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ABSTRACT

This master thesis proposes modified fathoming and bounding procedures for the bi-directional Time-Dependent Labeling algorithm (TDL) which is used solve Time-Dependent Elementary Shortest Path Problem with Resource Constraints (TDESPPRC). In this study TDESPPRC is solved as the pricing problem in the decomposition of the arc based formulation of Time-Dependent Vehicle Routing Problem with Time Windows (TDVRPTW). The aim of the fathoming proposed is to solve TDVRPTW more efficiently by not extending the unproductive labels in bi-directional TDL algorithm. Moreover, we introduce an arc bounding model to stop the extension of labels as an alternative to resource bounding used in bi-directional search. In addition, this thesis includes an effects analysis of a new customer on Kuehne+Nagel(K+N) Netherlands Fast Moving Consumer Goods (FMCG) and returns distribution network. This study focused on analyzing the current network performance of the distribution network and evaluating the future scenarios for K+N's future distribution network by a simulation study.

PREFACE

This document presents my master thesis study in the dual degree Master of Science program between Industrial Engineering Department of Middle East Technical University(METU) and Operations, Planning, Accounting, and Control (OPAC) research group in Industrial Engineering and Innovation Sciences Department of Eindhoven University of Technology (TU/e). This master thesis study started at TU/e with a research project conducted for K+N Netherlands. The project was completed in February, 2011 at TU/e. My thesis study continued with theoretical study at METU. Hence, this master thesis includes a one year work on both theoretical study and an applied research project. I would like to take the opportunity to show my gratitude to all the people I met during this period.

First of all, I would like to thank to my company supervisor Phillippe Van Cauwenbergh for providing me the great opportunity to work at Kuehne+Nagel and its fascinating work environment. I definitely learned a lot about during my stay in the Netherlands, especially at K+N. I would like to specially thank to Willem Jan Van Schijndel for his guidance, support and patience during the project. Besides, I thank to Peet Van Leest for sharing his knowledge and providing support in technical issues which helped me to successfully execute the assignment. I also thank to Jose Larco for his help during the project.

In special, I dedicate my gratefulness to my academic supervisor Tom Van Woensel for his guidance and constructive feedbacks during my master's education. He has always been very kind and helpful. It was my pleasure to be his student. I would also especially thank to my second supervisor Cem İyigün for his motivating and inspiring supervision. He has been very supportive and patient all the time. I am thankful for his pleasant collaboration. Moreover, thanks to Said Dabia, I had a very productive master's education and gained knowledge in different research areas. I am also thankful to him for his contribution to my research.

Last but not least, I want to thank to all my friends whom I feel very lucky to have, especially my assignment partner Pelin. She has been like a family to me for the last six years. I would like to end the preface by dedicating my master thesis to my parents who always believed in me and supported my decisions.

Selen Kökten

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INTRODUCTION

Logistics in general is concerned with the organization, movement and storage of material and people. Over the years the meaning of the term has gradually generalized to cover business and service activities. Providing the necessary subcomponents for manufacturing,having inventory on the shelf of a retailer, having the right amount and type of blood available for hospital surgeries are example of logistics activities. According to the definition of Council of Logistics Management (CLM),Logistics is the process of planning, implementing, and controlling the efficient, cost-effective flow and storage of goods, services, and related information from the point-of-origin to the point-of-consumption for the purpose of conforming to customer requirements. It is the one of the most important activities in modern societies. 8 to 14% of the company sales in EU countries is devoted to logistics, whereas this percentage changes from 2 to 5%. According the annual report, of the companies in USA spent 63% of their logistics costs for transportation services which move materials between facilities using vehicles and equipment such as trucks, tractors, trailers, crews, pallets, containers, cars and trains. Among the transportation services freight transportation: plays a key role in today's economies as it allows production and consumption to take place at locations very far from each other. Freight transportation accounts for even 2/3 of total logistics cost and has a major impact on the level of customer service. One of the important decisions in freight transportation is the vehicle fleet management. A warehouse supplies products to a set of retailers using a fleet of vehicles of limited capacity. To answer the questions such as how to assign loads to vehicles or how to determine the vehicle routes well defined mathematical models are constructed throughout the years. But they are extremely difficult combinatorial problems in the class called NP-hard problems. It is very unlikely to construct an algorithm that always finds the optimum in computation time that is polynomial in the size of the problem. Hence heuristics or approximation methods are employed most of the time to solve these problems. Especially meta-heuristics is widely used to solve more difficult variants of these problems.Ghiani et al. (2004)

In the first part of this thesis, we will introduce the introduce bounding procedures for the solution of ,a variant of vehicle routing problem, Time-Dependent Vehicle Routing Problem with Time Windows(TDVRPTW) which is solved by an exact method, Branch and Cut and Price (BCP) algorithm. In the framework of BCP, the pricing problem is a Time-Dependent Elementary Shortest Path Problem with Resource Constraints (TDESPPRC) and it is solved by bi-directional time-dependent labeling algorithm. Our motivation in this study is to reduce the number of paths produced by the labeling algorithm to solve TDESPPRC. We propose that the bounding procedure will speed up the BCP algorithm by decreasing the number of labels produced in the part of bi-directional time dependent labeling algorithm. To introduce the proposed methods, we first review the mathematical models for the well known variants of the Vehicle Routing Problem (VRP) which are Capacitated Vehicle Routing Problem (CVRP) and Vehicle Routing Problem with Time Windows (VRPTW) in addition to the TDVRPTW. Next, we review the solution methods exist in the literature for these problems. In chapter 3, we introduce the solution methodology for TDVRPTW by Dabia et al. (2011) and after, in Chapter 4, we introduce the fathoming and bounding procedure. We provide the computational results for the proposed models in Chapter 5 and conclude the first part of the thesis in Chapter 6. Moreover, Chapter 7 is devoted to the second part of the thesis in which we analyze the effects of a new customer on the FMCG and Returns distribution network of Kuehne+Nagel Netherlands. In this chapter, we present the analysis for the current distribution network of the company and the simulation study performed to search for the potential improvements in the future distribution network. We conclude the chapter after presenting the simulation results by a brief conclusion and future research directions for this study.

1.1 THE VEHICLE ROUTING PROBLEM

The Vehicle Routing Problem (VRP) aims to deliver every customer's demand from the home depot with a homogenized fleet of vehicles by minimizing the total cost of the routes. Every customer is visited only once and every vehicle starts and ends the route at the depot. Since the fist formulation of the problem by Dantzig and Ramser , the problem has been studied with many variants. In this section, we will first formulate the basic variant of VRP which is called Capacitated VRP (CVRP) to distinguish it from other variants of the problem. Then, Vehicle Routing Problem with Time Windows (VRPTW) will be introduced. Finally, we will define Time-Dependent Vehicle Routing Problem with Time Windows (TDVRPTW) which is an extension of VRPTW.

1.1.1 FORMULATION OF CAPACITATED VEHICLE ROUTING PROBLEM

The objective of CVRP is to minimize the total costs considering the following constraints:

- All customers should be visited only once,
- Sum of the customers' demands in a route should be smaller than the vehicle capacity,
- Number of routes should be equal to the number of vehicles or less than the number of vehicles;

given that

- Each customer has a deterministic demand q_i and it cannot be split,
- The vehicle fleet has K identical vehicles,
- Each vehicle has a capacity Q.

There are alternative formulations for CVRP. We will introduce a vehicle flow model and the set partitioning model by Toth and Vigo.

1.1.1.1 CVRP TWO-INDEX VEHICLE FLOW MODEL

The vehicle flow model of CVRP is formulated as integer linear programming on a complete graph $G(V, A)$ where $V = \{0, 1, ..., n\}$ is the vertex set and A is the arc set. In the formulation, 0 represents the depot and $V \backslash \{0\}$ represents the customers. The cost of traveling on arc $(i, j) \in A$ is defined as c_{ij} and these costs are asymmetric. The binary variable x_{ij} takes value 1 if arc (i, j) is traversed by a vehicle, 0 otherwise. Given a customer set $S \subset V \backslash \{0\}$, $r(S)$ is the minimum number of vehicles needed to serve set S. $\lceil \sum_{i \in S} q_i / Q \rceil$ is usually taken as the lower bound on $r(S)$ where the demand of the depot q_0 is 0.

$$\text{minimize} \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij}$$

subject to

$$\sum_{i \in V} x_{ij} = 1 \qquad \forall j \in V \setminus \{0\} \tag{1.1}$$

$$\sum_{j \in V} x_{ij} = 1 \qquad \forall i \in V \setminus \{0\} \tag{1.2}$$

$$\sum_{i \in V} x_{i0} = K \tag{1.3}$$

$$\sum_{j \in V} x_{0j} = K \tag{1.4}$$

$$\sum_{i \in S} \sum_{j \in S} x_{ij} \leq |S| - r(S) \qquad \forall S \subseteq V \setminus \{0\},\ S \neq \emptyset \tag{1.5}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i, j \in V \tag{1.6}$$

In the vehicle flow model, constraints (1.1) and (1.2) provides that only one arc enters and leaves each vertex associated with a customer, respectively. Constraints (1.3) and (1.4) also impose the degree constraints for the depot and can be modified to include less vehicles in the solution. (1.5) are the well-known *Generalized Subtour Elimination Constraints* which require that at least $r(S)$ arcs leave each customer set S.

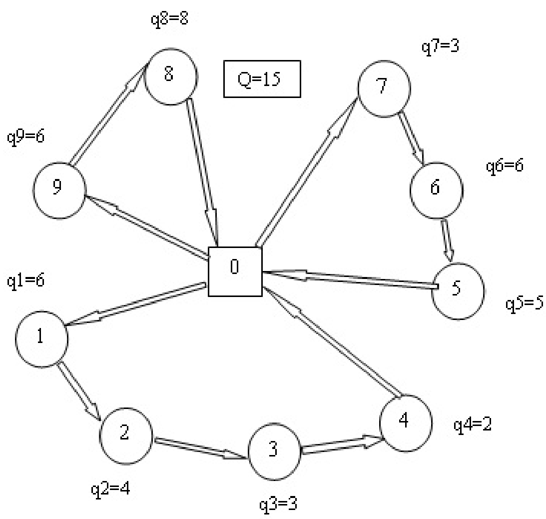

Figure 1.1: A solution for an example CVRP

1.1.1.2 CVRP SET PARTITIONING MODEL

In the set-partitioning model, the aim is to select the minimum number of paths to cover all customers given that the set of all feasible CVRP routes,Ω. In the formulation, $V_c = \{1, 2, ..., n\}$ is the set of customers. c_p is the cost of traversing on the path p. The constant a_{ip} is 1 if customer i is visited on the path p, 0 otherwise. The binary decision variable y_p takes value 1 if the path $p \in \Omega$ is included in the optimal solution, 0 otherwise. Based on the description of the variables and parameters, the mathematical programming formulation of the set partitioning model is given as follows:

P 1

$$\textit{minimize} \sum_{p \in \Omega} c_p y_p$$

subject to

$$\sum_{p \in \Omega} a_{ip} y_p = 1 \qquad \forall i \in V_c \tag{1.7}$$

$$\sum_{p \in \Omega} y_p = K \qquad \forall p \in \Omega \tag{1.8}$$

$$y_p \in \{0, 1\} \qquad \forall p \in \Omega \tag{1.9}$$

Constraints (1.7) impose that each customer is covered exactly once. (1.8) requires that exactly K routes are selected. However, this constraint can be modified to select less than K routes or set K can be defined as unbounded. The set-partitioning model can be adapted for many VRP models. We will refer to this formulation for other variants of VRP.

1.1.2 FORMULATION OF THE VEHICLE ROUTING PROBLEM WITH TIME WINDOWS

In the definition of VRPTW, all the constraints and assumptions for CVRP are valid. In addition,

- Customers must be visited within their time windows,

given that

- Every vertex i has an associated time window $[a_i, b_i]$ and a service time s_i,

- Hard time windows are considered which means that a customer should be visited within specific time windows,i.e. an arc (i, j) is feasible if and only if $a_i + t_{ij} + s_i \leq b_j$.

- For each arc $(i, j) \in A$ there is a defined travel time t_{ij}.

Below, we provide the three index network flow model and the set partitioning model for VRPTW.

1.1.2.1 VRPTW THREE INDEX NETWORK FLOW MODEL

VRPTW is formulated as mixed integer programming (MIP) on a complete graph $G(V, A)$ where $V = \{0, 1, ..., n, n+1\}$ is the vertex set and $A = \{(i, j) : i, j \in V\}$ is the arc set. In the formulation, the depot is represented by two different vertices such that 0 is the start depot and $n+1$ is the end depot. Hence,$V_c = V \setminus \{0, n+1\}$ represents the set of customers to be served. The cost of traversing on an arc (i, j) is denoted as c_{ij}. The sets $\gamma^+(S) = \{(i, j) \in A : i \in S\}$ and $\gamma^-(S) = \{(i, j) \in A : j \in S\}$ represent the arcs leaving and ending in the customer set $S \in V \setminus \{0, n+1\}$, respectively. They are shown as $\gamma^+(i)$ and $\gamma^-(i)$ instead of $\gamma^+(\{i\})$ and $\gamma^-(\{i\})$. The decision variable x_{ij}^k takes value 1 if arc (i, j) is traversed by the vehicle k. In addition, the decision variable w_i^k indicates the time when the service at vertex i starts if vertex i is visited by vehicle k, it is undefined otherwise. In addition, for the sake of simplicity, $x^k(B)$ is written instead of $\sum_{(i,j)\in B} x_{ij}^k$ for the set B. Following these notations, the mathematical programming model for VRPTW is given below:

$$\text{minimize} \sum_{k\in K}\sum_{(i,j)\in A} c_{ij}x_{ij}^k$$

subject to

$$\sum_{k\in K} x^k(\gamma^+(i)) = 1 \qquad \forall i \in V_c \qquad (1.10)$$

$$x^k(\gamma^+(0)) = 1 \qquad \forall k \in K \qquad (1.11)$$

$$x^k(\gamma^-(j)) = x^k(\gamma^+(j)) \qquad \forall k \in K, \forall j \in V\backslash\{0, n+1\} \qquad (1.12)$$

$$x^k(\gamma^-(n+1)) = 1 \qquad \forall k \in K \qquad (1.13)$$

$$w_i^k + t_{ij} + s_i \leq w_j^k + (1 - x_{ij}^k)M \qquad \forall k \in K, \forall(i,j) \in A \qquad (1.14)$$

$$a_i \leq w_i^k \leq b_i \qquad \forall k \in K, \forall(i) \in V \qquad (1.15)$$

$$\sum_{i\in N} q_i x^k(\gamma^+(i)) \leq Q \qquad \forall k \in K \qquad (1.16)$$

$$x_{ij}^k \in \{0,1\} \qquad \forall k \in K, \forall(i,j) \in A \qquad (1.17)$$

$$w_i^k \geq 0 \qquad \forall k \in K, \forall i \in V \qquad (1.18)$$

Constraints (1.10) require that a customer is visited by only one vehicle. Constraints (1.11) ensure that each vehicle leaves the depot once. Constraints (1.12) guarantee that a vehicle k can leave customer j if it enters to that vertex j, and vice versa. In constraints (1.13), it is required that each vehicle returns to the depot once. Constraints (1.14) ensure the time feasibility at the vertices where M is a large number. In addition, constraints (1.15) and (1.16) ensure the feasibility with respect to time windows and capacity.

1.1.2.2 VRPTW SET PARTITIONING MODEL

VRPTW set-partitioning formulation is same as CVRP set-partitioning model (P 1) where K route selection is not a constraint. In addition, the set Ω in VRPTW model represents all the feasible routes for VRPTW. The constraints in the network flow model are included in the set Ω. The number of feasible routes will be huge in number even for the medium sized problem instances. Although the solution approach for VRPTW will not be discussed here, we will elaborate more on the solution methodology of the set partitioning model of TDVRPTW in the next chapters.

1.1.3 PROBLEM DEFINITION: TIME-DEPENDENT VEHICLE ROUTING PROBLEM WITH TIME WINDOWS

TDVRP is defined by Malandraki and Daskin (1992) as follows: ”A vehicle fleet of fixed capacities serves customers of fixed demands from a central depot. Customers are assigned to vehicles and the vehicles routed so that the total time of the routes is minimized. The travel time between two customers or between a customer and the depot depends on the distance between the points and time of the day. Time windows for serving the customers may also be given as well as maximum allowable duration of each route.” Accordingly, we will consider TDVRP with time windows such that the service at the customers can only start within their time windows.

The general properties and the assumptions in the formulation of TVRPTW are also valid for TD-VRPTW. However, any additional or different parameters and variables are defined in the table below for the mixed integer programming of the problem.

Table 1.1: Description of Additional Variables and Parameters for TDVRPTW

$\delta_i(t)$	: Arrival time at node i given the dispatch time t at the depot
$\tau_{ij}(t_i)$	: Travel time from node i to j given that the departure time at node i is t_i
Z_{ij}	: Set of zones of the corresponding travel time function $\tau_{ij}(t_i)$ for arc (i, j)
Z_m	: A zone $\in Z_{ij}$ defined by two breakpoints
θ_m	: The slope of the the travel time function in the time zone Z_m
η_m	: An intersection with the y axis in the time zone Z_m
Z_{ij}^+	: Set of zones with $\theta_m > 0$
Z_{ij}^-	: Set of zones with $\theta_m < 0$
$w_i^k(m)$	: Equals w_i^k if the the service at node i starts in time zone Z_m, 0 otherwise

1.1.3.1 PROBLEM CHARACTERISTICS

VRPTW has been largely studied in the literature. However, scarce resource is found for the time dependent characteristics of this problem. With the motivation of modeling VRPTWs more realistically, time dependent characteristics is also considered in TDVRPTWs. In real life, when traveling between two locations,the speeds of the vehicles change due to traffic congestion. Therefore, the travel time between the two locations change depending on the time of the day. In this study, planning time horizon is divided into time zones to take into account the changing traffic congestion during the day and the speeds of the vehicles change depending within the time zones. Ichoua et al. (2003) introduced the *time* *dependent travel speed model* to formulate time dependency in vehicle routing problems. The model holds the "first-in-first-out" (**FIFO**) assumption, that is from the two identical vehicles leaving the same origin node for the same end nodes, the one which left the origin node at an earlier time always arrives at the end destination earlier than the other vehicle. The main property of the model is that the travel speed is a step function of the planning horizon. Therefore, speed changes when the boundary between two consecutive time zones is crossed and the travel time function turns into a stepwise continuous function of time as it is shown in Figure 1.2. Hence, for any time within a time zone, travel time is computed by using the breakpoints of the corresponding time zone.

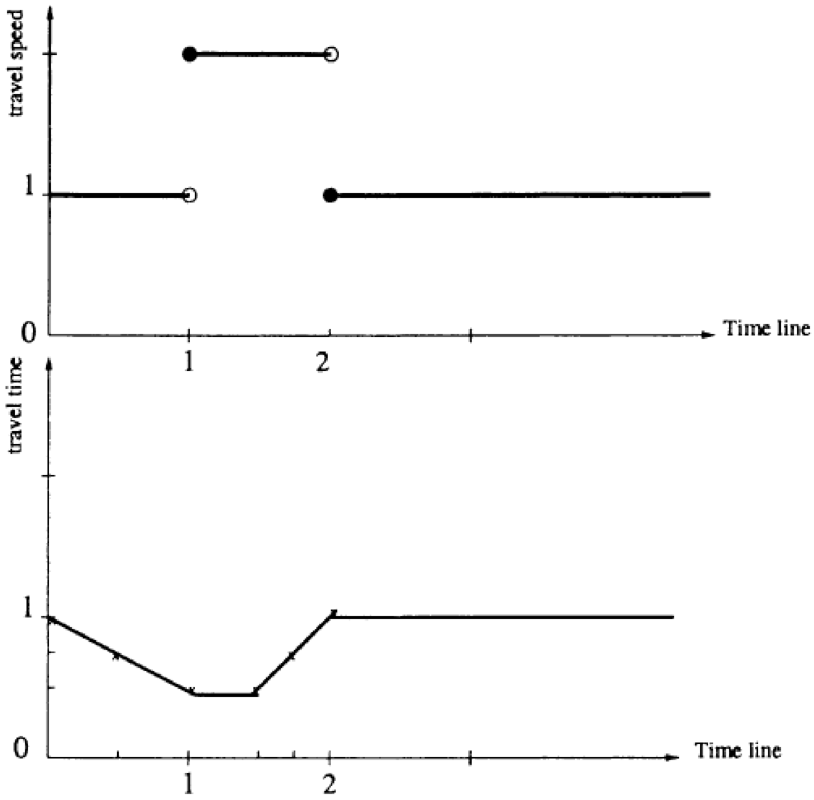

Figure 1.2: Travel Speed and the corresponding travel time function Ichoua et al. (2003)

As the travel times are time dependent, the arrival time of a partial path at an end node depends on the dispatch time from the depot. Due to FIFO property of the time dependent travel speed model, a later departure at the depot will always end up with a later arrival at the end node of the path. Therefore, if a path is infeasible for a dispatch time t, it will also be infeasible for a later dispatch time $t' > t$. Given a partial path with an end node i and parent node j, which is directly visited before i, the arrival time function $\delta_i(t)$ of the partial path with the dispatch time $\delta_0(t) = t$ from the depot is calculated as in equation (1.19). The arrival time function includes the service and waiting time at the end node visited.

$$\delta_i(t) = \delta_j(t) + \tau_{ji}(\delta_j(t)) \tag{1.19}$$

As the right hand side of the equation (1.19) is composed of piecewise linear functions, the arrival time function can be represented by the arrival time function breakpoints. Moreover, the optimal dispatch time from the depot to find the shortest duration of a path can also be calculated by using the arrival time function breakpoints such that

$$t^* = \arg\min_{t \in T} \{\delta_i(t) - t\} \tag{1.20}$$

where T is the domain for the feasible dispatch times from the depot.

