the assignment cost and utility cost respectively.

$$\min \quad \sum_{t \in T} w_t \sum_{m=1}^{ub_{trips}} \sum_{o \in O} Y_{t,m,o} + \sum_{t \in T} w_t U_t + M \sum_{o \in O} \tau_o \tag{4.10}$$

4.1.3 Constraints of the basic model

- *C1 – Exactly one trip for each order*: Each order has to be assigned to a single truck.

$$\sum_{t \in T} \sum_{m=1}^{ub_{trips}} Y_{t,m,o} = 1, \quad \forall o \in O, \tag{4.11}$$

where ub$_{trips}$ is the upper bound of orders that can be served (trips) by a truck within the day.

- *C2 –At most one order for each trip*: To ensure only one order is assigned to a truck at a time after serving another order, the following constraint restricts $Y_{t,m,o}$ below 1.

$$\sum_{o \in O} Y_{t,m,o} \leq 1, \quad \forall \quad m \in [1, ub_{trips}], \quad t \in T \tag{4.12}$$

- *C3 – Truck-order compatibility*:

$$Y_{t,m,o} \leq \max\{h_t - h_o, 0\} \quad \forall o \in O, \quad \forall t \in T, \quad m \in [1, ub_{trips}] \tag{4.13}$$

- *C4 - Time Window of the Terminal*: Trucks depart to serve its first order of the day after the start of inland terminal operations b_d. Also, the arrival of the truck after its last trip is within the terminal closing time e_d. Constraint 4.16 ensures all the intermediate trips occur within the terminal windows as well. In Constraint 4.15, o corresponds to the last order that the truck t serves for the day.

$$Z_{t,1} \geq b_d, \quad \forall t \in T, \tag{4.14}$$

$$Z_{t,ub_{trips}} \leq e_d - (2c_o + p_o), \quad \forall t \in T, \tag{4.15}$$

- *C5- Consistent arrivals and departure times of trips*: This serves as a temporal constraint for assignment of trucks i.e. it ensures no truck which is busy serving an order is assigned to another at the same time.

$$Z_{t,m-1} + \sum_{o \in O} (2c_o + p_o) Y_{t,m-1,o} \leq Z_{t,m}, \quad \forall t \in T, \quad m \in [2, ub_{trips}] \tag{4.16}$$

- *C6- Scheduling Breaks*: To schedule a 30-minute break after 6 hours of working, the following set of constraints are helpful. Model recognises that truck t has worked more than 6 hours with $C_{t,m}$ and identifies every trip that the truck t serves on working for 6 hours with $\alpha_{t,m}$ that acts as an exceeding flag. $\beta_{t,m}$ is helpful in identifying the first trip when truck t exceeds 6 hours of working time. Then $\gamma_{t,m}$, takes up value of 1 only if both the $\alpha_{t,m}$ and $\beta_{t,m}$ have value 1 which is ensured by 4.20 (AND logic). Table 4.2 provides the illustration for the break variables. As the truck *1* exceeds 360 minutes of working time (total trip duration) in its trip *3*, $C_{1,4}$ takes value 1 and it continues to be 1 for the next trip as well. $\alpha_{1,4}$ also has 1 and continues to be 1 for the subsequent trips. However, $\beta_{t,m}$ which acts as indicator when a truck exceeds 6 hours of working time has value of 1 once. here, it is $\beta_{1,4}$ which has value of 1 but no subsequent $\beta_{1,m}$ has value of 1. $\gamma_{t,m}$ which enforces a break has value 1 only i.e. when both $\alpha_{t,m}$ and $\beta_{t,m}$ are 1 and it happens to be 1 which occurs at $\gamma_{1,4}$ in this case.

$$MC_{t,m} \geq -360 + \sum_{n=1}^{m-1} \sum_{o \in O} (2c_o + p_o) Y_{t,n,o} \quad \forall n \in [1, m-1], \quad t \in T, \quad m \in [2, ub_{trips}], \tag{4.17}$$

$$M\alpha_{t,m} \geq \sum_{n}^{m} C_{t,n} \quad \forall \quad n \in [1, m], \quad t \in T \quad m \in [1, ub_{trips}] \tag{4.18}$$

$$M\beta_{t,m} \geq 2 - \sum_{n}^{m} C_{t,n} \quad \forall \quad n \in [1, m], \quad t \in T \quad m \in [1, ub_{trips}] \tag{4.19}$$

$$1 + 2\gamma_{t,m} \geq \alpha_{t,m} + \beta_{t,m}, \quad \gamma_{t,m} \leq \alpha_{t,m} \quad \& \quad \gamma_{t,m} \leq \beta_{t,m} \tag{4.20}$$

$$Z_{t,m} \geq Z_{t,m-1} + \sum_{o \in O} (2c_o + p_o) Y_{t,m,o} + 30\gamma_{t,m}, \quad \forall \quad t \in T, \quad m \in [2, ub_{trips}] \tag{4.21}$$

Truck Num	Order Num	Trip Num	departure Time	Trip duration	$C_{t,m}$	$\alpha_{t,m}$	$\beta_{t,m}$	$\gamma_{t,m}$
1	3	1	360	180	0	0	0	0
1	19	3	540	120	0	0	0	0
1	60	2	660	70	0	0	0	0
1	76	4	760	30	1	1	1	1
1	87	5	790	60	1	1	0	0

Table 4.2: Break variables illustration

- *C7 - Caps on driving time (540 minutes) and working time (720 minutes)*:

$$\sum_{o\in O}\sum_{m=1}^{ub_{trips}}(2c_o)Y_{t,m,o} \leq 540, \quad \forall t \in T, \tag{4.22}$$

$$\sum_{o\in O}\sum_{m=1}^{ub_{trips}}(2c_o + p_o)Y_{t,m,o} \leq 720, \quad \forall t \in T, \tag{4.23}$$

The following constraints help the model in finding solution of good quality.