1.1.3.2 TDVRPTW ARC BASED MODEL

The definition of the sets, variables and parameters are analogous to the ones in VRPTW. However, in the arc based formulation of TDVRPTW an additional time zone index m is added to the decision variables. The binary decision variable $x_{ij}^k(m)$ takes value 1 if arc (i, j) is traversed by the vehicle k and the departure time from node i is within time zone Z_m. $w_i^k(m)$ indicates the time when the service at vertex i starts if vertex i is visited by vehicle k if $x_{ij}^k(m) = 1$ and it is undefined otherwise. It is assumed that the demand at the start and end depot is zero and the set of vehicles K is taken as unbounded. Following the descriptions in Table 1.1, the mathematical programming model for TDVRPTW is given below:

$$\text{minimize} \sum_{k\in K}\sum_{(i,j)\in A}\sum_{m=1}^{|Z_{ij}|}(\theta_m w_i^k(m) + \eta_m x_{ij}^k(m))$$

subject to

$$\sum_{k\in K} x^k(\gamma^+(i)) = 1 \qquad \forall i \in V_c \tag{1.21}$$

$$x^k(\gamma^+(0)) = 1 \qquad \forall k \in K \tag{1.22}$$

$$x^k(\gamma^-(j)) = x^k(\gamma^+(j)) \qquad \forall k \in K, \forall j \in V_c \tag{1.23}$$

$$x^k(\gamma^-(n+1)) = 1 \qquad \forall k \in K \tag{1.24}$$

$$(1+\theta_m)w_i^k(m) - s_i + \eta_m \leq w_j^k(m) - s_j + (1 - x_{ij}^k(m))M \qquad \forall k \in K, \forall (i,j) \in A, \forall m \in |Z_{ij}| \tag{1.25}$$

$$w_i^k(m) \geq w_i^k - (1 - x_{ij}^k(m))M \qquad \forall k \in K, \forall (i,j) \in A, \forall m \in |Z_{ij}^+| \tag{1.26}$$

$$w_i^k(m) \leq min(w_i^k, Mx_{ij}^k(m)) \qquad \forall k \in K, \forall (i,j) \in A, \forall m \in |Z_{ij}^-| \tag{1.27}$$

$$a_i + s_i \leq w_i^k(m) \leq b_i + s_i \qquad \forall k \in K, \forall (i) \in V \tag{1.28}$$

$$\sum_{i\in N} q_i x^k(\gamma^+(i)) \leq Q \qquad \forall k \in K \tag{1.29}$$

$$x_{ij}^k(m) \in \{0,1\} \qquad \forall k \in K, \forall (i,j) \in A, \forall m \in |Z_{ij}| \tag{1.30}$$

$$r_m \leq w_i^k(m) < r_{m+1} \qquad \forall k \in K, \forall i \in V, \forall m \in |Z_{ij}| \tag{1.31}$$

Constraints (1.21) require that each customer is visited by one vehicle. Constraints (1.22) ensure that each vehicle leaves the depot once. Constraints (1.23) guarantee that a vehicle k can leave customer j if it enters to that vertex j, and vice versa. In constraints (1.24), it is required that each vehicle returns to the depot once. With (1.25) the time feasibility at the vertices is ensured. In addition, constraints (1.26) and (1.27) put bound on the value of $w_i^k(m)$ in case the departure from vertex i is at positive and negative slope region, respectively. Finally, inequalities (1.28) and (1.29) ensure the feasibility with respect to time windows and capacity.

1.1.3.3 TDVRPTW SET PARTITIONING MODEL

In the set partitioning model of TDVRPTW, Ω represents the set of all feasible paths p for TDVRPTW. The cost of a path c_p is the duration of that path and it is the difference between the end time e_p and the start time s_p of path p. The constant a_{ip} is 1 if customer i is visited on the path p and 0 otherwise. y_p is the binary decision variable which takes value 1 if the path $p \in \Omega$ is included in the optimal solution, 0 otherwise. Following these definitions, the formulation of set partitioning model is given in P2.

P 2

$$\textit{minimize} \sum_{p \in \Omega} c_p y_p$$

subject to

$$\sum_{p \in \Omega} a_{ip} y_p = 1 \qquad \forall i \in V_c \tag{1.32}$$

$$y_p \in \{0, 1\} \qquad \forall p \in \Omega \tag{1.33}$$

As the set of vehicles is assumed as unbounded. So,there is not a constraint on the number of vehicles selected as in P1.

In this thesis, TDVRPTW is solved by branch and cut and price algorithm which merges the enumeration approach of branch and bound algorithms with the polyhedral approach of cutting planes Padberg and Rinaldi (1991). In chapter 3, we refer to the BCP algorithm of Dabia et al. (2011) on TDVRPTW and introduce their solution approach.
In this chapter, we introduced the basic mathematical models for VRP, VRPTW and TDVRPTW before the solution methodology of TDVRPTW in this thesis is discussed. In the next chapter, we will review the related literature on the solution approaches for these problems.

CHAPTER 2

LITERATURE REVIEW

The vehicle routing problem was introduced by Dantzig and Ramser (1959). They considered the problem of gasoline delivery from a bulk terminal to service stations so that every customer's demand is satisfied and the total distance covered by the vehicle fleet is minimized. They formulated a mathematical model for the problem and solved it by an algorithmic approach. In 1964, Clarke and Wright developed a greedy heuristic to improve Dantzig and Ramser's approach. Since then the vehicle routing problem has been the most studied combinatorial optimization problem in the literature because of its practical relevance to real life applications and difficulty. In addition, the problem has been studied with many variants. In this section, we will briefly review the solution approaches on VRPs, VRPTWs and finally TDVRPTWs. In addition, the solution approaches of elementary shortest path problem with resource constraints in the column generation problem will be discussed.

2.1 VEHICLE ROUTING PROBLEM (VRP)

Study of VRP in the literature has given rise to several exact and heuristic solution techniques of general applicability. It can be shown as a specific case of traveling salesman problem (TSP) (VRP with one vehicle and infinite capacity) and is therefore a non-deterministic polynomial-time (NP) hard problem. Cordeau et al. (2007) VRP is considerably more difficult to solve than a TSP of the same size. Although TSPs with hundred or even thousands of customers can be solved by exact algorithms routinely, the most advanced exact algorithms can solve VRPs up to 100 customer with a success rate. However, heuristics can solve instances with more customers with flexibility to deal with many variants of VRP in practice.Laporte (2007) Therefore, considerable amount of research for solving VRPs is concentrated on heuristics. Below, exact algorithms and heuristics that mostly drew the attention of researchers are presented. A recent review on the solution procedures on VRP is provided by Laporte (2007) and

Cordeau et al. (2007). For a more detailed review on the variants of VRP, reader is refereed to the book edited by Toth and Vigo (2001b).

2.1.1 EXACT ALGORITHMS

An exact algorithm is an algorithm that solves a problem to optimality. NP-hard problems are a special kind of optimization problems for which most probably no polynomial time algorithm exists. It cannot be expected to construct exact algorithms that solve NP-hard problems in polynomial time unless $NP = P$. For some classes of problems there are hope of finding algorithms that solve problem instances occurring in practice in reasonable time though. Røpke (2005)
In the literature, exact methods for solving VRPs are generalized into three main categories:
Direct tree search methods: Christofides et al. (1981b) presents tree search algorithms by incorporating lower bounds computed from shortest spanning k-degree center tree and q-routes.Hadjiconstantinou et al. (1995) uses lower bounds obtained from a combination of two relaxations of the original problem which are based on the computation of q-paths and k-shortest paths.
Dynamic programming: Christofides et al. (1981a) introduced the dynamic programming formulation with the state-space relaxation method which provided an efficient way of reducing the number of states.
Integer linear programming: Naddef and Rinaldi (2002) solves the two index vehicle flow formulation of VRP with branch and cut algorithm by solving 15 instance at the root node. Another successful application of branch and cut algorithm is introduced by Baldacci et al. (2004) for two index vehicle flow formulation of VRP. Baldacci et al. (2008) presents a set partitioning formulation of the CVRP with additional capacity cuts which are the capacity and clique inequalities. Fukasawa et al. (2006) solves CVRP by combining branch and cut with the q-routes relaxation. The resulting branch and cut and price algorithm can solve important number of instances up to 100 vertices to optimality.

2.1.2 HEURISTICS

The heuristics developed for VRPs extended from classical heuristics to metaheuristics over ten years in the past 40 years. The early classical heuristics usually first finds a feasible solution in the construction phase and applies a post optimization procedure afterwards. On the other hand, metaheuristics uses mainly two two principles: local search and population search. In local search methods, an intensive exploration of the solution space is performed by moving at each step from the current solution to another promising solution in its neighborhood. Population search consists of maintaining a pool of good parent solutions and recombining them to produce offspring. Cordeau et al. (2002)

Next, the most promising heuristics methods to solve VRPs are presented:

Classical Heuristics: The classical heuristics is classified into two categories as constructive and improvement heuristics. The most well known constructive heuristics are savings algorithm Clarke and Wright (1964), sweep algorithm Gillett and Miller (1974) and a heuristics based on a two phase decomposition procedure Fisher and Jaikumar (1981). The general frameworks described in Thompson and Psaraftis (1993) and Kindervater and Savelsbergh (1997) encompass most available improvement heuristics.

Metaheuristics: Tabu search algorithms Gendreau et al. (1994), simulated annealing Osman (1993) and genetic algorithms and their variants are mostly available to solve VRPs in the literature. A recent review on VRP heuristics is provided in Cordeau et al. (2005).

2.2 VEHICLE ROUTING PROBLEM WITH TIME WINDOWS (VRPTW)

VRPTW has been solved in the literature by both exact methods (Kallehauge et al. (2005), Kallehauge (2008)) and heuristics (Bräysy and Gendreau (2005a), Bräysy and Gendreau (2005b)). In this section, we review the most promising solution techniques used in the literature.

2.2.1 EXACT ALGORITHMS

The research on the solution of VRPTW by exact algorithms mostly focuses on column generation methodology introduced by Dantzig and Wolfe (1960). Since VRPTW is hard to solve as an MIP, it is recommended to use Lagrangean relaxation (LR) or decomposition, for example Dantzig-Wolfe Decomposition (DWD), to break up the overall problem into a master problem (set partitioning formulation of VRPTW) and a subproblem. "*To date, the most successful decomposition approaches for the VRPTW cast the subproblem as a constrained shortest path structure. The master problem is an integer program whose solution cannot be obtained directly, so its LP relaxation is solved. The column generation process alternates between solving this linear master problem and the subproblem. The former finds new multipliers to send to the latter which uses this information to find new columns to send back. A lower bound on the optimal integer solution of the VRPTW model is obtained at the end of this back and* *forth process. This is then used within a branch-and-bound framework to obtain the optimal VRPTW solution. If the vehicles are identical, all subproblems will be equivalent and therefore it is necessary to only solve one.(Kallehauge et al. (2005) Applying cutting planes either in the master or the pricing subproblem leads to a branch-and-cut-price algorithm(BCP).*" Column generation is first used in a DWD framework by Desrochers et al. (1992). Feillet et al. (2004),Irnich and Villeneuve (2005),Chabrier (2006),Righini and Salani (2006), Jepsen et al. (2008), Desaulniers et al. (2008) proposed enhanced algorithms to solve the subproblem.

2.2.2 SPPRC AS THE PRICING PROBLEM IN COLUMN GENERATION

In most vehicle routing applications solved by column generation, the subproblem corresponds to a Shortest Path Problem with Resource Constraints (SPPRC) or one of its variant. In Irnich and Desaulniers (2005), the contribution of SPPRC to the success of column generation of this class of problems is based on there main reasons. Firstly, through the resource constraints, it constitutes a flexible tool for modeling complex cost structures for an individual route and a wide variety of rules that define the feasibility of a route. Secondly, because it does not possess the integrality property, the column generation approach can derive tighter bounds than those obtained from the linear relaxation of arc-based formulations. Thirdly, there exist efficient algorithms available for important variants of SPPRC. In many vehicle routing problems, the pricing problem is an Elementary Shortest Path Problem with Resource Constraints (ESPPRC). Feillet et al. (2004),Chabrier (2002),Rousseau et al. (2004) solved ESPRRC in the context of VRPTW. ESPPRC was proposed to solve by using Lagrangian relaxation by Beasley and Christofides (1989).

The most recent and promising method to solve ESPPRC recently is the label setting algorithm proposed by Feillet et al. (2004),Righini and Salani (2006). ESPPRC is solved by bi-directional label setting algorithm in Righini and Salani (2006) which uses Dijkstra's bi-directional shortest path algorithm that expands paths both forward from the start depot and backward from the end depot. The paths are spliced in the middle which reduces the running time of the algorithm since the running time is dependent on the length of the path. Figure 2.1 illustrates the comparison of mono and bi-directional search performance.

Furthermore Righini and Salani (2008) and Boland et al. (2006) proposed to solve ESPPRC by use of a decremental state space algorithm that iteratively solves a SPPRC by applying resources forcing nodes to be visited at most once. In Righini and Salani (2008), three methods to solve ESPPRC are proposed.

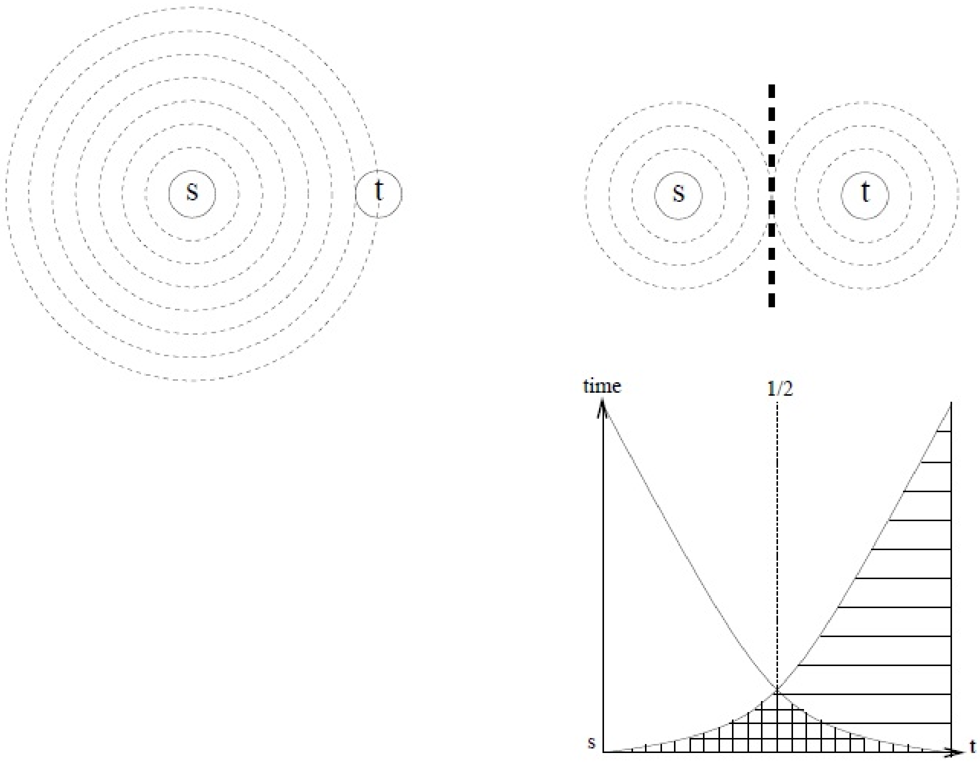

Figure 2.1: Comparison of mono-directional and bi-directional search to find a feasible path from node s to node t Petersen (2006)

The first method is exact dynamic-programming algorithm improved by new ideas, such as bidirectional search with resource-based bounding. The second method consists of a branch-and-bound algorithm, where lower bounds are computed by dynamic-programming with state-space relaxation where bounded bidirectional search can be adapted to state-space relaxation with different branching strategies and their hybridization. The third method, decremental state-space relaxation (DSSR), is a new one; exact dynamic-programming and state-space relaxation are two special cases of this new method. According to the experimental comparisons of the three methods,decrement state-space relaxation has the most promising results. In addition to Righini and Salani (2008),Chabrier (2006) successfully solved several previously unsolved instances of the VRPTW from the benchmarks of Solomon (1987) using a label-setting algorithm for the ESPPRC.

2.2.3 HEURISTICS

Classical Heuristics: Route construction, route improvement and composite heuristics are the reported in the literature as approximations methods to VRPTW. For a detailed review and comparison of the heuristics, the reader is referred to Bräysy and Gendreau (2005a).
Metaheuristics: The research focus on the approximation methods of TDVRPTW is on metaheuristics, mainly simulated annealing, tabu search Pisinger and Ropke (2007),Potvin et al. (1996) and mostly evolutionary algorithms yves Potvin and Bengio (1996),Homberger (2005).

2.2.4 TIME-DEPENDENT VEHICLE ROUTING PROBLEM WITH TIME WINDOWS (TD-VRPTW)

The solution methods proposed to solve TDVRPTW in the literature is mostly based on metaheuristics, especially tabu search (Ichoua et al. (2003), Woensel et al. (2008), Jabali et al. (2009)). On the other hand, for the time dependent vehicle problem, Malandraki and Daskin (1992) proposes heuristics based on nearest neighbor and cutting planes. Metaheuristics such as genetic algorithm by Haghani and Jung (2005) and ant colony optimization in Donati et al. (2008), Balseiro et al. (2011) are also present for time dependent vehicle routing problem.

CHAPTER 3

TDVRPTW SOLUTION METHODOLOGY

In this chapter, we refer to the exact solution method of Dabia et al.(2011) in which TDVRPTW is solved by branch and cut and price. The decomposition of the arc based formulation of TDVRPTW leads to a set partitioning model, described in Section 1.1.3.3, as the master problem and a time dependent elementary shortest path problem with resource constraint as the subproblem. However, the capacity constraint of the vehicles is handled in the master problem by the capacity cuts. Therefore, time is considered as the only resource constraint in the subproblem.In Figure 3.1, the general framework of the algorithm is presented with a flowchart. In this chapter, we will introduce the steps of the BCP algorithm through the column generation process, capacity cuts and the pricing subproblem.

3.1 THE MASTER PROBLEM

The set of feasible routes Ω can be a very large set even for medium sized customers. The set usually grows exponentially with the number of customers. Therefore, the master problem cannot be solved directly. The linear relaxation of the problem $P3$ is considered to handle the complexity of the problem.

P 3

$$\textit{minimize} \sum_{p \in \Omega} c_p y_p$$

subject to

$$\sum_{p \in \Omega} a_{ip} y_p = 1 \qquad \forall i \in V_c \tag{3.1}$$

$$y_p \geq 0 \qquad \forall p \in \Omega \tag{3.2}$$

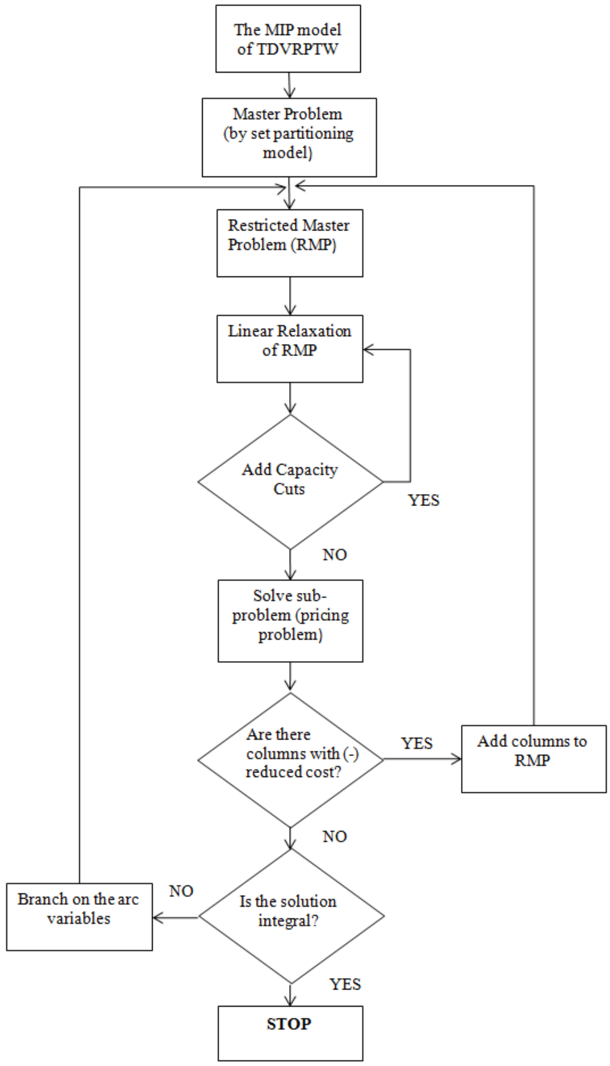

Figure 3.1: Flowchart of BCP algorithm for TDVRPTW

However, the linear programming model of the problem is not sufficient to handle the complexity of the problem. Therefore, the column generation methodology starts with a Restricted Master Problem(RMP) which considers a subset $\Omega' \subseteq \Omega$ of the feasible routes. However, RMP keeps growing during column generation process. With the definition of the master problem, the dual variable Π_i associated with the constraint 3.1 becomes

$$\bar{c}_p = e_p - s_p - \sum_{(i,j)\in A} \Pi_i x_{ij}. \tag{3.3}$$

Since the constant a_{ip} is 1 if customer i is visited on the path p and 0 otherwise, it can be rewritten as

$$a_{ip} = \sum_{(i,j)\in\gamma^+(j)} x_{ijp}. \tag{3.4}$$

where x_{ijp} is a binary variable which takes value 1 if arc (i, j) is traversed in path p. Hence, the reduced cost of a path becomes:

$$\bar{c}_p = e_p - s_p - \sum_{i\in V_c}\left(\Pi_i \sum_{(i,j)\in\gamma^+(j)} x_{ijp}\right) \tag{3.5}$$

$$= e_p - s_p - \sum_{(i,j)\in A} \Pi_i x_{ijp} \tag{3.6}$$

3.2 THE CAPACITY CUTS

In the formulation of the capacitated vehicle routing problem, we introduced the subtour elimination constraints which are the alternative formulations of the capacity cut constraintsToth and Vigo (2001a). In order to include the capacity cuts in the master problem, the arc variables x_{ij} are transformed into path variables y_p. With this addition of these capacity cuts, a new dual variable is introduced in the pricing problem for each of the inequalities. For, k capacity constraints defined by the set $S_1, S_2, ..., S_k$ and the corresponding k dual variables $\lambda_1, \lambda_2, ..., \lambda_k$, the reduced cost of a path p becomes

$$\bar{c}_p = e_p - s_p - \sum_{(i,j)\in A} \Pi_i x_{ij}^p - \sum_{l=1}^{k} \sum_{(i,j)\in A(S_l)} \lambda_l x_{ijp} \tag{3.7}$$

As the contributions of the dual variables λ and Π are aggregated into the dual variable φ_{ij}, the reduced cost $\bar{c}_p$ is defined as

$$\bar{c}_p = e_p - s_p - \sum_{(i,j)\in A} \varphi_{ij} x_{ijp} \tag{3.8}$$

In conclusion, by handling the capacity cuts in the restricted master problem, an additional dual variable is introduced in the reduced cost of a path. Accordingly,the objective of the pricing problem changes and vehicle capacity restrictions are not a constraint for the pricing problem. In the next section, the labeling algorithm used to solve the pricing problem is introduced.

3.3 THE PRICING PROBLEM

In the BCP framework of TDVRPTW, the pricing problem becomes Time-Dependent Elementary Shortest Path Problem with Resource Constraint (TDESPPRC)in which only resource is time.Dabia et al.(2011) introduces the time dependent labeling algorithm (TDL) with bi-directional search to solve TDESPPRC by adapting the solution method by Righini and Salani (2006) to the time dependent case of ESPPRC. In this section we introduce the bi-directional search algorithm for TDESPPRC.