- *C8 - Deadline-violated orders*: To identify late service of orders, delays are flagged using this constraint. This constraint ensures order o is served before its deadline. To explain how this constraint works, if order o is assigned to truck t as trip m, then $Y_{t,m,o}$ takes value of 1. Constraint 4.24 ensures $x_{t,m,o}$ takes value of 0 when $Y_{t,m,o}$ is 1. This compels the left hand side in Constraint 4.25 to less than or equal to 0. As the objective is to minimise tardiness, it tries to reduce tardy variable τ_o to zero. Hence, order o is served within its deadline (which makes $Z_{t,m}$ less than or equal to latest departure time d_o of the order o).

$$Y_{t,m,o} \leq M(1 - x_{t,m,o}) \quad \forall o \in O, \quad \forall t \in T, \quad m \in [1, ub_{trips}] \tag{4.24}$$

$$Z_{t,m} - d_o - M\tau_o \leq Mx_{t,m,o} \quad \forall o \in O, \quad \forall t \in T, \quad m \in [1, ub_{trips}] \tag{4.25}$$

- *C9 - Sequential trips*: This constraint ensures that the trip number of trucks are in a sequence (in increments of one).

$$\sum_{o\in O} Y_{t,m,o} \geq \sum_{o\in O} Y_{t,m+1,o} \quad \forall t \in T, \quad m \in [1, ub_{trips} - 1] \tag{4.26}$$

- *C10 - Truck Utility*: This constraint helps to indicate use of truck for service in the day.

$$MU_t \geq \sum_{m=1}^{ub_{trips}}\sum_{o\in O} Y_{t,m,o} \quad \forall t \in T \tag{4.27}$$

4.2 Optimal Trip Formulation

The goal of this model is to find how economical the assignments are by maximising the number of trips for every truck in the fleet. Here on-time service is a reward and no penalty for delay. It is the basic model described in the previous section but with the objective of maximising trips for the trucks. The decision variables and constraints are the same of the basic formulation with few exceptions.

4.2.1 Decision Variables

The study introduces an order service variable to restrict that an order is served by one truck $D_{o,t}$. The motivation for introducing $D_{o,t}$ instead of following the C1 of the basic model, is to reduce the number

Decision Variables	*Description*
$Y_{t,m,o}$	*Binary indicating that truck t serves order o in its m^{th} trip*
$Z_{t,m}$	*Continuous, specifies the departure time of truck t serving its m^{th} order*
$C_{t,m}$	*Binary indicating total working time of truck t is greater than 6 hours in the m^{th} trip*
$\theta_{t,m,o}$	*Binary indicating if truck t serves order o in its m^{th} trip within order deadline*
$\alpha_{t,m}$	*Binary indicating the trips that truck t drives on exceeding 6 hours of service*
$\beta_{t,m}$	*Binary to identify the trip m when truck t exceeds 6 hours of service for the first time*
$\gamma_{t,m}$	*Binary enforcing a break for truck t in its m^{th} trip*
$D_{o,t}$	*Binary to indicate if order o is served by truck t*

Table 4.3: Decision Variables of the optimal trip formulation

of constraints. However, this does not help in converging fast to solution. An order is said to be served on-time if it is served within its deadline. This is indicated by $\theta_{t,m,o}$ which is complimentary to τ_o of the basic model.
All decision variable definition is same as the basic model. The definition of new variables is as follows:

$$D_{o,t} = \begin{cases} 0, & if \quad Y_{t,m,o} = 1 \\ 1, & Otherwise. \end{cases}, \tag{4.28}$$

$$\theta_{t,m,o} = \begin{cases} 1, & if \quad Z_{t,m} \leq d_o \quad and \quad Y_{t,m,o} = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.29}$$

$$Z_{t,m} \in [b_d, e_d], \qquad \forall t \in T, \quad m \in [1, ub_{trips}] \tag{4.30}$$

An order is said to be served late if the start of the truck is beyond the latest departure time corresponding to the order.

$$\tau_o = \begin{cases} 1, & if \quad Z_{t,m} > d_o \quad and \quad Y_{t,m,o} = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.31}$$

$$C_{t,m} = \begin{cases} 1, & \textit{if truck t has operated more than 360 minutes from 1 to m-1 trips} \\ 0, & Otherwise. \end{cases}, \tag{4.32}$$

The truck operated time involves total trip duration of the truck during the day from trip 1 to *trip (m-1)*. $C_{t,m}$ has value of 1 for all trips that the truck drives after 360 minutes of working time.

$$x_{t,m,o} = \begin{cases} 0, & if \quad Y_{t,m,o} = 1 \quad and \quad \tau_o = 1 \\ 1, & Otherwise. \end{cases}, \tag{4.33}$$

$$\alpha_{t,m} = \begin{cases} 1, & if \quad C_{t,m} = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.34}$$

$$\beta_{t,m} = \begin{cases} 1, & if \quad C_{t,m} = 1 \quad and \quad C_{t,n} = 0 \quad \forall \quad n < m \\ 0, & Otherwise. \end{cases}, \tag{4.35}$$

The maximum number of trips possible in a day for any truck is represented by ub_{trips}.

$$\gamma_{t,m} = \begin{cases} 1, & if \quad both \quad \alpha_{t,m} = 1 \quad and \quad \beta_{t,m} = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.36}$$

4.2.2 Objective Function

The goal is to maximise number of orders served by a truck and with on-time service as a reward.

$$\max \quad \sum_{t\in T} \frac{w_{max}}{w_t} \sum_{m=1}^{ub_{trips}} \sum_{o\in O} Y_{t,m,o} + \sum_{t\in T} \sum_{m=1}^{ub_{trips}} \sum_{o\in O} \theta_{t,m,o} \tag{4.37}$$

4.2.3 Constraints of Optimal Trip Formulation

- *C1- Exactly one trip for each order*:

$$\sum_{m=1}^{ub_{trips}} Y_{t,m,o} \leq D_{o,t} \quad \forall t \in T \quad \forall o \in O \tag{4.38}$$

- *C2 –At most one order for each trip*: To ensure only one order is assigned to a truck at a time after serving another order, the following constraint restricts $Y_{t,m,o}$ below 1.

$$\sum_{o\in O} Y_{t,m,o} \leq 1, \quad \forall \quad m \in [1, ub_{trips}], \quad t \in T \tag{4.39}$$

- *C3 – Truck-order compatibility*:

$$Y_{t,m,o} \leq \max\{h_t - h_o, 0\} \quad \forall o \in O, \quad \forall t \in T, \quad m \in [1, ub_{trips}] \tag{4.40}$$

- *C4 - Time Window of the Terminal*: Trucks depart to serve its first order of the day after the start of inland terminal operations b_d. Also, the arrival of the truck after its last trip is within the terminal closing time e_d. Constraint 4.43 ensures all the intermediate trips occur within the terminal windows as well.

$$Z_{t,1} \geq b_d, \quad \forall t \in T, \tag{4.41}$$

$$Z_{t,ub_{trips}} \leq e_d - (2c_o + p_o), \quad \forall t \in T, \tag{4.42}$$

- *C5- Consistent arrivals and departure times of trips*: This serves as a temporal constraint for assignment of trucks i.e. it ensures no truck which is busy serving an order is assigned to another at the same time.

$$Z_{t,m-1} + \sum_{o\in O} (2c_o + p_o) Y_{t,m-1,o} \leq Z_{t,m}, \quad \forall t \in T, \quad m \in [2, ub_{trips}] \tag{4.43}$$

- *C6- Scheduling Breaks*:

$$MC_{t,m} \geq -360 + \sum_{n=1}^{m-1} \sum_{o\in O} (2c_o + p_o) Y_{t,n,o} \quad \forall n \in [1, m-1], \quad t \in T, \quad m \in [2, ub_{trips}], \tag{4.44}$$

$$M\alpha_{t,m} \geq \sum_{n}^{m} C_{t,n} \quad \forall \quad n \in [1, m], \quad t \in T \quad m \in [1, ub_{trips}] \tag{4.45}$$

$$M\beta_{t,m} \geq 2 - \sum_{n}^{m} C_{t,n} \quad \forall \quad n \in [1, m], \quad t \in T \quad m \in [1, ub_{trips}] \tag{4.46}$$

$$1 + 2\gamma_{t,m} \geq \alpha_{t,m} + \beta_{t,m}, \quad \gamma_{t,m} \leq \alpha_{t,m} \quad \& \quad \gamma_{t,m} \leq \beta_{t,m} \tag{4.47}$$

$$Z_{t,m} \geq Z_{t,m-1} + \sum_{o\in O} (2c_o + p_o) Y_{t,m,o} + 30\gamma_{t,m}, \quad \forall \quad t \in T \quad m \in [2, ub_{trips}] \tag{4.48}$$

- *C7 - Caps on driving time and working time*:

$$\sum_{o \in O} \sum_{m=1}^{ub_{trips}} (2c_o) Y_{t,m,o} \leq 540, \quad \forall t \in T, \tag{4.49}$$

$$\sum_{o \in O} \sum_{m=1}^{ub_{trips}} (2c_o + p_o) Y_{t,m,o} \leq 720, \quad \forall t \in T, \tag{4.50}$$

The following constraints are model-specific and helps in finding a good solution.

- *C8 - Deadline-violated orders*:

$$Y_{t,m,o} \geq \beta_{t,m,o} \quad \forall o \in O, \quad \forall t \in T, \quad m \in [1, ub_{trips}] \tag{4.51}$$

$$Z_{t,m} - d_o \leq M(1 - \beta_{t,m,o}) \quad \forall o \in O, \quad \forall t \in T, \quad m \in [1, ub_{trips}] \tag{4.52}$$

- *C9 - Sequential trips*:

$$\sum_{o \in O} Y_{t,m,o} \geq \sum_{o \in O} Y_{t,m+1,o} \quad \forall t \in T, \quad m \in [1, ub_{trips} - 1] \tag{4.53}$$

This is an assignment variable restricting one truck assignment to an order.

- *C10 – Exactly one truck assigned to one order*: This ensures that only one truck is assigned to an order.

$$\sum_{t \in T} D_{o,t} = 1, \quad \forall o \in O, \tag{4.54}$$

4.3 Matching Model

Matching model (also referred as matching truck model) follows the greedy assignment policy of assigning trucks as many trips (orders) as possible. In the matching model, trucks are decoupled from the fleet and are considered as a single entity. The idea is one-to-many assignment similar to stable admissions problem discussed in the literature. Considering one truck, the study aims to assign as many orders as possible to the truck. Like the optimal trip formulation described in section 4.2, goal of the matching model is to maximise the number of orders that a truck serves with on-time service rewards. The algorithmic idea of this approach is to choose one truck each time and then assign orders leaving out the already planned (truck-assigned) ones and continuing until all orders are assigned. Here, the approach for finding trips (orders) for trucks is greedy, in the sense, that finding trip plan of trucks one at a time.

Parameter	*Description*
E_o	*Order service parameter*

Table 4.4: Parameter of the matching model

Matching model introduces order service parameter E_o to indicate if an order is served. Served orders have E_o as 0 and yet to serve orders have value of 1. The selection strategy is to choose trucks starting from the cheapest in the fleet and the order of selection is as follows: terminal, regional, port, charter-regional and charter-port trucks. Due to this selection strategy, orders of a type are assigned to the trucks of same type as much as possible preventing resource occlusion. Decision variables in the matching model has no truck t index but the definitions are the same as the above models.

Decision Variables	Description
$Y_{m,o}$	*Binary indicating that truck serves order o in the m^{th} trip*
Z_m	*Continuous, specifies the departure time of the truck serving the m^{th} order*
C_m	*Binary indicating total working time of truck is greater than 6 hours in its m^{th} trip*
$\theta_{m,o}$	*Binary indicating if truck serves order o on-time in its m^{th} trip*
α_m	*Binary indicating that truck exceeds 6 hours of service in the m^{th} trip*
β_m	*Binary to identify the trip m when truck t exceeds 6 hours of service for the first time*
γ_m	*Binary enforcing a break for truck in the m^{th} trip*

Table 4.5: Decision Variables of the matching model

4.3.1 Decision Variables

$$Y_{m,o} = \begin{cases} 1, & \textit{if Order o is assigned to the truck considered as its } m^{th} \textit{order} \\ 0, & Otherwise. \end{cases}, \tag{4.55}$$

The maximum number of trips possible in a day for any truck is represented by ub_{trips}. So, $m \in [1, ub_{trips}]$.

$$Z_m \in [b_d, e_d] \tag{4.56}$$

$$C_m = \begin{cases} 1, & \textit{if the truck considered has operated more than 360 minutes from 1 to m-1 trips} \\ 0, & Otherwise. \end{cases}, \tag{4.57}$$

An order is said to be served on-time if it is served within its deadline. This is indicated by $\theta_{m,o}$ which is complimentary to τ_o of the basic model

$$\theta_{m,o} = \begin{cases} 1, & if \quad Z_{t,m} \leq d_o \quad and \quad Y_{m,o} = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.58}$$

$$\alpha_m = \begin{cases} 1, & if \quad C_m = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.59}$$

$$\beta_m = \begin{cases} 1, & if \quad C_m = 1 \quad and \quad C_n = 0 \quad \forall \quad n < m \\ 0, & Otherwise. \end{cases}, \tag{4.60}$$

$$\gamma_m = \begin{cases} 1, & if \quad both \quad \alpha_m = 1 \quad and \quad \beta_m = 1 \\ 0, & Otherwise. \end{cases}, \tag{4.61}$$

4.3.2 Objective Function

The primary goal is to assign as many orders as possible to each truck so the objective coefficient of assignment variable is larger than the on-time variable.

$$\max \quad \frac{w_{max}}{w_t} \sum_{m=1}^{ub_{trips}} \sum_{o \in O} Y_{m,o} + \sum_{m=1}^{ub_{trips}} \sum_{o \in O} \theta_{m,o} \tag{4.62}$$

4.3.3 Constraints of Matching model

- *C1- Exactly one trip for each order*:

$$\sum_{m=1}^{ub_{trips}} Y_{m,o} \leq E_o \quad \forall o \in O \tag{4.63}$$

- *C2 – At most one order for each trip - Assignment*:

$$\sum_{o \in O} Y_{m,o} \leq 1, \quad \forall \quad m \in [1, ub_{trips}], \tag{4.64}$$

where ub$_{trips}$ is the upper bound of orders that can be served (trips) by a truck within the day. Upper bound for trip is calculated as in basic model.