3.3.1 FORWARD TDL ALGORITHM

In the forward TDL algorithm, labels are extended from the start depot to the end depot through the successors of start depot and the extension is restricted by time which is the only resource considered. A forward label's ,L_f, extension is feasible until the earliest arrival time at the end node of the partial path is no further than a fixed time t_m. The functions in Table 3.1 are defined to describe the forward TDL algorithm.

Table 3.1: The attributes of label L_f

$v(L_f)$	: The last node visited on the partial path L_f
$c(L_f)$	: The sum of the dual variable associated with the arcs traversed on the partial path L_f
$\delta_{L_f}(t)$	: The arrival time function of L_f which gives the arrival time (including waiting and service time) at the end node $v(L_f)$ when the depot is left at time t .
$S(L_f)$	: The set of nodes visited along the partial path L_f

When a label L'_f is extended to a new path L_f by traversing an arc $(v(L'_f), j)$, the arrival time at node j is calculated as

$$\delta_{L_f}(t) = \delta_{L'_f}(t) + \tau_{v(L'_f)j}(\delta_{L'_f}(t)) \tag{3.9}$$

As a new node is visited along the path, the set of nodes visited and the sum of the dual variables of the path are updated as

$$S(L_f) = S(L'_f) \cup \{j\} \text{ and } c(L_f) = c(L'_f) - \varphi_{v(L'_f)j} \tag{3.10}$$

These extension of the label is feasible if node j is not visited before such that $S(L'_f) \cap \{j\} = \emptyset$ and the earliest arrival time to node j satisfies the condition $\delta_{L_f}(0) \leq min\left\{t_m, b_j + s_j\right\}$. As the label reaches the end node $v(L_f)$, the reduced cost of the path becomes

$$\bar{c}(L_f) = min_{t \in T} \left\{\delta_{L_f}(t) - t\right\} + c(L_f) \tag{3.11}$$

where T is the domain definition of $\delta_{L_f}(t)$.

In the extension of the labels, it is not desirable to extend labels that will not be part of an optimal solution. Therefore, dominance criterion are introduced for the dominance test in order to reduce the number of labels that are created during the execution phase of the TDL algorithm. Let $E(L_f)$ denote the set of all feasible extensions of L_f ,i.e. the partial paths departing at node $v(L_f)$ at time $\delta_{L_f}(0)$ and reaching the end depot $n+1$ satisfying the feasibility constraints. If $L \in E(L_f)$, then the label results from extending the path L_f by L is denoted as $L_f \oplus L$. With these definitions as building blocks, the domination is defined:

Definition 3.3.1 *Label L_f^2 is dominated by L_f^1 if*

1. $v(L_f^1) = v(L_f^2)$
2. $E(L_f^2) \subseteq E(L_f^1)$
3. $\bar{c}(L_f^1 \oplus L) \leq \bar{c}(L_f^2 \oplus L),\ \forall L \in E(L_f^2)$.

Definition 3.3.1 implies that label L_f^1 dominates L_f^2 if the partial paths end at the same depot, all feasible extensions of label L_f^1 is also a feasible extension of L_f^2 and extending the former label is not more costly than extending the latter. Since, the computational effort of extending all the paths to their feasible extensions is high, two propositions with efficient dominance criterion are introduced. We will not give a detailed explanation for these dominations since it is not in the scope of this thesis.

3.3.2 BACKWARD TDL ALGORITHM

The backward TDL algorithm works in the same way with forward TDL algorithm. However, the labels are extended from the end depot to its predecessors. A backward label's ,L_b, extension is feasible if the latest possible departure time from the end node is larger than the fixed time t_m. The following functions in Table 3.2 are defined to describe the backward TDL algorithm.

When a label L_b' is extended to a new path L_b by traversing an arc $(j, (v(L_b'))$, the arrival time function associated with the label L_b is computed as

$$\delta_{L_b}(t) = \delta_{L_b'}(t + \tau_{jv(L_b')}(\delta_{L_b'}(t))). \tag{3.12}$$

Table 3.2: The attributes of label L_b

$v(L_b)$	: The last node visited on the partial path L_b
$c(L_b)$	: The sum of the dual variable associated with the arcs traversed on the partial path L_b
$\delta_{L_b}(t)$	: The arrival time function of L_b which gives the arrival time (including waiting and service time)at the end depot when the end node $v(L_b)$ of the partial path is left at time t
$S(L_b)$	: The set of nodes visited along the partial path L_b

As a new node is visited along the path, the set of nodes visited and the sum of the dual variables of the path are updated as

$$S(L_b) = S(L'_b) \cup \{j\} \text{ and } c(L_b) = c(L'_b) - \varphi_{jv(L'_b)}. \tag{3.13}$$

These extension of the label is feasible if node j is not visited before such that $S(L'_b) \cap \{j\} = \emptyset$ and the latest possible departure time $t(L_b)$ at node j satisfies the condition $t(L_b) \geq (a_j + s_j)$. Furthermore, as the extension of the labels are bounded by time, the latest possible departure time should be $t(L'_b) \geq t_m$.

As the label reaches the end node j, the reduced cost of the path becomes

$$\bar{c}(L_b) = min_{t \in T} \{\delta_{L_b}(t) - t\} + c(L_b) \tag{3.14}$$

where T is the domain definition of $\delta_{L_b}(t)$.

Let $E(L_b)$ denote the set of feasible extensions of L_b, i.e. all partial paths departing at the start depot at time 0 and arrival time at node $v(L_b)$ is smaller than $t(L_b)$ which is the latest departure time from the fist node visited on L_b. As it is computationally expensive to extend all the labels, it is not desirable to extend labels that will not be part of an optimal solution. Therefore, efficient dominance tests are proposed to reduce the number of labels extended. We will not give a detailed explanation for these dominations since it is not in the scope of this thesis.

3.3.3 SPLICING FORWARD AND BACKWARD LABELS

After all the forward and backward labels are extended, they are combined to obtain a path. Let L_b be in the extension of forward path L_f. The labels are then merged to obtain a path $L = L_f \oplus L_b$ such that

1. $v(L) = n + 1$

2. $c(L) = c(L_f) + c(L_b)$

3. $S(L) = S(L_f) \cup S(L_b)$

4. $\delta_L(t) = \delta_{L_b}(\delta_{L_b}(t)), \forall t \in D_{\delta_{L_f}(t)}$ such that $D_{\delta_{L_f}(t)} \in D_{\delta_{L_b}(t)}$.

The bi-directional TDL algorithm generates paths all with negative reduced costs. Let $P = v_0 \rightarrow ... \rightarrow v_p$ be a path in the optimal solution, it is proposed that

Proposition 3.3.2 *Let v_i be a node in P. P can be found as $P = P_f \oplus P_b$ where $P_f = v_0 \rightarrow ... \rightarrow v_i$ is generated by the forward TDL algorithm and $P_b = v_i \rightarrow ... \rightarrow v_p$ is generated by the backward TDL algorithm.*

Let $P = v_0 \rightarrow v_1 \rightarrow v_i \rightarrow v_{i+1}...v_{p-1} \rightarrow v_p$ be an arbitrary path where v_0 is the start depot, v_p is the end depot and v_{i+1} is the node visited right after v_i. The *splicing node* is defined as :

Definition 3.3.3 *Node v_i is a splicing path of path P if*

- $\delta_{L_f}(0) \leq t_m$

and

- $\delta_{L_{i+1}}(0) > t_m$ *or,*

- $\delta_{L_{i+1}}(0) \leq t_m$ *and* $v_{i+1} = n + 1$.

The bi-directional TDL algorithm can generate duplicate paths and a path can be spliced at different nodes.However, any node that can be defined uniquely makes sure that a path spliced at that node is found only once. Therefore, according to the definition , it is proposed that

Proposition 3.3.4 *The splicing node of P exists and it is unique.*

For the proof of the propositions, the reader is referred to Dabia et al. (2011).

3.3.4 PRICING PROBLEM HEURISTICS

In BCP framework, pricing heuristics are used to generate columns with negative reduced cost in the pricing problem. If heuristics cannot find any more columns with negative reduced costs, then the bi-directional TDL algorithm is called to check if a path can be found with negative reduced cost. Therefore, for every node in the branching tree, TDL algorithm is called only once.

3.4 BRANCHING

Best bound strategy is used to select the next active node in the branch and bound tree. The branching is done on the arc variables. The pairs $(i, j), i, j \in V_c$ are searched such that the current fractional solutions expressed in arc pairs $(x^*_i j + x^*_j i)$ is close to 0.5. Then the branch on the tree node is $(x_{ij} + x_{ji}) \leq \lfloor (x^*_{ij} + x^*_{ji}) \rfloor$ and $(x_{ij} + x_{ji}) \geq \lceil (x^*_{ij} + x^*_{ji}) \rceil$. If $(x^*_{ij} + x^*_{ji})$ is integer for all pairs, then the a fractional value for x^{ij} is searched and branching is done on that instance instead. The algorithm uses strong branching and performs the branch that maximizes the lower bound in the weakest of two child nodes. 15 branch candidates in the first 10 nodes of the brnch and bound tree and 10 candidates in the rest is considered.

CHAPTER 4

BOUNDING MODELS ON BI-DIRECTIONAL TDL ALGORITHM

When introducing the bi-directional dynamic programming for elementary shortest path problem with more than one resource, Righini and Salani (2006) also proposed bounding procedures to limit the number of labels produced by :

- **Bounding for Fathoming:** Recognizes and fathoms states that cannot produce optimal solutions
- **Arc and Resource Bounding:** Stops the extension of forward and backward paths in order to reduce the number of labels generated, while preserving the guarantee that the optimal solution will be found.

  In arc bounding, this is done by computing the number of arcs that can be added to the corresponding partial path without exceeding the resource constraints. A multi-knapsack problem is solved and an upper bound on the number of vertices that can be added along the path after the last reached vertex of the label is obtained. If the number of nodes visited on the corresponding path is less than the result of the knapsack problem than the extension of the label is stopped.

  On the other hand, it is also possible to stop the extension of the paths when at least half of available amount of the selected resource is consumed. It is necessary to select a resource whose consumption is monotone along the path.

Within their computational experiments,Righini and Salani (2006) always uses fathoming with arc and resource bounding. In most of the instances with different resource constraints, resource bounded bi-directional dynamic programming outperforms arc bounded bi-directional dynamic programming. Although the performance of the bounded bi-directional search is better than mono-directional search in general, latter produces less labels for instances with tight time windows. Furthermore, arc bounding is useful only when the optimal path is made of a significant number of arcs Righini and Salani (2006).

In this study, TDESPPRC is solved with resource bounded bi-directional search without bounding for fathoming. In this chapter, we will develop

- A bounding technique in order to fathom unpromising states in bi-directional TDL algorithm,
- An arc bounding procedure for bi-directional search TDL algorithm.

4.1 BOUNDING FOR FATHOMING

The aim of the bounding technique proposed in this section is to limit the number of labels in the TDL algorithm. The labels whose extensions will lead to a worse solution than a known one are fathomed by applying the bounding procedure. Within the pricing algorithm, this technique should be applied after the dominance testes are done on forward on backward labels. In this section, we first introduce the fathoming technique on forward labels and then backward labels.

4.1.1 BOUNDING FOR FATHOMING ON FORWARD LABEL EXTENSION

For each of the non-dominated label L_f, we are looking for an upper bound $\overline{P}_{L_f}$ which is the maximum gain that can be obtained by extending that label using minimum resources. To find this upper bound, an optimization problem is solved to maximize the prize collected subject to available resources. The only resource considered in this problem is time. The cost of traveling on an arc is also defined in terms of time. It is the time between the arrival times of the two end nodes of an arc, called ***duration***. In addition, arrival time function includes the waiting time and the service time of the visited node. Therefore, *duration of traveling on an arc consists of the traveling time between two nodes, waiting time and service time at the end node*.

The description of the variables and parameters used in the optimization problem for fathoming **(P4)** is listed in Table 4.1.

For each of the non-dominated label L_f, optimization problem (P4) should be solved in order to decide whether to fathom the label:

Table 4.1: Description of Parameters and Variables

φ_{kj}	: Dual variable of traveling on arc (k, j)
$\gamma_{kj}(\eta_k)$	: Duration of traveling on arc (k, j) where η_k is the arrival time at node k
γ_j	: Minimum duration needed to visit node j
u_j	: Maximum prize collected when node j is visited
y_j	: Decision variable of visiting node j

P 4

$$\begin{aligned}
&\textit{maximize} \quad \overline{P}_{L_f} = \sum_{j\in V_c\setminus S(L_f)} u_j y_j + u_{n+1} \\
&\textit{subject to} \quad \delta_{L_f}(0) + \sum_{j\in V_c\setminus S(L_f)} \gamma_j y_j + \gamma_{n+1} \leq T \\
&y_j \in \{0,1\} \quad \forall j \in V_c\setminus S(L_f)
\end{aligned}$$

In the objective function of the problem ($P4$), we are searching for the maximum gain that can be collected by visiting unvisited customers, $V_c\setminus S(L_f)$, of label L_f within the planning horizon T. Due to FIFO property of the arrival time functions, a later dispatch time results in a later arrival at the end node of the path. Hence, to increase the allocated time for the unvisited nodes in the inequality constraint, the departure time at the start depot is taken as "0". Therefore, we consider the arrival time at the end node of the label L_f as $\delta_{L_f}(0)$. In the objective function, u_j is the maximum gain that can be collected by visiting node j. To find the maximum gain, the dual variable of a possible arc is reduced by the minimum duration of the outgoing arc since it is always needed when a node is selected such that

$$u_j = \max_{k\in\{V_c\setminus S(L_f)\}\cup\{v(L_f)\}} \begin{cases} \varphi_{kj} - \min_{\substack{\max\{(a_k+s_k),\delta_{L_f(0)}\}\leq\eta_k \\ \eta_k\leq(b_k+s_k)}} \gamma_{kj}(\eta_k) & \text{if} \begin{array}{l}(k,j)\in A, \\ \delta_{L_f(0)} \leq (b_k+s_k).\end{array} \\ -M & \text{otherwise.} \end{cases} \tag{4.1}$$

$$u_{n+1} = \max_{k\in\{V_c\setminus S(L_f)\}\cup\{v(L_f)\}} \begin{cases} \varphi_{kn+1} - \min_{\substack{\max\{(a_k+s_k),\delta_{L_f(0)}\}\leq\eta_k \\ \eta_k\leq(b_k+s_k)}} \gamma_{kn+1}(\eta_k) & \text{if} \begin{array}{l}(k,n+1)\in A, \\ \delta_{L_f(0)} \leq (b_k+s_k).\end{array} \\ -M & \text{otherwise.} \end{cases} \tag{4.2}$$

where M is a very big positive number. As defined before, $\gamma_{kj}(\eta_k)$ is the duration of traveling on arc (k, j) and depends on the arrival time at node k. Since we are searching for an upper bound on the prize collected by visiting all possible reachable nodes, the arrival time at node k is taken as the the arrival time at the end node visited on label L_f which is $\delta_{L_f}(t)$. The departure time from the depot, t, is taken as

0 to increase the search space on the arrival time function in order to find the minimum duration when calculating u_j and u_{n+1} which are defined in the equations (4.1) and (4.2), respectively. However, if $\delta_{L_f(0)}$ is smaller than the minimum possible arrival time at node k, then $(a_k + s_k)$ is taken as the arrival time of node k for reachable nodes. In addition, the upper bound on η_k is taken as $(b_k + s_k)$ since it is the maximum feasible arrival time at node k. To conclude, the aim is to calculate the maximum gain with regards to the end time windows. Therefore, we do not consider the lower bound by the start time windows of the nodes that can be visited as a feasibility condition.

γ_j, on the other hand, is the minimum resource used to visit node j. Following the same approach as in the calculation of u_j and u_{n+1} ,the bounds on the arrival time, η_k, are taken the same as in the equations (4.1) and (4.2). Therefore, the minimum time needed to visit node j, which is γ_j, and the end depot, which is γ_{n+1}, are defined as in the following:

$$\gamma_j = \begin{cases} \min_{\substack{k\in\{V_c\setminus S(L_f)\}\cup\{v(L_f)\} \\ \max\{(a_k+s_k),\delta_{L_f(0)}\}\leq\eta_k \\ \eta_k\leq(b_k+s_k)}} \left\{\gamma_{kj}(\eta_k)\right\} & \text{if } \begin{array}{l}(k,j)\in A, \\ \delta_{L_f(0)} \leq (b_k+s_k).\end{array} \\ b_{n+1} & \text{otherwise.} \end{cases} \tag{4.3}$$

$$\gamma_{n+1} = \begin{cases} \min_{\substack{k\in\{V_c\setminus S(L_f)\}\cup\{v(L_f)\} \\ \max\{(a_k+s_k),\delta_{L_f(0)}\}\leq\eta_k \\ \eta_k\leq(b_k+s_k)}} \{\gamma_{kn+1}(\eta_k)\} & \text{if } \begin{array}{l}(k,n+1)\in A, \\ \delta_{L_f(0)} \leq (b_k+s_k)\end{array} \\ b_{n+1} & \text{otherwise.} \end{cases} \tag{4.4}$$

where duration on arc (k, j) and $(k, n + 1)$ are calculated as

$$\gamma_{kj}(\eta_k) = \underbrace{\tau_{kj}(\eta_k)}_{\text{Travel Time}} + \underbrace{\max\left\{0, a_j - (\eta_k + \tau_{kj}(\eta_k))\right\}}_{\text{Waiting Time}} + \underbrace{s_j}_{\text{Service Time}} . \tag{4.5}$$

$$\gamma_{kn+1}(\eta_k) = \tau_{kn+1}(\eta_k) + \max\{0, a_{n+1} - (\eta_k + \tau_{kn+1}(\eta_k))\} + s_{n+1}. \tag{4.6}$$

By solving the knapsack problem, an upper bound $\overline{P}_{L_f}$ is obtained on the maximum gain that can be collected by extending the label L_f. If

$$\underbrace{\min_{t\leq t(L_f)}(\delta_{L_f}(t) - t) + c(L_f)}_{\text{Reduced Cost of } L_f} - \overline{P}_{L_f} \geq UB, \tag{4.7}$$

then the label L_f is fathomed. In the inequality (4.7), $\min_{t \leq t(L_f)}(\delta_{L_f}(t) - t)$ is the minimum duration of the label L_f and $c(L_f)$ is the sum of the dual variables associated with arcs traversed along the partial path L_f. To find the minimum duration,departure time from the depot is searched over the arrival time function breakpoints. The departure time from the start depot which results in the minimum duration belongs to a breakpoint. Moreover, UB represents an incumbent upper bound which is the value of a known feasible solution. UB is calculated by comparing the reduced costs of the columns found in the solution of the linear relaxation of RMP. If this value is positive, than UB is taken "0" such that $\text{UB} = \min\{0, \min\{\text{column reduced cost}\}\}$. By subtracting the upper bound,$\overline{P}$, from the reduced cost of the label L_f, a lower bound on the reduced cost of a total path by extending label L_f is obtained. Notice that, when solving the optimization problem ($P4$), only the reachable nodes from L_f can be in the extension. In conclusion, if the lower bound on the reduced cost of a potential path is not better than the reduced cost of a known feasible solution, then the label L_f should be fathomed. The intuition behind this rule is that if we cannot get a better solution by extending a label with maximum gain and minimum resource, than it is not meaningful to keep the label in the set of non dominated labels and we can fathom it.

4.1.2 BOUNDING FOR FATHOMING ON BACKWARD LABEL EXTENSION

As in the fathoming procedure proposed for forward labels, the same steps are followed for fathoming backward labels. However, we should customize the problems,parameters and their calculation steps according to backward label extension.

For each of the non-dominated label L_b, optimization problem (P5) should be solved for the decision of fathoming L_b:

P 5

$$\begin{aligned}
&\text{maximize} \quad \overline{P}_{L_b} = \sum_{j \in V_c \setminus S(L_b)} u_j y_j + u_0 \\
&\text{subject to} \quad \sum_{j \in V_c \setminus S(L_b)} \gamma_j y_j + \gamma_0 \leq t(L_b) \\
&y_j \in \{0,1\} \quad \forall j \in V_c \setminus S(L_b)
\end{aligned}$$

In the objective function of the problem ($P5$), we are searching for the maximum gain that can be collected by traversing unvisited customers, $V_c \setminus S(L_b)$, of label L_b within the planning horizon T. To increase the allocated time for the unvisited nodes in the inequality constraint, the latest possible departure time $t(L_b)$ is taken as the departure time from $v(L_b)$. Hence, the available time for traversing the unvisited nodes of label L_b becomes $t(L_b)$. The maximum gain that can be collected by visiting node j and the start depot, 0, is calculated by subtracting the minimum duration of an incoming arc from the dual variable of that arc :

$$u_j = \max_{k\in\{V_c\setminus S(L_b)\}\cup\{v(L_b)\}} \begin{cases} \varphi_{jk} - \min_{\substack{\max\{(a_j+s_j),t'(L_b)\}\leq\eta_j \\ \eta_j\leq(b_j+s_j)}} \gamma_{jk}(\eta_j) & \text{if } \begin{array}{l}(j,k)\in A,\\ t(L_b)\leq(b_k+s_k)\end{array} \\ -M & \text{otherwise.} \end{cases} \tag{4.8}$$

$$u_0 = \max_{k\in\{V_c\setminus S(L_b)\}\cup\{v(L_b)\}} \begin{cases} \varphi_{0k} - \min_{\substack{\max\{(a_0+s_0),t'(L_b)\}\leq\eta_k \\ \eta_0\leq(b_0+s_0)}} \gamma_{0k}(\eta_0) & \text{if } \begin{array}{l}(0,k)\in A,\\ t(L_b)\leq(b_k+s_k)\end{array} \\ -M & \text{otherwise.} \end{cases} \tag{4.9}$$

where M ia a very big positive number. In the equation (4.8, $\gamma_{jk}(\eta_j)$ is the duration of traveling on arc (j,k) and depends on the arrival time at node j. The arrival time η_j is restricted by the time windows of that node. However, if the earliest possible departure time from the end node $v(L_b)$, which is denoted as $t'(L_b)$, is between the time windows of node j, then $t'(L_b)$ is taken as the arrival time for reachable nodes. Node k is reachable from node j if there exists an arc between (j,k) and the latest possible departure time of L_b, $t(L_b)$, is not larger than $b_j + s_j$.