- *C3 – Truck-order compatibility*:

$$Y_{m,o} \leq \max\{h_t - h_o, 0\} \quad \forall o \in O, \quad \forall \quad m \in [1, ub_{trips}] \tag{4.65}$$

Temporal constraint for assignment of trucks are:

- *C4 - Time window of the Terminal*: All trucks depart for its first trip (order service) after the start of the terminal and returns to the terminal before the end of last trip.

$$Z_1 \geq b_d, \tag{4.66}$$
$$Z_{ub_{trips}} \leq e_d - (2c_o + p_o), \tag{4.67}$$

- *C5 - Consistent arrival and departure time of trips*:

$$Z_{m-1} + \sum_{o \in O} (2c_o + p_o) Y_{m-1,o} \leq Z_m, \quad \forall \quad m \in [2, ub_{trips}] \tag{4.68}$$

- *C6- Scheduling Breaks*:

$$MC_m \geq -360 + \sum_{n=1}^{m-1} \sum_{o \in O} (2c_o + p_o) Y_{n,o} \quad \forall n \in [1, m-1], \quad t \in T, \quad m \in [2, ub_{trips}], \tag{4.69}$$

$$M\alpha_m \geq \sum_{n}^{m} C_n \quad \forall \quad n \in [1, m], \qquad m \in [1, ub_{trips}] \tag{4.70}$$

$$M\beta_m \geq 2 - \sum_{n}^{m} C_n \quad \forall \quad n \in [1, m], \qquad m \in [1, ub_{trips}] \tag{4.71}$$

$$1 + 2\gamma_m \geq \alpha_m + \beta_m, \quad \gamma_m \leq \alpha_m, \quad \gamma_m \leq \beta_m \tag{4.72}$$

$$Z_m \geq Z_{m-1} + \sum_{o \in O} (2c_o + p_o) Y_{m,o} + 30\gamma_m, \quad \forall m \in [2, ub_{trips}] \tag{4.73}$$

- *C7 - Caps on driving time and working time*:

$$\sum_{o \in O} \sum_{m=1}^{ub_{trips}} (2c_o) Y_{m,o} \leq 540, \tag{4.74}$$

$$\sum_{o \in O} \sum_{m=1}^{ub_{trips}} (2c_o + p_o) Y_{m,o} \leq 720, \tag{4.75}$$

- *C8 - Deadline-violated orders*:

$$Y_{m,o} \geq \theta_{m,o} \quad \forall o \in O, \quad \forall \quad m \in [1, ub_{trips}] \tag{4.76}$$
$$Z_m - d_o \leq M(1 - \theta_{m,o}) \quad \forall o \in O, \quad \forall \quad m \in [1, ub_{trips}] \tag{4.77}$$

- *C9 - Sequential trips*:

$$\sum_{o \in O} Y_{m,o} \geq \sum_{o \in O} Y_{m+1,o}, \quad m \in [1, ub_{trips} - 1] \tag{4.78}$$

Features	Basic model	Optimal trip model	Matching truck model
Constraints	-	C1 varies and C8, C10 are replaced with another	C1 sames as optimal trip. No C10 constraint
Objective	Primary: Minimise order deadline violations. Secondary: costs of assignment and utility. Optimises for entire fleet at once	Primary: Maximise orders served by a truck. Secondary: maximise on-time service. Optimises for entire fleet at once.	Same as optimal trip but optimises considering one truck at a time.
Truck Utility	variable U_t	No truck utility variable.	No truck utility variable.
On-time indicator	tardy variable τ_o	on-time variable $\theta_{t,m,o}$	on-time variable $\theta_{m,o}$
Order service	-	Indicated by $D_{o,t}$ variable	indicated by order parameter E_o

Table 4.6: Difference in features of the three models

This chapter presents two fleet assignment policy and provides the linear programming formulation based on the policies framed.

Chapter 5

Computational Experiments and Results

This chapter explains the features of the test instances, elaborates the results on the basis of solution attributes of the models and compares with actual routing.

5.1 Instance Description

To test the performance of models, the study has collected operation data for 12 days involving list of orders to serve on the day and trucks available for service in the day. Among the 12 instances, few consists of days with high number of orders to serve especially Oct 17, 2019 and Dec 19, 2019 instances have 143 orders. Also, Nov 7, 2019 and Dec 19, 2019 instances are most busy among the 12 instances. Table 5.1 presents the instances with terminal start and closing time, terminal-operational window, number of orders for the day, total service (trip) duration for the day respectively. The total service (trip) duration is the sum of service duration of orders booked on the day. This indicates the how busy the day is. Terminal (operational) windows specifies the available time duration for serving orders. It is the difference between the opening time and the closing time of the terminal.

Instance Date (dd-mm-yy)	Terminal Start time (hr)	Terminal Closing time (hr)	Terminal Window (hr)	Number of Orders for the day	Total Service (trip) Duration (hr)
23/09/2019	04:45	18:00	13:15	104	179 hr 35 mins
07/11/2019	04:00	18:00	14:00	133	310 hr 40 mins
08/11/2019	04:30	18:00	13:30	111	216 hr 25 mins
11/11/2019	04:15	18:00	13:45	93	173 hr 20 mins
12/11/2019	04:40	18:00	13:20	116	214 hr 20 mins
13/11/2019	03:00	18:30	15:30	125	224 hr 55 mins
14/11/2019	04:45	18:00	13:15	103	189 hr 25 mins
15/11/2019	04:50	18:00	13:10	87	176 hr 35 mins
17/10/2019	05:25	18:00	12:35	143	243 hr 40 mins
09/12/2019	04:00	18:00	14:00	122	235 hr 25 mins
19/12/2019	05:25	18:00	12:35	143	283 hr 10 mins
17/01/2020	04:00	18:00	14:00	102	203 hr 15 mins

Table 5.1: List of Instances considered for testing model performance

5.2 Results and Analysis

This section presents the results of three models introduced in the Chapter 4 and explains the solution quality on four attributes: utility and assignment costs, number of trucks used, service on-time percent and computation time. The study considers orders without deadline violation as orders served on-time. On-time service percent is the percentage of orders planned (served) without deadline violation with respect to the total orders in the day instance. All computation times of the models are in seconds. Number of trucks used is the number of trucks that the model utilises to produce solution. Utility and assignment costs are calculated on the basis of the objective function 4.1.2 in the basic model. Also, this section presents the results of relaxing break and tardy variables of the basic model, further compares it with matching truck (greedy approach) model.

5.2.1 Results of Basic Model

The results of the basic model serves as the starting point for further computation experiments. From testing, the study infers that the basic model provides good quality solution but computation times are quite high (little more than 1hr) even for sub-optimal solution. Table 5.2 lists the instant-wise solution quality of the basic model: utility and assignment cost (Cost in the table), relative optimality gap (Rel opt. gap), computation time in seconds, number of trucks used (as num of trucks), and number of orders planned with deadline violations (as deadline violations). The relative optimality gap is as high as 0.99 for Oct 17, 2019 and Dec 19, 2019. It is because, the model heavily penalises (as high as a million) for each delivery violation. For the basic model, the idea is to have time limits for computation first until 10 minutes (600s). If the model does not converge to a solution or if it provides a solution with high number of delivery violated orders (more than 50% of the total orders) , then the study sets 1 hr (3600s) as computation time limit.

Date	Cost	Rel Opt. Gap	Computation Time (s)	Num of Trucks	Num of Deadline violations
23-09-19	396	0.01	611.54	22	0
07-11-19	716	0.02	3642.16	35	0
08-11-19	500	0.04	3618.2	25	0
11-11-19	446	0	71.66	21	0
12-11-19	572	0	58.32	28	0
13-11-19	701	0	127.46	27	0
14-11-19	500	0	27.68	28	0
15-11-19	487	0	15.72	29	0
17-10-19	698	0.99	3618.98	31	1
09-12-19	621	0	543.66	32	0
19-12-19	810	0.99	3623.89	31	9
17-01-20	459	0	36.28	27	0

Table 5.2: Instant wise - Results of the Basic Model

5.2.2 Results of Optimal trip Model

From the results of optimal trip model, the study infers that it provides costlier solutions than the basic model. In fact it is costlier, than the actual routing. It is because, this model aims to maximise the number of trips for trucks in the fleet, it aims to use the trucks with higher capability the most i.e. the charters and the port truck the most. Also, in all instances, number of trucks used by the optimal trip model is more than that of basic model. For three instances of Nov 7, 2019, Oct 17, 2019, and Dec 9, 2019, it does not converge to sub-optimal solution even with 2 hours of computation time. However, for the instances that the model solved, it has comparable computation time with that of the basic model. The study does not take optimal trip model into consideration for further experimentation and analysis due its poor solution quality.

Table 5.3 tabulates the results of optimal trip model with the 9 instances it solved: utility and assignment costs, relative optimality gap, computation time in seconds, number of trucks used and number of deadline violated orders.

Date	Cost	Rel Opt. Gap	Computation Time (s)	Num of Trucks	Num of Deadline violations
23-09-19	1053	0	154.96	25	0
08-11-19	1227	0	223.95	28	0
11-11-19	1262	0	234.74	25	0
12-11-19	1610	0	378.32	30	0
13-11-19	1815	0	826.49	36	0
14-11-19	1380	0	186.72	25	0
15-11-19	1329	0	231.76	35	0
19-12-19	1663	0	833.8	42	0
17-01-20	1430	0	262.23	29	0

Table 5.3: Instant wise - Results of the Optimal trip Model

5.2.3 Results of Matching truck Model

The solution quality of matching truck formulation depends on the order of truck it considers for optimising. So, the study considers trucks for trip plans in terms of the ascending order of their utility cost. In the sense, cheap trucks are considered first then the costlier ones. Of all the three models, matching truck formulation converges fast to solution, due to the greedy trip planning of trucks. This model uses the least number of trucks and second most economical after the basic model. However it slightly performs poorer than the basic model on the number of deadline violations. It is due to the objective function, where the study gives a larger coefficient for assignment variable $Y_{m,o}$ than the on-time $\theta_{m,o}$ variable. Table 5.4 represents the utility and assignment cost (as cost), computation time in seconds, number of trucks used and the number of deadline-violated orders.

Date	Cost	Computation Time (s)	Num of Trucks	Num of Deadline violations
23-09-19	469	16.98	17	1
07-11-19	1002	28.6	31	0
08-11-19	617	45.47	21	2
11-11-19	566	36.13	19	0
12-11-19	707	47.8	22	3
13-11-19	856	67.54	21	0
14-11-19	605	33.9	18	5
15-11-19	622	37.62	17	3
17-10-19	804	83.94	25	0
09-12-19	842	80.68	26	0
19-12-19	909	69.45	29	2
17-01-20	574	35.87	20	1

Table 5.4: Instant wise - Results of the Matching truck Model

5.2.4 Relaxation of Basic Model

Though the results of basic model are better in terms of costs and trucks used, the computational time of basic model is quite high. However, relaxing the tardy variables (τ_o, $x_{t,m,o}$) and break variables ($C_{t,m}$ $\alpha_{t,m}$,

$\beta_{t,m}$, $\gamma_{t,m}$) to continuous [0,1] converges fast to optimal solution. The values of the relaxed variables remain integer in solution of all the 12 instances.