γ_j, on the other hand, is the minimum resource used to visit node j. Following the same approach as in the calculation of u_j and u_0, the bounds on the arrival times, η_j and η_0, are taken the same as in the equations (4.8) and (4.9). Therefore, the minimum time needed to visit node j, which is γ_j, and the start depot, which is γ_0, are defined as in the following:

$$\gamma_j = \begin{cases} \min_{\substack{k\in\{V_c\setminus S(L_b)\}\cup\{v(L_b)\} \\ \eta_j\geq\max\{(a_j+s_j),t(L_b)\} \\ \eta_j\leq(b_j+s_j)}} \left\{\gamma_{jk}(\eta_j)\right\} & \text{if } \begin{array}{l}(j,k)\in A,\\ t(L_b)\leq(b_k+s_k).\end{array} \\ b_0 & \text{otherwise.} \end{cases} \tag{4.10}$$

$$\gamma_0 = \begin{cases} \min_{\substack{k\in\{V_c\setminus S(L_b)\}\cup\{v(L_b)\} \\ \max\{(a_0+s_0),t(L_b)\}\leq\eta_0 \\ \eta_0\leq(b_0+s_0)}} \{\gamma_{0k}(\eta_0)\} & \text{if } \begin{array}{l}(0,k)\in A,\\ t(L_b)\leq(b_k+s_k)\end{array} \\ b_0 & \text{otherwise.} \end{cases} \tag{4.11}$$

where duration on arc (j,k) and $(0,k)$ are calculated as

$$\gamma_{jk}(\eta_j) = \underbrace{\tau_{jk}(\eta_j)}_{\text{Travel Time}} + \underbrace{\max\left\{0, a_k - (\eta_j + \tau_{jk}(\eta_j))\right\}}_{\text{Waiting Time}} + \underbrace{s_k}_{\text{Service Time}}. \tag{4.12}$$

$$\gamma_{0k}(\eta_0) = \tau_0(\eta_0) + \max\left\{0, a_k - (\eta_0 + \tau_{0j}(\eta_0))\right\} + s_0. \tag{4.13}$$

By solving the knapsack problem, an upper bound $\overline{P}_{L_b}$ is obtained on the maximum gain that can be collected by extending the label L_b. If

$$\underbrace{\min_{t \le t(L_b)}(\delta_{L_b}(t) - t) + c(L_b)}_{\text{Reduced Cost of } L_b} - \overline{P}_{L_b} \ge UB, \tag{4.14}$$

then the label L_b is fathomed.

In the inequality (4.14), $\min_{t \le t(L_b)}(\delta_{L_b}(t) - t) + c(L_b)$ is the minimum duration of the label L_b and $c(L_b)$ is the sum of the dual variables associated with arcs traversed along the partial path L_b. To find the minimum duration, departure time from the depot is searched over the arrival time function breakpoints. The departure time from the start depot which results in the minimum duration belongs to an arrival time function breakpoint. Moreover, UB represents an incumbent upper bound which is the value of a known feasible solution which is the same value calculated in fathoming forward labels. By subtracting the upper bound,$\overline{P}_{L_b}$, from the reduced cost of the label L_b, a lower bound on the reduced cost of a total path by extending label L_b is obtained. Notice that, when solving the optimization problem ($P5$), only the reachable nodes from L_b can be in the extension. In conclusion, if the lower bound on the reduced cost of a potential path is not better than the reduced cost of a known feasible solution, then L_b shouldn't be in the set of non-dominated labels and we can fathom it.

4.1.3 IMPLEMENTATION OF FATHOMING TO BCP FRAMEWORK

The fathoming procedure is implemented on the TDL algorithm of the solution procedure of TDVRPTW by BCP. Therefore, the knapsack problems 4 and 5 are implemented in the pricing problem for the non-dominated labels. If the forward or the backward labels satisfy the inequalities 4.7 and 4.14, then they are fathomed and their extensions to form a path is not considered anymore. Hence, we expect to produce less number of labels when the pricing algorithm is called in the BCP algorithm.

4.2 ARC BOUNDING

Another way to reduce to stop the extension of forward and backward labels is arc bounding instead of resource bounding. In this bounding technique, it is aimed to stop the extension of a backward or forward label if the maximum number of vertices that can be added to that label is less than the number of visited nodes on the label. Following the notation in Table 4.1, an upper bound on the number of arcs that can be added to the path L_f without exceeding the available resource is obtained by solving a similar optimization problem as in ($P4$):

P 6

$$\begin{aligned} &\textit{maximize} && \sum_{j \in V_c \setminus S(L_f)} y_j + 1 \\ &\textit{subject to} && \delta_{L_f}(0) + \sum_{j \in V_c \setminus S(L_f)} \gamma_j y_j + \gamma_{n+1} \leq T \\ &y_j \in \{0, 1\} && \forall j \in V_c \setminus S(L_f) \end{aligned}$$

If the solution of the problem ($P6$) is less than the number of nodes visited on the label L_f, $|S|$, then the extension of the label is stopped. The remaining part of the path will be generated by the labels extended in the other direction due to the bi-directional search.

In a similar way, the same procedure is followed to stop the extension of the backward labels. The knapsack problem that is solved to find the upper bound on the maximum number of nodes that can be visited on a backward label L_b is given in ($P7$) below:

P 7

$$\begin{aligned} &\textit{maximize} && \sum_{j \in V_c \setminus S(L_b)} y_j + 1 \\ &\textit{subject to} && \sum_{j \in V_c \setminus S(L_b)} \gamma_j y_j + \gamma_0 \leq t(L_b) \\ &y_j \in \{0, 1\} && \forall j \in V_c \setminus S(L_b) \end{aligned}$$

CHAPTER 5

COMPUTATIONAL RESULTS

5.1 DATA SET

The test instances are derived from Solomon test instances which are originally designed by Marius Solomon in 1983 for VRPTW with 100 customers. The instances used in this thesis are from Dabia et al. (2011) which adapts the original test instances of VRPTW for TDVRPTW. The instances are designed taking into several factors. These factors are listed as follows.

- **Geographical distribution of the customers:** The customers can be in Randomly(R), Clustered(C), Randomly Clustered (RC) categories according to their displacements.
- **Width of the time windows:** The time windows of the customers is classified into two categories as (1) with tight time windows and (2) as the wide time windows.
- **Number of customers:** The number of customers in the test instances are up to 100 customer. We will present the results for 25, 50 and 100 customers.

Time dependency is adapted to test instances by considering different speed profiles. The speed profiles change during the planning horizon due to road congestion. In addition to the speed profiles, different type of links connect these speed profiles. Three different links: slow, normal and fast represent the type for the change of speed within city center, traveling from highways to city center and within the highways. These links are selected randomly and is the same for all instances. The speed profiles with 3 type of links can be found in the Appendix A. The planning time horizon is divided into five planning time zones with regards to the speed profiles. The zones are defined as $Zone1 = [0, 0.2T[, Zone2 = [0.2T, 0.3T[, Zone3 = [0.3T, 0.7T[, Zone4 = [0.7T, O.8T[$ and $Zone5 = [0.8T, T[$ where T is the end time window of the end depot b_{n+1}.

In the notation *DTm.n*, ”D” shows the type of geographic distribution of customers, ”T” represents the width of the time windows, ”m” denotes the number of the instance and finally ”n” shows the number of customers to be served.

5.2 COMPUTATIONAL RESULTS

The procedures proposed in chapter 5.2 for the BCP framework were tested on Intel(R) Core(TM)2 Quad CPU, 2.83 GHz, 4 GB of RAM computer. The linear relaxation of the master problem is solved by LP solver CLP from open source framework COIN, COIN-OR (2011). The knapsack problems were solved in the bounding procedures by using the optimization IBM ILOG CPLEX version 12.1 including ILOG Concert Technology libraries,IBM (2011).

In Appendix B, we present the computational results for the TDVRPTW instances with 25 and 50 customers solved by BCP framework in which the solution to the pricing problem TDESPPRC is found by resource bounded bi-directional TDL algorithm and the instances when fathoming is implemented. The average of the percentage improvements (according to Dabia et al. (2011)) in the number of labels produced can be seen in Table 5.1 below:

Table 5.1: Average % decrease in the number of labels by data type

Instance type	*Average % decrease*	*# of instances solved*
R1m.25	9%	12
R2m.25	93%	2
RDm.25	21%	14
C1m.25	51%	7
C2m.25	57%	3
CDm.25	52%	10
RC1m.25	6%	5
RC2m.25	73%	2
RCDm.25	25%	7
Overall Average	**32%**	**31**

The results in Table 5.1 show that the ”best improvement on average in the total number of labels produced” is in the data type with randomly located customers who have wide time windows. However, if we base the comparison only according to the geographical distribution of the customers, it is seen that the best improvement was obtained for the instances with customers who have clustered displacements.

Moreover, Table 5.2 shows the % decrease in the number of labels based on the time windows of the customers. The average % decrease in the instances with customers with wide time windows is larger than the one with tight time windows.

Table 5.2: % decrease in the number of labels according to the classification of time windows

	T=1	*T=2*
% decrease	21%	63%
# of instances solved	24	7

Furthermore, on average 33% and 31% less labels are produced in the extension of backward and forward labels, respectively. In addition, in 8 instances out of 31, less number of columns are generated in column generation and pricing algorithm is called less frequently in 5 instances out of 31 instances solved compared to the results of Dabia et al. (2011). Although solving the knapsack problem in the fathoming procedure increases the time spent solving the exact pricing algorithm, we observed that in 10 instances the time to solve an instance decreased.

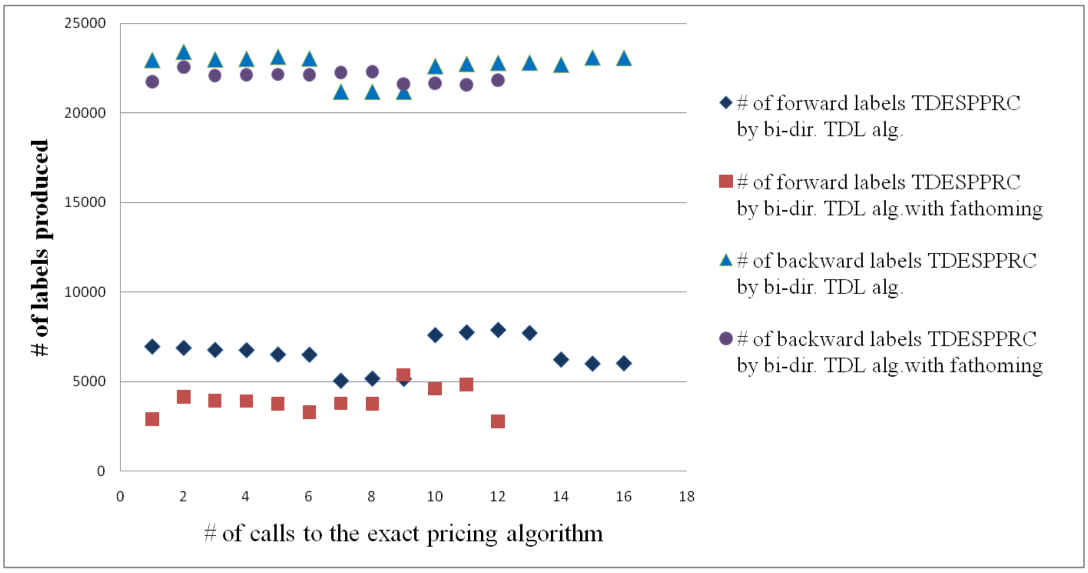

Figure 5.1: Solution of r104.25 with and without fathoming

A good example is given in Figure 5.1 for the instance *r104.25* in which labels are produced more efficiently with fathoming. Hence, in the BCP framework less columns are generated and less number of calls are made to the pricing problem which led the algorithm to find the optimal solution in less time. To give it in figures, without fathoming, r104.25 is solved in 74116 seconds by generating 16 columns.

However, r104.25 is solved in 1053.44 seconds by generating 12 columns when fathoming is introduced to bi-directional TDL algorithm.

The results for the instances with 50 customers is given in Appendix B. As in the case with 25 customers, there is a larger improvement in the instances with clustered geographical distribution of the customers in terms of number of labels produced as shown in Table 5.3. In addition, among these instance, we could reduce the time to solve the instance *r109.50, c101.50 and c106.50*.

Table 5.3: decrease in the total number of labels produced by instance

r101.50	r105.50	r109.50	r110.50	c101.50	c106.50	rc101.50
16%	95%	12%	2%	89%	93%	2%

As discussed in chapter , in the original problem solved by Dabia et al. (2011) by bi-directional search, the author already uses resource bounding. When we implemented arc bounding, in the test instances we realized that the resource bounding performs much better than arc bounding. Therefore, here we do not present the results when arc bounding is implemented instead of resource bounding.

CHAPTER 6

CONCLUSION

In this study we implemented fathoming and arc bounding procedure to the pricing problem of TD-VRPTW in BCP framework. In the analysis performed for the instances solved, we realized that the fathoming procedure works well in general for the instances with clustered geographical distribution of the customers and instances with customers having wide time windows, in terms of the number of labels produced. In addition, the efficient production of forward and backward labels led to a decrease in the solution time in 13 instances out of 38 in total. In the other instances we could not improve the existing solution by Dabia et al. (2011).

6.1 FUTURE RESEARCH DIRECTIONS

With the introduction of bi directional dynamic programming by Righini and Salani (2006), researchers' attention increased to solve the resource constrained elementary shortest path problems by bi-directional search algorithm within the branch-and-price and branch-and-cut-and-price algorithms. This led to the emerge of more promising methods to solve ESPPRC. One of these methods is the decremental state space relaxation proposed by Righini and Salani (2008). The method has comparable computational performances with exact dynamic programming when the resource constraints are very tight. Therefore, the future extension of this research could be implementing decremental state space relaxation to solve ESPPRC.

CHAPTER 7

EFFECTS ANALYSIS OF A NEW CUSTOMER ON KUEHNE NAGEL NETHERLANDS FMCG DISTRIBUTION NETWORK

Logistics plays an increasingly important strategic role for organizations that strive to keep pace with market changes and supply chain integration. Meade (1998)Therefore, third party logistics (3PLs) play an increasing role in the supply chain of the companies who outsource logistics activities. The main advantage of outsourcing services to 3PLs is that these 3PLs allow companies to get into a new business, a new market, or a reverse logistics program without interrupting forward flows; in addition, logistics costs can be greatly reduced. Accordingly, an important reason for the growth of 3PL services is that companies compete in a number of businesses that are logistically distinct due to varied customer needs. Most providers have specialized their services through differentiation, with the scope of services encompassing a variety of options ranging from limited services (for example transportation) to broad activities covering the supply chain.Fuller et al. (1993). In addition, 3PLs have also become important players in reverse logistics since the implementation of return operations requires a specialized infrastructure needing special information systems for tracking/capturing data, dedicated equipment for the processing of returns, and specialist trained nonstandard manufacturing processes. Some 3PLs, on the other hand, offer complete supply chain solutions on warehousing, order fulfillment, and especially value-added services such as repackaging, re-labeling, assembly, light manufacturing, and repair.Ko and Evans (2007)

In this chapter, we will introduce an effects analysis of a new customer on the Dutch distribution network of Kuehne+Nagel (K+N), a 3PLs firm who provides its customers integrated services including all aspects of logistics planning, control and execution. Recently, Kuehne+Nagel signed a contract with a new customer PepsiCO whose main business is manufacturing, marketing and distribution of grain-based snack foods, beverages and other products. PepsiCo decided to outsource its warehousing, freight management and distribution operations in the Netherlands in order to improve customer service by responding even quicker to changing market demands while at the same time reducing supply chain costs as well as the environmental impact of its transportation activities. Therefore, the company decided to have a contract with Kuehne+Nagel for 10 years and outsource its logistics activities.The company chose Kuehne+Nagel since KN ensured an integrated and flexible solution that copes with the daily patterns and seasonality of the food industry with their in depth knowledge of Fast Moving Consumer Goods (FMCG) industry. Within the scope of 10 year contract, K+N provides supply chain solutions tailored to PepsiCo's specific needs. By integrating PepsiCo into Kuehne + Nagel's Dutch distribution network, fewer kilometers will be needed to transport salty snacks, cereals and nuts from manufacturing sites to the distribution center in Utrecht and further to retailers throughout the Netherlands. In addition, Kuehne + Nagel will develop a new state-of-the-art, multi-user FMCG warehouse in Utrecht, equipped with high bay storage and automatic layer picking during the first year of the agreement.http://knet.int.kn/ (2011)

The aim of the study that will be provided in this chapter is to give an insight to K+N logistics team about the possible effects of the new customer on K+N distribution network and evaluate possible alternative scenarios for the operational changes by constructing a simulation model. In the next sections, we introduce the 3PLs company, the problem definition in detail, our solution methodology and the corresponding simulation study performed to evaluate the future scenarios on K+N distribution network.

7.1 KUEHNE+NAGEL (K+N)

Kuehne+Nagel delivers integrated supply chain solutions to its customers. It has many locations in more than 100 countries all over the world with over 58,000 employees. K+N offices are mainly located in Africa, Asia Pacific, Europe, Middle East, and North America (http://knet.int.kn/ (2011)). The countries in the global logistics network are listed in Appendix C. The key business activities and market positions in the located regions are built on the company's world class capabilities which are

- Seafreight,
- Airfreight,
- Contract logistics and lead logistics
- Road and rail logistics.

The company provides logistics services to virtually all key industry sectors including aerospace, automotive, FMCG, high technology, industrials, oil and gas logistics, pharma and healthcare and retail.

7.2 K+N NETHERLANDS CONTRACT LOGISTICS

The company has been present in the Netherlands since 1955. In addition to sea freight and air freight activities, contract logistics also contributes to the company's business within Netherlands.

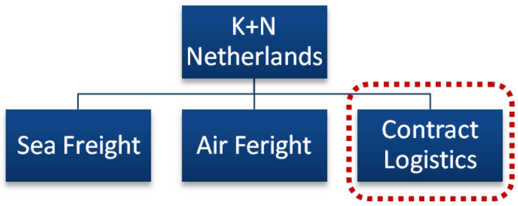

Figure 7.1: Key Business Activities of K+N in Netherlands

In the scope of contract logistics, K+N provides service to different customer profiles. Contract logistics in the company is divided into three business units:

- Technology Solutions,
- Fast Moving Consumer Goods (FMCG),
- Returns.

The contract logistics in K+N Netherlands is specialized in solutions to high technology and FMCG. In addition, reverse logistics activities for the FMCG customers are also provided. In the further sub-sections, business units, their functions and specialized facilities for these business units are explained. To provide a general view, K+N warehouses located in the Netherlands are shown in Figure 7.2. The company has many warehouses allocated to different business units to cover the distribution of goods. Besides these warehouses are specialized according to the main customers they are dedicated to.

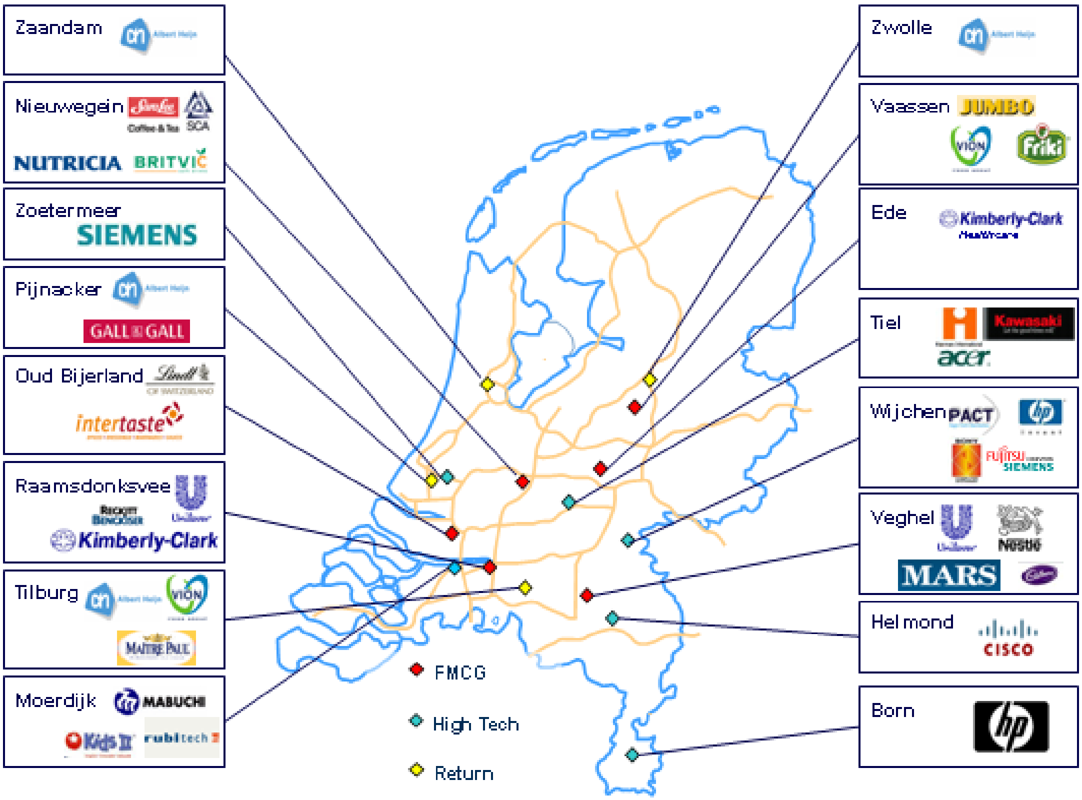

Figure 7.2: Contract Logistics - Netherlands

7.2.1 TECHNOLOGY SOLUTIONS

Facilities in Moerdijk, Zoetermeer, Tiel, Helmond, Born and Wijchen are dedicated to the Business Unit Technology Solutions. Products such as engines, small spare parts, complete communication systems, printers, etc. are stored and distributed over these warehouses. Also, this business unit is specialized in aftermarket sales technology in terms of Reverse Logistics and Service Logistics. A detailed overview of the facilities can be seen in Appendix D.

7.2.2 FMCG

FMCG is the biggest division of contract logistics within Netherlands. The distribution and storage of the retail goods to the retail distribution centers are provided by Kuehne+Nagel. The warehousing and dispatching of the retail goods are mainly handled in K+N FMCG facilities located in Nieuwegein, Veghel and Raamsdonskveer.

Facility Nieuwegein: The facility is located on 34,000 m^2. The unloading and loading of the goods are handled manually or by Automatic Layer Picker (ALP) system. The facility is specialized for FMCG Food warehousing and it is utilized for only national distribution. The main customers served via Nieuwegein are Sara Lee, Nutricia, SCA and Britvic. Among these customers, products for SCA are distributed over Benelux and the customer Britvic is leaving the network.

Facility Veghel: The facility is located on 103,000 m^2 and composed of three buildings. The buildings have different properties. One of them is a high bay warehouse with ALP. The facility serves as a national distribution center for Mars, Unilever and Nespresso and it serves as a duty free DC for Mars, Cadbury, Ferrero and Nestle. In addition, it serves for International Travel Retail (ITR) of Mars, Ferroro, Cadbury and Nespresso. Therefore, the facility is mostly specialized for these main customers.