Instance	Basic without break constraints (C6)					Relaxing Tardy variables without breaks (C6)				
Date	Cost	Rel Opt Gap	Computation Time (s)	Num of Trucks	Num of Deadline Violations	Cost	Rel Opt Gap	Computation Time (s)	Num of Trucks	Num of Deadline Violations
23-09-19	394	0	183.81	22	0	392	0	8.35	21	0
07-11-19	701	0	16.29	33	0	701	0	12.31	32	0
08-11-19	500	0.99	614.87	23	1	480	0	15.37	21	0
11-11-19	446	0	68.38	21	0	446	0	11.19	20	0
12-11-19	572	0	21.73	29	0	572	0	10.33	28	0
13-11-19	701	0	65.53	28	0	701	0	21.09	27	0
14-11-19	500	0	9.54	27	0	500	0	11.42	25	0
15-11-19	487	0	9.35	26	0	487	0	8.25	24	0
17-10-19	677	0.99	623.08	28	8	653	0	25.87	26	0
09-12-19	621	0	111.76	32	0	621	0	27.94	28	0
19-12-19	735	0.99	629.96	32	22	713	0	19.36	27	0
17-01-20	459	0	28.26	26	0	459	0	10.67	24	0

Table 5.5: Instant wise - Results of the Basic model without break constraints and Basic model without break constraints but with tardy variables relaxation

Instance	Basic model with break variables relaxed					Basic with tardy and break variables relaxed				
Date	Cost	Rel Opt Gap	Computation Time (s)	Num of Trucks	Num of Deadline Violations	Cost	Rel Opt Gap	Computation Time (s)	Num of Trucks	Num of Deadline Violations
23-09-19	394	0	186.68	21	0	392	0	12.47	22	0
07-11-19	721	0.02	635.38	35	0	701	0	23.28	31	0
08-11-19	510	0.06	628.51	25	0	480	0	18.56	22	0
11-11-19	446	0	621.16	24	0	446	0	5.71	20	0
12-11-19	572	0	106.83	27	0	572	0	7.35	27	0
13-11-19	701	0	175.00	25	0	701	0	15.95	27	0
14-11-19	500	0	28.37	26	0	500	0	6.86	25	0
15-11-19	487	0	18.40	27	0	487	0	5.80	27	0
17-10-19	726	0.99	631.12	29	16	653	0	12.72	26	0
09-12-19	621	0	161.49	31	0	621	0	20.06	31	0
19-12-19	769	0.99	631.08	34	20	713	0	9.10	29	0
17-01-20	459	0	59.85	26	0	459	0	8.45	22	0

Table 5.6: Instant wise - Results of the Basic model with break variables relaxation and Basic model with tardy and break variables relaxation

Table 5.5 provides the results of the basic model without break constraints with two case: one, without any relaxation, and two, with τ_o and $x_{t,m,o}$ relaxed. Likewise, Table 5.6 presents the results of the basic model with only break variables ($C_{t,m}$ $\alpha_{t,m}$, $\beta_{t,m}$, $\gamma_{t,m}$) relaxed, and basic model with both tardy and break relaxed: in terms of utility and assignment costs, relative optimality gap, computation time, number of trucks used, number of deadline violated orders. Table 5.7 represents the instance-wise solution attributes of basic (relaxed) model and matching truck in terms of utility (use) and assignment cost, number of trucks used, percentage of on-time plans (service) and computation times in seconds. The study relaxes these variables in a step by step way to understand how it affects the computation time. From the results, it is evident that relaxing both break and tardy variables in the basic model converges to quick solution of good quality. The computation time of such a relaxation is comparable to the matching truck model.

Instance	Use & Assignment Cost			Num of Trucks Used			On-time Service Percent			Computation time(s)	
Date	Actual	Basic	Matching	Actual	Basic	Matching	Actual	Basic	Matching	Basic	Matching
23-09-19	917	392	469	34	22	17	89.42	100	99.04	12.47	16.98
07-11-19	1378	701	1002	42	31	31	67.67	100	100	23.28	28.6
08-11-19	1023	480	617	38	22	21	56.76	100	98.2	18.56	45.47
11-11-19	709	446	566	28	20	19	75.27	100	100	5.71	36.13
12-11-19	993	572	707	33	27	22	100	100	97.41	7.35	47.8
13-11-19	1012	701	856	32	27	21	100	100	100	15.95	67.54
14-11-19	793	500	605	30	25	18	100	100	95.15	6.86	33.9
15-11-19	773	487	622	35	27	17	100	100	96.55	5.8	37.62
17-10-19	1064	653	804	38	26	25	67.13	100	100	12.72	83.94
09-12-19	1133	621	842	34	31	26	60.66	100	100	20.06	80.68
19-12-19	1096	713	909	42	29	29	86.01	100	98.6	9.09	69.45
17-01-20	726	459	574	37	22	20	93.14	100	99.02	8.45	35.87

Table 5.7: Instance wise solution attributes of Basic model and Matching Truck model

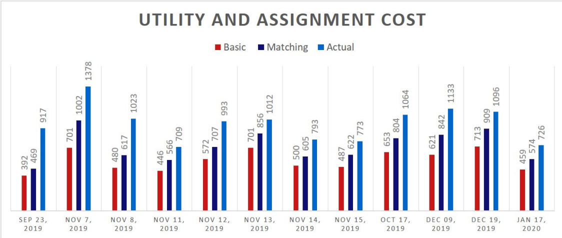
5.2.5 Comparison - Basic (relaxed) model and Matching Truck model

From the results, it is clear that the matching truck model provides solution with less number of trucks than the basic model. This means that matching model promotes better utilisation of trucks than the basic model. However, unlike the basic model, the matching truck model slightly compromises on the on-time service. In terms of utility and assignment cost, basic model yields cheaper assignment plans than the matching truck formulation. Considering computation times, matching truck and basic models are comparable. Table 5.8 compares the overall solution attributes of the Matching truck and the basic model with actual routing.

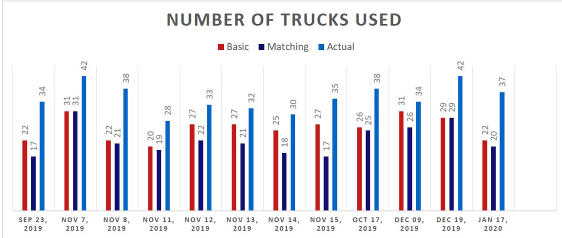
Solution Attributes	Actual Routing	Basic (relaxed)	Matching Truck
On-time service / plans	82.13 %	100 %	98.77 %
Cost with Actual	-	42.11 % less	26.20 % less
Trucks Used With Actual	-	26.95% less	37.11 % less
Average Computation times	-	12.19s	48.67s

Table 5.8: Overall Results of Basic Model (with tardy and break variables relaxed) and Matching Truck Formulation

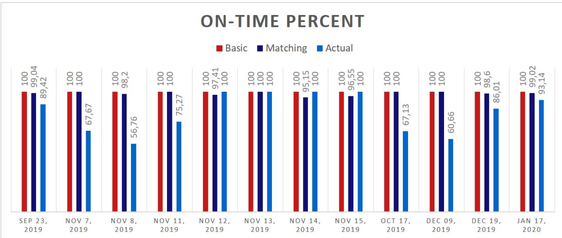
In terms of solution objective: Basic model with relaxation performs superior as it minimises deadline violations, gives the most economical assignment. However, for infeasible cases, with lesser number of trucks than the lower bound, then basic model does not provide any solution. For such infeasible cases, matching truck provides a partial assignment plan, meaning it assigns as many orders as possible to the given list of trucks and leaves other orders unassigned. This assignment will be particularly useful on days where there are too many orders (due to congestion at the port) and the company can not serve them by themselves with the existing fleet and known charters. Then, they can plan to sell those unassigned orders to other logistics providers (which is quite unusual but happens on certain days).



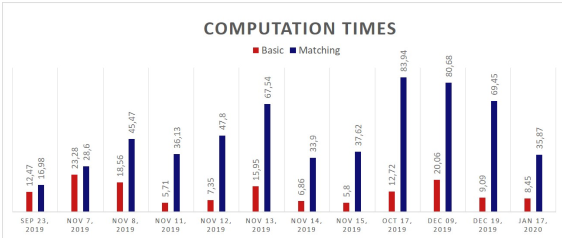
(a) Utility and Assignment cost



(b) Number of trucks used



(c) On-time Service Percent



(d) Computation times in seconds

Figure 5.1: Performance of the Basic (relaxed) and Matching models compared with actual routing

Figure 5.1 depicts the instance wise solution attributes of the Matching truck, the basic model and that of actual routing. Figure 5.2 represents the trip duration per truck in a day for the instances. From the results, matching truck model improves the utilisation of truck in day with all the instances more than the basic model.

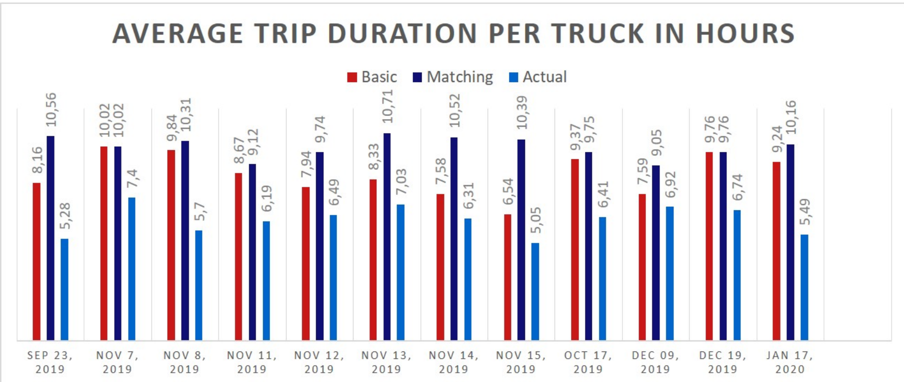


Figure 5.2: Instance wise comparison of Basic (relaxed) model, matching truck model and Actual routing in total trip duration per truck

5.2.6 Limitations of analysis

In models, the study assumes to be a delivery violation of order if the truck starts later than the latest departure from the terminal as there is no data mentioning when the truck reaches the service node. Also, there are no time stamps of when the truck has returned to the terminal after service. The records are available for the departure timestamps for serving order. With these limitations, the study has analysed the results. However, including these timestamps will provide more insights into the analysis. Also, the deterministic parameters of the model are calculated from the past experiences of driving to nodes and agreed process duration with customers. Changing the values of these parameters will yield different results.

5.3 Operational Challenges

With the help of the MILP model, the study has solved the following operational challenge that the planners face.

- *Driver preferred assignments*: Few customers place multiple container requests on a day with appropriate time intervals. Also, certain drivers prefer driving to certain customers as many times as possible. To satisfy such driver preferences, the study proposes to set truck and order hierarchy combinations so that so that model satisfies driver preferences. Table 5.9 has the truck trip plans of truck numbers 8 and 9 on Nov 8, 2019 instance. The drivers on truck 8 and 9 (with truck hierarchy 3) prefer to drive to a specific customer whose order numbers are 6, 7, 8, 9, 10, 11, 12, 13 with order hierarchy of 2. There are no other trucks and orders in the instance with same hierarchy values. In the Table5.9 departure time, service and driving duration and order deadlines are in minutes.

Truck Num.	Order Num.	Trip num.	Departure time	Service duration	driving duration	Order deadline
8	6	1	270	95	35	360
8	7	2	365	95	35	480
8	8	3	490	95	35	600
8	9	4	585	95	35	750
9	10	1	270	95	35	360
9	11	3	435	95	35	480
9	12	4	530	95	35	600
9	13	5	625	95	35	660
9	40	2	365	70	15	390
8	51	5	680	140	35	720
9	69	6	720	60	15	750
9	76	7	780	140	35	960
8	87	6	820	170	70	960

Table 5.9: Restricting two trucks to a serve a specific customer (with time units in minutes)

This chapter evaluates the performance of matching truck model and basic model on the basis of solution attributes and explains the approach for resolving operational challenges.

Chapter 6

Conclusion

This chapter concludes the research, provides recommendations to the company and discusses possible directions of future work.

6.1 Conclusion

The research proposes two suitable policies of fleet assignment: first, using an economical approach - minimise the fleet utility and assignment costs along with heavy penalty for deadline violations, and second, a greedy approach to maximise utility of a truck with on-time service rewards. The results of the basic and greedy (matching truck) model performs better than the actual routing of trucks on three solution attributes: On-time performance, fleet utility and assignment costs, and number of trucks used. The computation times of both the models are comparable. The goal of the research is to evolve a system of assigning orders to fleet of trucks which is fulfilled. The system has overcome the manual errors and reduces manual effort of truck planning significantly. The research adds flexibility to truck planning as the planners can visualise results and if feasible (containers, trucks are available) can prepone delivery of orders of the following day after negotiating with the concerned customers. Also, the models promote better utilisation of trucks than the actual routing.

6.2 Recommendations to the company

- *Real-time assignment costs*: In the model, the research assumes utility cost of trucks based on the logic of operational capability. Calculating actual cost of use and assignment will provide more relevant solution. This is one of the recommendations to the company.
- *Planning Dashboard*: To visualise the results, the study presents a dashboard similar to a Gantt chart with scheduled trips for trucks. It provides a summary of which truck serves which order, the trip number with departure time from terminal and service duration for each trip. Figure 6.1 illustrates the dashboard with solution of basic model to Feb 03, 2020 operational day where each trip is distinguished by a color, truck identity (ID) one the vertical axis with orders assigned against truck ID. Horizontal axis has terminal operational windows. The dashboard is developed in *tableau*.
- *Structured instance data specification*: As the planners are quite new to python integrated development environment (which is used as part of the study to build the models), and if they mistakenly type or change, then it will be detrimental to model. So, the study has developed simple dialog box to specify instance data for ease of use for the planners. Figure 6.2 shows the dialog box developed with two text boxes to provide order list and available truck list.
- *Daily data on truck and drivers*: The study recommends the company to record the daily driver preferences, off-times if these are taken into consideration for fleet assignment. Also, recording the time stamps daily mentioned in section 5.2.6.