Facility Raamsdonksveer: The facility is located on 40,000 m^2. The unloading and loading of the goods are handled manually or by ALP system. The facility serves as a manufacturing consolidation center for its customers. There are approximately 400 types of dangerous goods stored and handled in the facility. Therefore, the operations done within the facility differ from other facilities. The employees get special training to deal with the dangerous goods. The main customers served are Kimberly Clark Consumer, Reckitt Benckiser and Unilever Home and Personal Care.

More information about these warehouses and smaller facilities (Vaassen, Ede, Oud Beijerland) are provided in Appendix D.

7.2.3 RETURNS

The facilities in Zaandam, Zwolle, Tilburg and Pijnacker serve as return centers. These four return centers are recently taken over from Albert Heijn. The return centers are responsible for performing needed operations for all return goods such as boxes, packaging and crates which return from approximately 900 Albert Heijn stores in The Netherlands. There are different types of returns in the network:

- One type of return is collected from Albert Heijn distribution centers and delivered to K+N return centers. These type of returns are composed of wastes, boxes, recycle bottles and empty crates. These returns are sorted and processed in return centers and some of them are delivered back to the sourcing units. For example, after empty crates are washed in Tilburg facility, they are delivered back to the sourcing unit.
- The second type of return is the scheduled returns. These returns are collected from the retailer distribution centers and brought back to the K+N warehouses. These types of returns are mostly the

excess promotions.

- The third type of returns is composed of wrong deliveries. These type of returns have to be collected from the retailer distributions centers and delivered back to the K+N warehouses.

More information for the return centers can be seen in Appendix D.

7.2.4 CURRENT DISTRIBUTION (AS IS) NETWORK FOR FMCG and RETURNS

The company provides storage and distribution of FMCG to its customers. The transportation activities over the distribution network include:

- ***Primary Transport:*** Collection of goods from the sourcing units to K+N distribution centers,
- ***Secondary Transport:*** Delivery of goods from K+N distribution centers to retail distribution centers,
- All type of ***returns*** explained in section 7.2.3,
- ***Inter K+N:*** Delivery of all type of products between K+N depots,
- ***Direct Shipments:*** Pick-up and delivery orders from the customer site to the end customer's delivery address.

As it is listed, both forward and backward logistics are performed in the distribution network of FMCG within K+N Netherlands. The transportation activities over the distribution network are shown in the following figure:

This current distribution network in other words "AS IS" network runs with the following characteristics:

- Transport home base warehouses: Veghel, Raamsdonskveer , Nieuwegein
- Supporting home bases: Vaassen ,Ede, Oud Beijerland
- Retail return centers: Zaandam, Zwolle, Tilburg, Pijnacker.

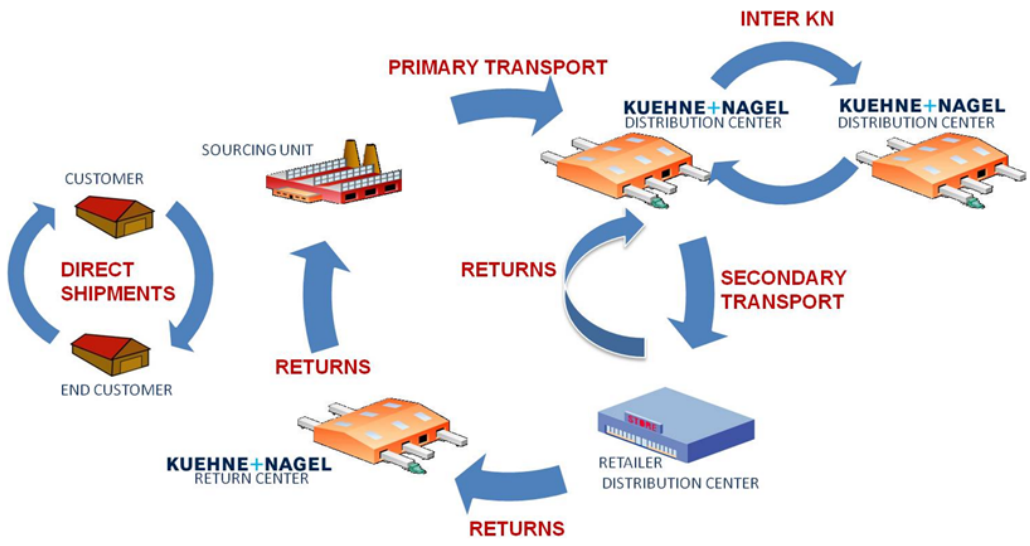

Figure 7.3: Current Distribution Network - FMCG and Returns

PLANNING OVER AS-IS NETWORK The planning over the distribution network is done by the planners on site. Every planner is responsible for his/her own trucks and truck drivers. The aim of the planners is to optimize the flows taking into account both the inbound and outbound logistics. The planners use the tool ”Intertour” for the transport optimization. However, in the current situation, planners do not utilize the optimization part of the software. Instead, the software is used as a visualization tool to plan the routes manually. After the routes are planned, these routes are assigned to the trucks to check the capacity. Hence, the capacity allocation is done as the second step. For the secondary transport, generally customer orders are consolidated and delivered to retail distribution centers. However, in these processes, there is not a complete integration of forward and reverse logistics because of the complexity of the network. The most important factors that affect the transportation planning are the customers' market pressure and strict time windows of the end customers. The company has three types of customer orders which are called Type A, Type B, Type C. Type C orders have lead time of 2 days, type B orders have lead time of 1 day and type A orders belongs to the orders delivered to Albert Heijn Retail Distribution Centers (RDCs). Type A orders are given at 12:00 every day and have to be delivered to Albert Heijn RDCs at night. In addition, according to the interview done with the transport planning manager, 80% of the deliveries have a specific time which means the delivery is assigned to the same day of the week to the same time window.

7.3 PROBLEM DEFINITION

”3PLs’ logistics networks typically differ from the logistics networks owned by single company. The primary purpose of the company-owned network is to take care of its own products and customers. However, 3PLs’ networks must consider a number of various clients over time. The network design issues can be divided into two categories with respect to the material flows: forward flow and reverse flow. Current 3PLs tend to provide logistics services for both flows.”Ko and Evans (2007)
As mentioned before, Kuehne + Nagel is a 3PL that performs both forward and reverse logistics for a variety of customers. For a 3PL to survive in the market, it is important to satisfy its customers with a high customer service level and low costs. In the dynamic environment of the retail sector it is important to take control over the costs and re-develop the existing network to keep pace with the changing market requirements.
Recently, K+N had a new contract with a new customer, PepsiCo. PepsiCo has products with lightweight but high volume products. The company expects an increase of approximately 50 % in the transportation activities with the addition of the new customer to the existing network. Therefore, it is important to analyze the current and future network, define the strategies for the future with the changing structure of the network.
System boundary is defined to decide which part of the network is in interest in Figure 7.4. The distribution network of the business units FMCGs and returns is in the system of interest since they are the components of the system that will be directly affected by the changing conditions. Among FMCGs and returns, we are not interested in the distribution over out of home (OOH) customers in Belgium (and partially in Netherlands) since the distribution is outsourced. The planning and distribution of goods are done by outsourcing transport companies. In addition, the facilities Vaasen, Ede and Oud Beijerland are described as supporting home bases which means they are not warehouses but there are trucks assigned to these facilities and most of the trucks start and end the trip in these facilities. Therefore, these facilities are also taken in the system boundary. In the environment of the system, there will be customers, end customers and subcontractors since they will be affected by the changes in the system.

The system boundary is defined but with PepsiCO there will be new opportunities and alternatives in the system. With the PepsiCo contract, the products will be distributed via K+N network by January 2011 which will lead to several changes in the network. With the addition of PepsiCo, it is foreseen an extension of the transport network activities. Therefore, a new warehouse will be opened in Utrecht by 2012 and the facility in Nieuwegein will be closed. The view of the main warehouses in the current (AS

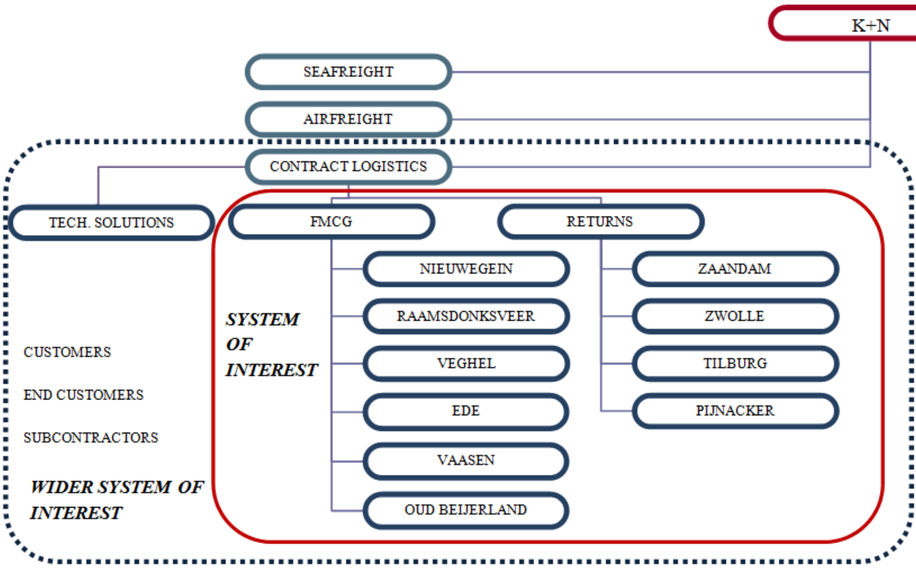

Figure 7.4: System of interest in terms of business units and facilities

IS) and the future (TO BE) networks are provided on the maps in Figure 7.5.

In addition to the changes in warehouses with PepsiCO contract, the firm will be able to use 3 LZVs (Langere en Zwaardere Vrachtautocombinatie) which are 25 meter long vehicles. The firm wants to know how to utilize these LZVs in TO BE network, including the decision of automatic or non-automatic unloading. Further investment on these vehicles is also in consideration if it is profitable. Moreover, more night and weekend deliveries are in consideration with changing conditions.

The company does not know precisely how much value is added by its recent customer to the network. Besides, it is not known how much value will be added by PepsiCo to the existing network and which companies will be more or less valuable when PepsiCo enters into the network. Hence, the company is looking for an assessment of the customer contributions to the network.

As mentioned before, in the current situation the primary transport is done between a specific warehouse and sourcing unit and the products of that sourcing unit is done via that specific warehouse. Another topic for the customer contribution is that the effect of change in the network in case of changing the gravity of the customer to other warehouses.

All in all, it is clearly seen that the new customer PepsiCO will change the AS IS network and there will be new alternatives over the distribution network. For the future of the distribution network, it is important to know the effect of PepsiCO over the AS IS and analyze further alternatives for TO BE.

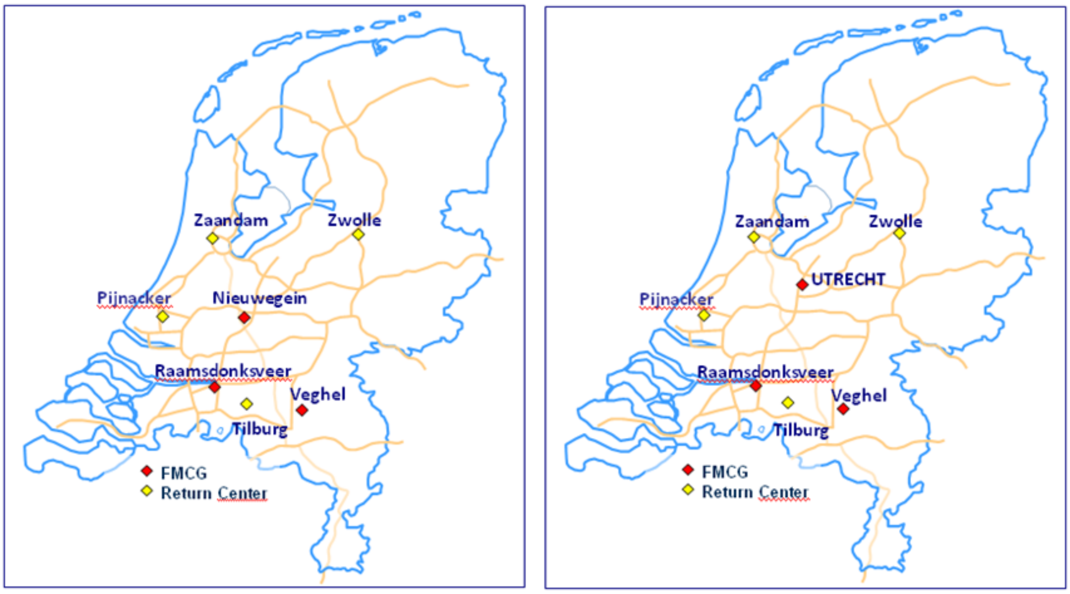

Figure 7.5: The AS IS network (on the left) and the TO BE network (on the right)

However, one important thing is to know about the current performance of AS IS network which will also guide us in the further phases of the research. The possible causes for the need of analysis of the AS IS network is given in the cause-effect diagram in Figure 7.6.

In accordance with the information and problems provided, it is necessary to define the research scope and the research questions in terms of what should be done in the further phases of the study.

7.4 RESEARCH DESIGN

As the distribution network is introduced and problems are described, it is decided to go through the following steps during the research study:

- There is a lack of analysis in the current system. As the first step; the current situation of the distribution network in the system of interest should be analyzed. The performance of the current distribution network should be measured to evaluate the efficiency and the effectiveness of AS IS network.
- The second step is the measure the impact of the new customer on the current network and operational processes.

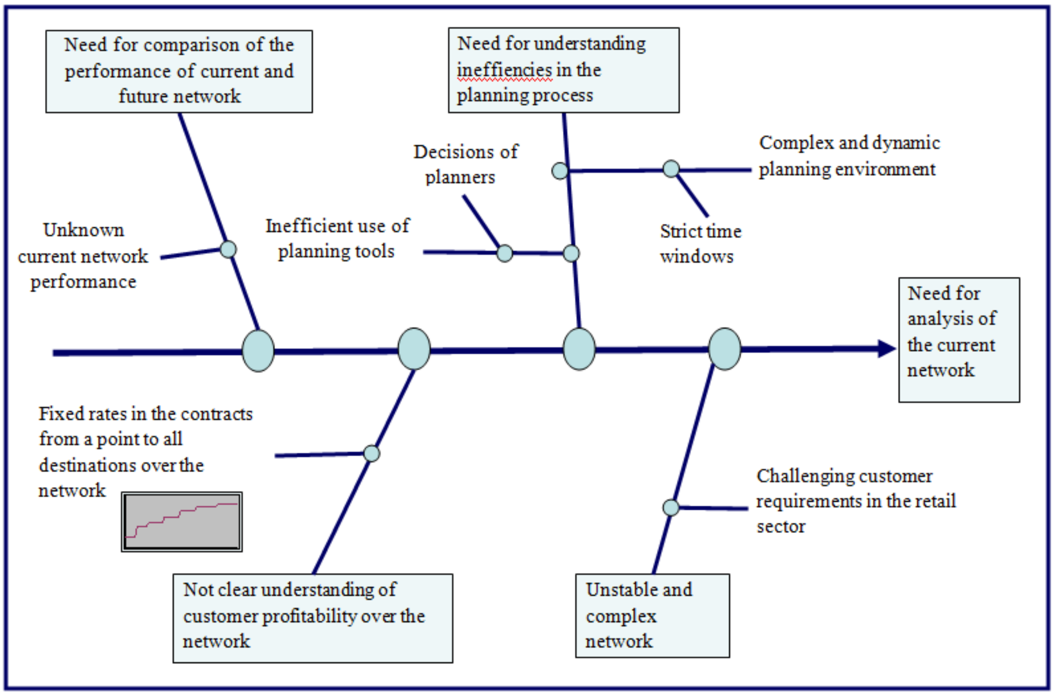

Figure 7.6: Cause-effect diagram for the analysis of the current network

- Finally, in line with the second step, what if analysis of the possible alternatives should be performed. In what if analysis, it is important to define different scenarios and alternatives to reach an optimized solution. The steps in the research scope are summarized in Figure 7.7. It is clearly seen that every step leads to a research question.

Throughout the study, in every research question same measures is used to evaluate the network performance and alternatives over the network. These performance measures are:

- Empty KMs traveled vs. Loaded KMs
- Capacity utilizations of the trucks
- Number of deliveries per period
- Order fulfilments
- Number of vehicles required per vehicle type
- Kilometers traveled and hours spent for each trip.

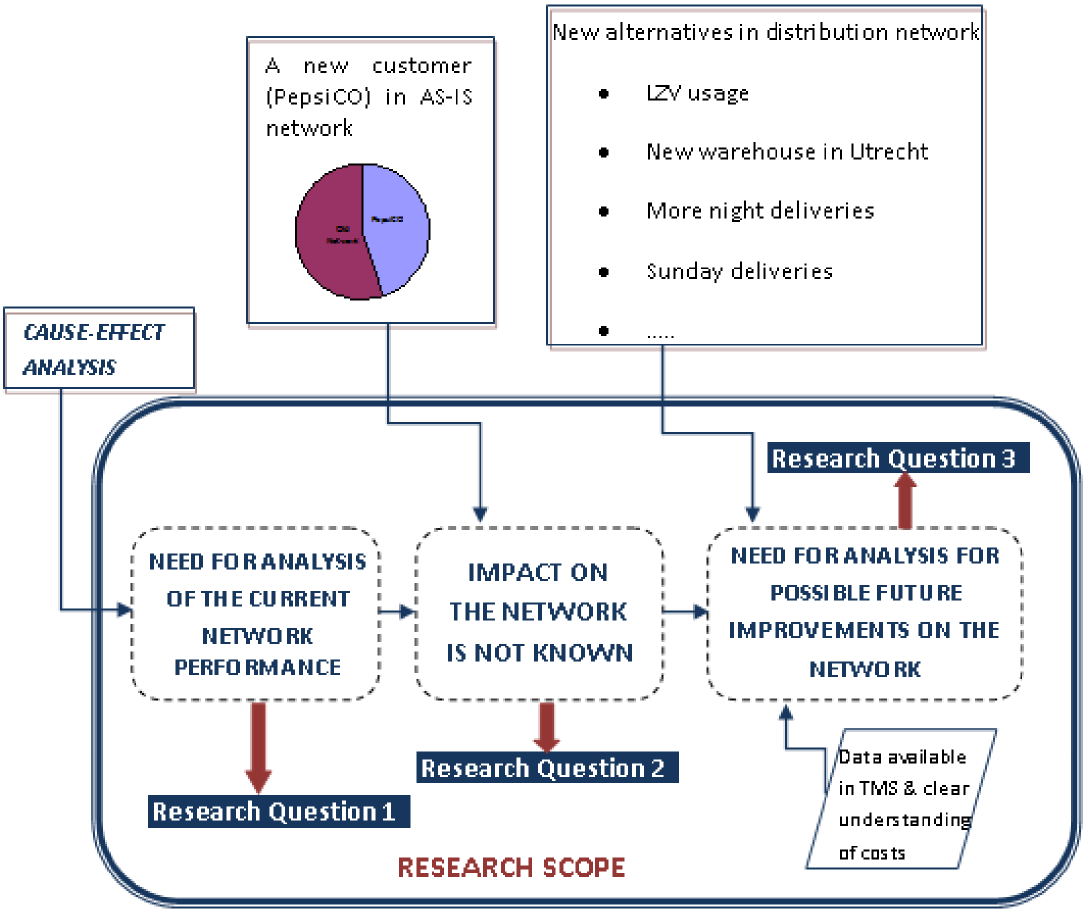

Figure 7.7: Research Scope

7.4.1 RESEARCH QUESTION 1

How does the current distribution network perform in K+N Netherlands for FMCGs and returns?

The objective of the first research question is to gain an insight on the current network performance of the company. Therefore, it is necessary to process the past data in order to derive quantitative results for performance measures. In addition to understanding the past performance, it is aimed to compare the performance of the network with the theoretical optimum. Hence, the approach that should be followed for this part is to first model the current network. For this, we can construct a simulation model, and then verify and validate the model so that we can compare the actual costs and simulation costs. According to the research conducted, the software SHORTREC is a suitable tool for simulation study. It is an automated trip routing and scheduling system and optimizes transport and distribution planning. The optimum allocation of the vehicle fleet by efficiently filling in trips, combined with the fastest routes, enables the user to agree more accurate delivery times with its clients. In addition, the best planning can be determined in a unique situation by comparing various scenarios. Accordingly, we can compare the performance of the current network with the optimum solution found by SHORTREC.

7.4.2 RESEARCH QUESTION 2

How will the new customer affect the performance of the current distribution network with FMCGs and returns?

The objective of the second research question is to see the affect of the new customer in the network in terms of transportation costs. Therefore, the approach that should be followed for the second research question is to construct the model with the new customer included in the network. For the simulation study it is decided to use the software SHORTREC.

7.4.3 RESEARCH QUESTION 3

How to minimize costs in an expanding network within a dynamic environment?
How to utilize alternative methods to find the optimum solution for FMCGs and returns network?
There will be new alternatives to be evaluated such as

- A new warehouse: This alternative includes the new warehouse that will be opened in Utrecht.
- New vehicles (LZVs) utilized: In this alternative, it is aimed to evaluate the optimal use of LZVs.
- Operational changes in the system:
- Allowing more night deliveries and more Sunday deliveries: With this alternative, the company will be assumed to work for 24 hours over 7 days a week.
- Overnight stay of truck drivers which also means multi-day planning.

With the new warehouse the network will become TO BE network. Hence, the alternatives should be evaluated to minimize the costs over TO BE network. In Figure 7.8, the structure of the research design is provided. The research will be conducted starting with analysis of the AS IS network followed by measuring the impact of PepsiCo. Lastly TO BE network will be constructed and new alternatives over TO BE network will be evaluated. Throughout this study, detail planning is not in research scope since the network is dealt with at high level. Therefore, it is more convenient to conduct the research with SHORTREC in which the planning over the FMCG network can be determined and various alternatives can be compared. Accordingly, the defined alternatives can be evaluated in an easy manner by using SHORTREC.