- *Planned downtime*: Occasionally, truck drivers take time off during the day due to their appointments. Then the truck will be unavailable for service. The study recommend to introduce dummy orders in the order list and restricting that order to be able to serve by the specific truck only. The approach is similar the driver preferred assignments where exclusive hierarchy combinations are introduced to dummy orders and trucks that has planned downtime.

- *Promoting use of a specific truck*: The company has plans to purchase electric trucks (or more sustainable trucks). To promote the use of such trucks, the study suggests to consider lesser utility cost for such trucks than the other trucks of the same type. Due to less use cost, the model assigns as many orders as possible to the sustainable trucks.

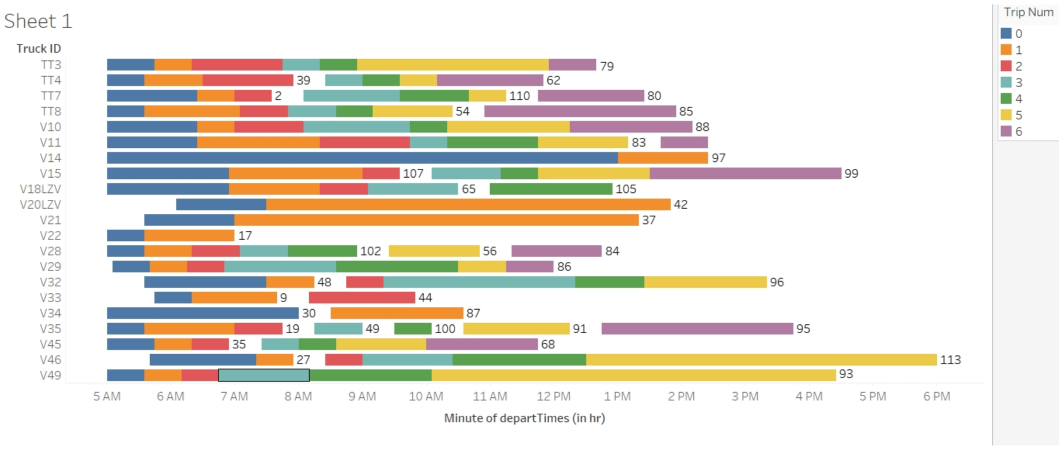


Figure 6.1: Dashboard for fleet assignment with solution of basic model to Feb 3, 2020 operational day

6.3 Future work

- *Real-time Assignment*: The study considers a set of orders to be served on the day well beforehand for fleet assignment. However, introducing new orders during the day, including delays due to traffic on peak times, unforeseen truck break downs during the day may hamper the plans (solution) that the model provides. So, assigning trucks with orders real-time will be challenging and may require a decentralised planning approach. Also, real-time tracking of trucks is necessary for such an assignment which is not available at present.

- *Flexible time windows*: The study takes time window from the start of the day (b_d) to the delivery deadline for serving orders. Changing time windows of service or driver-truck availability may lead to changing the model. So flexible time windows will be challenging to solve and is one of the possible extensions of the models.

- *Violation Tolerances*: Certain customers accept delays up to 30 minutes and even, few are satisfied if trucks deliver (or pickup) container within the day. To see if there are changes in solution attributes, the study proposes to classify customers (service nodes) as three types: *Strict* customers who want on-time service, *Moderate* customers accept delivery delays up to 30 minutes, *Tolerant* customers who are satisfied with service within the day. Penalising delays based on customer delivery violation tolerance and testing the case may provide us further insights.

- *Order of Truck Optimisation*: In greedy (matching truck) formulation, results are obtained by considering trucks in ascending order of their utility costs. Changing this strategy, testing with lower bounds of each truck type and then the rest of the trucks available in the fleet may lead to different results.

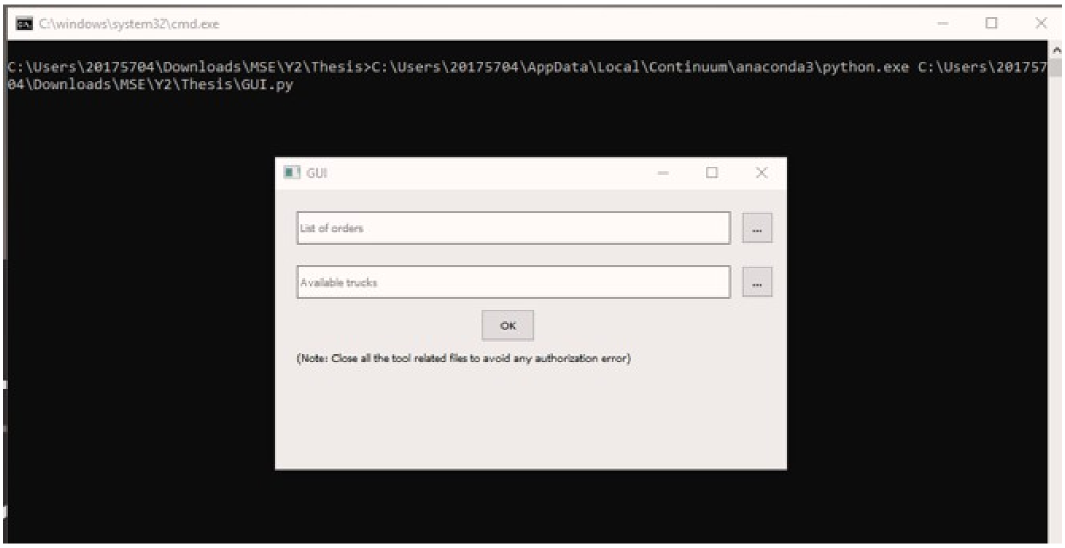


Figure 6.2: Structured instance data specification for the basic model

- *More data and testing*: The study has tested the models with data of 12-day instances. Taking more data instances and testing the models may provide better insights. Also, assigning fleet with the results of the model on a operational day will be helpful in understanding the real-time relevancy of the solution.

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