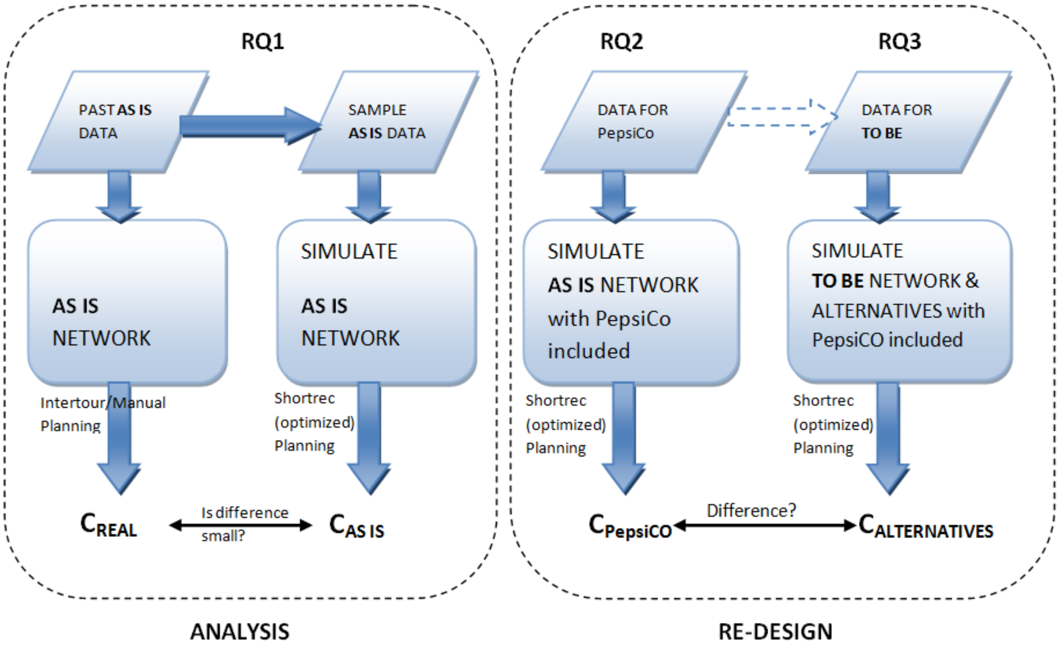

Figure 7.8: Structure of Research Design

7.5 AS IS NETWORK

The data to perform the necessary analysis for AS IS network were collected from the Transportation Management System (TMS) of the company. However, it is important to select the data within the system boundary. The transportation services within the company are performed by their own trucks, subcontractors and charters. When the company cannot satisfy the demand of its customers by its own trucks, subcontractors' trucks are utilized. In addition, there are two different uses of charters. The first type of charter firms work for Kuehne + Nagel but make their own planning. The second type of charter service is used when there is excess demand within the distribution network. We exclude the first type of charter firms in the analysis since they are responsible of their own planning. Therefore, the data collected for the analysis do not include the trips performed by these companies such that 20 carriers out of 50 are excluded in the analysis.

To perform analysis of the transportation network of the company 26 weeks data were collected. However, it was costly in terms of time and effort, to make the analysis for all the collected data. Therefore, three representative weeks were chosen for the analysis, simulation and the comparison of the two. The total kilometers covered and the total demand volume were taken into account to select the representative weeks. The distance calculations in the system are based on the theoretical distances and a common weight-volume measure, which is called chep equivalent units, is used for all types of products in the company database. Moreover, in the selection, the weeks with very high or very low demand were ignored. The weeks in which there were national holidays or the weeks in vacation time were also ignored. Thus, the following weeks were chosen for the analyses in general:

- High volume week: Week 35
- Medium volume week: Week 11
- Low volume week: Week 23

Kilometers covered for the 26 weeks data on a weekly basis can be seen in Figure 7.9.

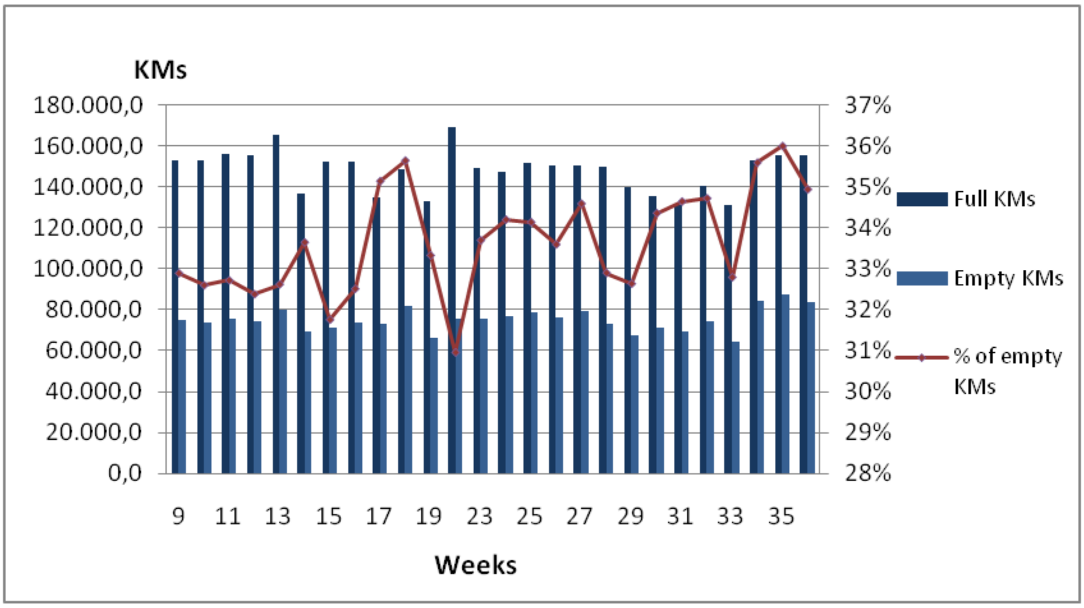

Figure 7.9: Total overview kilometers traveled in 26 weeks

A general statistics of the empty and full kilometers is provided in Table 7.1.

Table 7.1: Summary of the kilometers covered

	Minimum	Average	Maximum
Full KMs	130906	148036	168795
Empty KMs	64039	75072	87318
Total KMs	195300	223108	245802
% of empty KMs	31%	34%	36%

Figure 7.10 shows the KMs traveled per trip execution type. In the graph, when refer to K+N KMs, the temporary workers hired to service customers by using KN trucks is also included. Though, it is seen that KMs covered by subcontractor firms increases from the week with low level of demand, KMs covered by K+N owned trucks decreases.

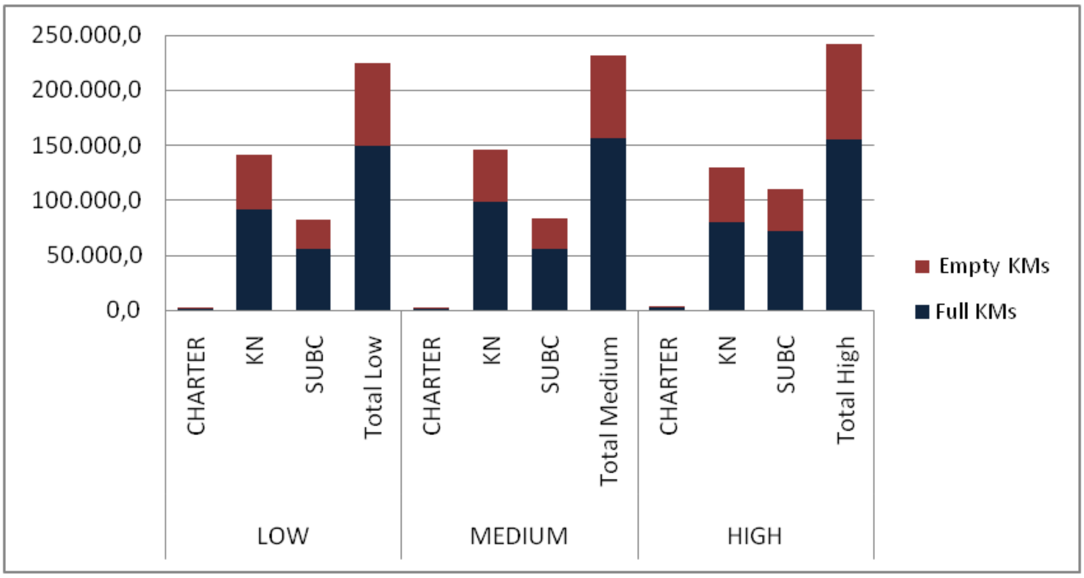

Figure 7.10: Trip execution type KM distributions

In Figure 7.11, we also see the decrease in the number of trips performed in AS IS network decrease from low to high. However, the average trip length is much higher in the week medium and high than the week low. Thus it can be concluded that, KN used its own trucks more efficiently when then demand level increased. This is also due to the temporary workers hired in this period. The temporary workers were only utilized at the week with high level of demand. Temporary workers were used in 15 weeks in total out of 26 week data.

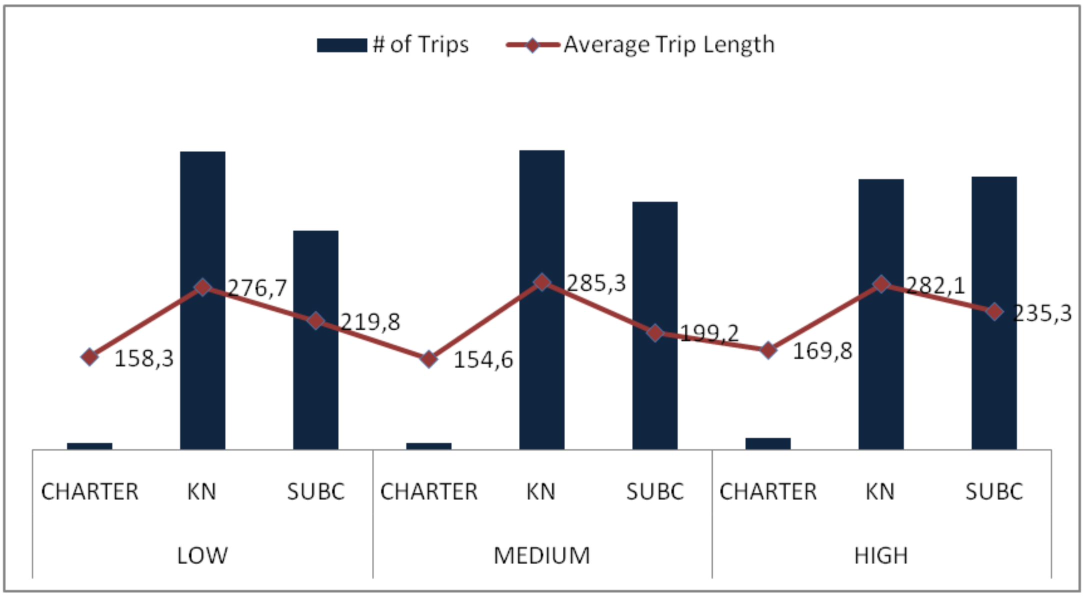

Figure 7.11: Number of trips vs. average trip length

7.6 SIMULATION STUDY

7.6.1 SIMULATION TOOL

In order to simulate the TO-BE Network, commercial routing software SHORTREC was used as the simulation tool to solve the VRPTW. SHORTREC is a program for trip and route planning developed by ORTEC consultants. The route planning indicates the best route for a vehicle to take between two or more addresses. The trip planner, on the other hand, assigns orders to the entire vehicle fleet in an efficient way. The objective of the program is to minimize the total related costs by taking into account various type of restrictions such as

- Heterogeneous and fixed vehicle fleet
- Multiple capacity constraints of vehicles (volume, height and weight)
- Product requirements (eg. Cooling)
- Handling of backhaul customers (suppliers)
- The sequence of the service of the customer (first or last)
- Load capacity

- Multiple service intervals (loading and unloading time windows)
- Distance
- Depots
- Drivers' working hours
- Driving times.

By the allowance of these factors, SHORTREC makes efficient plans for the user. These plans can be analyzed in various ways and can be adapted according to the planner's preferences. Although SHORTERC is an automated planning system, manual adjustments can be made within trips after the planning is done. The software has many different interfaces which makes it easier for the user to make modifications in the plan. In addition, the scenario analysis option enables to draw up various plans and compare them with each other. Furthermore, the output of the software provides detailed reports about the kilometers driven, the overtime of drivers, service levels etc. All in all, SHORTREC has many features for efficient route planning. However, it is important for the user to define the requirements before deciding to implement the software. The tool's comparison with different vehicle routing softwares in terms of their specifications, features and capabilities is presented in Hall (2006). The detailed solution approach of SHORTREC is beyond our knowledge. However, there is basic information in the literature (Kant et al. (2008) and Poot et al. (1999)) about how the software handles real life vehicle routing problem restrictions.

7.6.2 SHORTERC SOLUTION METHODOLOGY

SHORTREC first finds a basic solution by construction heuristics and then improves the first solution by improvement heuristics. Sequential insertion algorithm and saving based algorithm are used as constructive heuristics to find a feasible solution. The main idea behind the insertion algorithm is to add non-served customers to the current plan by inserting them at the best position. Once it is not possible to insert a customer into the current trip anymore, the algorithm starts with a new trip Poot et al. (1999). Figure 7.12 summarizes the steps for the sequential insertion algorithm used in SHORTREC.

In order to overcome the unattractive view of the results of the sequential insertion algorithm, SHORTREC developers also used saving based algorithm. The idea behind the algorithm is to start with each

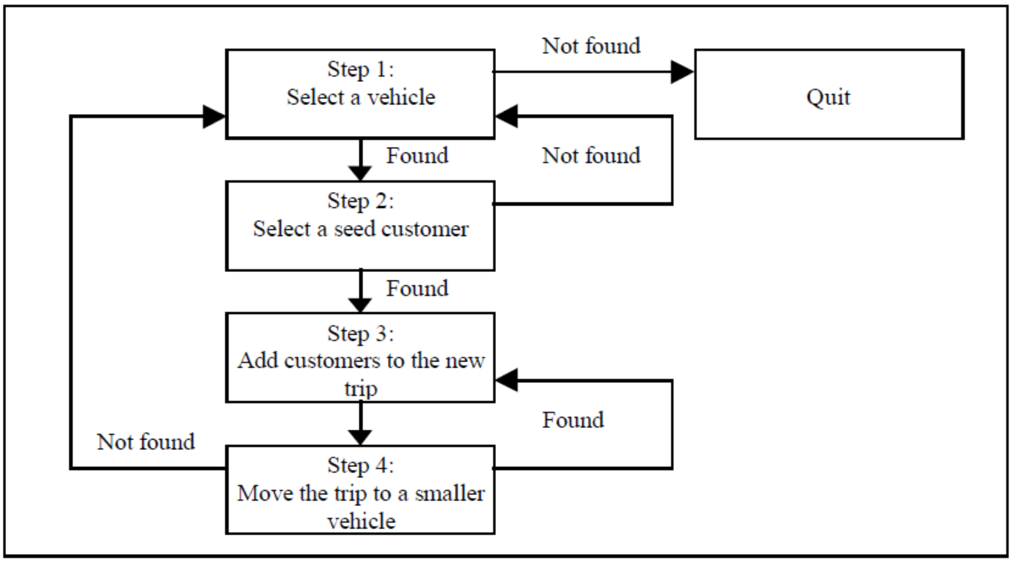

Figure 7.12: The Sequential Insertion Algorithm for VRP Poot et al. (1999)

customer in a separate trip and then try to find improvements on this solution (”savings”) by combining the customers of two trips into one trip without changing the order in which the customers are visited Poot et al. (1999). In order to handle the real life restriction of vehicle routing problem, adjustments were made on the algorithm. The main steps of the saving based algorithm are summarized in Figure 7.13.

After the basic solution is found variable neighborhood search is utilized as improvement heuristics. Several neighborhood structures (the opt algorithms) are used, the order and frequency of which can be determined by the user. In a way, these neighborhoods are used as building blocks, to create a heuristic solution method that is adapted to the specificities of the routing problem at hand. By this way the solver can be adapted by the user, so that a balance is reached between computing time and solution quality. Moreover, a large degree of control over the length of the search can be defined. Schittekat (2010). In the version of SHORTREC used in this study, a repetition cycle of the following option settings can be formed and a maximum run time can be specified in total and for each of the options to improve the basic solution:

1. **Basic Solution:** The basic solution involves preliminary allocation of orders to vehicles (trips). The basic algorithm adds the orders to the schedule, and then all other algorithms seek to improve it. The basic algorithm is the so called construction algorithm; the following are the enhancement algorithms

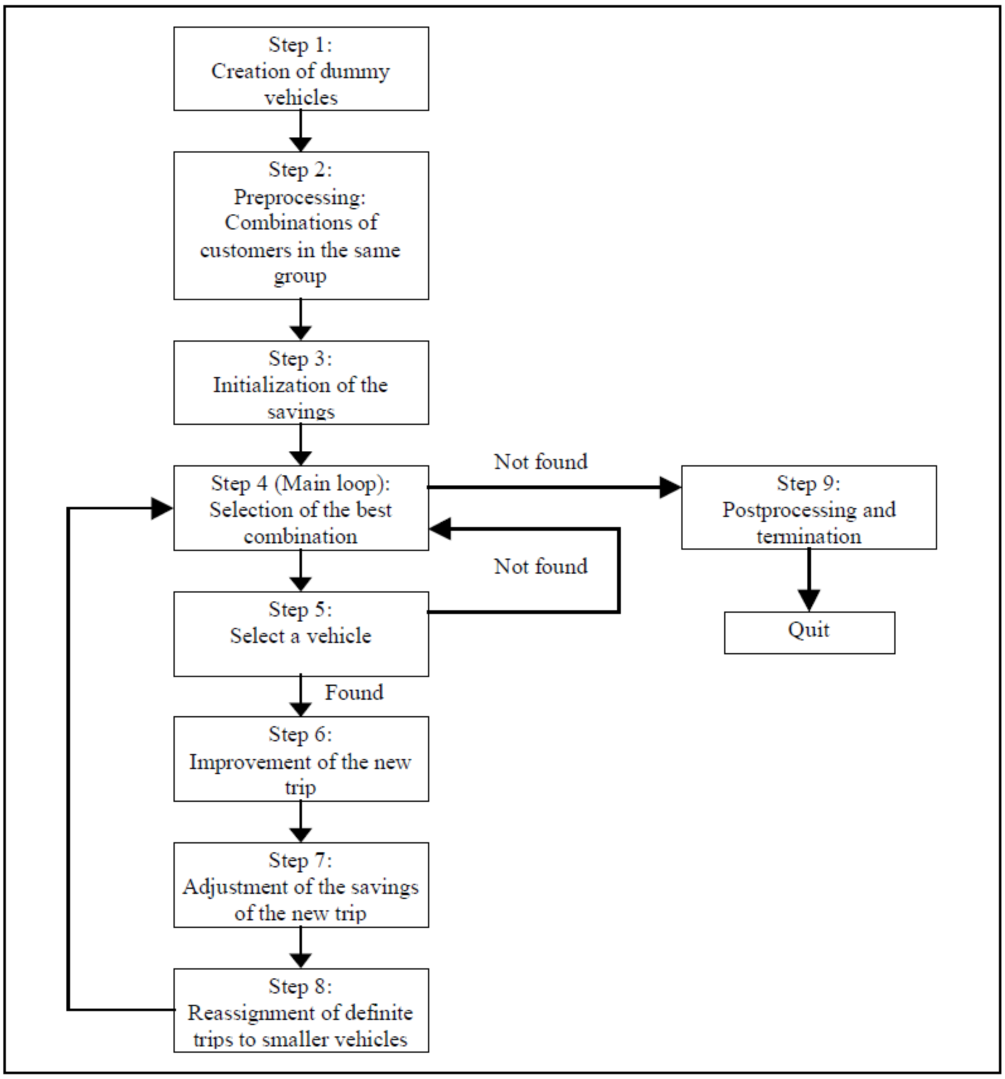

Figure 7.13: The Savings Based Algorithm for VRP Poot et al. (1999)

and their calculation times can be adjusted.

2. **Optimize within trip**: SHORTREC seeks to improve on the sequence of orders assigned to each trip, so as to reduce the cost of the plan. The optimization process does not involve moving orders within trips.

3. **Replacing of orders:** The optimization option involves assessing each possible pair of planned trips to establish whether a cost saving is possible by moving one or more orders from one trip to the other.

4. **Optimize within trips:** This procedure is a combination of the optimization options 7 and 8.

5. **Equalize workload:** SHORTREC tries to equalize the number of hours worked in different trips.

This is done by applying a notional surcharge the time that each vehicle is in use in excess of the average. If this optimization option is activated, the plan is liable to become more expensive in terms of kilometers covered and overall resource utilization time. However, the work will be more evenly distributed across the vehicle fleet.

6. **Selection of cheapest vehicles:** This optimization process involves assigning each complete set of tasks to the vehicle that can perform at the lowest cost. SHORTREC's basic solution is based only on capacity and availability. Some trips may, therefore, initially be assigned to vehicles that are relatively expensive to operate or are locate a considerable distance from the trip's starting point. The purpose of this optimization process is to identify vehicles that could do the work more cheaply, because they are either cheaper to operate or located more conventionally.

7. **Trip swapping:** In the context of this optimization process, each pair of trips is assessed, to see whether the cost of the plan could be reduced by swapping them over.

8. **Stop swapping:** This option also entails trying to minimize the cost of the plan. Every trip pairing examined to assess the cost implications of swapping some of their orders (i.e. moving one or more orders from trip A to trip B and one or more orders from trip B to trip A.)

A view of the option settings for the opt algorithms in SHORTREC can be seen in Appendix E. In addition to these explanations, the reader is referred to Close (2009) for a more detailed explanation of SHORTERC solution approach.

7.6.3 SIMULATION MODEL PARAMETERS SETTINGS

In order to simulate the transportation system of the company, the parameters in the simulation software were defined and estimated. The data collected from the TMS were used in order to estimate the parameters. Furthermore, an Excel tool is created to transfer the data from TMS into simulation input so that further simulations can be performed for other purposes in the company. The parameters were tested on the AS-IS network simulations and then utilized in the TO-BE network simulations.

7.6.3.1 PLANNING HORIZON

In the sample simulation runs, the rolling horizon was taken as one week in order to simulate the representative weeks at one time. However, the results couldn't be validated with the real figures of the AS-IS network. Therefore, the planning horizon was taken as one day for the simulation. Another arrangement was done in order to plan the night delivery orders. These orders couldn't be planned when the working hours of the depots and the vehicle fleet were taken as 24 hours. For example, the orders to be delivered at 23:30 or 00:30 couldn't be planned since the vehicle cannot return the depot in 30 minutes from the delivery address or cannot leave the depot and be at the delivery address in 30 minutes. Hence, in the simulations, the working hours of the depots, trucks and drivers were taken as from 00:01 to 30:00. It was tested that the six hours extension would be sufficient to prevent the planning problem discussed. Unfortunately, with this setting all the possible scenario analysis for operational changes within the system such as multi-day planning were eliminated.

7.6.3.2 LOADING AND UNLOADING TIMES

The unloading and loading time analysis was done for the depots and non-depot points separately because of two reasons. Firstly, in the company database, only the vehicle arrival and departure times at an address exist. Therefore, the time between the arrival and departure time not only includes the time required to load or unload the orders but also the waiting time at the address. Secondly, when drivers arrive at the depot, the trailers are already loaded.The drivers only couple the trailer to the truck. Time is needed only for paper work. This is the same for unloading. The drivers only uncouple the trailer and do the paperwork when they arrive to the depot with loaded truck. Therefore, the time between the departure and arrival times in the database does not include any information about the times of the loading and unloading processes. On the basis of this information, the following calculations were done for the loading and unloading time analysis.

DEPOT LOADING AND UNLOADING TIMES The loading and unloading time of the orders at the depot does not depend on the number of pallets loaded at the depots. Therefore, a simple average of the loading and unloading durations was taken.

NON-DEPOT LOADING AND UNLOADING TIMES The following times are meant by the loading and unloading times at non-depots:

- The loading time at customer's pick-up address for direct shipment
- The loading time at sourcing unit for primary transport

- The unloading time at end customer's delivery address for direct shipment
- The unloading time at customer's delivery address for secondary transport.

Every driver is responsible for loading and unloading the orders at specified points on the route. Differently from the loading and unloading times at the depots, the times in this section also depend on the loaded or the unloaded quantities. Moreover, the duration in the database includes the time for loading or unloading activity, waiting time at the point and the time needed for paperwork. In order to calculate the times for the simulation, a linear regression model was constructed such that the dependent variable in the model is the loading/unloading time and the loaded/unloaded quantity is the only explanatory variable. Figure 7.14 and Figure 7.15 shows the loaded quantity line fit plots respectively. The descriptive statistics for the two regression models is provided in Appendix F.

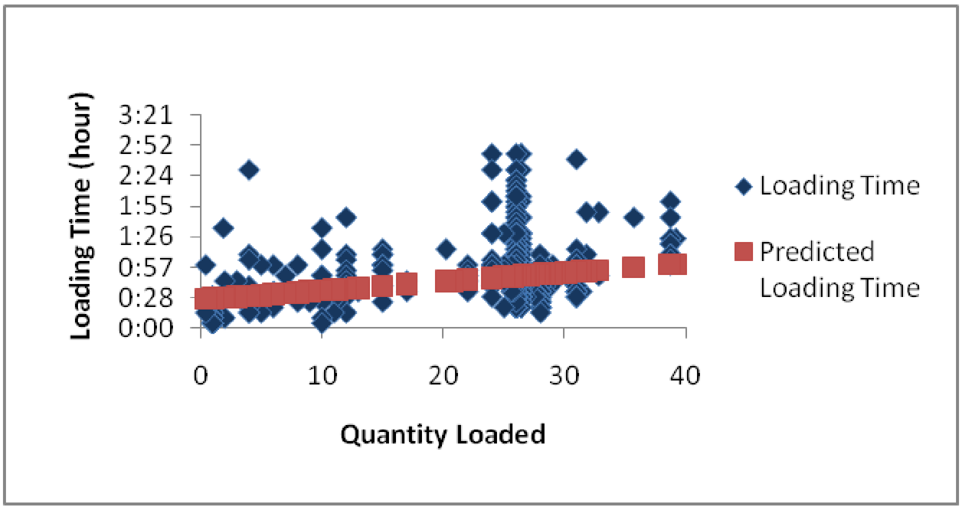

Figure 7.14: Quantity loaded line fit plot

Based on the results of the two regression models the fixed and variables times for loading and unloading times at customers' addresses were defined. However, in the test simulations, it is realized that the loading and unloading times in total is larger than the actual figures. Hence, it was decided to decrease the fixed times for loading and unloading activities considering that the durations also includes the waiting times at the depots. In conclusion, the parameters for loading and unloading times are defined as in Table 7.2.

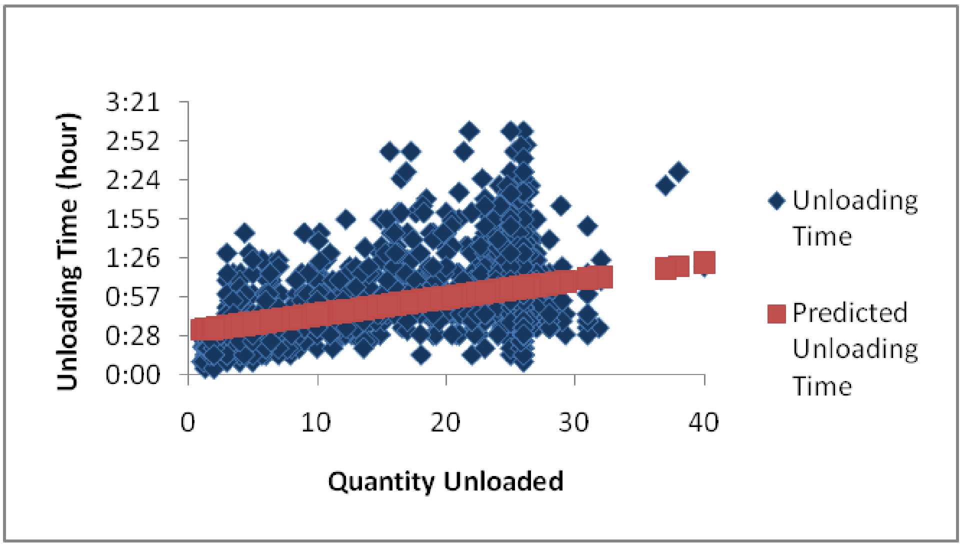

Figure 7.15: Quantity unloaded line fit plot

Table 7.2: Loading and unloading time parameters

	Depots		Non-Depots	
	Loading Time	Unloading Time	Loading Time	Unloading Time
Fixed Time (min.)	27	27	24	30
Variable Time per chep equivalent unit (min.)	0	0	1	1

7.6.3.3 FIXED AND VARIABLE COSTS

The fixed cost of utilizing a truck in the planning horizon was provided by the logistics engineers in the firm. In the simulations, the fixed cost of utilizing a KN truck is the lowest and utilizing a charter truck is the highest. A comparison of the costs are presented in Figure 7.16.

The variable cost a truck based on the kilometers traveled and hours spent are calculated using shipment costs. To calculate the shipment costs all weekly costs were summarized. Average hour and kilometer costs were calculated based on these total weekly costs. These costs are also used in the contracts with the customers. The variable cost comparison for each vehicle type is provided in Figure 7.17.

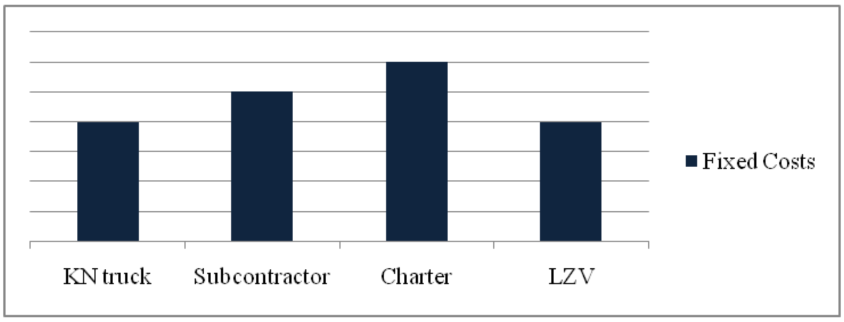

Figure 7.16: Fixed cost comparison of utilizing a truck

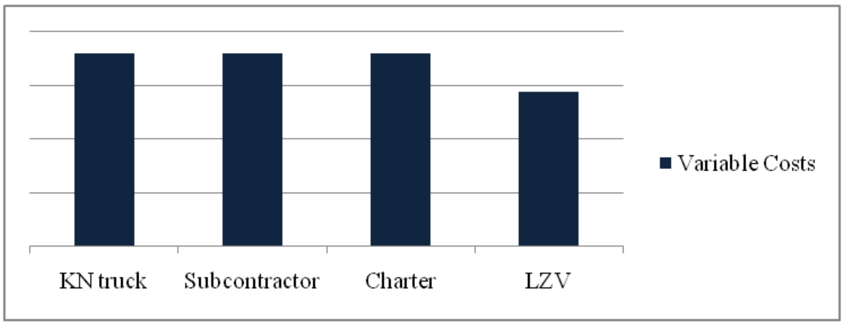

Figure 7.17: Variable cost comparison of utilizing a truck

7.6.3.4 THE OPT ALGORITHMS SETTINGS

The opt algorithms which were used for improving the basic solution and constructing a complete solution are described in section 7.6.2. According to the list of these options, the following sequence of opt algorithms were utilized to obtain the complete solution:

1. The solution starts with the basic solution

2. The repetition cycle starts and repeated five times with the following sequence of opt algorithms:

   a.Selection of the cheapest vehicle

   b.Optimize within trips

   c.Trip swapping

   d.Equalize workload

   e.Optimize within trips

f.Trip Swapping

7.6.4 VERIFICATION and VALIDATION OF THE SIMULATION MODEL

7.6.4.1 VERIFICATION

Verification is defined by Law and Kelton (1991) as determining that a simulation computer program performs as intended. Based on this definition, the companies who use SHORTREC as a vehicle routing and simulation tool are the main references to verify the simulation software. Quak and Koster (2005) used SHORTREC to calculate the impacts of different time window pressure scenarios for fourteen Dutch retailers. In addition, SHORTREC is used by several of the retail organizations involved in their study. Moreover, several implementations were made for companies such as Coca-Cola Enterprises, InBev, BP, DHL, Yellow Transportation, Philips, Royal Ahold etc. Kant et al. (2008),Hall (2006)

7.6.4.2 VALIDATION

"Validation is concerned with determining whether the conceptual simulation model (as opposed to the computer program) is an accurate representation of the system under study"Law and Kelton (1991). In this study, actual figures of three representative weeks were compared with the results in SHORTREC in order to validate settings in the software program.

Table 7.3: AS IS network actual figures and simulation results

		Weekly Average			Weeks' Average
		HIGH	MEDIUM	LOW	
# of trucks:	ACTUAL	125	126	117	122.67
	SIM. AS IS	122	119	108	116.33
	%Δ (ACTUAL-SIM.)	2%	6%	8%	5%
# KMs:	ACTUAL	63892	65139	59275	62768.67
	SIM. AS IS	64877	61460	57666	61334.33
	%Δ (ACTUAL-SIM.)	-2%	6%	3%	2%
# of hours:	ACTUAL	1991	1969	1853	1938.67
	SIM. AS IS	1931	1790	1662	1794.33
	%Δ (ACTUAL-SIM.)	3%	9%	10%	7%

In Table 7.3, a summary of the actual figures and the simulation results in terms of the number of trucks utilized, kilometers covered and number of hours worked for the representative weeks is given. These figures were accepted as good enough to validate the simulation results. However, it was observed that the performance of the software decreases as the number of orders increases, i.e. the number of orders approaches to 1000 for a day. The percentage difference between the simulation and the actual figures increases from the week with high level of demand to the week with low level of demand. Although we expected the simulation software would perform better than the actual performance of the network, in some cases we see that the actual figures are better than the results of the simulation tool. For example, in the case of the week with high demand level, the average kilometers covered for the actual figures are even lower than the planning results. Therefore, this issue was considered when interpreting the results of the TO BE network. In addition, in order to test this argument, very small orders which were assigned to the same address were combined. This combination was allowed up to 20% of the vehicle capacity not to affect the planning process of the software. Thus fewer orders were obtained for all the days within representative weeks. In conclusion, average number of trucks used decreased for all weeks. However, kilometers covered and number of hours worked increased for the week with low demand. The detailed figures for Table 7.3 and AS IS network with combined orders can be seen in Appendix G.

7.6.5 TO BE NETWORK SIMULATION

The definition of TO BE network and the changes with this definition are described with the problem definition in Section 7.3. To validate the simulation settings, a base simulation model was constructed and TO BE network simulation was constructed with some changes on this base simulation model. The changes are listed below:

- The orders in the TO BE network are the combination of the AS IS orders and PepsiCO orders. To select the representative PepsiCo orders, the same approach was followed with AS IS orders. However, only the data of PepsiCo with medium level demand week were used due to data inaccuracy. Therefore, TO BE network was planned to be simulated with three representative weeks with additional PepsiCo orders with medium demand level.
- The vehicle fleet in the TO BE network is the combination of the AS IS trucks and the trucks utilized by PepsiCo before the contract. The new trucks are included in the simulation as

  22 additional trucks owned by KN,

  3 LZVs and

5 subcontractors' truck.

- All orders that belong to the depot Nieuwegein are simulated as if they are distributed by the new warehouse that will be opened in Utrecht, Lageweide.

One important decision in TO BE distribution network simulation was to allocate the transportation lines that LVZs would be in use since every vehicle in the simulation model has to be assigned to a depot. It is not possible in SHORTREC to optimally decide on the allocation decision. Therefore, the lines with most full truck load orders were defined over 26 week data. The lines with most frequent full truck loads per day were selected. The selected lines can be seen in AppendixH. For the decision of allocating the three LZVs (taken over from PepsiCo) to depots, four alternative scenarios were created. The allocation of LZVs to depots for different scenarios is represented in Table 7.4.

Table 7.4: Alternative Scenarios for LZV allocations

ALLOCATION	S0	S1	S2	S3
LZV1	UTRECHT	UTRECHT	UTRECHT	UTRECHT
LZV2	UTRECHT	UTRECHT	VEGHEL	VEGHEL
LZV3	UTRECHT	VEGHEL	VEGHEL	RAAMSDONKSVEER

Moreover, for the case of addition of extra LZVs to the transportation network which is defined as scenario "S4", 10 more LZVs were added to each depot and simulations were performed. The results are presented in the next section.

7.6.6 SIMULATION RESULTS

Simulation results of the scenarios S0, S1, S2 and S3 for the weeks with low, medium and high level weeks can be seen in Appendix I. The averages for the simulation days are given in Table 7.5 for each scenario. The aim was to simulate TO BE network with different allocations of LZVs to defined depots in Table 7.4. In the figures, it can be noticed that 5% of the available trucks are not used. In the results of the AS IS network simulation for validation, it can also be seen that 5% of trucks are not utilized. Therefore, based on this argument, it may be concluded that with the addition of PepsiCO to the AS IS network, the performance of the network would not change.

According to results in Table 7.5, there is not a big difference between the scenarios chosen. This is due

Table 7.5: Average figures for the simulation results

	S0	S1	S2	S3
KMs	82175.3	82012.5	82050	81621.4
% of Empty KMs	35%	35%	35%	35%
# of Hours	2340.7	2340.3	2341.7	2177.8
# of Available Trucks	149.8	149.8	149.8	149.8
# of Trucks Used	142.9	142.9	142.9	142.8
% of trucks Used	95%	95%	95%	95%
# of LZVs Used	3	3	3	3

to the size of the network. Changing the assignment of LZVs to different locations does not affect the performance of the network significantly. This conclusion led us to simulate the network in an alternative scenario ”S4” where 10 extra LZVs are assigned to each depot in TO BE network. Table 7.6 represents the results for scenarios S0 and S4. In addition, detailed results are given in Appendix J. The results

Table 7.6: Average simulation results for scenarios ”S0” and ”S4”

	S0 Avg.	S4 Avg.
KMs	81486.8	80457.7
% of Empty KMs	35%	35%
# of Hours	2298.6	2279.2
# of Available Trucks	148.3	148.5
# of Trucks Used	130.7	140.4
% of Trucks Used	88%	95%
# of LZVs Used	15.5	3

in Table 7.6 show that adding more LZVs to TO BE network will not make a big difference such that the KMs covered decreased by only 1.26% on average in S4. The percentage of empty KMs traveled did not change and the number of hours worked on average decreased by 0.86%. The chep equivalent units carried per km in each scenario is also compared as an alternative performance indicator. While the chep equivalent units carried per km is 11.8 in scenario S0, it is 11.7 in scenario S4 which means on average less chep equivalent units are carried per km by utilizing more LZVs in the latter scenario. Although the number of available trucks utilized decreased in S4 compared to S0, on average 12.5 more LZVs are used in S0 instead. The allocation of the average number of LZVs used is listed in Table 7.7 which shows that all the extra LZVs are used in Utrecht for all the simulation days. However, it is not needed to utilize the LZVs for other depots as much as in the case of Utrecht. For example, the LZVs assigned to Raamsdonksveer, Ede and Oud Beijerland are not utilized at all as we restricted the usage of the LZVs to lines on which most FTL orders are carried per day.

Table 7.7: Allocation of LZVs used

	Utrecht	**Veghel**	**Vaassen**
Day 1	13	1	1
Day 2	13	1	1
Day 3	13	1.5	1.5
Day 4	13	1.5	-
Day 5	13	2	2

7.7 CONCLUDING REMARKS

In the final section dedicated to the research project of Kuehne+Nagel Netherlands, we summarize what has been done and recommend future research directions.

7.7.1 CONCLUSION

The aim of the project conducted for Kuehne+Nagel was to analyze the affect of the new customer in the distribution network of FMCG and returns. To reach this aim, it was proposed to simulate the network by the routing software SHORTREC since detailed planning was not in the scope of the project. In the project, firstly, AS-IS network was analyzed and three representative weeks for the simulation was chosen. These representative weeks were used to validate the results of the simulation tool with the actual figures calculated from the TMS of K+N. Since SHORTREC is an optimization tool, we expected that the simulation results would be better than the actual figures. However, it was observed that this argument was not always true, especially when the number of orders increased the performance of the simulation tool decreased. Based on this observation, in the scenarios created for TO-BE network, it can be concluded that with the additional trucks and LZVs taken over from the new customer to the distribution network, there will not be a change in the performance of the distribution network of Kuehne+Nagel. Nevertheless, it is not necessary for K+N to buy new LZVs with the aim of increasing the network performance. But it is clear that, if new LZVs are utilized within the network, they should be assigned to the new depot which is to be constructed in Utrecht.
One important issue with the project was that because of the restriction of the software, not all the performance indicators mentioned in the beginning could be measured or alternative scenarios could be simulated. For example, as we had to choose the planning horizon as 29 hours in order to simulate the night deliveries, overnight stay of truck drivers or central planning could not be evaluated. However, with the Excel tool coded in VBA to generate SHORTREC input from the data of TMS, a template was

built for the company to simulate further scenarios in the future. As the distribution network of K+N has a very dynamic environment, it is better for the company to have a standard for the simulations and build more scenarios on it.

Last but not least, compared to the current regional planning system ,where route planning is performed manually by on site planners ,the routing software could perform good enough. In terms of costs, the planning software can be less costly to the company compared to the manual route planning if it is implemented.

7.7.2 FUTURE RESEARCH DIRECTIONS

At the accomplishment of this project, it is noticed that there are directions for future research in the transportation network design of the distribution system of the company.

First of all, during the AS-IS analysis, it is observed that the company plans customers' orders regionally. It will be interesting to re-cluster these customers in order to optimize the network efficiency and comparing it with the current assignment of the customers to the depots. There can be improvement opportunities to increase the performance of the distribution network.

Secondly, instead of regional planning, improvement opportunities can be searched by central planning. This can be an interesting future research though the implementation would require a lot of effort.

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APPENDICES

APPENDIX A

SPEED PROFILES

Table A shows the speed profiles used to include the time dependency in the Solomon instances. The travel time breakpoints are calculated as in the procedure described in Ichoua et al. (2003) by using these speed profiles.

Table A.1: Speed Profiles

	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
Fast	1.5	1	1.67	1.17	1.33
Normal	1.17	0.67	1.33	0.83	1
Slow	1	0.33	0.67	0.5	0.83

APPENDIX B

RESULTS

The explanation for the columns in the tables used in this Appendix are given as in the following:

- ”Instance” : Name of the instance
- ”Forw. labels” : Total number of labels produced by forward TDL algorithm
- ”Back. labels” : Total number of labels produced by backward TDL algorithm
- ”Σ labels” : Total number of labels produced in the pricing problem
- ”Time” : The total time spent to solve an instance
- ”Tree” : The size of the branching tree
- ”N.cols” : Number of columns produced by column generation
- ”N.pric exact” : Number of calls to the exact pricing algorithm.

Tables B.1 and B.3 summarize the results for the case (Initial) in which pricing problems is solved as TDESSPRC by bi-directional TDL algorithm for instances with 25 and 50 customers, respectively. In addition, Tables B.2 and B.4 show the results when fathoming is implemented in the pricing problem ,which is indicated as (Initial+Fathoming) for the instance with 25 and 50 customers, respectively.

Table B.1: Computational results for instances with 25 customers (Initial)

Instance	Forw. labels	Back. labels	Σ labels	Time	Tree	N. cols	N. pric exact
r101.25	133	155	288	0.063	0	162	1
r102.25	984	7002	7986	0.593	0	311	3
r103.25	14436	68898	83334	15615	2	778	9
r104.25	105128	362044	467172	74116	4	823	16
r105.25	970	966	1936	0.234	0	241	3
r106.25	2568	13415	15983	1482	0	404	4
r107.25	9384	41399	50783	5335	0	676	4
r108.25	79362	224115	303477	58079	2	911	9
r109.25	5993	4844	10837	0.952	0	459	5
r110.25	5773	7703	13476	1248	0	413	3
r111.25	38882	149892	188774	22495	8	708	20 2
r112.25	476583	502501	979084	157951	26	1276	55
c101.25	5475	1483	6958	0.515	0	423	2
c102.25	402253	343139	745392	151025	6	2914	22
c103.25	4333772	8577834	12911606	33685.1	6	5528	25
c105.25	69714	13131	82845	12418	4	1361	15
c106.25	6884	3080	9964	0.733	0	479	4
c107.25	229615	102148	331763	62837	10	2599	26
c108.25	1330492	501380	1831872	337071	36	5020	129
rc101.25	14490	9447	23937	7691	14	1035	32
rc105.25	11849	11705	23554	3058	2	698	9
rc106.25	8744	4906	13650	0.826	0	406	4
rc107.25	32235	11322	43557	3448	0	1022	4
rc108.25	135129	45378	180507	24.71	0	968	5
r201.25	167881	8637	1325956	13993	2	914	10
r202.25	965449	996932	12306101	5746.73	0	778	3
c201.25	660	25690	26350	1778	0	702	1
c205.25	5148	387209	1006441	250897	0	1177	4
c208.25	150398	4360321	1580432	12876.1	0	3033	7
rc201.25	1315775	10181	4510719	772688	2	1546	12
rc205.25	984611	21830	1962381	928892	0	1310	5

Table B.2: Computational results for instances with 25 customers (Initial+Fathoming)

Instance	Forw. labels	Back. labels	Σ labels	Time	Tree	N. cols	N. pric exact
r101.25	131	128	259	0.453	0	162	1
r102.25	981	6859	7840	26598	0	311	3
r103.25	7584	45286	52870	322095	2	778	9
r104.25	47167	264122	311289	1053.44	4	816	12
r105.25	964	928	1892	3369	0	241	3
r106.25	2494	13254	15748	74725	0	404	4
r107.25	8169	40032	48201	276371	0	676	4
r108.25	69151	218995	288146	1352.04	2	911	9
r109.25	5052	4596	9648	33478	0	459	5
r110.25	5732	7471	13203	69842	0	413	3
r111.25	38155	148453	186608	943323	8	708	20
r112.25	474519	494809	969328	5659.37	26	1276	55
c101.25	622	266	888	2808	0	423	2
c102.25	276836	234750	511586	2447.08	6	2881	23
c103.25	1166775	4253207	5419982	57410.1	6	5528	25
c105.25	54277	4177	58454	133786	4	1361	15
c106.25	2129	639	2768	7036	0	460	4
c107.25	157244	19595	176839	386571	10	2532	23
c108.25	1072969	215616	1288585	6324.08	32	5151	109
rc101.25	13355	8866	22221	67.33	14	1036	31
rc105.25	10091	9499	19590	66784	2	670	8
rc106.25	8723	4662	13385	69233	0	406	4
rc107.25	32212	10970	43182	266809	0	1022	4
rc108.25	135035	44081	179116	1770.42	0	968	5
r201.25	62105	3197	65302	256996	2	914	10
r202.25	639173	539461	1178634	11224.8	0	778	3
c201.25	39	110	149	0.921	0	702	1
c205.25	299	35892	36191	208667	0	1077	4
c208.25	7703	1979448	1987151	15639.3	0	3031	7
rc201.25	671029	4970	675999	2246.37	2	1562	11
rc205.25	750276	15811	766087	4020.93	0	1310	5

Table B.3: Computational results for instances with 25 customers (Initial)

Instance	Forw. labels	Back. labels	Σ labels	Time	Tree	N. cols	N. pric exact
r101.50	2311	2309	4620	0.889	0	567	3
r105.50	28273	13175	41448	16239	2	1330	8
r109.50	84082	73983	158065	25366	2	1560	12
r110.50	1920768	1884639	3805407	848.77	44	3217	100
c101.50	1104023	109248	1213271	196031	6	5309	25
c106.50	1893087	234841	2127928	409487	10	6864	42
rc101.50	1858406	1336968	3195374	1328.1	696	5998	1059

Table B.4: Computational results for instances with 25 customers (Initial+Fathoming)

Instance	Forw. labels	Back. labels	Σ labels	Time	Tree	N. cols	N. pric exact
r101.50	2311	1553	3864	12465	0	567	3
r105.50	964	928	1892	182116	2	1330	8
r109.50	75211	63970	139181	1595.16	2	1560	12
r110.50	1915469	1818913	3734382	62453.3	44	3217	100
c101.50	75211	63970	139181	2053.11	6	5429	21
c106.50	75211	63970	139181	4849.31	10	6918	42
rc101.50	1814061	1322109	3136170	15734.6	686	6243	1063

APPENDIX C

GLOBAL LOGISTICS NETWORK OF K+N

Table C.1: The Global Logistics Network of KUEHNE+NAGEL

Africa	**Europe**	**Asia Pacific**	**Middle East**	**North America**	**South & Central America**
Angola	Albania	Afghanistan	Azerbaijan	Canada	Argentina
Equatorial Guinea	Austria	Australia	Bahrain	Mexico	Bolivia
Kenya	Belarus	Bangladesh	Egypt	United States	Brazil
Mauritius	Belgium	Cambodia	Iran		Chile
Mozambique	Bosnia & Herzegovina	China	Israel		Colombia
Namibia	Bulgaria	Hong Kong/China	Jordan		Costa Rica
Nigeria	Croatia	India	Kazakhstan		Cuba
Réunion	Cyprus	Indonesia	Kuwait		Ecuador
South Africa	Czech Republic	Japan	Lebanon		El Salvador
Tanzania	Denmark	Korea	Qatar		Guatemala
Uganda	Estonia	Macau/China	Saudi Arabia		Honduras
Zambia	Finland	Malaysia	Turkey		Nicaragua
Zimbabwe	France	Maldives	Turkmenistan		Panama
	Germany	New Zealand	United Arab Emirates		Peru
	Greece	Pakistan	Uzbekistan		Puerto Rico
	Hungary	Philippines			Uruguay
	Ireland	Singapore			Venezuela
	Italy	Sri Lanka			
	Latvia	Taiwan			
	Lithuania	Thailand			
	Luxembourg	Vietnam			
	Macedonia				
	Malta				
	Netherlands				
	Norway				
	Poland				
	Portugal				
	Romania				
	Russian Federation				
	Serbia				
	Slovak Republic				
	Slovenia				
	Spain				
	Sweden				
	Switzerland				
	United Kingdom				
	Ukraine				

APPENDIX D

K+N NETHERLANDS FACILITIES

Table D.1: Facilities dedicated to technology solutions business unit

TECHNOLOGY SOLUTIONS			
	Zoetermeer	**Moerdijk**	**Tiel**
Characteristics	Dedicated solution for Siemens 2,500 m2 500 m2 shelving Spare parts operation	12,000 m2 Very high security level, 24/7	54,000 m2, 3,000 m2 office 4 bulk compartments of 30,400 m2 Tapa C Secured 67 Docks Fully sprinkled
Key Capabilities	Centrally Located High Security Level RF Based Complete Service Offering 24/7 Standby Service	Warehousing X-dock Transport Management Multi modal transport solutions Custom solutions, incl. fiscal representative Buyers consolidation	Warehousing Multi modal transport solutions Transport Management Value Added Services RF based operation
	Wijchen - PACT	**Helmond**	**Born**
Characteristics	7.000 sqm x-dock for High Tech TAPA A secured Security & zero-damage driven processes Trucking and delivery to a.o. Benelux, FR,	22,000 m2 High Security Level / TAPA C Operating hours Mon-Fri 24 hours	21,025 m2 886 m2 office High security level
Key Capabilities	Highly Secured Transport network Visibility during transport 1 single IT system in all countries Customized IT support Control Tower, pro-active process control	Return logistics (quarantine area) Warehousing Packing and Labeling Transport Management Configuration Customs activities (cust. clearance) RF based / paperless operation	Warehousing Multi modal transport solutions Transport Management Value Added Services

Table D.2: Facilities dedicated to FMCG business unit

FAST MOVING CONSUMER GOODS			
	Veghel	**Raamsdonksveer**	**Nieuwegein**
Characteristics	103,000 m2 (three buildings) High bay Warehouse	40,000 m2 36 Loading docks Automatic Layer Picker (ALP)	34,000 m2 Automatic Layer Picker (ALP) Centrally Located
Key Capabilities	Warehousing (ALP) / Factory Warehousing Raw materials and Packaging National Distribution / Primary Transport Transport co-ordination Co-packing RF based / paperless operation Complete service offering	Manufacturing Consolidation Centre National distribution Co-packing Very high security level RF based / paperless operation Multilingual	FMCG Food oriented Multilingual Complete Service Offering National Transport
	Oud Beijerland	**Ede**	**Vaassen**
Characteristics	5,600 m2 Ambient storage 200 m2 temperature Controlled area	23,000 m2 10,0 m free height Fully sprinkled Centrally located	16,000 m2 Crate Washing Machines
Key Capabilities	Warehousing Co-packing Transport Management Custom solutions RF based / paperless operation Multilingual	Warehousing and Co-packing RF based / paperless operation Focused on non food customers Multilingual	National platform Chilled distribution Cross docking activities Conditioned Warehousing Services (crate and pallet rental/washing) Complete chilled service offerings

Table D.3: Facilities dedicated to returns business unit

	Pijnacker	Tilburg
Characteristics	14,000 m2 700 - 1,000 trucks a day	1,000 m2 Crates washing machine 14,000 m2 Sorting area 1,750 m2 Docks in-out
Key Capabilities	Inhouse Return Centre: Processing of returns and waste Processing of re-usable packaging Crate and pallet washing/rental RF based / paperless operation Multilingual	Multi user crate and washing centre Crates rental / pallet rental FTL transport Pool management Receiving, sorting and sending returns Control returning goods
In addition to these return centers Zaandam and Zwolle are taken over from Albert Heijn.		

APPENDIX E

SHORTREC OPTION SETTINGS

Figure E.1: Option Settings for Opt Algorithms in SHORTREC

APPENDIX F

DESCRIPTIVE STATISTICS FOR REGRESSION MODELS OF LOADING AND UNLOADING TIMES

Table F.1: Summary output of loading time regression model

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.215178
R Square	0.046302
Adjusted R Square	0.045309
Standard Error	0.017337
Observations	963

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.014024	0.014024	4.665.616	1.5E-11
Residual	961	0.288865	0.000301		
Total	962	0.302889			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 90.0%*	*Upper 90.0%*
Intercept	0.018918	0.002198	8.608.555	2.99E-17	0.0153	0.022536
Quantity Loaded	0.000589	8.63E-05	6.830.532	1.5E-11	0.000447	0.000732

Table F.2: Summary output of unloading time regression model

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.410407
R Square	0.168434
Adjusted R Square	0.167908
Standard Error	0.018167
Observations	1582

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.105623	0.105623	3.200.301	2.55E-65
Residual	1580	0.521463	0.00033		
Total	1581	0.627086			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 90.0%*	*Upper 90.0%*
Intercept	0.022071	0.001033	2.137.099	3.23E-89	0.020371	0.023771
Quantity Unloaded	0.000883	4.93E-05	1.788.938	2.55E-65	0.000801	0.000964

APPENDIX G

AS IS NETWORK SIMULATION RESULTS

Table G.1: Results for the week with high level of demand

	(1) ACTUAL				
	DAY 1	**DAY 2**	**DAY 3**	**DAY 4**	**DAY 5**
# of trucks:	120	123	132	130	122
# of km:	58956	68849	65724	69340	56592
# of hours:	1888	2131	2017	2131	1790
	(2) ORDERs AS IS				
	DAY 1	**DAY 2**	**DAY 3**	**DAY 4**	**DAY 5**
Total costs:	73175	83343	85655	86071	72918
# of scheduled orders:	904	1008	1052	1082	907
# of unscheduled orders:	0	8	0	4	0
# of trips:	275	323	303	310	284
# of trucks:	117	123	129	130	112
# of km:	57867	70584	68954	69271	57707
# of hours:	1779	2042	2051	2041	1744
	(3) SMALL ORDERs COMBINED				
	DAY 1	**DAY 2**	**DAY 3**	**DAY 4**	**DAY 5**
Total costs:	66571	76013	78294	77917	66207
# of scheduled orders:	706	740	785	760	698
# of unscheduled orders:	0	1	0	0	0
# of trips:	262	301	286	292	267
# of trucks:	106	112	119	120	102
# of km:	55340	66588	62920	62433	53485
# of hours:	1656	1862	1851	1842	1549

Table G.2: Results for the week with medium level of demand

	(1) ACTUAL				
	DAY 1	DAY 2	DAY 3	DAY 4	DAY 5
# of trucks:	127	125	127	127	122
# of km:	63133	64047	69004	68639	60870
# of hours:	1983	1982	2057	2053	1771
	(2) ORDERs AS IS				
	DAY 1	**DAY 2**	**DAY 3**	**DAY 4**	**DAY 5**
Total costs:	73385	76811	80768	77114	72456
# of scheduled orders:	941	987	978	985	937
# of unscheduled orders:	1	0	0	0	0
# of trips:	257	279	281	269	258
# of trucks:	119	119	124	119	113
# of km:	56490	63241	65651	62717	59199
# of hours:	1696	1866	1854	1852	1680
	(3) SMALL ORDERs COMBINED				
	DAY 1	**DAY 2**	**DAY 3**	**DAY 4**	**DAY 5**
Total costs:	80954	79360	81877	77892	61528
# of scheduled orders:	668	682	667	663	617
# of unscheduled orders:	1	0	0	0	0
# of trips:	209	203	193	182	243
# of trucks:	119	115	117	110	96
# of km:	79536	81953	85040	82446	54664

Table G.3: Results for the week with low level of demand

	(1) ACTUAL				
	DAY 1	**DAY 2**	**DAY 3**	**DAY 4**	**DAY 5**
# of trucks:	118	116	116	116	121
# of km:	49467	64533	60835	66713	54827
# of hours:	1608	1941	1907	2063	1747
	(2) ORDERs AS IS				
	DAY 1	**DAY 2**	**DAY 3**	**DAY 4**	**DAY 5**
Total costs:	66483	66005	73669	77973	66197
# of scheduled orders:	828	853	922	951	796
# of unscheduled orders:	1	1	1	11	0
# of trips:	249	250	252	288	247
# of trucks:	104	105	114	116	100
# of km:	57311	52673	59234	65102	54011
# of hours:	1531	1600	1719	1869	1592
	(3) SMALL ORDERs COMBINED				
	DAY 1	**DAY 2**	**DAY 3**	**DAY 4**	**DAY 5**
Total costs:	55529	67198	64345	65889	60309
# of scheduled orders:	620	826	706	693	716
# of unscheduled orders:	0	0	5	6	0
# of trips:	207	248	226	247	222
# of trucks:	90	104	99	100	93
# of km:	45467	56531	52479	55938	50443
# of hours:	1357	1635	1539	1579	1484

APPENDIX H

SELECTION OF LINES WITH MOST FREQUENT FULL TRUCK LOAD ORDERS

As the number of full truck load orders are calculated on the distribution lines, the average figures for the number of FTL orders are derived. LZVs are allowed to serve only on these lines.

Table H.1: Transportation lines with full truck load orders

From Address Description		**To Address Description**		**FTL orders**	**~ FTL/day**
City	**Customer**	**City**	**Customer**		
Rotterdam	Unilever Nederland	*Veghel*	Kuehne+Nagel	2041	15.7
Utrecht	Den Koffiefabriek	*Utrecht*	Kuehne+Nagel	1271	9.78
Oss	Vdbn Sourcing Unit	*Veghel*	Kuehne+Nagel	844	6.49
Vaassen	Kuehne+Nagel Log.	*Wezep*	Plukon Poultry BV	889	6.84
Veghel	Vetipak	*Veghel*	Kuehne+Nagel	638	4.91
Joure	De Nl Tea (M008)	*Utrecht*	Kuehne+Nagel	360	2.77
Veghel	Kuehne+Nagel	*Veghel*	Vetipak	341	2.62
Wezep	Plukon Poultry BV	*Veghel*	Jumbo S.	320	2.46
Vaassen	Kuehne+Nagel	*Beilen*	Super de Boer	219	1.68
Veghel	Kuehne+Nagel	*Veghel*	Vetipak	211	1.62
Vaassen	Kuehne+Nagel Log.	*B. Spakenburg*	Mayonna B.V.	194	1.49
Beilen	Super de Boer	*Vaassen*	Kuehne+Nagel Log.	193	1.48
Zwolle	K+N Log. MCO	*Wezep*	Plukon Poultry BV	179	1.38
Veghel	Jumbo Supermarkten	*Vaassen*	Kuehne+Nagel Log.	176	1.35

APPENDIX I

TO BE NETWORK SIMULATION RESULTS

Table I.1: Results for the week with low level of demand

		SIM. TO BE, WEEK : LOW				SIM. STATISTICS		
		S0	S1	S2	S3	MIN.	AVG.	MAX.
DAY 1	KMs	70757	70757	70757	70757	70757	70757	70757
	% Empty	36%	36%	36%	36%	36%	36%	36%
	# of Hours	2037	2039	2039	2039	2037	2039	2039
	# of Available Trucks	145	145	145	145	145	145	145
	# of Trucks Used	131	131	131	131	131	131	131
	# of LZVs Used	3	3	3	3	3	3	3
DAY 2	KMs	80256	80256	80099	80099	80099	80178	80256
	% Empty	35%	35%	35%	35%	35%	35%	35%
	# of Hours	2266	2269	2265	2265	2265	2266	2269
	# of Available Trucks	143	143	143	143	143	143	143
	# of Trucks Used	138	138	138	138	138	138	138
	# of LZVs Used	3	3	3	3	3	3	3
DAY3	KMs	83141	83213	83284	83265	83141	83226	83284
	% Empty	34%	34%	34%	34%	34%	34%	34%
	# of Hours	2286	2288	2291	2290	2286	2289	2291
	# of Available Trucks	143	143	143	143	143	143	143
	# of Trucks Used	142	142	142	142	142	142	142
	# of LZVs Used	3	3	3	3	3	3	3
DAY 4	KMs	88740	88812	88812	83265	83265	87407	88812
	% Empty	35%	35%	35%	36%	35%	35%	36%
	# of Hours	2478	2481	2483	2454	2454	2474	2483
	# of Available Trucks	143	143	143	143	143	143	143
	# of Trucks Used	143	143	143	143	143	143	143
	# of LZVs Used	3	3	3	3	3	3	3
DAY 5	**KMs**	75011	75011	75082	75082	75011	75047	75082
	% Empty	35%	35%	35%	35%	35%	35%	35%
	# of Hours	2043	2046	2047	2047	2043	2046	2047
	# of Available Trucks	148	148	148	148	148	148	148
	# of Trucks Used	122	122	122	122	122	122	122
	# of LZVs Used	3	3	3	3	3	3	3

Table I.2: Results for the week with medium level of demand

		SIM. TO BE, WEEK : MEDIUM				SIM. STATISTICS		
		S0	S1	S2	S3	MIN.	AVG.	MAX.
DAY 1	KMs	72619	71945	72380	69260	69260	71551	72619
	% Empty	34%	35%	35%	34%	34%	34%	35%
	# of Hours	2100	2085	2084	2084	2084	2088	2100
	# of Available Trucks	154	154	154	154	154	154	154
	# of Trucks Used	139	138	138	138	138	138	139
	# of LZVs Used	3	3	3	3	3	3	3
DAY 2	KMs	82455	82455	82455	82455	82455	82455	82455
	% Empty	33%	33%	33%	33%	33%	33%	33%
	# of Hours	2421	2422	2425	2424	2421	2423	2425
	# of Available Trucks	152	152	152	152	152	152	152
	# of Trucks Used	146	146	146	146	146	146	146
	# of LZVs Used	3	3	3	3	3	3	3
DAY3	KMs	86481	86552	86552	86536	86481	86530	86552
	% Empty	35%	35%	35%	35%	35%	35%	35%
	# of Hours	2422	2422	2426	2425	2422	2424	2426
	# of Available Trucks	154	154	154	154	154	154	154
	# of Trucks Used	154	154	154	154	154	154	154
	# of LZVs Used	3	3	3	3	3	3	3
DAY 4	KMs	87107	87107	87107	86118	86118	86860	87107
	% Empty	35%	35%	35%	34%	34%	35%	35%
	# of Hours	2537	2536	2536	2511	2511	2530	2537
	# of Available Trucks	154	154	154	154	154	154	154
	# of Trucks Used	150	150	150	150	150	150	150
	# of LZVs Used	3	3	3	3	3	3	3
DAY 5	KMs	78010	79255	79255	79236	78010	78939	79255
	% Empty	33%	34%	34%	34%	33%	34%	34%
	# of Hours	2202	2205	2208	2202	2202	2204	2208
	# of Available Trucks	149	149	149	149	149	149	149
	# of Trucks Used	139	139	139	139	139	139	139
	# of LZVs Used	3	3	3	3	3	3	3

Table I.3: Results for the week with high level of demand

		SIM. TO BE, WEEK : HIGH				SIM. STATISTICS		
		S0	S1	S2	S3	MIN.	AVG.	MAX.
DAY 1	KMs	71834	71905	71905	71886	71834	71883	71905
	% Empty	34%	34%	34%	34%	34%	34%	34%
	# of Hours	2173	2175	2177	2174	2173	2175	2177
	# of Available Trucks	147	147	147	147	147	147	147
	# of Trucks Used	136	136	136	136	136	136	136
	# of LZVs Used	3	3	3	3	3	3	3
DAY 2	KMs	90447	90447	90447	90447	90447	90447	90447
	% Empty	35%	35%	35%	35%	35%	35%	35%
	# of Hours	2579	2576	2579	2578	2576	2578	2579
	# of Available Trucks	150	150	150	150	150	150	150
	# of Trucks Used	150	150	150	150	150	150	150
	# of LZVs Used	3	3	3	3	3	3	3
DAY3	KMs	92159	92159	92159	92159	92159	92159	92159
	% Empty	34%	34%	34%	34%	34%	34%	34%
	# of Hours	2660	2663	2665	264	264	2063	2665
	# of Available Trucks	159	159	159	159	159	159	159
	# of Trucks Used	159	159	159	159	159	159	159
	# of LZVs Used	3	3	3	3	3	3	3
DAY 4	KMs	95903	92603	92675	95975	92603	94289	95975
	% Empty	37%	37%	37%	37%	37%	37%	37%
	# of Hours	2653	2639	2639	2650	2639	2645	2653
	# of Available Trucks	157	157	157	157	157	157	157
	# of Trucks Used	156	157	157	156	156	157	157
	# of LZVs Used	3	3	3	3	3	3	3
DAY 5	KMs	77710	77710	77781	77781	77710	77746	77781
	% Empty	36%	36%	36%	36%	36%	36%	36%
	# of Hours	2254	2259	2261	2261	2254	2259	2261
	# of Available Trucks	149	149	149	149	149	149	149
	# of Trucks Used	139	139	139	139	139	139	139
	# of LZVs Used	3	3	3	3	3	3	3

APPENDIX J

SIMULATION RESULTS FOR SCENARIOS S0 AND S4

Table J.1: Results of scenarios S0 and S4

		SIM. TO BE (S0)		SIM. TO BE (S4)	
		LOW	**MEDIUM**	**LOW**	**MEDIUM**
DAY 1	KMs	70757	72619	69163	72701
	% Empty	36%	34%	36%	35%
	# of Hours	2037	2100	1976	2076
	# of Available Trucks	145	154	145	154
	# of Trucks Used	131	139	116	128
	# of LZVs Used	3	3	15	15
DAY 2	KMs	80256	82455	79145	84395
	% Empty	35%	33%	34%	35%
	# of Hours	2266	2421	2254	2408
	# of Available Trucks	143	152	143	152
	# of Trucks Used	138	146	123	137
	# of LZVs Used	3	3	16	14
DAY 3	KMs	83141	86481	83758	91469
	% Empty	34%	35%	33%	36%
	# of Hours	2286	2422	2361	2521
	# of Available Trucks	143	154	143	153
	# of Trucks Used	142	153	136	145
	# of LZVs Used	3	3	15	17
DAY 4	KMs	88740	87107	90182	90643
	% Empty	35%	35%	34%	33%
	# of Hours	2478	2536	2517	2556
	# of Available Trucks	143	154	143	153
	# of Trucks Used	143	150	139	142
	# of LZVs Used	3	3	15	14
DAY 5	KMs	75011	78010	74240	79172
	% Empty	35%	33%	35%	33%
	# of Hours	2043	2202	2100	2217
	# of Available Trucks	148	149	148	149
	# of Trucks Used	132	139	114	127
	# of LZVs Used	3	3	17	17